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Research Paper

# A Multi-Period Model for Optimal Changi Airport Check-In Counter Operations

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**Abstract**
Growth in air passenger flow has caused severe congestion at the airport check-in counter, posing a significant problem for airport management. Particularly during the check-in process, the necessary authorities must coordinate sufficient facilities with adequate staffing levels. The airport check-in counter problem (ACCAP) is a field concerned with establishing the optimal number of check-in counters to balance operating expenses and passenger wait times in order to reduce airport congestion. Expanding the number of counters and staff to a minimum operating cost is able to prevent the congestion problem from escalating without incurring further operating expenses. This paper focused on proposing optimal scheduling of airport check-in counters operations, including staffing. A dynamic model with multi-period principles is adapted to address the aforementioned problem by balancing the trade-off between service performance and operational cost. As a case study, data from Singapore Changi International Airport was utilized. The findings are also discussed in terms of the flow of passengers throughout the airport check-in procedure and operations. As a result, the number of activated counters is minimized throughout all shifts by applying the dynamic model at the average service time. At the same time, there are fewer passengers in the queue.

**Keywords**
Airport Check-in, Scheduling, Counter Allocation, Multi-period Model

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## 1. INTRODUCTION

Airport congestion and delays are caused by rapid air transport demand growth (Zografos et al., 2017). However, due to an unprecedented crisis due to the outbreak of the Covid-19 pandemic in 2020 (although some countries experience Covid-19 in late 2019), almost all airports have been paralyzed (Dabachine et al., 2020). The number of passengers remained relatively consistent before Covid-19 until plummeting dramatically due mainly to the pandemic from 2019 to 2020. Nevertheless, the situation is showing a steady recovery path and the number of passengers is likely to increase.

Increased passenger numbers would initiate airport congestion problems (Bruno et al., 2019; Parlar and Sharafali, 2008), especially in crucial areas such as check-in counters. The inability to accommodate passenger demand within capacity usage would incur delay costs to the airport terminal management (Pita et al., 2013). For this reason, it is important for airport management to sustain and maintain the availability of infrastructure (Rajapaksha and Jayasuriya, 2020). However, increasing the airport capacity is not an option because that would require additional funding (Xu et al., 2014) yet the airport terminal management must reduce congestion to guarantee that all passengers may board their flights on time.

Proper organization of the staff at these check-in counters directly influences passenger congestion and delay (Xin et al., 2014). In terms of the length of the queue and waiting periods, this setup achieves a balance between operational costs and the passenger's level of acceptable service (Bruno et al., 2019). Moreover, better service, shorter queues, and quicker check-ins for passengers will all result from more effective use of check-in counters (Lalita and Murthy, 2022). In the case of restricted financing sources, increasing the number of counters and staff would incur more operating expenses; therefore, improving the current system at the minimum costs is the most effective way to handle this scenario.

Looking at this issue, this paper improves the airport's operation of check-in counters at the Singapore Changi International Airport, by applying a multi-period model specifically for solving the operational problem as proposed by Bruno et al. (2019). Using this model, we can determine the appropriate number of active check-in counters for departing aircraft in order to reduce operating expenses. In addition, we noticed that the presence of mathematical modelling for addressing the problem for the airport check-in counter allocation (or in short, ACCAP) was rather challenging, despite being one of the most crucial phases of air travel. Consequently, utilizing a mathematical modelling approach to solve the corresponding issue is a significant advantage. The remainder of the paper is structured as follows: Section 3 reviewed the relevant literature of the study area, Section 4 describes the dynamic multi-period model and the data acquisition, and Section 5 discussed the results. Finally, the entire work of this paper is enclosed in Section 6.

## 2. EXPERIMENTAL SECTION

### 2.1 Past Related Studies

The ACCAP study focuses on allocating an adequate number of check-in counters so that the passenger waiting time is minimized and satisfactory service can be provided to the passengers over a given planning horizon with respect to certain constraints (Nandhini et al., 2012). The ACCAP involves the optimization procedures in the decision making of service management.

Simulation approaches had gained attention from several studies. Van Dijk and Van Der Sluis (2006) projected a combination of simulation and integer programming (IP) to solve the counters for check-in at Brisbane Airport Corporation (BAC) and Dutch airport Schiphol. The BAC was also utilized by Paloma Garcia (2017) as case study, but using only on the simulation approach to analyze all the possibilities of different situations on BAC such as variability in demand, services working, queuing type or redirection between areas. Meanwhile, Bevilacqua and Ciarapica (2010) integrated queueing theory into the proposed simulation model. The simulation showed that optimization of average queuing times was preferred in a common check-in.

A deterministic approach was adapted in solving ACCAP, such as Hsu et al. (2012) which utilized binary integer programming (BIP) to minimize the total service time for the assignment of passengers. The authors indicated that a much wider network, such as the inclusion of check-in counters in the solution process, must be considered to ensure a faster passenger check-in process. Meanwhile, Al-Sultan (2015) integrated IP and stochastic approach to propose the schedule for the check-in counter at the international airport in Kuwait so that the total counters and staffing periods at these counters can be reduced. Meanwhile, the stochastic approach was used to allocate the operational and staff scheduling at these counters.

Araujo and Repolho (2015) applied three version of mixed integer linear programming (MILP) formulation to a case study in Amsterdam Airport Schiphol using the simulated and dynamic model. The MILP formulations were applied to two check-in systems in ACCAP which are the common ACCAP (CACCAP) and the dedicated ACCAP (DACCAP). Both proposed deterministic models are able to find the total counters of check-in per time interval, but DACCAP is able to compute the solution for each flight. Stochastic elements were also found in dynamic models' approach in solving the ACCAP such as study by Parlar and Sharafali (2008). The proposed model was based on the multi-server queue by computing and generating the transient queueing probabilities. The study aimed to optimize the opening of the number of counters for passengers check-in over a specific period. Meanwhile, dynamic opening and closing of counters approach was being used by Nandhini et al. (2012). The authors provide a satisfactory service level to passengers by reducing the average queuing time. Similarly, Marintseva (2014) focused on the problem of check-in technologies at the Boryspil airport in Ukraine. The authors adapted queuing theory of M/M/s model to find the optimal check-in counter operating periods. As a result, the waiting time at the check-in area could be minimized by almost one hour.

Focusing on parallel queuing, Parlar et al. (2018) focused the problem of ACCAP for a single flight. The authors found the optimal counters for check-in by deploying a real-event dynamic method. In 2018, Parlar et al. (2018) analyzed the suitable number of counters for check-in at Singapore Changi International Airport using the event-based dynamic programming model. Meanwhile, Bruno and Genovese (2010) developed a dynamic mathematical model for both static and dynamic airport check-in problems by minimizing the expenses associated with the check-in service via optimal resource allocation. In 2014, Bruno et al. (2014) developed supplementary variants of the dynamic model. The authors proposed a dynamic capacitated lot-sizing model and applied it to several practical logistic applications, including ACCAP. In 2019, Bruno et al. (2019) integrates staff scheduling within the proposed dynamic ACCAP model. The authors applied the model in Italy.

Our work focused on improving the facility operation, including providing an optimal number of staff at the counters for check-in. Hence, the dynamic multi-period model proposed by Bruno et al. (2019) is applied to solve the problem of the check-in counter operation at the selected case study, i.e., the Singapore Changi International Airport. Next section presents the dynamic multi-period model.

### 2.2 A Multi-period Model for Airport Check-in Counters Allocation Problem

Let the planning horizon, $T$ be divided into a finite number $N$ indexed by $t(t = 1, 2, ..., N)$. Each $t$ is assumed to be identical periods of length $l$. Each departing flight $f(f = 1, 2, ..., F)$ in such time horizon is characterized a time window, in which check-in operations can be performed. Assuming that check-in counter service times are consistent and passenger arrivals increase over time, a queue will undoubtedly form. Hence, these passengers in the queue, with notation $I_{ft}$, is assumed will be served during the subsequent period. Thus, the dynamic multi-period model proposed by Bruno et al. (2019) is consuming this scenario as the conservation flow of passengers.

The remaining indices, sets, parameters, and decision variables of the model are as follows:

$T$ Planning horizon;
$N$ Number of periods in which the planning horizon is subdivided, indexed by $t$;
$l$ Length of single period;
$J$ Set of shift types that can be selected for check-in counters operators;
$F$ Index of departing flights in the considered planning horizon;
$q_f$ Average service time to process a single passenger of flight $f$ at check-in counters;
$d_{ft}$ Arrival of passengers of flight $f$ during period $t$;
$\gamma$ Service level to be guaranteed i.e., minimum number of passengers to be accepted expressed as percentage of arrivals;
$C_j$ Cost for shift type $j$ in $J$;
$a_{kt}^j$ Binary parameter equal to 1 if and only if the shift $j$ in $J$, activated in the period $k$ covers the period $t$ (with t > k);
$\beta_{ft}$ Binary parameter equal to 1 if and only if the check-in time window for flight $f$ is closed in period $t$;
$x_t^j$ Number or operators starting the shift type $j$ at the beginning of period $t$;
$q_{ft}$ Passengers of flight $f$ accepted at the check-in counters in period $t$;
$I_{ft}$ Passengers of flight $f$ in queue at the check-in counters at the end of period $t$;

The dynamic multi-period model as follows:

$$\text{Min } Z = \sum_{j=1}^{J} \sum_{t=1}^{N} c_j x_t^j \tag{1}$$

where

$$\beta_{ft} I_{ft} = 0; \forall f = 1, 2, \ldots, F, \forall t = 1, 2, \ldots, N \tag{2}$$

$$I_{ft} = I_{f(t-1)} + d_{ft} - q_{ft}; \forall f = 1, 2, \ldots, F, \forall t = 1, 2, \ldots, N \tag{3}$$

$$\sum_{f \in F} I_{ft} \leq (1-\gamma) \sum_{f \in F} d_{ft}; \forall t = 1, 2, \ldots, N \tag{4}$$

$$\sum_{f \in F} p_f q_{ft} \leq l \sum_{f \in F} \sum_{k=1} a_{kt}^j x_t^j; \forall f = 1, 2, \ldots, F, \forall t = 1, 2, \ldots, N \tag{5}$$

$$x_t^j \geq 0; \forall j \in J, \forall t = 1, 2, \ldots, N \tag{6}$$

$$q_{ft}, I_{ft} \in \{0, 1\}; \forall f = 1, 2, \ldots, F, \forall t = 1, 2, \ldots, N \tag{7}$$

The objective function of the model as shown in (1) aims to minimize the total cost for the activated counters at all times and across all shifts. Equations (2)-(5) present the constraints of the model. Constraint (2) dictates that passengers of each flight $f$ will only be attended to during their designated check-in time windows. Additionally, this constraint guarantees that no queue forms outside of the flight $f$ check-in time windows. Constraint (3) sets passenger flow conservation limits, i.e., within the check-in time windows, passengers are served or else wait in a queue. Therefore, guarantees that all passengers are served within the operational times of the check-in counter. Inequalities (4) restrict the queue to a specified percentage based on the arrival of passengers. Inequalities (5) represent the level of service capacity. Finally, constraints (6) and (7) characterize the decision variables of the model.

### 2.3 Data Acquisitions

Singapore Changi International Airport has become a global leader in the airport industry in less than 30 years, according to the prestigious publication Business Traveler (Bok, 2015) and has become a global leader in the airport business (Lee et al., 2014). The airport has been the Skytrax Airport of the Year winners since 2013 (Wu and Tsui, 2020). Prior to Covid-19, Changi Airport handled around 68.3 million passengers in 2019, representing a 4.0% growth over the previous year, via 100 airlines serving 400 cities in approximately 100 countries and territories worldwide (Lee et al., 2022). Airport passenger traffic has increased significantly since the pandemic ended, and this trend is expected to continue.

Table 1 provides information from Parlar et al. (2018) regarding airport check-in counters, including the total number of counters used, the number of available counters for each 5-minutes duration, and the number of passengers ($M$). As seen, $M$ has an average of 149 passengers for every flight, ranging from 81 to 261 passengers. With a range of 1 hour 8 to 2 hours 45 minutes, the average operation time for the check-in counter is 1 hour 34 minutes. It is observed that the minimum counter needed for the check-in process is one, while the maximum is four. The total number of counters used reflects the assumption that each counter has the same amount of staff allocation. The operation of these counters for every five minutes, as shown in the final column of Table 1. In general, as time increases, the number of operational counters in 5 minutes period decreases. Although these numbers are consistent with the operation of check-in counters but are highly dependent on the quantity of passengers arriving at each time interval. Parlar et al. (2018) discovered that around six passengers arrived at the check-in counter, with the average waiting time for each flight ranging from 57 seconds to 16 minutes and 28 seconds.

Instead of the number of passengers in each queue, Parlar et al. (2018) assigned enumerators to each activated counter for observing the system operation. Therefore, the pattern used to

**Table 1.** Details of the Operation of Counters of 14 Randomly Selected Flights (Source: Parlar et al. (2018))

| Flight, $f$ | $M$ | Check-in Counter Operational Times | Duration (hour:min) | Number of Counters Used |
|---|---|---|---|---|
| F01 | 81 | 03:59-05:28 | 01:29 | 1 |
| F02 | 156 | 04:00-05:20 | 01:20 | 3 |
| F03 | 121 | 03:48-05:58 | 02:10 | 2 |
| F04 | 131 | 05:06-06:28 | 01:22 | 2 |
| F05 | 111 | 08:35-10:00 | 01:25 | 4 |
| F06 | 137 | 10:35-11:50 | 01:15 | 3 |
| F07 | 145 | 10:57-12:22 | 01:25 | 2 |
| F08 | 185 | 12:55-15:15 | 02:20 | 2 |
| F09 | 151 | 14:55-16:03 | 01:08 | 4 |
| F10 | 167 | 15:50-17:15 | 01:25 | 3 |
| F11 | 131 | 16:45-18:05 | 01:20 | 2 |
| F12 | 138 | 18:45-20:05 | 01:20 | 3 |
| F13 | 261 | 18:58-20:32 | 01:34 | 4 |
| F14 | 172 | 21:25-00:10 | 02:45 | 2 |

**Table 2.** Total Activated Check-in Counters for Each Shift $\left(\sum_t^T x_t^j\right)$, for Three Scenarios

| Scenario | Total Number of Check-in Counters for All $t$ for Each Shift $j$ $\left(\sum_t^T x_t^j\right)$ | | |
|---|---|---|---|
| | Morning | Afternoon | Night |
| Actual | 26 | 40 | 26 |
| $p_f$ = 1.5 | 24 | 40 | 25 |
| $p_f$ = 4.0 | 32 | 42 | 29 |

distribute the total number of passengers for each time period follows the International Air Transport Association's (IATA) distribution, as obtained from Ahyudanari (2003). To suit the model of Bruno et al. (2019), information of Table 1 was modified according to 10-minute time interval (as presented in Figure 1).

The time periods were classified into three shifts, namely morning, afternoon, and night shifts. Figure 1 illustrates the arrival of passengers regarding the shift and the flight. Flights F01 through F05 are covered during the morning shift, which is between 00:10 and 9:50. Check-in activities for the afternoon shift occur between 10:00 and 18:00, covering flights F06 to F11. Finally, the night shift is from 18:10 to 00:00 and includes flights F12 to F14. Meanwhile, the number of activated counters for check-in of each shift is depicted in Figure 2. The morning shift has a maximum of two activated counters, the afternoon shift has one activated counter, and the night shift has a maximum of two activated counters. Please note that each activated counter is expected to have one working staff. Meanwhile, for this study, it is assumed that the cost of staffing the counter is constant throughout shift $j$.

The $\beta_{ft}$ is based on the estimated departure time for each flight $f$. It is assumed that the check-in counter would be open for three hours. Subsequently, the departure time was set 30 minutes after the counter closing time. For instance, the departure time for flight F01 is 6.30 a.m., hence it is assumed

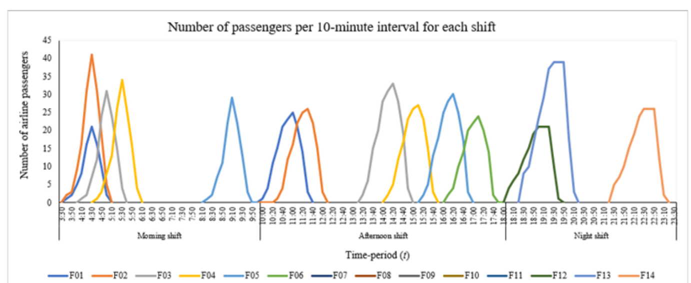



**Figure 1.** Passengers' Arrival Distributions Based on IATA Arrival Distribution (Source: Ahyudanari (2003))

that the check-in counter will be open three hours prior, at 3.30 a.m., and close 30 minutes prior, at 6.00 a.m. It is presumed that all passengers could check in before the flight's departure. The value of $p_f$ parameter was set to 1.5 and 4.0 minutes. The average service time is 1.5 minutes, while the maximum service duration is 4 minutes. The service level, $\gamma$, denotes the guaranteed service level as the expenses of check-in processes that must be minimized by taking queue length into account, i.e., the number of passengers who are still in line. The value of $\gamma$ is set consistently at 0.2 or 20% of service level is guaranteed to passengers, it is regarded that less than 80% of passengers are still in queue at the check-in counters at the end of time $t$. The problem is solved by CPLEX solver using a PC with

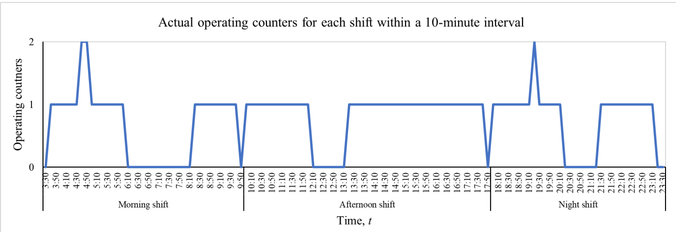



**Figure 2.** Actual Operating Counters for Each Shift Within a 10-minutes Interval

configuration: Intel Core i5 CPU 3.1 GHz, RAM 12.00 GB, and 64-bit Windows 10 operating system

## 3. RESULT AND DISCUSSION

The check-in counter operators were assigned based on the optimal number of counters to be opened in each shift. Some of these counters may be unused due to the unpredictable arrival pattern every flight. During off-peak hours, the number of unused counter(s) or operational capacity can be minimized. This can be identified by modifying the number of counters based on value $\gamma$=0.2 and $p_f$ at 1.5 and 4.0.

The optimal number of activated counters is shown in Table 2 for three scenarios, which are, the actual, $p_f$ =1.5 and $p_f$ =4.0. From Table 2, for the morning shift, for actual scenario, from 12:01 a.m. and 10:00 a.m. there are 26 check-in counters are activated (with a 10-minute interval) for all five flights F01, F02, F03, F04, and F05. When $p_f$ =1.5, the optimal number of activated counters is reduced to 24, and when $p_f$ =4.0, this number increased to 32. This indicates that additional counters must be activated to serve airline passengers when the service time increases. Figure 3 illustrates the activated counters for each shift for better understanding.

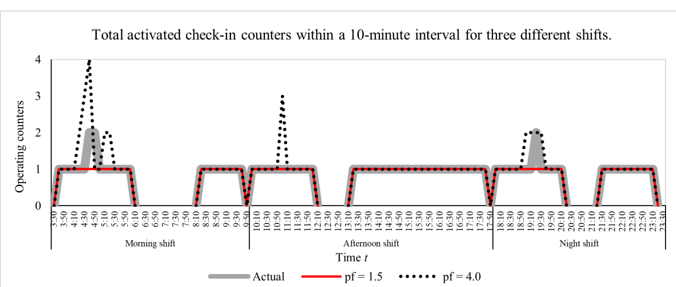
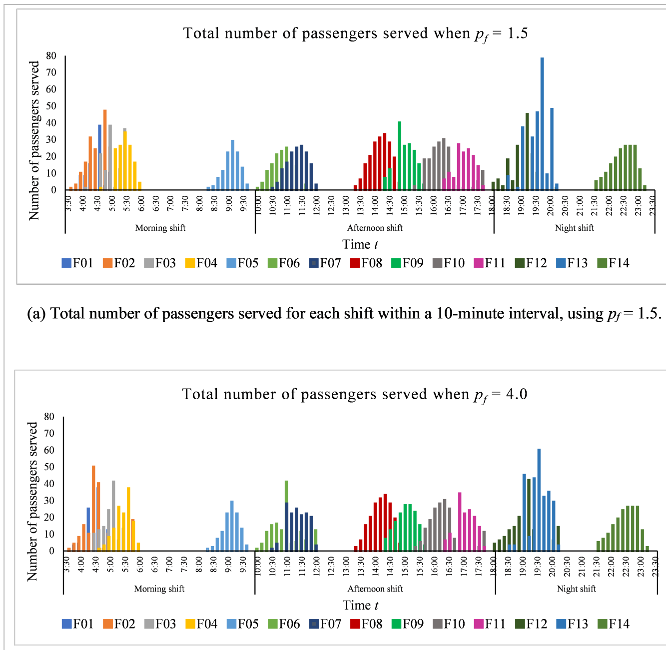



**Figure 3.** Total Number of Check-in Counter for Each Shift Within a 10-minute Interval, Under Three Different Shifts

Figure 4 depicts the total number of passengers served by the activated counters by shift, using $p_f$ values of 1.5 and 4.0. Figures 4(a) and 4(b) show that for both $p_f$ values, some passengers served for each 10-minute time interval for each flight are slightly different. Figure 5 is derived from both Figures 4(a) and 4(b) that highlight the number of passengers served by flight F13. For each value of $p_f$, the highest number of passengers served by the activated counter occurs at a different time. When pf is 1.5, 78 passengers are served at 19:40, however when $p_f$ is 4.0 only 60 passengers are served at 19:30. When the maximum service time, $p_f$ is used, fewer passengers will be served. It could be noted that the average service time required to process a single flight passenger at the check-in counter has a substantial impact on the total number of passengers in queue. In addition, for our study, because a single check-in counter is activated for each flight during the night shift, it is anticipated that this situation may occur. This is investigated further utilizing the decision variable of the number of passengers in the queue ($I_{ft}$).




(a) Total number of passengers served for each shift within a 10-minute interval, using $p_f$ = 1.5.

(b) Total number of passengers served for each shift within a 10-minute interval, using $p_f$ = 4.0.

**Figure 4.** Total Number of Passengers Served for Each Shift Within a 10-minute Interval, Using Two Service Times

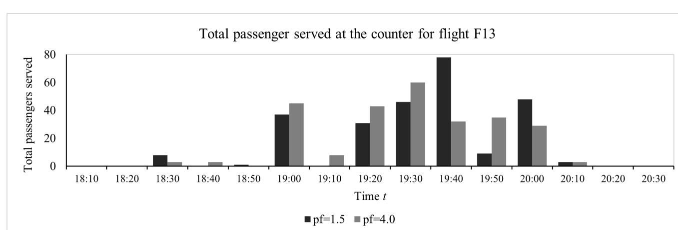



**Figure 5.** Total Number of Passengers Served for F13 Within a 10-minute Interval, Using Two Service Times

Table 3 depicts the number of passengers in queue for $p_f$ values of 1.5 and 4.0 while keeping a service level, $\gamma$ at 0.2. The actual number of passengers for each shift is shown in the same table. It is found that for $p_f$ = 1.5 and 4.0, the highest

**Table 3.** Number of Passengers in the Queue at Check-in Counters $\left(\sum_t^T \sum_f^F I_{ft}\right)$

| Shift | Actual Number of Passengers $(M)$ | Passengers of All Flight $f$ in Queue at Check-in Counters at the End of Period $t$ $\left(\sum_t^T \sum_f^F I_{ft}\right)$ | |
|---|---|---|---|
| | | $p_f$ =1.5 | $p_f$ =4.0 |
| Morning | 600 | 227 (38%) | 254 (42%) |
| Afternoon | 916 | 132 (14%) | 220 (24%) |
| Night | 571 | 247 (43%) | 221 (39%) |

**Table 4.** Comparison Between the Actual and Predicted on the Total Activated Counters at All Time $t$ and for All Flight $f$ for Each Shift $j$ $\left(\sum_t^T x_t^j\right)$

| Shift | Actual | $p_f$ = 1.5 | Difference (%)* | Actual | $p_f$ = 4.0 | Difference (%)* |
|---|---|---|---|---|---|---|
| Morning | 26 | 24 | -7.70% | 26 | 32 | 23.10% |
| Afternoon | 40 | 40 | - | 40 | 42 | 5% |
| Night | 26 | 25 | -3.80% | 26 | 29 | 10.30% |

*Note:- Difference (%) = (Predicted – Actual)/Actual × 100%

number of passengers in the queue during the night shift was 247 (43%) and 221 (39%), respectively. The afternoon shift has the most passengers despite being the shortest queue, i.e., $p_f$ = 1.5 is 132 (14%) and $p_f$ = 4.0 is 220 (24%). As indicated earlier, the night shift is most likely to have the longest queue length because each flight has just one activated counter. From Table 2, we can see that the total counters that were activated for all times $t$ and flight $f$ during the night shift for both $p_f$ values are the least ones. Meanwhile, the afternoon shift has the highest number of total activated counters; hence, this shift is expected to have the shortest queues.

Table 4 provided a summary of the findings based on the actual, projected, and difference percentage values. For service times of 1.5 minutes, the model underestimates the total number of activated counters during the morning and night shifts. For maximum service times, i.e., 4.0 minutes, the model overestimated the total number of activated counters throughout all shifts. The average absolute percentage difference between actual and predicted outputs is 8.4%. From the findings, the model's suitability for system operation monitoring, particularly for the cause-and-effect analysis, has been demonstrated. Clearly, less counters for check-in were activated at time $t$ due to a shorter average service time to process a passenger. Thus, more passengers can be accepted at time $t$ in the designated capacity level. The model can estimate the optimal check-in counters based on system capacity and service availability.

This study utilizes two service times, namely, the average service times and the maximum service times that guarantee a service level of 80%. When the service time is relatively short, only 24 counters should be activated during morning shift, 40 counters during afternoon shift, and 25 counters during night shift. Meanwhile, extended service times requires more counters, specifically 32 counters for the morning shift, 42 counters for the afternoon shift, and 29 counters for the night shift. Consequently, the utilized multi-period model was able to identify the appropriate number of total activation counters for Changi Airport, precisely for the corresponding airlines. Our study shows that there is a direct correlation between the optimal number of active check-in counters, the total number of passengers served during each 10-minute interval, and the total number of passengers waiting in the queue are existing.

## 4. CONCLUSION

This study focuses on optimizing the facility's operations, including supplying the optimal number of check-in counters, so that overall demand can be served at a maximum level at the minimum cost. This paper utilized the dynamic multi-period model developed by Bruno et al. (2019) to solve the check-in counter operation problem at the selected case study, i.e., Changi International Airport in Singapore. The applied model demonstrates that the number of passengers in the queue increases in relation to service level guarantees. The results obtained clearly minimize the total cost for the activated check-in counters at all times and throughout all shifts, especially when the average service time is 1.5 minutes. Clearly, there is a direct correlation between the optimal number of active check-in counters and the total number of passengers served during each 10-minute interval, as well as the total number of passengers waiting in the queue. Utilizing the dynamic model, the airline check-in flow at the counters can be optimized. Furthermore, the results show any adjustments would have direct effects on airport operations. If a more comprehensive dataset is used, airport operations will undoubtedly become more productive and economical. Additionally, this study shows a decision-making model that employs the dynamic characteristics of a multi-period model can provide insights on management's decision-making solutions. Further enhancements to the mathematical model presented in this paper could be constructed to replicate the real-world scenario, such as integrating specific measurements for counter activation for each time period and flight or imposing a limit on the total number of employees working at activated counters.

## 5. ACKNOWLEDGMENT

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