The Airport Check-in Counter Allocation Problem: A Survey

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Abstract

An important passenger service area that has an impact on passenger satisfaction and airport revenue is the check-in counters. The check-in counter allocation problem consists of allocating adjacent counters to airlines at an airport and scheduling the counters through the day subject to operational constraints. It is a special form of the well-known RCPSP and an NP-hard problem. In addition, the continuous demand for the highest possible number of counters throughout the day by each airline makes it a daily challenge for airport operators. As the counters are a resource, this problem is equivalent to the adjacent resource scheduling problem, making the solutions for this problem extendable to any adjacent resource scheduling problem. Decisions made at the check-in counters affect the movement of passengers in the airport and bad decisions can result in chaos. Since the 1980s several authors have proposed a multitude of models with variations in the optimization criteria, modeling, airport requirements, and airport layouts. This article presents a state-of-art survey on the airport check-in counter allocation problem by focusing on relevant models and algorithms. Relevant literature is discussed based on the type of problem solved, objectives considered and methodology considered. The value

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This research aims to help airport operators in planning and allocation of check-in counters, increase airport revenue, improve passenger flow within existing constraints, and optimize utilization of the existing infrastructure.

**Keywords:** Check-in counters, Counter allocation, Constrained resource scheduling, Constrained packing problem.

## 1 Introduction

Air-travel has become the most preferred mode of travel. The increase in economic growth and the average household income has contributed to the growth of the aviation industry (Zhang and Graham 2020). The number of scheduled aircrafts has only increased year to year since 2004, excepting for the closure of air transport worldwide due to Covid-19 related lockdowns. As the passenger traffic is set to increase again, airports have to brace themselves for a lot of passenger related congestion at different points in the airport. Check-in counter allocation is an important resource scheduling problem at airports. The ever increasing demand for airport resources has made careful planning and optimal use of resources a necessity. Delay due to inadequacy or inefficient management of airport facilities may result in penalty for the airline companies (Hsu and Chao 2005). It has been found that 80% of the passenger delay at airports is due to waiting for check-in (Takakuwa and Oyama 2003), (Parlar et al. 2013). To overcome this problem, kiosks were introduced in airports. Abdelaziz et al. (2010) study outcomes of introducing kiosks at Cairo airport. Passengers with baggage were asked to use luggage-drop counters after check-in at kiosks. This reduced waiting time at kiosks for check-in, but resulted in waiting at luggage drop areas. Though airlines rely on kiosks for management of queue and congestion at airports, their use mainly depends on the convenience for check-in as well as luggage drop. Adding additional counters at the airport is not generally a choice as it requires area in the airport, conveyor belts and also interlinking of the existing multilevel system of baggage transit with the new belt.

Therefore, efficient usage of check-in counters will improve service levels at airports, result in smaller queue lengths for airport operators and faster check-ins for passengers. As most of the passenger waiting time is spent in the check-in area at an airport, a reduction impacts public perception of the level of service and indirectly enhances the airport revenue due to the increased stress free time in the commercial areas of the airport (Hsu and Chao 2005), (Lin and Chen 2013), (Parlar et al. 2013).

To achieve all the above objectives in counter allocation, different optimization techniques have been used in the literature. This paper...
reviews all the methods proposed for counter allocation. The techniques discussed in this paper for allocating adjacent counters can be applied to other adjacent resource allocation problems, such as: warehouse space optimization where warehouse area has to be assigned to customers for storage for a certain time, berthing problem at shipyards, where berthing space has to be allocated to ships given the ship size and time for which it docks at the shipyard (see Bierwirth and Meisel (2010)), for assignment of computer hard disk memory (if contiguous allocation of memory is required (see Duin and De Sluis (2006))) and other resource scheduling problems where jobs cannot be shifted in time but resource requirements may be satisfied by any set of adjacent resources and may vary with time.

Efforts at reviewing resource usage at airport terminals have not explicitly focused on check-in counter utilization. Cheng et al. (2012) and Wu and Mengersen (2013) have reviewed models presented in literature for resource scheduling at airport terminals. Cheng et al. (2012) reviews theory of allocating and scheduling resources by grouping existing literature into three parts, viz., methods of integrating airport operation data, methods of predicting passenger flow at airport terminals, and optimization of allocating and scheduling passenger service resources at airport terminals. Wu and Mengersen (2013) review airport passenger terminal models by classifying them based on usage scenarios. Wu and Mengersen (2013) review work related to capacity planning, operational planning and design, security policy and airport performance. Cheng et al. (2012) and Wu and Mengersen (2013) do not study the check-in counter allocation problem in airport terminals. In this article, the authors provide technical guidance to the reader on how to evaluate the existing methods on counter allocation and appropriately model. This article simplifies the usage of existing knowledge by proposing a unified framework for modelling the counter allocation problem. Under this framework, we scrutinize different works based on their applicability, constraints, objectives considered and the time taken to solve the problems. This work gives any airport operator the ability to navigate through the articles published since four decades ago and implement a suitable model.

This article has five sections. Section 2 describes the check-in counter allocation problem. Section 3 classifies different methods in the literature by the problem type addressed and its limitations. Section 4 discusses different approaches for modelling the check-in counter allocation problem. Section 5 gives the conclusion.
2 The Check-In Counter Allocation Problem

Airports are divided into airside and landside areas. Airside operations consist of scheduling flights on the runways and other related on-air flight operations. Landside operations consist of scheduling and organization of the processes that passengers need to undergo before boarding a flight. It is imperative that airport landside operations focus on timely boarding of passengers and flight departures. For ease of operation, an airport has designated areas for different pre-boarding operations for passengers, such as check-in, security check, immigration, etc. In most airports, the check-in area consists of multiple structures of counters arranged around a conveyor belt in a u-shape. This structure is referred to as an island. Many such islands make up the check-in area (see Fig: 1).

Though all the counters are not physically adjacent to one another, this is supposed to be the case for simplicity in modelling the problem. Moreover, counters can be rearranged according to physical layout at later stages for implementation of the solution. In most of the literature discussed in this paper, a two dimensional space is used as a representation of the counters in the planning horizon (see Fig. 2). The planning horizon is the time period for which counter assignments are computed. To model the problem, the planning horizon is divided into smaller Time Intervals (also Time Windows(TWs)). The length of the TW has to be chosen while modelling a problem. Too small TWs mean less time for staff to handle operations and large TWs can consist of large variations in passenger arrivals. Fig: 2 shows counter allocation by Dijk and Sluis (2006) with a TW length of 60 min, planning horizon of 10 hours with resource availability of 15 counters. Here, the numbers represent the flights, ‘d’ represents the desk number or counter number.
and ‘t’ represents TWs. Since resource requirement times are fixed, it is not possible to shift items horizontally, only vertical movement is allowed.

These counters are owned by the airport operator and suitably leased to airlines. The airport operator has to issue the minimum number of adjacent counters required for each flight/group of flights. Adjacent counters are important for passenger and airline convenience, airline visibility and operations, and for ease in baggage management and sorting, since baggage from adjacent counters of an island is collected at one baggage collection center. Typically, airlines demand more counters from the airport operator than required, for ease in providing service and visibility at the airport (see Fig. 3 from Chun (1996)). This creates problems for the airport operator, who has to now simultaneously satisfy the real need for counters, ensure optimal allocation to all airlines and minimize changeover operations. A changeover operation consists of staff of one airline closing the counters at the end of a TW and shifting to other counters for continuing the check-in process in subsequent TW(s). To minimize the changeover operations, counters were traditionally allocated to a flight for its entire check-in time. Since this type of allocation would result in a waste of counter time due to time-varying arrival distribution, time-varying counter requirements are proposed (Dijk and Sluis (2006), Bruno and Genovese).
This results in structures known as polyominoes (see Fig. 2 for each flight (or a group of flights). Actual counter requirement (for illustration see Fig. 5) from Dijk and Sluis (2006) is computed using the arrival distribution of passengers (for illustration see Fig. 4 from Chun and Mak (1999), where arrival distribution is computed for flights in the morning, afternoon and evening), and an appropriate load factor.

Load factor is defined as the percentage of passengers of an airplane seat capacity expected to finally board the flight. The counter allocation problem is reduced to determining counter requirement of flights and then placing the resulting polyominoes, that can be moved only vertically, in the counter-TW area in an optimal way.

It has been observed that time-varying or dynamic counter allocation (Fig. 6) provides on-time service and consequently results in significant savings in terms of counter time, operation costs and reduced queue size (Joustra and Van Dijk (2001), Dijk and Sluis (2006)). In contrast, static counter allocation assumes constant counters in the check-in period. In both types of allocation, two or more flights of an airline can be grouped together for assignment if the demand for coun-
ters overlaps in some TWs, i.e., if flights are scheduled for departure a few hours apart. It is general practice by airlines to assign common counters to a set of flights with simultaneous demand in at least one TW. The demand for counters is treated as demand for one departure. This enables passengers of an airline to use the same counters irrespective of the flight boarded. Dedicated counters on the other hand exclusively serve passengers of a single flight. Both allocations are used in airports based on opportunities available to group flights. This allows the airlines to minimize the counter operating cost and changeover operations also. In most of the models proposed for counter determination, minimizing the counter operating cost is the objective. Counter operating cost includes the cost of operating baggage belts, the cost of staff operating the check-in counters, queue cost and the cost of delay. Hsu and Chao (2005) construct various cost functions related to facility management.

Some of the challenges to this problem, as discussed by Snowdon et al. (1998), are estimating the passenger arrival distribution, the complexity of determining the passenger mix (number of passengers using different services), changes to the resources (mainly check-in facilities) available depending on the arrival distribution, ensuring passenger service levels are attained and evaluating flight data in order to group flights which can benefit from common counters vis-a-vis dedicated counters. Initial attempts to solve the problem through simulation improved the prevailing methods for counter allocation. Atkins et al. (2003) propose simulation to compare operational strategies and to determine the optimal staff levels required. Chun (1996) and Chun and Mak (1999) use simulation for counter determination and counter allocation. Real life modelling of the check-in process at airports has been presented by Jonstra and Van Dijk (2001) and Dijk and Sluis (2006) for check-in at Schiphol airport in Amsterdam. Atkins et al. (2003) at
Vancouver airport, Bruno and Genovese (2010) at Naples International Airport, Lous (2011) at the Copenhagen airport, Al-Sultan (2016) at an airport in Kuwait and Felix and Reis (2017) at the airport of Lisbon and Chun (1996), Chun and Mak (1999) at the Hong Kong airport etc. The counter allocation problem with the adjacency restriction is NP-complete (Dijk and Sluis (2006), Duin and Der Sluis (2006)) and cannot be solved in polynomial time. The complexity of the problem has been studied in detail by Duin and Der Sluis (2006). All the models proposed for counter allocation including the above real-world applications have been classified on the basis of the problem solved. These methods are discussed in detail below.

2.1 Determining Optimal Number of Check-in Counters

This section discusses the problem of determining counter requirement for a flight or a set of consecutive flights of an airline. The number of counters allocated to a flight (or group of flights) depends on the arrival pattern of passengers, the queueing area available, queue length in an interval and restrictions on waiting time. Different authors have modelled the problem with different constraints, different objectives and different facilities (eg: counters and kiosks). Before studying these models, we present a basic model for counter determination:

\[
\begin{align*}
\text{Min} & \quad \sum_{ij} x_{ij} \\
\text{subject to} & \quad \sum_j a_{ij} s_i \leq \sum_j x_{ij} t \\
& \quad x_{ij} \geq 0 \text{ are nonnegative integers.}
\end{align*}
\]

In this formulation, \(x_{ij}\) is the number of counters assigned to the \(i^{th}\) flight in the \(j^{th}\) TW, \(a_{ij}\) is the average number of arrivals for \(i^{th}\) flight in \(j^{th}\) TW (this is obtained from passenger surveys conducted at the airport), \(s_i\) is the average service time per passenger for the \(i^{th}\) flight, ‘t’ is the length of each TW. This formulation provides resources exactly in proportion to airline requirement. This results in counter allocation with peaks and troughs exactly like the passenger arrival distribution. Since airport operators mandate airlines to limit waiting times and counter queue lengths, the only way to improve the solution to this model and get more rectangular polyominoes is to postpone the check-in of some passengers while respecting the service level requirements. Note that with even a slightly more rectangular structure of the
counters allocated (see Fig. 7b), changeover operations are reduced, improving the basic solution (see Fig. 7a).

2.1.1 Mathematical Models for Counter Determination

Published work on check-in counter determination is described briefly in the following paragraphs.

Park and Ahn (2003) published a paper for optimal assignment of check-in counters. Their paper aims to assign counters based on passenger arrival distribution at the airport. Other factors considered are aircraft type (standard or chartered), aircraft size, time allowed for check-in, passenger arrival distribution, ticket status (economy, business, first class etc), processing time of staff at the check-in counters and load factor assumed. A passenger survey at the airport (in Park and Ahn (2003)) determines the variation in load factors during peak and non-peak hours and the resulting arrival patterns. The airport arrival patterns are then used as input to a regression model to determine the cumulative arrival pattern based on time before departure. Counters are allocated to airlines directly in proportion to the estimated passenger arrivals. This kind of allocation may not result in an optimal assignment of counters to airlines since the overall cost to the airport operator or queue lengths among other things are not considered.

Bruno and Genovese (2010) propose the following static model to determine the optimal number of counters for flights with the objective of reducing counter cost and queue length.
Minimize \[ z = \sum_j \sum_t (h_j I_{jt} + s_j x_{jt}) \] subject to

\[ I_{jt} = I_{j(t-1)} + d_{jt} - q_{jt}, \quad j = 1, 2, ..., J, \quad t = 1, 2, ..., N, \] \hfill (6)

\[ p_j q_{jt} = C_t x_{jt}, \quad j = 1, 2, ..., J, \quad t = 1, 2, ..., N, \] \hfill (7)

\[ \sum_j p_j q_{jt} \leq C_t, \quad t = 1, 2, ..., N, \] \hfill (8)

\[ I_{jt} = 0, \quad t \in T_j \] \hfill (9)

\[ q_{jt}, I_{jt} \geq 0, \quad j = 1, 2, ..., J, \quad t = 1, 2, ..., N, \] \hfill (10)

\[ x_{jt} \in \{0,1\}, j = 1, 2, ..., J, t = 1, 2, ..., N. \] \hfill (11)

The following notations are used in the above model. \( h_j \) is the cost associated with queue related to flight \( j \), \( s_j \) is the desk opening cost for flight \( j \), \( T \) is the planning horizon (usually one day), \( l \) is the length of the TWs considered, \( N \) is the number of TWs, \( J \) is the number of flights scheduled in \( T \), \( p_j \) is the average desk service time for flight \( j \), \( d_{jt} \) is the service demand for flight \( j \) in TW \( t \), \( C_t \) is the available check-in time based on counters operating in TW \( t \), \( I_{jo} \) is the number of passengers of flight \( j \) waiting before counters open for flight \( j \), \( T_j \) is the set of TWs in which counters for flight \( j \) do not operate.

Decision variables are: \( I_{jt} \), the number of passengers in queue for flight \( j \) at the end of TW \( t \), \( q_{jt} \), the number of passengers of flight \( j \) to be accepted for service in TW \( t \). Even though \( x_{jt} \), the binary variable representing the possibility of checking-in passengers for flight \( j \) in TW \( t \), is defined as a decision variable, it is not, since this is fixed in advance and cannot be restructured. Constraints (6) represent the change in queue length between two successive TWs. Constraints (7) ensure that enough counter time is available for passenger check-in in TWs where check-in is possible. Constraints (8) ensure the overall service capacity is as required, constraints (9) forces all passengers of flight \( j \) to be accepted by the closing time of check-in service for flight \( j \).

Bruno and Genovese (2010) propose models for both static (see model (5)-(11)) and dynamic counter allocation. Both the models define the number of passengers in queue for a flight and the passengers accepted for service in each TW as decision variables. In the static model presented above, the total cost of counter operation and the cost of queue is minimised (see objective function (5)). In the dynamic model, counters operating in each TW and the cost associated with queue are minimized. The authors derive mathematical formulations from the Capacitated Lot Sizing problem in literature (see Bitran and
Yanasse (1982) and Florian et al. (1980). The authors also present a real-life airport management study at the Naples airport.

The model presented by Araujo and Repolho (2015) is an extension of the model by Bruno and Genovese (2010). Araujo and Repolho (2015) present two models for determining counter requirement for flights and aim to determine the optimal number of counters for flights operating at an airport. ILPs are presented for dedicated and common counter check-in. Following is the ILP for dedicated counter allocation.

\begin{align*}
\text{Minimize} & \quad z = \sum_j \sum_t (h_j, I_{jt} + s_j x_{jt}) \\
\text{subject to} & \quad I_{jt} = I_{j(t-1)} + d_{jt} - q_{jt}, \ j = 1, 2, ..., J, \ t = 1, 2, ..., N, \\
& \quad \sum_j p_j q_{jt} \leq C_t, \ t = 1, 2, ..., N, \\
& \quad I_{jt} = 0, \ t \in T_j \\
& \quad I_{jt} \leq \alpha (d_{jt} + I_{0jt}), \ j = 1, 2, ..., J, \ t = 1, 2, ..., N, \\
& \quad q_{jt}, I_{jt} \geq 0, \ j = 1, 2, ..., J, \ t = 1, 2, ..., N,
\end{align*}

An additional service level constraint (such as constraint (16) for dedicated counter allocation as above) is added to both models to ensure that only a small percentage of passengers, \( \alpha \), remain in queue at the end of a TW. The service level is chosen by the airport operator. The models predict the counter requirement for flights (or for a group of flights). The model solutions are analysed using simulation for model validation in different scenarios that may occur at the airport. Once the models are validated, the corresponding solution is implemented by allocating adjacent counters to each flight using the ILP by Dijk and Sluis (2006). Though a service level constraint is added to the model, the waiting time of passengers and the maximum queue length allowed are not considered. It can be easily proved that model solution does not follow FIFO and due to this counter usage may be different than expected.

Lalita et al. (2019) propose a model ((18)-(22)) for determining the optimal number of counters with postponement of service times. The model considers the passenger arrival distribution, where \( d_{ji} \) is the arrivals in TW \( i \) for flight \( j \), \( u_{ji} \) is the number of arrivals (in TW \( i \)), served in TW \( i \) and \( v_{ji} \) is the number of passengers arrivals for flight \( j \) served in TW \( i + 1 \). \( P \) denotes the time horizon for these departures. Let \( i_o(1) \) denote the counter opening time of the first departure and \( i_c(1) \) denote its closing time, then, \( P = \{i_o(1), i_o(1) + 1, \ldots, i_c(D)\} \), \( P_j = i_o(j), i_o(j) + 1, \ldots, i_c(j) \) and \( d_{ji} = 0 \) for all \( (j, i) \) such that \( i \notin P_j \).
Constraints (19) and (20) ensure that all passengers are served, constraint (21) ensures that enough counter time is available for serving all the passengers of all the flights. The formulation makes the resulting counter allocation more rectangular by postponing service to the next TW for some passengers. It also limits the waiting time by length of two TWs and follows the FIFO queue discipline. Adding a service level constraint to this model may improve counter allocation. Lalita et al. (2019) also propose a model for adjacent check-in counter assignment, discussed in section 2.2.

Minimize \[ z \] (18)

subject to

\[ u_{ji} + v_{ji} = d_{ji}, \forall \ i \in P, \ j = 1, 2, \ldots, \hat{D}, \] (19)

\[ v_{ji,(j)} = 0 \ \forall \ j = 1, 2, \ldots, \hat{D}, \] (20)

\[ \sum_j s_j(u_{ji} + v_{j(i-1)}) \leq \omega c_i \ \forall \ i \in P, \] (21)

\[ c_i \leq z \ \forall \ i \in P, \] (22)

\[ u_{ji}, \ v_{ji} \text{ and } c_i \ \forall \ i \in P, \text{ are nonnegative integers.} \] (23)

Hsu et al. (2012) also propose an ILP to determine the number of check-in facilities required for a departure from the airport. Check-in facilities considered are the counters and kiosks, online check-in, and barcode check-in. Check-in services offered by these facilities are: ticket purchase, check-in, boarding pass and checking baggage, each offering one or more services. Each facility may offer different check-in services. The model proposed aims to minimize the passenger waiting time, operation costs and counter requirements. The authors explore dynamic allocation of different check-in facilities and passengers at the airport. For modelling the problem only two types of check-in facilities, counters and kiosks are considered. Passengers are assigned different facilities based on service requirement. The model proposed is based on the dynamic model by Nikolaev et al. (2007). The services required by passengers and their arrival times are predicted and are an important input to the model. The assignment of the \( n \)th passenger by the model depends on the assignment of the \( (n - 1) \)th passenger. Therefore, for dynamic assignment of passengers, various possible scenarios are analysed. Due to this, the model takes more than 3 hours to solve for 15 passenger arrivals. In view of this the authors have used clustering algorithms (in heuristics) for solving the model. A real life scenario has been presented in the study to show improved counter utilization rates on using the model at an airport in Taiwan. A brief analysis of the modelling of the problem suggests that the success of the model is entirely dependent on the willingness of the passengers to use the
check-in facility assigned to them. The model may fail to generate an effective solution at airports where passengers prefer to use other facilities, it may cause the check-in facilities operating at the airport at certain TWs to be insufficient.

Determining the counter requirement at an airport is necessary but sometimes, the capacity of check-in counters at an airport also needs to be assessed. It is essential in decision making for airport expansion. Airport terminal capacity is assessed by Brunetta et al. (1999), Fayez et al. (2008) and Pacheco and Fernandes (2003). Kıyıldı and Karasahin (2008) present a fuzzy logic method to determine check-in capacity at Antalya airport in Turkey.

Capacity of a check-in counter is computed as the number of passengers and luggage that can be checked-in in one hour. In the model, possible passenger and luggage combinations are determined. Number of passengers travelling together and the number of bags (luggage carried by a person/group) is randomly generated and fuzzy logic is used to predict the processing time. It was observed that the processing time is highly correlated with volume of luggage (high $R^2$). Fuzzy models are used to calculate the capacity of each check-in counter in terms of the number of persons served and the number of luggage items checked-in. This is used to calculate the check-in capacity of the airport which is compared with the current passenger arrivals and growth rate at the airport for adding new resources to the airport.

Hwang et al. (2012) present a mathematical model for optimizing check-in counters, kiosks, part-time staff and full-time staff required during each shift in a week at airports. Their model assumes static counter allocation and defines the number of passengers using counters and kiosks in a shift as parameters. The study conducted gathers information on counter requirements and cost of operation in the presence of various factors including the day of the week and varying load factors. The authors compute the ratio of counters to kiosks that would be best suited for serving a flight. Model solutions are verified for optimizing cost in different scenarios using simulation. The authors conclude that usage of kiosks reduces the operational costs and that services can be improved by installing additional kiosks. Regarding the average waiting time, the study concludes that check-in counter cost can be reduced by limiting passenger service time. Though the observation is fact-based, it is not clear as to how this may be achieved. This recommendation also contradicts the existing counter planning strategies of using average service time to determine counter allocation instead of fixing service time per passenger. Reducing service time per passenger would definitely make the counter allocation problem easier, but it may not be always possible to limit passenger processing time.

Simulation has been used for counter determination by Chun (1996), Chun and Mak (1999) and Dijk and Sluis (2006).
2.2 Adjacent Counter Allocation

The most challenging problem at an airport is adjacent counter allocation for a flight while simultaneously maximizing counter utilization. Chun (1996) first addressed this problem by defining structures called counter profiles.

A counter profile is a two-dimensional shape that defines the check-in counter resource requirement for a flight. In the algorithm proposed by Chun (1996), different operators are presented to change the shape of the counter profile to check for a convenient fit for allocation in the counter-TW rectangle of fixed dimensions. All possible shapes are considered for every counter profile (see Fig. 8). Placing a counter profile in a two-dimensional counter TW space ensures adjacency of counters. Algorithm by Chun (1996) starts with selecting one possible counter profile for a flight, it is assigned a location in the counter TW space (also Gantt Chart), all the relevant constraints are checked, if some of the constraints are violated (i.e. if the specific shape of the counter profile cannot fit in the Gantt Chart), the algorithm backtracks by removing the previous allocation to a flight and freeing up space. The counter profile shapes may need to be changed in order to accommodate the remaining flights. Chun (1996) simulated different possible shapes of the counter profile, similar to fitting pieces of a puzzle randomly until an acceptable solution was reached. If the order in which flight counter profiles are allocated does not have a feasible solution, the algorithm involves backtracking to remove flight allocations. This results in a time consuming hit and trial process for counter allocation. An ILP is presented by Dijk and Sluis (2006) for the same problem.

Fig. 8: Possible variations of the 2-4-6 Counter Profile
The ILP considers all possible arrangements of a counter profile in the counter-TW area, till an optimal solution is obtained. Due to this, the ILP takes a long time to converge to a feasible solution (especially for large flight departures). The formulation is effective for small size problems compared to the real-world problems of the day. In the static counter allocation problem considered by Yan et al. (2004) and Yan et al. (2005), each counter has one or two service lines to provide check-in service to passengers. To allocate adjacent counters, the authors define each block as a set of service lines. Tang (2010) defines each block as a set of adjacent counters. Two blocks may overlap as a service line/counter may belong to both (see Fig. 9).

Service lines are demanded by airlines in accordance with the passenger arrival pattern and the number of passengers on the flight. Yan et al. (2004) propose a static model to assign blocks to flights. The objectives of the study are to allocate counters to minimize passenger walking distance and reduce inconsistency in counter location. Allocation to different blocks of counters on different days of the week for the same flight is defined as an inconsistency. Inconsistency values are introduced as the airlines prefer to have the same block of counters allocated for flights in a week.

Passenger walking distance is calculated for possible flight assignments to a block and all possible blocks to which a flight can be assigned are considered in the model. For a given flight and block combination, it is the average distance a passenger walks after check-in from the block allocated till boarding. An ILP is proposed for minimizing the passenger walking distance subject to allowable inconsistency. The constraints of the ILP need preprocessing to exclude redundant constraints. Since the solution method lacks scalability, three heuristic models are proposed to solve the problem. The first model provides the assignment for a day. Based on this, inconsistency values are set
and the second model is solved for a minimum inconsistency value. Then, the third model is solved for the final assignment of flights to blocks. A heuristic is thus provided for solving the model for a single day. This heuristic has been used in real-life modelling at an airport in Taiwan. The models are used for allocating 140 counters to 70 flights departing from the airport. The number of variables exceed 80000 and constraints exceed 70000. Results from the case study conducted for Taiwan Airport show reduction in the passenger walking distance by 4%.

Yan et al. (2005) study the dynamic counter allocation problem. Their objective is to allocate adjacent counters to flights by minimizing the total inconsistency in blocks allocated to a flight. Blocking plans are similar to blocking by Yan et al. (2004). Each counter may have many service lines (as also defined by Yan et al. (2004)) and the service line requirement for each flight in each TW is known. Since the number of service lines differ from one block to another, additional lines need to be opened or closed between successive TWs. This adjustment of service lines between two consecutive TWs is considered an inconsistency. From the inconsistency values attached to blocks pairwise, the inconsistency value in flight allocation on a day is computed. The problem was solved by an ILP, allocating a block (possibly different) to each flight in each TW. Due to the complexity involved in computing the inconsistency values, the problem becomes increasingly complex with increase in number of flights, and the authors propose a heuristic algorithm. The heuristic for the problem divides it into subproblems, each of which is solved. Each subproblem comprises of equal counters and flight departures. An exchange mechanism between the two parts is proposed to proceed further (similar to the evolutionary algorithm by Mota (2015)). The exchange of two flights, one selected from each group, (with overlapping departure times), and then re-solving for a solution is continued till a reduction in inconsistency is achieved. The allowable inconsistency value is chosen as appropriate. The solution with the least inconsistency value (according to the stopping criterion) is chosen. The order of exchanges effects the final solution, hence, further improvements to the heuristic algorithm are suggested. For large problems, dividing flights into two groups may be insufficient. Due to this number of groups is increased and the solution algorithm is improved. A disadvantage is the increase in complexity of the problem with additional subgroups, as a result of increase in the number of flights.

2.2.1 Mathematical Models to ensure Adjacency

Dijk and Sluis (2006) model the problem combining both simulation and integer programming. The objectives of the study are to determine
the minimal counter requirement for each flight and then to allocate counters at the airport with adjacency maintained. The problem is solved in two stages. In the first stage terminating simulations are run to determine counter requirement till the solutions satisfy service level requirements. In the second stage, an ILP is solved for adjacent allocation of counters. The study presents ILPs for both variable and constant counter allocation. These models ensure adjacency of the counters allocated to each flight and solve to an optimal solution. The ILP for variable counter allocation is given below:

\[
\text{Minimize } D \tag{24}
\]

subject to

\[
n_{ft} \leq d_{ft} \leq D, \quad \forall f \text{ and } t = a_f, \tag{25}
\]

\[
d_{ft} + n_{gt} \leq d_{gt} \text{ or } d_{gt} + n_{ft} \leq d_{ft}, \quad \forall f, g \text{ and } t \in I_f \cap I_g, \tag{26}
\]

\[
d_{ft} - d_{ft-1} \leq \max\{0, n_{ft} - n_{ft-1}\}, \quad \forall f \text{ and } t \in (a_f, b_f], \tag{27}
\]

\[
d_{ft-1} - d_{ft} \leq \max\{0, n_{ft-1} - n_{ft}\}, \quad \forall f \text{ and } t \in (a_f, b_f], \tag{28}
\]

where, \(D\) is the total number of counters required, \(I_f\) is the check-in interval of flight \(f\) (or counter operating time), \(n_{ft}\) is the number of desks required for the check-in process of flight \(f\) in period \(t\) (\(t \in I_f\)), and \(d_{ft}\) is the largest desk number assigned to flight \(f\) in period \(t\) (\(t \in I_f\)). Constraint (25) ensures that counters assigned to flights do not exceed \(D\), constraint (26) ensures that two flights are not assigned the same counter in a TW and also avoids overlap, constraints (27) and (28) ensure that required counters are opened or closed at the beginning of a TW. Model inputs are the counter requirements \(n_{ft}\) for flights determined using simulation. Queuing theory and simulation methods are both evaluated, it is observed that queueing theory cannot be applied since the arrival distribution of passengers for different flights is not homogeneous and cannot reach a steady state. Simulation and the model ((24)-(28)) were applied to data from a Dutch airport and it was observed that increased problem size (increase in number of flights and planning horizon) resulted in an increase in computation time. A similar mathematical model is presented by Duin and Der Sluis (2006). The model is adapted from RPSP (see Pinedo and Chao (1998)).

Lalita et al. (2019) also present an ILP for allocating adjacent counters. The ILP ((31)-(35)) has been shown to solve problems with a large number of departures in less time compared with formulations by Araujo and Repolho (2015) and Bruno and Genovesi (2010). Tasks are defined as time-varying counter requirement for one or more departures (see Fig.10). This definition is similar to that of counter profiles by Chun and Mak (1999). The difference being that there cannot be
multiple task structures whereas the shape of a counter profile can be changed using different operators. A counter-TW pair, \((k, i)\) is fixed and variables \(w_{ki}\) and \(m_t\) are defined by

\[
\begin{align*}
  w_{ki} &= \sum_{t \in T_i} \sum_{h=1}^{c_i(t) \wedge k} y_{tk}(k-h+1), \\
  m_t &= \max\{c_i(t) : i_o(t) \leq i \leq i_c(t)\},
\end{align*}
\]  

(29)  

(30)

where \(i_o(t)\) is the counter opening time and \(i_c(t)\) is the counter closing time for task \(t\), \(T_i\) is the set of all tasks \(t\) such that \(i_o(t) \leq i \leq i_c(t)\), \(w_{ki}\) is the number of tasks that use counter-TW combination \((k, i)\), \(y_{tk}\) is a binary variable, equal to 1 if task \(t\) starts at counter \(k\), and \(\sum_k ky_{tk} + m_t - 1\) is the largest counter number used by task \(t\).

Minimize \(s\)  

subject to

\[
\sum_{t \in T_i} \sum_{h=1}^{c_i(t) \wedge k} y_{tk}(k-h+1) \leq 1 \text{ for all } (i, k),
\]  

(32)

\[
\sum_k y_{tk} = 1 \text{ for all } t,
\]  

(33)

\[
\sum_k ky_{tk} + m_t - 1 \leq s, \text{ for all } t,
\]  

(34)

\[
y_{tk} \in \{0, 1\} \text{ for all } t, k,
\]  

(35)

Constraint (32) ensures that no counter is allocated to more than one task in any TW. Constraint (33) ensures that each flight is allocated counters and constraint (34) limits the total number of counters used to \(s\).
2.3 Some Real-life Airport Applications

This section discusses models proposed for solving real-life airport problems. We focus on the airport problem considered by the authors, inputs required for the models considered, and prominent disadvantages and advantages to using these models. Joustra and Van Dijk (2001) present a simulation model and Dijk and Sluis (2006) present ILPs in addition to simulation for check-in counter allocation, Atkins et al. (2003) present a simulation model with input data on pre-board screening, shift scheduling, passenger arrivals, and level of service for determining staff scheduling and resource requirements. Simulations were run till the staff schedule obtained satisfied the level of service at the airport. Operations in airports vary in type of check-in, type of queue permitted, flexibility of counter usage (for business or economy class), passenger behaviour, common or dedicated counters, check-in periods, baggage collection centers and sorting of baggage, queuing area etc. Consequently, simulation models consider different features and requirements of the airport under consideration. Bruno and Genovesi (2010) present two models for counter determination. The model by Lous (2011) considers the baggage belt direction, amount of baggage allowed per baggage area, the maximum number of people allowed to queue at a counter, adjacency of counters allocated, counter location preferences by an airline, but aiming to create a flexible model results in a complicated model, and involves a large number of additional computations, especially in allocating preferred counters to airlines. In the study by Al-Sultan (2016), some counters are always kept unused in each zone of the airport to cushion the airport operator against sudden increase in traffic. The author overlooks the model objective function which is constant, the model is thus defective and consequently, the objective of minimizing the counters allocated may not be achieved. Felix and Reis (2017) developed a hybrid discrete-event and agent based simulation model to assess the performance of check-in process at the airport of Lisbon. Passenger behaviour, the sequence of tasks performed in the check-in area and the physical layout of the check-in area are incorporated in the model. The variations in the check-in process are attributed to variation in these aspects. The model by Felix and Reis (2017) is comparable to the model by Lous (2011) in that it considers almost the same set of factors effecting passenger check-in.

In Felix and Reis (2017), the simulation model proposed aims to explore various scenarios at check-in area and enables airport operators to choose the best position and assignment of different types of check-in facilities (counters, kiosks, etc) to airlines (counters and kiosks differ in the services offered). However, in Lous (2011), baggage collection centers with limited capacity and limited queuing area are incorporated.
in the ILP proposed. Trakoonsanti (2016) also models the problem for an airport in Thailand. The excel based software SimQuick is used to build the model for simulation. The arrival distribution of passengers, check-in service time (or its distribution), type of queue, are input to the software. Different structures at the airport such as the check-in counters, entrances, exits, queue capacity, and other processes can be defined and average time for passenger flow through these processes including the check-in counters can be observed. The paper concludes with different results on the efficiency of counter allocation in terms of passenger waiting times and queue length.

3 Different Approaches to Counter Allocation

This section discusses different approaches for check-in counter assignment. The approaches used to model the problem are classified below based on the problem solved and procedures used.

3.1 Simulation for Counter Allocation

Initial attempts to solve the counter allocation problem were made by simulation of resource requirement at airports. Constraint satisfaction algorithms were presented by Chun (1996) and Chun and Mak (1999). Subsequently, simulation of passenger flow at the airport terminal was proposed by Wong and Liu (1998) and passenger flow from terminal entrance to boarding was simulated by Kiran et al. (2000). Wong and Liu (1998) focus on passenger traffic characteristics and their impact on terminal operations. Simulation of resources may also be done to identify delays at the check-in system and create scenarios that will improve the efficiency (Appelt et al. (2007)). Real-time system data was used by Ros Prat (2017) to simulate system behaviour and test different conditions and scenarios with the objective of optimizing the check-in procedure at Brisbane Airport. The author presents a dynamic check-in procedure where rapid changes in the check-in procedure are possible in real-time. Simulation was used for counter determination by Dijk and Sluis (2006). For analysis of counter allocation and waiting time of passengers, Bevilacqua and Ciarapica (2010) compared both waiting times and other parameters estimated by queuing theory and simulation. Chun (1996) presents algorithms by modelling the problem as a multidimensional placement problem. Chun (1996) proposes a two-dimensional approximation for counter scheduling where space (counters) and time are assumed to be part of a Gantt chart. The constraint satisfaction algorithms presented consider all possible counter profiles for each flight. The final version of the algorithm aims to further
improve the solution by considering different shapes per counter profile and by imposing constraints on the minimum number of counters allocated to a flight based on the queue length restrictions. The main drawback of this method is that final allocation depends on the order of flights chosen by the algorithm for allocation. For the final algorithm, counter profile globs are defined as multidimensional objects which include additional dimensions such as queue lengths, waiting time and baggage restrictions. Also, in case all the flights cannot be allocated to counters, despite re-shaping the counter profile globs and minimizing the counters allocated, the algorithm backtracks, de-assigns the most recent allocation and proceeds to allocate for another flight. This is a major drawback for airports with a large number of departures. There may be too many backtracks in deriving the final solution. Also, the final allocation depends on the order of the flights chosen. Choosing the best counter profile has not been addressed in this paper, which is very much needed for arriving at a good decision.

Chun and Mak (1999) present an intelligent resource simulation system (IRSS). IRSS predicts the check-in counter requirement at an airport. This is a software which takes the airport flight data, passenger turn up data, check-in counter data, and other model parameters as input to generate a simulation model. The IRSS proposed also has a graphic user interface to simulate and animate the check-in counter queueing for a single flight. Simulation parameters such as tolerable passenger waiting time, queue lengths, service rates, check-in times for flights, the number of check-in counters, number of passengers or time of departure can be changed to match the reality at the airport and to observe the change in counter allocation. The objective is to find a counter profile (a counter assignment solution) which saves the maximum counter time compared to the current counter allocation and maintains the desired service level quality. The authors also account for the stochastic processes such as arrival rates. The Check-in Counter Allocation System (CCAS) presented by Chun (1996) together with the IRSS are capable of addressing check-in counter allocation problem at an airport and were used together in the Kai Tak International Airport. The solutions obtained are evaluated by analysing the waiting times of passengers and queue lengths. Though the algorithm tries to achieve the best possible solution, a major disadvantage is that not all possible counter profiles can be simulated. The authors examine some counter profiles to arrive at the best counter allocation (Chun (1996)). Due to this we cannot ensure that the service quality level provided is the best possible. Also, for a large number of flights and time windows, algorithms with simulation will take a large amount of time.

Bevilacqua and Ciarapica (2010) present a case study and an analysis of counter allocation through simulation. Their objective is to cal-
calculate minimum counter requirement of each flight such that average waiting time does not exceed the maximum allowable limit. Passenger arrivals and counter operations are simulated for a single flight or a group of flights. Poisson distribution was used to generate arrivals. The model assumes steady state of the system. In the case study presented, counter operations are modelled as a queueing theory system and stability conditions for common check-in were calculated. Simulation analysis shows that common check-in is better than dedicated check-in. Simulation results are compared with standard results from queuing theory. The effect of varying arrival time distribution and number of counters allocated to a flight on the average waiting time is computed. It is observed that queuing theory is more applicable for common check-in and simulation is more suited for dedicated check-in.

Using simulation for decision making process has the main disadvantage that it explores only a small subset of the whole possible scenarios that can be reached by the system under study, thus reducing its optimization potential (Mota (2015)). To overcome this problem many authors have proposed mathematical models for determining counter requirements and for ensuring adjacency in counter allocation. Some of the models are discussed in the sections 2.1.1 and 2.2.1.

3.2 Network Model for Counter Allocation

Tang (2010) developed a network flow model for allocating blocks of counters to airlines. The network flow model aims to optimize counter usage at a Taiwan airport. The model uses predefined blocks of counters at the airport and opening and closing counter times of flights. Each flight is defined using an arc, the opening time and the closing time form connecting nodes. Arcs are used to denote sequential flight allocations in a counter block (Fig. 11a).

The opening time, closing time and counter requirements for a flight are inputs to the model, as determined by airlines. An ILP meeting all the constraints at the airport is proposed. Flights, set of nodes and arcs that can be assigned to a block are all inputs to the model resulting in a counter block flow network for each block. A network can also be used to represent all the possible flight assignments to a block in a day (Fig. 11b). The main advantages of the network flow method are allocation of adjacent counters and convenient representation of the flight sequence allocated to a counter block. The model involves preprocessing to eliminate redundant constraints (in the example presented by Tang (2010), about 30% of the constraints are redundant) and computing parameters before constructing the model. Due to this preprocessing, running time varies exponentially with input size (the number of flights scheduled and the number of counter blocks allowed). The model is used to find near-optimal solutions at the Tai-
taoyuan International Airport, though implementation becomes extremely complicated for assigning time-varying counters to flights. The main drawback of their model is that the counters are predivided into blocks for allocating to airlines which results in a lot of preprocessing. Since multiple blocks can be built with the same counter, the number of possible blocks can be very large complicating the process of counter allocation.

3.3 Evolutionary Algorithms and Counter Allocation

Some authors have proposed genetic and evolutionary algorithms for the check-in counter allocation problem (Yeung and Chun (1995), Mota and Alcaraz (2015), Mota (2015), Mota and Zuniga (2013)). Evolutionary techniques are a group of methods inspired by common evolutionary processes. These techniques are expected to provide good solutions, i.e. solutions that are close to optimal but may not be optimal (see Goldberg (1989) and Mota (2015)). The efficiency of these techniques relies highly on parameters that drive the selection procedure (see Mota (2015) and Affenzeller et al. (2009)). Genetic algorithms are a part of evolutionary techniques. Genetic algorithms (GAs) are defined as efficient, adaptive and robust search and optimization processes that are applied in large and complex search spaces. GAs are modelled on the principles of natural genetic systems where the genetic information of each individual or potential solution is encoded in structures called chromosomes. GAs compute a fitness function for directing search in more promising areas. Each individual has an associated fitness value, which indicates its degree of goodness with respect
to the solution it represents. GAs search from a set of points called a population and various biologically inspired operators like selection, crossover and mutation are applied to obtain better solutions (Bandyopadhyay and Pal (2007)).

Yeung and Chun (1995) use fitness directed scheduling to develop an airport check-in counter allocation system based on genetic algorithms. Populations of individuals are genetically bred according to Darwinian principles, i.e., reproduction of the fittest and crossover operations. Each individual represents a check-in counter allocation plan for one day (it is the allocation on a Gantt Chart). Each individual also has an associated fitness measure. Fitness measure is in terms of the number of overlaps found in an allocation plan. Lesser the overlaps, fitter the allocation plan. The fittest individual is the best allocation plan for that day. A population of individuals is randomly created and fittest individuals are selected for the crossover operation. The crossover operation is to create offspring counter allocation plans from the selected individuals in the population. By recombining randomly chosen assignments of the fittest allocation plans, we produce new allocation plans. This new population replaces the previous population and the entire process is repeated to create new generations. The best allocation plan that appeared in any generation is the best plan for check-in counter allocation problem.

Mota (2015) presents a methodology that combines evolutionary techniques and simulation and aims to provide a solution which is better than the solution obtained by applying these techniques independently. The algorithm uses a brute-force approach. Flights are allocated sequentially, taking into account all the constraints in flight allocation such as no overlap, counters opened three hours before departure etc. After all the flights are allocated an initial solution is obtained. This is similar to the algorithm first-fit. In order to get varying solutions, the flight order is changed before each allocation. A population of Counter allocation plans is thus obtained. Next, the solutions are converted into vectors (chromosomes) with information that will be used by the evolutionary algorithm. Crossover operations are performed (see Fig.12) to improve the existing solutions such that feasibility of the generated solution is maintained. To perform a crossover between any two initial solutions, flights are selected randomly from each of the two solutions and compared. For a pre-decided percentage of flights, with matching counter opening and closing times, counter locations are interchanged. The crossover procedure is performed on solutions with higher fitness values. The resulting solutions with a high measure of fitness are then retained and again crossed over. Though feasibility of the resulting solution is ensured, the computation time to determine feasibility for crossover is very large and increases with the size of the input. For instance, for an airport with about 2500 depar-
Fig. 12: Crossover of two solutions

In a week, to perform a crossover, 2500*2500 flight combinations need to be checked for possibility of a crossover. The cost function is computed for each generation and checked for improvement. Since the problem is multi-objective, an objective function is computed as a fitness measure. In the algorithm proposed, the solutions are improved till a stop condition is reached. The stop condition is arbitrarily determined and feasible solutions obtained this way are analysed in real-life conditions using simulation.

A major problem with genetic and evolutionary techniques is that the solution(s) with best fitness may not be anywhere near optimal, but is only relatively better among the allocations generated. Larger the initial population of counter assignments higher the possibility of improving the initial solution. For \( n \) flights, the algorithm by Yeung and Chun (1995) needs \( (1 + \left(\frac{n}{2}\right)) \times 2^n \) steps, where \( 2^n \) is the number of possible recombinations of two counter allocations. This results in unnecessarily prolonged and time consuming calculations for eliminating poor solutions, thus, the number of steps for the algorithm increase exponentially with \( n \).

### 3.4 Queuing Theory and Counter Allocation

Parlar and Sharafali (2008) propose a dynamic programming technique based on queuing theory for determining the counter requirement of a flight. Queueing theory results are used to model the problem. A pure death process is used to model the arrivals. An exponential service time distribution is assumed (Erlang distribution is also explored).
The rate of service is observed as proportional to the queue size, hence, service rate is assumed to be state-dependent. The exact forms of distributions of the arrival rate and the service rate are found. These are used to calculate the expected number of passengers in the system and the cost of passengers waiting to be served. Since the arrival rate is time dependent and the arrival process is non-stationary, arrivals are observed and counter operating time is divided into smaller subintervals with constant arrival rate. The arrival rate is then estimated. A dynamic programming model is then used to determine counters to be opened. Counter opening or closing decisions are expected to be made every 20 minutes to minimize the total expected cost. Parlar and Sharafali (2008) propose a model to determine optimal time varying counter allocation for a single flight. Parlar et al. (2013) propose static counter allocation policy for a single flight. Their objective is to minimize the expected total cost of waiting, counter operation, and passenger delay which the authors show to be convex in the number of counters allocated. The authors also introduce a service level constraint to ensure that a certain percentage of passengers are served in each TW.

4 Related Scheduling Problems

Two problems related to ACAP, the two dimensional strip packing problem and resource constrained project scheduling (RPSP), have been studied extensively (see Lodi et al. (2002), Amoura et al. (2002), Blazewicz et al. (1986), Duin and Der Sluis (2006) for further details). The two dimensional strip packing problem comprises of allocating rectangular items to a larger standard size rectangle with the objective of minimizing waste. The problem, \( P{\mid}fix{\mid}C_{\text{max}} \) in multiprocessor scheduling, after swapping time and place is equivalent to the adjacent resource allocation problem with rectangular units (for further details see Duin and Der Sluis (2006) and Amoura et al. (1997)). The problem with irregularly shaped units, such as polyominoes (see Fig.2), is similar to RPSP. Hence, a well known integer programming formulation of RPSP (see Pinedo and Chao (1998), Duin and Der Sluis (2006)) can be modified to solve ACAP (Duin and Der Sluis (2006)).

Duin and Der Sluis (2006) discusses similarities of the counter allocation problem with other resource allocation problems in literature such as the two-dimensional strip packing problem (see Lodi et al. (2002)) and the resource constrained project scheduling problem (see Blazewicz et al. (1986) and Du and Leung (1989)).

Staff rostering/human resource management problems at the airport check-in counters are discussed by Lin et al. (2015), Zamorano et al. (2018), Rodić and Baggia (2017) and Xin et al. (2014). Xin et al.
discusses both counter allocation and staff rostering. Bruno et al. (2018) propose a model to optimize shift scheduling decisions of desk operators and service level measured in terms of passenger waiting times at the counters. A real-life case study has been presented for two airports in Italy. Hsu and Chao (2005) study optimal facility purchase and replacement. Brunetta et al. (1999) evaluates an airport terminal and estimate delays due to facilities such as the check-in counters. Fayez et al. (2008) estimates the passenger flow through the airport. Efficient use of airport capacity is discussed by Pacheco and Fernandes (2003). Yan et al. (2008) and Yan et al. (2014) have worked on reassignments of counter allocations in case of sudden unexpected events at the airport such as change in flight schedule, baggage belt malfunction, airport closure and other disturbances to the planned counter allocation. A mathematical formulation has been presented by Yan et al. (2014) with the objective of reducing the impact of unforeseen circumstances at the airport. An inconsistency for a flight is defined as the deviation between original and reassigned counters. The model aims to reduce the inconsistencies in assignment. A heuristic is proposed for solving the model. The model is modified into two relaxations to obtain an upper bound and lower bound. The two relaxations of the model are repeatedly solved till the difference between the two is lower than a predefined limit. The main advantage of the formulation is that it helps the airport authorities with reassignment of counters to restore normalcy and contain the impact of a disturbance to as few flights as possible. Some numerical validation to the model is given. A major disadvantage is that all flights may not be reassigned adjacent counters. Different counters in different TWs may result in confusion for the customers, as it is not possible to shift passengers in a queue from one counter to another.

5 Conclusion

Various methods of solving the counter allocation problem at airports are presented in this paper. It is observed that determining counter requirements for flights and then allocating adjacent counter space is most suitable to obtain a practical solution to the problem.

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