OPTIMIZATION OF AIRPORT CHECK-IN SCHEDULING AT PASSENGER TERMINAL

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Abstract: The check-in area of airport terminal is one of the busiest sections at airports at certain periods. The passengers are subjected to queues and delays during the check-in process. These delays and queues are due to constraints in the capacity of service facilities. In this project, the airport terminal is decomposed into several check-in areas. The airport check-in scheduling problem requires both a deterministic (integer programming) and stochastic (simulation) approach. Integer programming formulations are provided to minimize the total number of counters in each check-in area under the realistic constraint that counters for one and the same flight should be adjacent and the remaining number of counters in each area should be fixed during check-in operations. By using simulation, the airport system can be modeled to study the effects of various parameters such as number of passengers on a flight and check-in counter opening and closing time.

Keywords: Airport terminal, Integer programming, Scheduling, Simulation.

I. INTRODUCTION

The common characteristics of busy international airports usually involve serving a large number of different airlines, a large number of flights over day, and accommodating various types of aircrafts. The increase of air traffic has also affected the passenger facilities of airport terminals due to the major rise of passenger flow. Two important objectives in this respect are customer satisfaction and cost effectiveness. Both objectives are important for check-in processes, with queues on the one hand and limited capacities on the other. Over the last couple of years there has been a strong development of self-service check-in facilities. Nevertheless, traditional check-in counter will certainly remain present for a number of reasons such as security, logistical baggage aspects and, last but not least, traveler preference for personal treatment and ease of use. The quality of service is the degree of passenger satisfaction when receiving some services from the system.

At many airports, however, check-in capacity is a scarce resource and during specific hours the number of check-in counters can appear to be rather restrictive

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for the total demand. Consequently, long waiting times at check-in counters may be encountered. This in turn, especially in situations of dedicated check-in as generally preferred by (non-domestic) airlines, may lead to undesirable long queues and excessive waiting times at check-in counters.

For airlines this may result in daily conflicts and contention with other airlines for available check-in resources. For airports, considerations might arise for the necessity of check-in capacity expansions in the near future.

An efficient planning of check-in capacities is therefore required at various levels: at daily and operational level to determine the number of counters and opening and closing hours for each individual flight, at weekly level for flight allocation and reservations, at monthly level for contract negotiations with airlines and finally at yearly level for the total counter capacity required.

Clearly, for any of these levels an optimization of capacity resources is thus required at the most detailed level of its daily utilization, as depending on the primary queuing processes and flight demands. In this project, software was designed to estimate the optimum arrangement of check-in zones areas and to evaluate and improve operational and personnel planning.

Much work has been centered on the airport check-in optimization problem. P.E. Joustra et al. [6] introduced practical simulation approach to evaluate checkin at airports. In Yan *et al.* [7] only the pure deterministic scheduling problem is studied. In Atkins *et al.* [2], the total staffing requirements are determined during the day at four security points based on the total passenger flows. A related approach as applied to check-in counter scheduling is presented in Chun [3]. Here simulation is combined with constraint based reasoning which leads to a repetitive algorithm for optimization under constraint patterns. The approach seems of interest but does not seem to guarantee a formal optimization. Nico M et al. [5] has also centered on a combined stochastic and deterministic approach with corresponding tools. The research purely considered the check-in planning problem at the level for which the flight demands are known. T. Huisman et al. [8] proposes a solvable queueing network model to compute performance measures of interest without requiring timetable. A historical queueing reference for the check in service process, in contrast, is the paper by Lee and Longton [1]. And van Dijk [4] introduced practical problems for simulation and queueing theory.

In the current project, we will purely consider the check-in planning problem at the level for which the flight demands are known. That is, with the flights and check-in times for these flights known at a daily level. The number of actual travelers and the traveler arrival times and the check-in times will be estimated. We will study the situation when the airport terminal is decomposed into several check-in zones areas and the airport check-in scheduling problem requires both a deterministic (integer programming) and stochastic (simulation) approach. In the operations research approach, the optimization essentially involves two steps:

Step 1: Deals with scheduling and thus deterministic nature which is an optimization (minimization) of the total number of counters and staffing hours in each check-in zones (areas).

Step 2: Deals with queuing and thus stochastic aspects which is a computation and optimization of the number of counters for an individual flight (or group of flights that share a common check-in), in order to meet a specified service level (in term of waiting times). The stochastic approach for step 2 would at best lead to a feasible planning and would not meet the objective of minimizing the overall counter capacities (staffing hours and number of counters). The deterministic approach would ignore the essential stochastic aspects that are intrinsically involved and related to the other objective: customer satisfaction (waiting time perceptions and service norms).

A two-step, or more precisely, a combination of a stochastic and deterministic, approach is thus required, for both of which standard OR-tools are widely available:

- 1. Queueing and simulation tools;
- 2. MP (ILP and LP) tools.

In practice though, check-in planning is often governed by pragmatic checkin rules based on expert rules of thumb and executional simplicity. In general, at best either one of the two approaches is adopted in combination with manual or spreadsheet calculations. In other words, the potential of OR modelling and ORtools, particularly not a combination of them, seems to remain rather unexploited for check-in planning.

II. DATA COLLECTION AND PROBLEM DESCRIPTION

We will apply our model for Kuwait international airport (KIA). KIA has one terminal that has four passenger check-in zones areas. Each zone area has different total number of check-in counter capacity. Zones 1 and 4 have 32 counters. While zones 2 and 3 have 18 counters. We have collected all flights departure schedule for one week period such as airlines flight number, type of aircraft, departure time and day. The check-in process is usually about two hours period. The check-in process starts three hours before flights departure and closes before one hour before departure. Our interest is to estimate the number of departure passengers per flight and check-in counters for all airlines.

The allocation of check-in counters was done manually without any simulation tools. The predicted resource demand was derived from experience and represented only an approximation. The check-in counters at KIA were managed centrally by the directorate general of civil Aviation (DGCA). This government authority made daily assignments of counters to airlines or their designated ground handling agents. This problem required an accurate estimation of the actual check-in counter requirement for each departing flight.

The process of checking in passengers is stochastic, and the number of required check-in counters varies with factors such as number of passengers, type of aircraft, Airlines Company and destination will all influence the amount of resources to be allocated. Due to this complexity, it is practically impossible for a human to predict resource requirements accurately on a daily basis. Previously, check-in counter allocation was performed manually at the KIA based on prior experience and simple heuristics. In zone area, the procedure starts by selecting airlines with the most check-in counter requests. Airlines with more flights and check-in counter requests are allocated first. Whenever a resource conflict is encountered, the affected airlines are notified, and conflicts are resolved through verbal negotiation. This procedure continues until all the check-in counter requests from all the airlines have been allocated. The major drawback with this procedure is that it relies on the resource requirements provided by the airline and the experience and skill of the human schedulers. However, airlines tend to request many more counters than actually needed to provide better service to their passengers. Unfortunately, the airport was already overcrowded and could not afford to underutilize their check-in counters. At the same time, it was impossible for a human to judge whether requests made by an airline were reasonable without a simulation tool.

We have investigated for each airline flights the demanded number of checkin counters for. Usually it depends on the number of passengers and the type of aircraft. The required number of check-in counters should satisfy two basic goals. The first basic goal is that there should be enough counters to process all the passengers boarding the flight before counter closing time. The other goal is related to service quality. Depending on the historical data and the requested number of counters for each airline, we have concluded that on the average the number of passengers that can be served for one counter during check-in period is about 40 passengers for all airlines. Since the type of aircraft for some airlines flights is changeable due to technical reasons in KIA, we will estimate the number of departure passengers per flight or airline. To estimate the number of departure passengers and flights frequency for all airlines. For each airline, we divide the number of departure passengers by flights frequency to get the estimated number of departure passengers per flight.

In this project, we will let the value β be the assumed number of passengers that can be served for one counter during check-in period. To estimate the required number of check-in counters, we divide the estimated number of departure

passengers per flight by β . For example, if the estimated number of departure passengers per flight for an airline is 200 passengers and let β = 40. Then the required number of check-in counters for this airline is 5 counters.

From the collected data, we have 881 departure flights and with 40 airlines. We have calculated the required number of counters for whole week for each check-in zones for the current airline to zone allocation. Fig. 1 describes the current situation for required number of counters if we let $\beta = 40$. We can notice from the graphs that the required number of counters exceeds the capacity especially at night flights in zone 2 and 3. The capacity for these two zones is only 18 counters. While zone 1 and 4 have 32 counters.





Figure 1: The current situation for the required number of counters when $\beta = 40$

III.INTEGER PROGRAMMING FORMULATIONS

Once the required numbers of counters, or rather counters hours, for each individual flight (or group of flights in the case of partial common check-in) are determined as outlined in Section 2, we will define the optimum airline to zone assignment while minimizing the number of check-in counters for each zone. And a minimization of the counter capacities and staffing hours for all flights, given that the counter requirements for each flight are known.

According to the airport officials, each airline should be assigned to one zone area in passenger terminal. In each zone, there are a limited number of check-in counters. So the total number of counters assigned does not exceed the counters capacity for each zone for all times. We will let the value α be the remaining number of counters in each zone. The total number of assigned counters should not exceeds the difference between α and the maximum capacity of each zone. The benefit of using the value α is to let a remaining number of counters in each zone in case of operating extra flights or an immediate need of extra counters due to the increasing of passengers in peak hours times. For example, if we let $\alpha = 7$ the number of check-in counters in each zone area will be as follow:

Check-in counters in zones 1&4 equal to 32-7=25 counters.

Check-in counters in zones 2&3 equal to 18-7=11 counters.

For every season during a year, airline flights schedule is repeated every week which starts from Monday and ends on Sunday. We will let the value t represents the time period by minutes for a whole week. The value t takes values from 1 till 10,080. For example, if t = 60 that refers to Monday at 01:00am.

3.1. Identify decision variables

Notations

n: Total number of airlines.

m: Total number of zones.

t: Time period.

 α : The remaining number of counters in each zone.

 β : The number of passengers that can be served for one counter during check-in period.

 c_{ti} : Expected number of passengers at time t for airline i.

*cc*_{*i*}: Counter capacity for zone j.

Binary variable
$$x_{i,j} = \begin{cases} 1 & \text{If airline } i \text{ assigned to zone } j \\ 0 & \text{Otherwise} \end{cases}$$

3.2. Constraints and objective function

The problem of minimizing the total number of counters, given the counters requirements and the adjacency constraint, can be formulated as:

Minimize
$$\sum_{j=1}^{m} \sum_{i=1}^{n} x_{i,j}$$

The constraints:

1.
$$\sum_{j=1}^{m} x_{i,j} = 1$$
, $(\forall i, 1 \le i \le n)$.

2.
$$\sum_{i=1}^{n} (c_{t,i} x_{i,j}) / \beta \le cc_j - \alpha$$
$$(\forall j, t, 1 \le j \le m, 1 \le t \le 10,080)$$

The first constraint ensures that every airline *i* should assigned to one zone *j* while the second constraint ensures that the total number of assigned counters for all airlines that assigned to zone *j* at time *t* should not exceed the difference between α and the maximum capacity of each zone. When $x_{i,j} = 1$, the value of $c_{t,i}x_{i,j}$ is refers to the expected number of passengers for airline *i* which assigned to zone *j* at time *t*. when we divide this value by β we get the required number of counters for airline *i* assigned to zone *j* at time *t* which refers to the time period by minutes for a whole week.

The IP model was implemented using the GAMS modelling language. When we solved the IP model, we let β = 40 and the maximum value of α that we can put to get a feasible solution is 7 counters. Fig. 2 represents the output for the required number of counters after solving the IP model.



Figure 2: Output for the required number of counters after solving the IP model when $\beta = 40$.

4. SIMULATION APPROACH

The check-in process encounters a number of variable and stochastic aspects. The variability of flight patterns over months, weeks and days up an hourly level of how many flights are to be checked-in during which hours. Depending on the time scale of capacity and check-in planning prior to the actual operations, for example at yearly or monthly levels, these variabilities are to be regarded as subject to uncertainty (stochastics).

In this paper, we will consider the check-in planning problem at the level for which the flight demands are known. That is, with the flights and check-in time for these flights know, say at a daily level. In addition, the number of actual travelers for each flight was estimated (see Section II). Nevertheless, a number of aspects remain uncertain as the traveler arrival times and the check-in times.

Simulation is used to evaluate and improve operational and personnel planning in order meet a service level for each separate flight. We used C sharp programming language to apply the simulation model. We have collected the necessary data to look for the appropriate data distribution for passengers interarrival times for each airline. Expertfit and Input Analyzer were used to come up with the appropriate data distributions. Inter-arrival times mostly fit to Gamma (2.907407, 14.700486), and the distribution of one counter service time is assumed to be Uniform (1, 3). In the simulation model, we will compare between the actual and IP results for airlines to zone allocation .Passengers are treated as individual entities and we have put in our consideration the opening and closing time for each counter for each flight, the expected number of passengers for each airline and the required number of counters for each airline. Fig.3 presents an example for the amount of passenger arrival time three hours before the departure time of a flight. The figure illustrates 100 passengers arrival pattern before flight departure time after fitting the Gamma distribution. The standard planning would allocate a fixed number of 3 counters during the 2 hours checkin period. Furthermore, Fig.3 is very close to the real situation in (KIA) since all of the flights are international flights and most of the passengers tend to arrive early especially the passengers with a long-haul flight to avoid missing the flight. By simulation (as well as measurements), this led to mean waiting times of approximately 20 minutes. More seriously though, during the first opening hour, during which over 60% of all passengers have arrived, excessive waiting times in the order of 40 minutes were measured, while 10 minutes in the second hour.

We wish to minimize the total number of counters and staffing hours under the realistic constraint requirements and the capacity in each check-in zone using the fact of passengers arrival pattern. Thus, we need to find the best possible optimal allocation. The number of check-in counters during the opening period does not need to be constant. For example, it is thus allowed to adjust these



Figure 3: Passengers arrival pattern

numbers beforehand, say by the hour, as based upon the arrival pattern or even dynamically as based upon the actual number of passengers waiting. This feature can be exploited for check- in allocation in order to reduce the number of counters and staffing hours. For a minimization of the counter capacities and staffing hours for all flights, we will compare three Integer Programming formulations scenarios:

- (i) In scenario 1, the number of counters is constant during the working hours.
- (ii) While scenario 2 we reduce one counter in the second hour after opening the counter and
- (iii) In Scenario 3, we add one extra counter in the 1st hour and reduce two counters in the 2nd hour after opening the counter.

The number of check-in counters during the opening period for the current situation at KIA is constant during the working hours (same as scenario 1). From the actual one week KIA data, the total staffing working hours for scenario 1 is 5,582 hours. While in scenario 2 and 3 is 4,604 hours (18% change). Each airline has different daily or weekly flights frequency with different expected number of passengers which leads to different waiting time and queue length. When we applied the IP model, the airlines were rescheduled to zone area. We have noticed that about half of the flights that were in zone 2 and 3 have moved to zone 1 or 4. Table I represents the simulation results for passenger average waiting time for both actual or current situation and IP result for airline to zone allocation. The saving percentage is calculated by taking the difference between passenger average waiting time for the actual situation and passenger average waiting time for the IP model for airline to zone allocation and divided by passenger average waiting time for the actual situation. For scenario 1, the maximum value of α that we can put to get a feasible solution is 7 counters when $\beta = 40$ and only 2 counters in case of β = 30. For the other scenarios, the maximum value of α is 6

counters for scenario 2 and 3 counters for scenario 3 when $\beta = 40$. In case of $\beta = 30$, the maximum value of α is 3 counters for scenario 2 and 2 counters for scenario 3.

Table I Simulation Desults For Decompose Average Weiting Time (Minutes)

| Simulation Results for Lassenger Average Waiting Time (Windles) | | | | | | | |
|---|--------------|-----------|----------|--------------|-----------|----------|--|
| | $\beta = 40$ | | | $\beta = 30$ | | | |
| Scenario | Actual | IP Result | % Saving | Actual | IP Result | % Saving | |
| 1 | 61.072 | 41.615 | 32% | 23.050 | 20.524 | 11% | |
| 2 | 48.752 | 54.088 | -11% | 22.669 | 19.449 | 14% | |
| 3 | 27.130 | 33.740 | -24% | 17.553 | 17.349 | 1% | |

Due to the flights shifting from zone to another, there are few cases when the actual allocation gives lower passengers average waiting time than the IP results since the expected number of travelers is differ from airline to another. Scenario 3 for IP results gives minimum average waiting time especially when we choose $\beta = 30$. In this case, the staffing working hour will increase to 2,429 hours. The required number of counters for the period facing the peak of passenger arrivals will generally be larger than the required number for the constant counter capacity case.

In the actual airline allocation, the required number of counters exceeds the capacity multiple times during the week. While in the IP model, we used the constraint of zone capacity and let α be the remaining number of counters in each zone. Table II shows the maximum required number of check-in counters during the whole week. The required number of check-in counters in the actual airline allocation exceeds the capacity in zone 2 and 3 in scenario 1 and 2 and zone 2, 3 and 4 in scenario 3 which may lead to undesirable long queues and excessive waiting times at check-in counters. While in the IP model, there are remaining check-in counters in all times during the week which can be used in case of operating extra flights or an immediate need of extra counters due to the increasing of passengers in peak hours times.

Since the current situation at KIA is using scenario 1 which the number of check-in counters during the opening period is constant during working hours, triple win was so obtained. Not only in minimizing check-in counters (staffing) hours but also in minimizing average waiting time and having remaining check-in counters in all times during the week.

The three Scenarios for the IP model result are summarized in Table III. For $\beta = 40$, 61.072 minutes average waiting time was simulated for the actual airline allocation (see table I). A minimization of **45**% and 18% for average waiting time and check-in counters (staffing) hours with at least 3 counters remaining during the whole week that can be met in scenario 3 using the IP model airline allocation.

| maximum nequire number of cheek in counter During the throte freek | | | | | | | | |
|--|----|------------|-----------|------------|-----------|------------|-----------|--|
| | | Scenario 1 | | Scenario 2 | | Scenario 3 | | |
| | β | Actual | IP Result | Actual | IP Result | Actual | IP Result | |
| Zone 1 | 30 | 19 | 30 | 18 | 29 | 24 | 30 | |
| (32 Counters) | 40 | 14 | 24 | 13 | 22 | 18 | 29 | |
| Zone 2 | 30 | 35* | 16 | 33* | 15 | 38* | 16 | |
| (18 Counters) | 40 | 27* | 10 | 26* | 12 | 29* | 13 | |
| Zone 3 | 30 | 31* | 16 | 26* | 13 | 30* | 16 | |
| (18 Counters) | 40 | 23* | 11 | 23* | 10 | 23* | 14 | |
| Zone 4 | 30 | 28 | 30 | 26 | 28 | 33* | 30 | |
| (32 Counters) | 40 | 21 | 24 | 21 | 21 | 25 | 25 | |

 Table II

 Maximum Required Number of Check-in Counters During the Whole Week

* The required number of check-in counters exceeds the capacity.

For $\beta = 30$, 23.050 minutes average waiting time was simulated for the actual airline allocation. A minimization of 25% and 12% for average waiting time and check-in counters (staffing) hours with at least 2 counters remaining during the whole week can be met in scenario 3 using the IP model airline allocation.

Therefore, in the combination with the two steps results for the IP and the simulation approach, KIA should consider applying scenario 3 since it gives better results among the other scenarios in terms of minimizing both check-in counters (staffing) hours and average waiting time in case of $\beta = 40$. The average waiting time can be decreased from 33.74 minutes to 17.349 minutes but the check-in counters working hours will be increased to 2,429 hours (see table III). Furthermore, if an airline have an immediate need of extra counters due to the increasing of passengers during the week there are still at least 3 counters remaining even in peak hours times. In rare cases, some airlines are considering the need to operate an extra flight. KIA officials should negotiate with those airlines to operate this extra flight in a time other than the peak hour period during the day to avoid any risk may lead to undesirable long queues and excessive waiting times at check-in counters.

Table III Summary for IP Model Result

| | | Total s | Total staffing working hours | | Average waiting | | Remaining number | |
|----------|--------------|--------------|---------------------------------|--------------|-----------------|--------------|--------------------------|--|
| Scenaric | o Counters | working | | | time (Minutes) | | of counters (α) | |
| | requirements | $\beta = 40$ | $\beta = 30$ | $\beta = 40$ | $\beta = 30$ | $\beta = 40$ | $\beta = 30$ | |
| 1 | Constant | 5,582 | 8,011 | 41.615 | 20.524 | 7 | 2 | |
| 2 | Variable | 4,604 | 7,033 | 54.088 | 19.449 | 6 | 3 | |
| 3 | Variable | 4,604 | 7,033 | 33.74 | 17.349 | 3 | 2 | |
| | | | | | | | | |

5. CONCLUSION

In this study, we have developed a check-in allocation for airport terminal which decomposed to several check-in zones which have different counters capacity. We have made a combination of a stochastic and deterministic OR-approach for real world applications. For the check-in problem this combination concerns a two-step approach: Step1: Mathematical (integer) programming in order to minimize the staffing and counters capacities for each zone. Step 2: Simulation in order to study the queuing processes. The combination was illustrated and shown to be fruitful for a real numerical check-in data. Due to the fact of passengers arrival pattern at the check-in zones, we have compared two Airlines to zone check-in allocations (Actual and IP Results) for 3 scenarios for counters staffing hours. The first scenario deals with constant counter capacity while the other two scenarios deal with variable counter capacity by the hour.

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