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Multi objective gate assignment models for increasing shopping revenues at airports

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Abstract

In this study, multi objective models that aim to increase the shopping revenues at airports are investigated. The aim of the proposed multi objective model is to assign passengers to specific gates near shopping facilities in order to increase shopping revenues at airports. Using the data obtained from previous studies, proposed multi objective models are tested. Results revealed that it is possible to assign more passengers to gates located near to the shopping facilities without increasing passenger walking distances.

Introduction

Nowadays, airport operators obtain most of their revenues from commercial activities such as retail, duty free, car parking, etc. (Graham, 2008). They believe that an airport can be a leisure attraction and primary destination in its own right (Freathy & O'Connell 1999). Besides, surveys about airport retail showed that most passengers plan to shop in airports (Entwistle, 2007). Apart from this motivation for shopping in airports, it is also known that passengers waiting times to board influence their possibilities for consumption in airports (Torres *et al*.2005). This makes waiting passengers a source of revenue for airport operators.

Then the question is: Without increasing the total time that passenger spend inside the terminal, can we increase the passenger waiting time to increase the possibility of shopping? In order to achieve this, passengers should spend less time to reach departing gates. Motivated from this idea, we aim to find a gate assignment plan such that both the total passenger walking distance is minimized and the number of passengers assigned to the gates close to shopping facilities (*called as selected gates*) are maximized. To find such a gate assignment plan, we proposed different multi-objective models. The offered models include objectives such as maximizing the number of passengers assigned to selected gates and maximizing the number of passengers assigned to all gates to increase shopping revenues at airports.

Literature review

Presently, airport operators have to manage airport resources better due to increasing air traffic. One of the problems encountered in airports is the gate assignment problem which aims to find a suitable gate to an arriving aircraft. Up to date, many single and multi-objective models have been proposed to solve GAP. In fact, various researchers argued that GAP is a multiple objective problem rather than a single objective problem (Yan & Huo, 2001; Dorndorf *et al*., 2007; Wei & Liu, 2009). Most of the proposed multi-objective models (Cheng, 1997; Yan & Huo, 2001; Zhu *et al*. 2003; Lim *et al*. 2005; Hu & Di Paolo, 2007; Ding *et al*. 2005; Drexl & Nikulin, 2008; Pintea *et al*. 2008; Maharjan & Matis 2012; Kim *et al*., 2013; Tang & Wang, 2013; Neuman & Atkin, 2013) are solved by aggregating these multiple objectives into a single objective function using weighted-sum aggregations.

Only in a small number of studies methods other than weighted-sum approaches (Drexl & Nikulin 2008; Nikulin & Drexl, 2010; Wei & Liu 2007) are encountered. Among these approaches just the ones proposed by (Drexl & Nikulin, 2008) and (Nikulin & Drexl, 2010) were Pareto-based ones. In this study, the interaction between the multiple objectives is examined using a Pareto-based solution approach. Thus, the offered study is one of the few Pareto approaches in literature.

Not only the solution approach, but also the considered sets of objectives aimed to increase shopping revenues at an airport are not dealt before. The considered objectives aiming to increase potential shopping revenues are most similar to the objective of airline preferences which tried to assign some flights to predetermined gates. Although some studies

(Dorndorf *et al*.,2007; Drexl & Nikulin, 2008; Nikulin & Drexl, 2010) considered the objective of airline preferences before, discussion about how this objective interacts with others is relatively limited. More, models aiming to increase potential shopping revenues of an airport have not been met before.

Multi objective gate assignment models

The basic Gate Assignment Problem (GAP) can be defined as assigning a set of flights/aircraft to a set of appropriate gates in an airport to minimize the cost of assigning a flight to a gate. GAP mainly includes two sets of constraints; each flight must be assigned to a gate (or apron), and one gate can process only one aircraft at the same time. By considering this basic problem definition, we proposed multiple objective models for assessing the possibility of increasing shopping revenues.

In the first, the goal is to maximize the number of passengers assigned to selected gates. Whereas in the second model, the first goal is to maximize the number of passengers whose flight is assigned to a gate. The overall aim of the second model is to see whether forcing the model to assign more passengers to gates indirectly increases the number of passengers assigned to selected gates as well. In the third model, our overall aim is to increase the number of passengers assigned to the selected gates by minimizing the variance of the slack time at selected gates. By better utilizing the available gate time, we are trying to assign more flights to the gates. It is hoped that this would lead to more passengers in the gates. Apart from objectives related to maximizing the number of passengers assigned to selected gates, the second goal for the models is to minimize the total passenger walking distance of the passengers. The aim of offering different objective functions to achieve the same goal (maximizing the number of passengers assigned to selected gates) is to see which of them better serves our goal.

The following notations are used to model the problem.

A_j: arrival time of flight j
D_j: departure time of flight j
d_j: the distance between the waiting hall and the gate j
m: number of gates
M: set of gates (including Apron)
N: set of flights
n: number of flights
pn_i: the number of passengers of flight i
R: is the set of selected gates (gates close to shopping facilities)
$y_{i,j}$: a zero-one variable showing whether flight i is assigned to gate j or not

The first model includes the objective of minimizing the total passenger walking distance and maximizing the number of passengers assigned to the selected gates.

$$min \sum_{j \in M} \sum_{i \in N} pn_i d_j y_{i,j}$$

$$max \sum_{j \in R} \sum_{i \in N} pn_i y_{i,j}$$

The second model tries to minimize the total passenger walking distance and to maximize the number of (arriving or departing) passengers assigned to all gates.

$$min \sum_{j \in M} \sum_{i \in N} pn_i d_j y_{i,j}$$

$$max \sum_{j \in R} \sum_{i \in N} pn_i y_{i,j}$$

Finally, the third model includes the objective of minimizing the total passenger walking distance and minimizing the variance of the slack (idle) time of the gates s_{ij} which are close to shopping facilities.

$$min \sum_{j \in M} \sum_{i \in N} pn_i d_j y_{i,j}$$

$$min \sum_{j \in R} \sum_{i \in N} s_{i,j}^2$$

This objective of minimizing the variance of the slack time of all gates is formulated by Bolat (2000) as a surrogate objective function,

$$min \sum_{j \in R} \sum_{i \in N} s_{i,j} = \sum_{j \in R} (L_{n+1,j} - L_{0,j}) - \sum_{i \in N} G_i$$

where $L_{n+1;j}$ denotes the latest available time of gate j, $L_{0;j}$ denotes the earliest available time of gate j and G_i denotes the ground time of the flight i, $G_i = D_i - A_i$. To compute the ground time of a flight G_i, arrival time A_i and departure time D_i of the flights should be known. When using this objective, the following constraints (Bolat 2000) are also considered;

$$E_{i,j} \geq A_i y_{i,j} \quad \forall i,j$$
$$E_{i,j} \geq L_{i-1} y_{i,j} \quad \forall i,j$$
$$L_{i,j} = E_{i,j} + G_{i,j} y_{i,j} \quad \forall i,j$$
$$s_{i,j} = E_{i,j} - L_{i-1,j} \quad \forall i,j$$
$$s_{n+1,j} = L_{n+1,j} - L_{n,j} \quad \forall i,j$$
$$E_{i,j}, L_{i,j}, s_{i,j}, s_{n+1,j} \geq 0 \quad \forall i,j$$

In the presented models, if a flight is assigned to a gate (other than gate m+1 which represents Apron). Then, the slacks in a gate can be calculated by considering the entering time $E_{i;j}$ and ground time $G_{i;j}$ of the assigned flights in that gate. Besides, the models are subject to following basic set of constraints.

The first set of constraint ensure that each flight must be assigned to a gate or Apron (gate m + 1).

$$\sum_{j \in M} y_{i,j} = 1, 1 \leq i \leq n$$

On the other hand, the following constraint set guarantees that one gate processes only one aircraft at the same time.

$$y_{i,k} y_{j,k} (D_j - A_i)(D_i - A_j) \leq 0, 1 \leq i,j \leq n, k \neq m+1$$

That is, if there is an overlap between the ground times of flights, i and j; these flights could not be assigned to the same gate.

TPLS+ PLS algorithm

The basic gate assignment problem is an NP-hard problem (Obata, 1979). Thus, the developed models are solved with a hybrid local search algorithm namely: Two Phase Local Search (TPLS) combined with a Pareto Local Search (PLS) algorithm which is

TPLS algorithm is a scalarization-based technique, including two subsequent steps. In the first step, TPLS obtains a solution for at least one of the objectives whereas in the second step, TPLS uses this solution generated by the single objective algorithm as a seed to start scalarizations. To generate a starting solution, a constructive heuristic is used. This heuristic algorithm first sorts the flights w.r.t. passenger numbers. Then, the flight with the highest passenger number is assigned to the gate with the shortest distance to the exit. This algorithm heuristically aims to generate a good solution to the gate assignment problems which generally includes the objective of minimizing total passenger walking distance. After finding a starting solution, this solution is used to start scalarizations.

Using scalarizations, multiple objectives are transformed into a single objective using weights. This is needed to find the non-dominated solutions. After solving the single objective problems, the algorithm updates the archive with these new solutions. In this study, the following weight vector is supplied to the TPLS algorithm to scalarize objective functions. This weight vector $\mathbf{w}_1$ = (0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 0.99, 1) indicates the weights for the first objective. The weights for the second objective are determined by $\mathbf{w}_2 = 1\text{-}\mathbf{w}_1$.

The steps of the TPLS algorithm are as follows;

Step 1. *Generate a solution for one of the objectives or for all objectives using a single objective algorithm*
Step 2. *Add these solutions to the archive*
Step 3. *Repeat the following until the objectives are scalarized with all the weights in the set of weights.*
Choose a weight to scalarize the objectives.
Generate solutions for the scalarized problems.
Update the archive with the generated solutions from the scalarized problems.
Step 4. *Filter the dominated solutions from the archive and end.*

After obtaining a set of solutions using the TPLS algorithm, a dominance-based multi objective algorithm called PLS, have been utilized. PLS randomly select an unexplored solution from the archive and search the neighbors of this solution fully. During the search, PLS accept a new solution if it is not dominated by any solution in the archive (Paquete *et al*. 2004). If the new solution dominates some solutions in the archive these dominated solutions are removed from the archive and the new solution is added to the archive. The search continues until all the unexplored solutions in the archive are fully explored. It is worth mentioning that a maximum size is not defined for the archive.

The steps of the TPLS algorithm are as follows;

Step 1. *Set the status of the solutions in the archive to unexplored.*
Step 2. *Repeat until all the solutions in the archive has a status of explored.*
Step 2.1. *Select one random solution from the initial set of non-dominated solutions in the archive.*
Step 2.2. *Repeat the following until all the neighbors of the selected solution s is explored.*
Step 2.3. *Explore the neighborhood of the selected solution s.*
Step 2.3.1. *If accepted solution s* is non-dominated w.r.t. the other solutions in the archive, update archive with the newly found solution s*. Set the status of the accepted solution s* as unexplored.*
Step 2.4. *Change the status of the selected solution s as explored.*
Step 3. *End*

During the search, a solution is represented as a string having the number of elements equal in the number of flights. The length of a string represents the assigned gate number. To search the solution space, two different moves are utilized. First move is called exchange move. In this move, the gates of the two subsequent flights are exchanged. If both subsequent flights are already assigned to Apron, then the flight with the bigger number is assigned to a random gate. The other move is called greedy move. In this move, first a set of selected flights are assigned to Apron, then they are reassigned to the gates with the shortest walking distance if possible.

Results

The models are tested on a problem proposed by Wei & Liu (2007) based in the data collected from Beijing International Airport. The problem includes 117 flights and 10 gates from 07:00 to 18:00. The problem is solved by considering 10 gates and 117 flights from 07:00 to 18:00. For this problem, it is assumed that gates 2, 3, 6 and 7 are close to shopping facilities. The distance from gates to the waiting hall (in meters) is obtained from Yu & Song (2013) and presented in Table 1. The algorithm had no parameters to adjust. Nevertheless, due to the stochastic nature of the search process, each model is run for 15 times. The obtained non-dominated points are presented in Table 2.

Table 1. Data related to gates (Yu & Song, 2013)

Gates	*Distance to waiting hall (meters)*
1-2 3-4 5-6 7-8 9-10	100 200 300 400 500
APRON	1500

Table 2. Solutions obtained

	Number of Passengers Assigned to Selected Gates	*Total Passenger Walking Distance (meters)*	*Variance of Slack Time*
Model 1	10,221 10,378 10,411 10,456 10,434 10,489	10,632,700 10,655,500 10,658,800 10,806,200 10,804,000 10,809,500	-
Model 2	9,795	10,579,400	-
Model 3	9,795 9,795 9,873 9,932 9,707 9,573 9,476 9,714 9,681 9,846 9,846 9,755 9,477 9,537	10,579,400 10,592,800 10,724,400 10,790,100 10,834,600 10,851,800 11,032,100 11,817,600 11,853,900 11,886,900 11,897,900 11,928,600 12,122,400 12,233,800	18,627 18,157 17,650 17,475 16,608 15,012 14,259 13,538 13,314 12,417 12,403 11,599 11,559 11,367

For the first model, a non-dominated front is obtained. However, for the second model only a single solution is reached. The reason for such a solution is that, the objectives of second model are found to be completely conflicting objectives. Because trying to assign more passengers to gates means that total passenger walking distance would increase in turn. However, the model tries to reduce the total passenger walking distance as well, using the other objective.

The second model assigned 23,028 passengers to the gates with a total passenger walking distance of 10,579,400 meters. When the number of passengers at selected gates (gates 2, 3, 6 and 7) is calculated, it is found out that in total 9,795 passengers could be assigned to gates close to shopping facilities. When this solution is compared to the non-dominated set of solutions of the first model, it can be seen that the second model reaches a solution that is worse in terms of the number of passengers assigned to specific gates. However, this solution is better in terms of the total passenger walking distances.

On the other hand, results of the third model indicated that the model did not behave as expected. That is, forcing the model to reduce the slack at the selected gates did not enable one to assign more passengers to the selected gates. For example, in an assignment with a variance of slack time equal to 16,608 assigned 9,707 passengers were assigned to selected gates whereas, in an assignment with a variance of slack time equal to 11,599, 9,755 passengers were assigned to selected gates. In other words, reducing the slack time at gates does not guarantee an increase on the number of assigned passengers.

Yu & Song (2013) solved the same problem using Squeaky Wheel Optimization (SWO) algorithm in order to minimize average passenger walking distance. Using this algorithm they obtained (approximately) 14,877,480.8 meters total passenger walking distance (for an average passenger walking distance of 571.4635 meters). Using the improved version of the algorithm, they obtained an (approximately) 14,585,150.2 meters total passenger walking distance (average passenger walking distance of 560.2347 meters). Compared to these results, obtained results generated a gate assignment plan having a much smaller total passenger walking distance.

Conclusions and Future work

In this study, multi objective models aiming to increase possible shopping revenues of airports are proposed. The overall aim of these mathematical models was to increase the number of passengers at the gates close to shopping facilities and to decrease the total passenger walking distances so that passengers could have more time to shop inside the terminal. A hybrid algorithm namely TPLS+PLS have been used to solve the offered multi-objective models. Among the proposed models, the first model which is the more specialized one, generated the best result in terms of passenger walking distance and number of passengers assigned to gates close to shopping facilities. This indicates that with specialized models like the first model, better gate assignments can be obtained in-line with the marketing practices of an airport. To obtain more realistic models, it is planned to extend these models further by adding constraints that consider taxi-time, towing or gate blockage.

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