

A Simulation-Evolutionary Approach for the allocation of Check-In Desks in Airport Terminals

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Abstract. The aeronautical industry is still under expansion in spite of the problems it is facing due to the increase in oil prices, limited capacity, and novel regulations. The expansion trends translate into problems at different locations within an airport system and are more evident when the resources to cope with the demand are limited or are reaching to their limits. In the check-in areas they are appreciated as excessive waiting times which in turn are appreciated by the customers as bad service levels. The article presents a methodology that combines evolutionary algorithms and simulation in order to give the best results taking into account not only the mandatory hard and soft rules determined by the internal policies of a terminal but also the quality indicators which are very difficult to include using an abstract representation. The methodology uses an evolutionary algorithm to satisfy the different mandatory restrictions such as minimum and maximum number of check-in desks per flight, load balance in the check-in islands, opening times of check-in desks and other restrictions imposed by the level of service agreement. Once the solutions are obtained, they are evaluated using a simulation model of the terminal that takes into account other aspects of the problem such as arriving profiles of the passengers, the opening times and the physical configurations of the facility under study with the objective to determine which allocation is the most efficient in real situations in order to maintain the quality indicators at the desired level

Keywords. Simulation, Heuristics, Terminal, Check-In, Evolutionary Algorithms

Introduction

The aeronautical industry is still under expansion in spite of the problems it is facing due to the increase in oil prices, limited capacity, and novel regulations. The expansion trends translate into problems at different locations within an airport system and are more evident when the resources to cope with the demand become scarce. In

the airfield these problems appear as queues in the runways with the corresponding delays; inside the terminals they are appreciated as huge queues in the security filters and in the check-in counters as excessive waiting times which in turn are appreciated by the customers as bad service levels. The planning departments of the airports are concerned about these problems and they are currently looking for better ways to manage the scarce resources while the traffic and number of passengers are also increasing. The traditional way of facing such problems has been just the expansion of the terminal facilities and the increase of resources at hand (i.e. addition of more counters, security filters or even runways). In the particular case of the Terminals, the decision makers that manage these systems need to allocate the increasing traffic using the current resources taking into account not only the limitations such as budget, limited areas for expansion, availability of resources but also the ones imposed by the internal policies which take into account metrics that are associated to the satisfaction of the customers. These metrics which are commonly called as Level of Service indicators (LOS) measure some characteristics associated with the comfort inside the terminal such as available area per passenger or the speed at which the passenger can travel inside the terminal. Table 1 illustrates some of the typical values used by airports to evaluate their level of comfort inside terminal areas [3].

Table 1. Typical Values for Level of Service Indicators

Activity	Situation	Level Of Service (m ² /Pax)					
		A	B	C	D	E	F
Waiting and Circulating	Moving about freely	2.7	2.3	1.9	1.5	1.0	Less
Bag Claim Area	Moving with Bags	2.0	1.8	1.6	1.4	1.2	Less
Check-In Queues	Queued, with Bags	1.8	1.6	1.4	1.2	1.0	Less
Hold Room	Queued without bags	1.4	1.2	1.0	0.8	0.6	Less

Due to the current situation, the operations research techniques appear as the ones that are able to tackle the aeronautical problems in the most efficient way taking into account all the different restrictions of a problem. Furthermore when these techniques are applied using a proper cost function they can generate solutions that not only satisfy the current restrictions but also give solutions with high potential of improving the current performances.

The use of optimization techniques are able to give optimal or close-to-the-optimal solutions to problems that are deterministic in nature; on the other hand simulation approaches have the advantages that they are able to describe the studied systems under different abstraction levels and can also consider the stochastic nature of the processes that participate in the system under study. Unfortunately when simulation is used as a decision support tool it presents the disadvantage that it only explores a small subset of the whole possible scenarios that can be reached by the system under study thus reducing its optimization potential.

The article presents a methodology that combines the two approaches in order to give the best results for a common in an abstract representation. The methodology uses in the first phase of the approach an evolutionary algorithm in order to satisfy the measurable restrictions such as minimum and maximum number of check-in desks per

flight, load balance in the check-in islands, opening times of check-in desks and other restrictions imposed by the LOS. The solutions are then encoded as chromosomes and then the typical operations of an evolutionary algorithm are performed in order to obtain the best promising solutions using a particular cost function. Once the solutions are obtained, they are tested using a simulation model of the terminal that takes into account not only the arriving profiles of the passengers but also the opening times, physical configurations of the facility under study and the interactions between passengers when they flow inside the terminal. These elements are used to determine which allocation is the most quality-efficient in a close-to-real scenario in order to maintain the LOS indicators in the desired level. The proposed implementation has been developed using information of a real terminal but it can be easily adapted to another one with different restrictions imposed by the correspondent LOS agreements.

1. A combined Approach: Evolutionary algorithms and simulation

1.1. Evolutionary Approach

The evolutionary approach is a method inspired by common evolutionary processes found in nature [4].

The general idea behind an evolutionary algorithm is the representation of a solution in the form of a vector of decision variables.

Let us assume that we have a discrete search space X and a function

$$f: X \rightarrow \mathbb{R}$$

The general problem is to find:

$$\min f, x \in X$$

Here x is a vector of decision variables, and f is the objective function. Such a problem is commonly called discrete or combinatorial optimization problems [2].

The idea of an evolutionary algorithm is to represent the actual decision variables of the original problem into a different form which has correspondence with the original ones. In line with biological usage of the terms, it has become customary to distinguish the ‘genotype’—the encoded representation of the variables, from the ‘phenotype’—the set of variables themselves.

In the general evolutionary problem the representation is one of the main challenging procedures of the approach. Since most of the representations are not bijections of the original problem some of the obtained solutions are not feasible when they are implemented using the original variables.

1.2. Simulation

Simulation is the imitation of the operation of a real system or process over time. Simulation is used to generate artificial history and data of a system, and the

observation of that artificial history to draw inferences concerning the operating characteristics of the real system [1].

The behaviour of a system as it evolves over time is studied by developing a simulation model. This model usually takes the form of a set of assumptions concerning the operation of the system. These assumptions are expressed in mathematical, logical, and symbolic relationships between the entities, or objects of interest, of the system. Once developed and validated, a model can be used to investigate a wide variety of “what-if” questions about the real-world system. Potential changes to the system can be simulated in order to predict their impact on system performance. Simulation can also be used to study systems in the design stage, before such systems are built. Thus, simulation modelling can be used both as an analysis tool for predicting the effect of changes to existing systems, and as a design tool to predict the performance of new systems under varying sets of circumstances. Nowadays and with the evolution of computer capacities, computer simulation is also able to develop very accurate models and graphically appealing that can represent a system under different abstraction levels depending on the objective of the study. In order to analyse the performance of systems is necessary to execute several experiments with the simulation model in order to have insight about the behaviour of the system under study.

Unfortunately the main limitation of this approach is that when it is used as a decision support tool it cannot ensure the best outcome since the experiments only explore a subset of the whole different configurations of the system under study. Thus the decision making supported in the simulation experiments always has a certain level of uncertainty which can be minimized when the simulation methodology is applied correctly.

2. The Check-In Allocation Problem

The inefficient management of resources at hand (ground services, personnel, desks, filters, etc.) are appreciated as congestions in terminals. The congestion can be appreciated in several points throughout the passenger-boarding process; for example in the check-in desks, the security filters, passport control and sometimes on the boarding gate. These problems have been traditionally faced by the aviation industry through the increase of physical resources (e.g. increase in the check-in desks, increase in the number of security filters etc.). Furthermore the increase in competition between airlines has forced them to optimize their resources at hand in order to reduce their costs and keep competitive.

The general check-in allocation problem consists in allocating the available desks of a terminal in such a way that the allocation satisfies a series of restrictions imposed by the airport and the companies through a service contract. These restrictions may change depending on the airport, the airlines, the region it serves and the type of terminal [6].

The check-in allocation problem is a very-well known problem in airport terminals and has been studied by some authors using also evolutionary approaches or mathematical formulations [5][9][10]. These approaches have the drawbacks that do not take into account all the different elements present in the check-in area of the terminal or the interactions between passengers inside the terminal or with other

elements of the facility. On the other hand the increase of passenger traffic in airports makes necessary the developing of novel decision support tools that take into consideration all the different elements that are part of the area under study and not only an abstract representation of it.

Furthermore the traffic increase caused mainly by the competition between airlines to market liberalization and the increasing number of low-cost airlines will force the need of an efficient allocation of check-in desks inside terminals if the LOS are to be maintained.

The study presented in this paper deals with the problem of performing the check-in allocation desks in a terminal taking into account not only the internal policies and quality indicators but also the interactions between passengers and the physical facilities of a terminal. The different rules and information data have been provided by a terminal in the Middle East under a confidentiality agreement. We shall refer to this airport, when applicable, as “the airport”.

2.1. Description of the Problem

The problem consists of performing the check-in desks allocation satisfying a series of hard and soft rules. The hard rules are the ones that must be satisfied by the approach and the soft rules are the ones that are desirable to be satisfied but can be violated when there is no other available option.

a) Hard Rules

Overlap Verification: The current allocation will be aligned always with the allocation of the previous month in order to avoid having allocated the same check-in desks or near-by for the last flights of the previous month and for the first flights of the current month.

Balanced Loads: Allocating flights to check-in counters will consider an aspirational usage of 20% for each of areas A, B, C, D and E. The acceptable deviance is 1% on daily basis and 5% on each 2-hours window. Fig. 1 illustrates the different zones of the terminal.

Number of Desks: Allocating flights to check-in counters will consider a minimum standard of one check-in counter per 45 passengers.

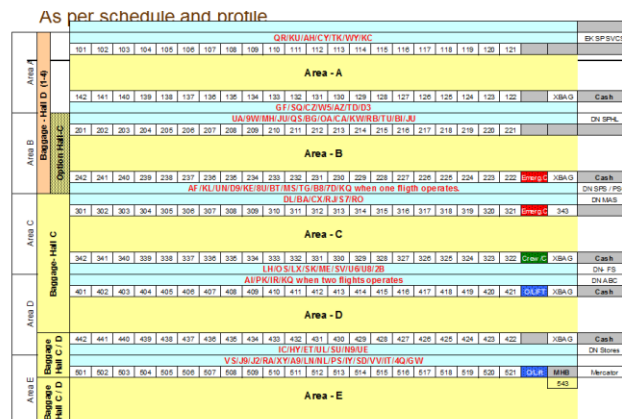


Figure 1. The check-in areas in the terminal

Luggage Halls: Since there are two different luggage halls, it is mandatory that the flights are allocated in check-in desks that share the same luggage hall. Figure 2 illustrates a diagram with the two luggage conveyors systems.

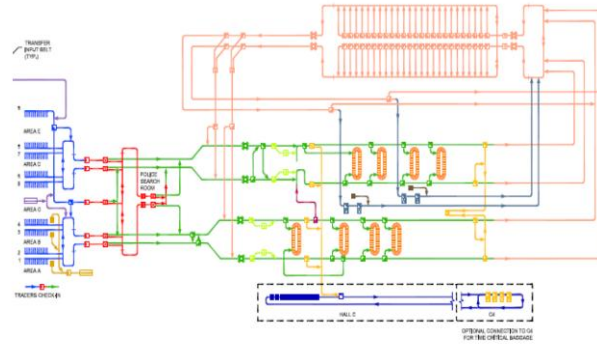


Figure 2. The luggage-halls diagram

b) Soft Rules

Optimized Queuing / Circulation Areas for heavy flights: The allocation will avoid placing more than 3 heavy flights on the same row / island at any given one-hour window.

Optimized Queuing / Circulation Areas for any flights: The allocation will avoid placing 2 flights on consecutive counters at any given one-hour window. The recommended practice is to leave at least one counter free between two flights – for redundancy and flexibility purposes.

Airline Preferences: Airline preferences for allocation of their flights to specific rows or fixed desks will be collected officially during meetings and the solution will consider their requests, only after complying with all the allocation rules.

3. Methodology

The methodology proposed to give solution to this problem is a combination of an evolutionary algorithm and simulation in order to include as much as possible the constraints imposed by the airport and the requirements of the airlines. The simulation environment allows to evaluate the interaction between elements that otherwise could not been included in the model such as passenger-passenger interactions, pax speeds etc.

Fig. 3 presents the diagram that illustrates the different steps in the methodology.

The first approach of the methodology takes into account only some of the aforementioned hard and soft rules, namely:

- Overlap of Flights
- Counters are opened 3 hours in advance
- It calculates the number of counters needed in a base of 45 pax/counter
- It leaves a check-in desk in between flights

- The flights are allocated in the correspondent sections of the check-in area so that the luggage does not end in a different luggage hall
- It allocates the check-in desks in a random way trying to distribute the flights uniformly (load balance)

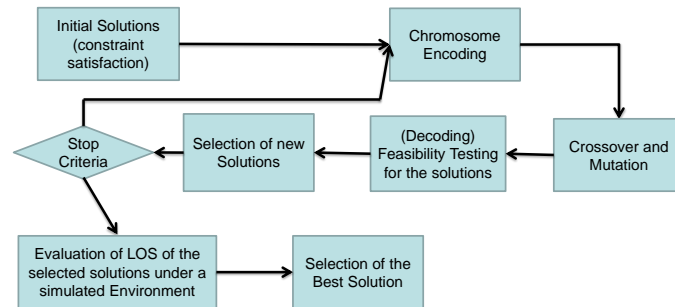


Figure 3. The evolutionary-simulation methodology

Taking into account these constraints an initial set of solutions is generated following a set of allocation rules.

The initial solutions are obtained through an allocation algorithm approach providing only feasible solutions which do not take into account any cost function.

The restrictions are satisfied using the following rules:

- An empty check-in desk is left between flights
- The number of check-in desks needed are calculated dividing the number of pax by 45 and limiting up to 5 check-in desks per flight
- There is no overlapping between flights
- The check-in desks are opened 3 hours-prior to departure

Once the initial solutions are generated the next challenging task is the transformation of the solutions into vectors with the information that will be used by the evolutionary algorithm.

1) Chromosome Encoding

The following information composes the chromosomes of the evolutionary algorithm:

1. Flight ID (string)
2. Check-In Desk Opening time (min.)
3. Check-In Desk Closing time (min.)
4. Initial Check-In Counter (integer)
5. Final Check-In Counter (integer)
6. Check-In Allocation Soft Rules (Integer)
7. Check-In Allocation Hard Rules (Integer)

The first field of information holds the ID of the correspondent flight. The second and third fields refer to the time the Check-In counters are open. The next two fields provide the information related to which check-in counters were initially allocated for

the flight. Finally the last two fields are related to the number of check-in desks needed to satisfy the hard and soft rules.

2) Crossover

Since the opening time and closing time cannot be changed, the numbers of desks are the ones that can be used by the algorithm to provide new solutions.

In this approach the crossover will be performed in two points of the solutions. The initial and final Check-In desks will be used as the crossover points for generating new potential solutions.

3) Feasibility Testing

There will be a couple of tests performed by the algorithm in order to evaluate the feasibility of the solutions. The first feasibility test will be performed once the crossover has been performed; this test is performed in the following way. It will evaluate if the allocation does not violate the hard rules (field #7). If the new solution does not violate the hard rules it will be kept as a feasible check-in desk allocation.

The crossover is performed in a random way varying the number of crossovers of the new solution.

4) Cost Function Evaluation

Once several feasible solutions are obtained the cost function $F(v1,v2,v3,v4)$ is evaluated where,

v1: number of flights that do not respect the 1 check-in desk in between flights

v2: balance loads for the solution in accordance with the policies imposed by the airport

v3: number of heavy flights in the same island during 1-hour window

v4: distribution of flights in the islands

The exact values of the function have been kept confidential due to the aforementioned non-disclosure agreement with the airport.

The whole evolutionary process is performed using the values of the function to calculate the goodness-of-fit of the different allocations and the selection process is carried out based on those values.

The most promising solutions are then selected and the process starts all over again until certain number of iterations is reached (stop criteria).

5) Final Evaluation

The best solution is selected for the final evaluation in the simulated environment of the check-in area of the correspondent terminal. This evaluation will provide a better estimation of the quality levels that can be achieved in the real system.

It is important to mention that certain requirements are needed for the simulator in order to have the best evaluation of the quality indicators, that is:

- agent-based
- high-description level
- It must allow interaction agent-agent, agent-objects
- Independent behaviour for each of the simulated entities

There are some simulators in the market that satisfy these requirements [8] thus the methodology can be implemented making use of the one that suits best the objective of the study.

The use of the simulated scenario allows testing the potential best solutions in a close-to-real environment. Sometimes occur that solutions do not perform well in the real system once they are implemented. The latter could be caused by some obstacles present in the facilities (e.g. big columns, trolley stations, etc.) that cause that a potential good solution is not because congestion has been generated due to the interaction pax-pax or pax-object.

4. Case Study

The methodology has been used to develop an initial solver for the check-in desk allocation for the airport. The initial approach will be used to evaluate the feasibility of the approach and once it has been validated as a decision support tool it will be extended to an operational one.

An initial flight plan has been used for testing the approach, and its implementation in the simulated environment. Table 2 presents the flight plan used for the example presented here.

Table 2. Departure Flight Schedule

Airline	Pax	Dep. Flight	Departure Time
AIC	90	EK 975	7:10
UAL	220	EK 807	8:00
CHH	100	EK 9999	8:20
RNA	110	EK 604	8:00
PIA	120	EK 414	7:30
AFR	130	EK 8866	10:00
CSN	140	EK 582	7:00
DLH	90	EK 853	11:00
KLM	90	EK 815	10:00
ABQ	90	EK 7777	12:00
SAI	90	EK 570	14:00
NAX	90	EK 835	14:00
SWR	285	EK 847	10:20
ROT	306	EK 705	18:00
BBC	120	EK 8888	22:00
AUA	116	EK 221	21:10
KQA	314	EK 432	18:30
BAW	206	EK 530	15:40
AFL	337	EK 650	21:20
KLM	120	EK 814	15:20

The titles of the columns are self-explanatory; Table 2 was constructed from real information provided by the airport for a particular area of the terminal. This information will be used for the initial development.

1) Initial solution

The initial solution (the satisfaction problem) can be represented in a matrix where the horizontal axis represents time and the vertical one represents the check-in desks. Fig. 4 exemplifies the representation of the initial solutions.

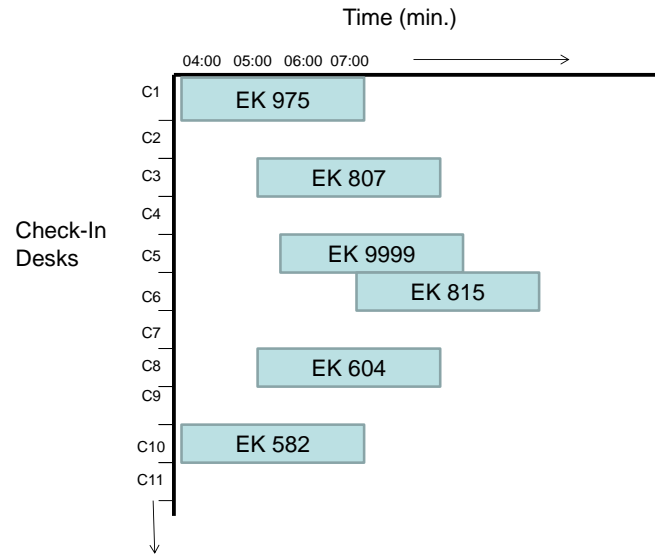


Figure 4. Example of allocation

As the main outcome from the initial phase some initial solutions are generated and used as the initial population of the evolutionary algorithm. The feasible solutions are encoded as explained in the previous section and then the evolutionary algorithm generates new solutions.

Table 3 presents the evolution of values for the cost function when 50,000 iterations have been performed.

Table 3. Values of the cost function

ITERATIONS	AVG. COST VALUE	% Improvement
1	1.36	
10	1.012	25.58823529
20	0.6714	50.63235294
30	0.468	65.58823529
40	0.4228	68.91176471
45	0.3542	73.95588235
60	0.15068	88.92058824
624	0.145276	89.31794118
891	0.13397	90.14926471
3858	0.126434	90.70338235
6605	0.125325	90.78492647
6914	0.112363	91.73801471
31600	0.11074	91.85735294

Fig. 5 illustrates the evolution of the cost function versus the number of iterations.

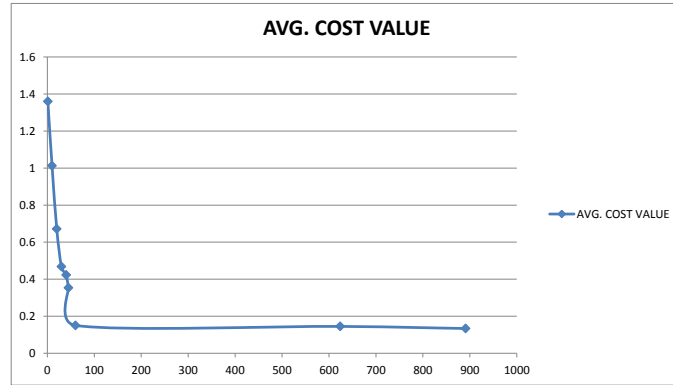


Figure 5. Convergence of the cost function

It can be appreciated that the solution converges rapidly to a more stable value demonstrating its potential for a decision support tool.

The model of the terminal area has been developed using a general purpose simulation software called SIMIO [7] . The simulator has been selected for the study since it possesses most of the characteristics mentioned in previous sections. Fig. 6 presents a snap-shot of the simulation model.

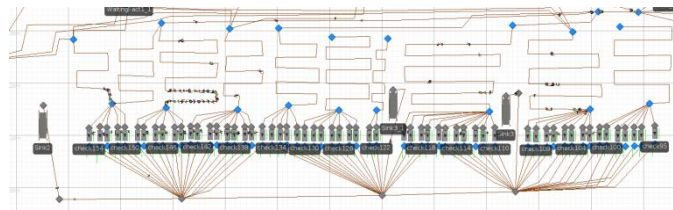


Figure 6. The simulated environment

In the general case the arrival profiles of the passengers are taken as homogeneous for every passenger in the terminal since the objective of the article is to present only the methodology as an approach for supporting decisions in operation planning.

In order to appreciate the potential of the methodology the initial allocation and the optimized one have been tested in the simulated environment. The LOS indicators have been evaluated using the simulation model for the simulated area. Table 4 presents the indicators obtained for the two scenarios.

Table 4. Level of Service Indicators

Check-In Area	AVG. LOS (m ² /pax)
Initial Allocation	1.1113
Improved Allocation	2.1223

5. Conclusions And Future Work

The article presents the key elements to develop an approach that combines an evolutionary approach and simulation that performs the check-in desk allocation for optimizing the LOS indicators in a terminal. The algorithm provides different feasible configurations which were selected using a cost function that penalizes the violation of the soft rules imposed by the internal policy of the airport. Once the solutions are obtained, they are evaluated using a simulated environment that takes into account other elements of the problem such as physical locations, queue policies, arriving profiles for the passengers etc. The results show that the methodology is able to provide good solutions with few iterations and the reliability of the solutions is increased with the simulated model. The constraints that cannot be included in the evolutionary algorithm can be added to the simulation model in order to evaluate which solution is the one that gives best results for the objectives of the airport. The presented methodology can be easily extrapolated to other terminals but the simulation model of the correspondent terminal must be developed.

As a future work it will be tested the approach using the complete flight plan of the terminal and it will be compared to a real one in order to determine the level of improvement that can be achieved. Also in future implementations a meta-model can be integrated in the evolutionary algorithm in order to develop a stand-alone tool for decision making.

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References

- [1] Banks, J., Carson J.S., Nelson,B.L., "Discrete Event System Simulation", 2nd Edition, Prentice Hall, 1996.
- [2] C. Reeves."Genetic Algorithms", *Handbook of Metaheuristics*,Kluwer Academic Publishers, 2003.
- [3] De Neufville, R and Odoni, A, "Airport systems – planning, design and management", McGraw Hill, New York, 2003.
- [4] Goldberg, David E., "Genetic Algorithms in Search, Optimization, and Machine learning", Addison-Wesley, Reading, MA, 1989.
- [5] G.Bruno, Genovese. A., "A Mathematical Model for the Optimization of the Airport Check-In Service Problem", *Electronic Notes in Discrete Mathematics*, 2010
- [6] Kasda, A., Caves, R.E.. "Airport Design and Operation", 2nd Edition, Elsevier, 2007.
- [7] SIMIO HOMEPAGE: <http://www.simio.com>
- [8] Swain, J. "Software survey: Simulation-Back to the future.", *ORMS-Today* 38 (5), 2011.
- [9] B.K.Wang, H.W.Chun, "Check-In Counter Allocation using Genetic Algorithm", *Proc. Of the 7th Conf. on Artificial Intelligence and Expert Systems Applications*, San Francisco, 1995.
- [10] C.Hsu, C. Chao, K.Y. Shih, "Dynamic allocation of check-in facilities and dynamic assignment of passengers at air terminals", *Computers and Industrial Engineering*, 2012, vol.63 , pp. 410-417