Cellular Automata Model for Crowd Behavior Management in Airports

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Abstract. At the airports, everything must work with remarkable precision and coordination, especially since their operational processes involve managing a large number of moving human groups in order to minimize waiting and service times of individuals, as well as to eliminate phenomena resulting from the interaction of large crowds, such as crowding and congestion around points of interest. The aim of the study is the development of an integrated automated simulation model for human behavior and traffic in the spaces of an airport. Thus, the model simulates the behavior of the human crowds in different operational areas of an airport. The area of the airport is divided into levels that are characterized by differences in the way that people move within. A fully analytical model based on the computational tool of the Cellular Automata (CA) was realised as well as an obstacle avoidance algorithm that is based on the A star (A*) algorithm. According to its structure, the model is microscopic and discrete in space and time while inherent parallelism boosts its performance. Its prominent feature is that the crowd consists of separate, autonomous or non-autonomous entities rather than a mass. During the simulation, each entity is assigned unique features that affect the person's behavior in the different areas of the airport terminal.

Keywords: Crowd modelling · Cellular Automata · Airport · A* algorithm · Obstacles · Simulation

1 Introduction

Almost recent studies on the full assessment of airports have shown that there is an imbalance between passenger terminal design and airspace planning even at major airports [1]. This stems from the fact that traditionally greater emphasis is put on the development and analysis of the airspace of the airport than on the design of the spaces used by the passengers. An immediate consequence of this potential design deficiency is the congestion problems encountered at passenger terminals in many airports around the world, a problem that is growing as the

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number of people using airports continues to grow at a skyrocketing rate [1]. An airport consists of three areas: (a) airspace, (b) the runway and (c) the passenger terminal(s), whereas each of these sectors is characterized by different types of flow. Airspace is the part of the airport used by different types of aircraft, the airfield is characterized by different aircraft movements in the ground and includes both landing and take-off, while the passenger terminal is the part of the airport that is occupied by flows of people, passengers and non-passengers, but also luggage. Passenger terminals are an important element of the airport structure. They are designed to serve passengers and usually consist of complex and often expensive buildings. Large airports are built to serve tens of millions of people per year [1]. Naturally, an airport's capacity is directly related to demand characteristics, operational parts, and service specifications set by the airport managing authority. Passengers travelling at the airport terminal are often forced to wait and therefore delays due to overcrowding and queues arise, usually resulting from reduced service capacity and inadequate design of the terminal facilities or terminal terminals of the airport's passengers.

An indicator of the efficiency of an airport terminal is the number of passengers served daily [2,3]. Overcrowding and congestion are major problems for hundreds of thousands of passengers. This problem has worsened over the last few years due to increased security measures at airports [2]. Therefore, capacity planning in the airport terminal planning process is more important than ever, which suggests the need for more accurate analysis methods. However, the uncertainty associated with future levels of passenger demand and the complexity of airport terminals makes this work particularly difficult. The problem of designing the service capacity of an airport terminal is concerned with identifying optimal design and capacity expansion of different terminal areas, given the uncertainty regarding both future demands and expansion costs. Analytical modeling of passenger flows at airport terminals under transitory demand is difficult due to the complex structure of the terminal. To the best of our knowledge, the airport terminal passenger capacity planning problem has not been studied holistically, meaning that the studies usually either do not take account of scalability or focus only on a specific area of the terminal [5].

One of the first models of passengers' behavior within an airport is presented in [4]. This study refers to the behavior of passengers at the airport terminal as well as to their needs. Other studies are focusing on the passengers processing times and the importance of dealing with that problem [5–7]. Studies that focus on continuously variable states indicate that such states can hardly be solved due to the complexity of the flow at an airport terminal [1]. Thus, most of them include simulations to model these random and complex flows. In these studies, simulation results are used to estimate the capacities required to make various processes more efficient [8]. In [9] the aim is to understand the dynamics of the discretionary activities of passengers. Focusing on microscopic modeling, very efficient models have been proposed that describe agents' behavioral characteristics [10–12]. A very effective model that is able to simulate the passenger behavior in situations of congestion is Cellular Automata (CA). CA describe the behavior of each person as an individual and the result of the overall system is emerging from the interactions between people that are close one to each other. CA models are widely used in crowd control [13–17], or more specifically, in controlling the disembarking or emergency evacuation of people in an airplane [18].

The main contribution of this study can be summarized as the development of a multi-parameterized, topological oriented simulation model for describing human moving behavior and traffic in the areas of an airport. The model is based on CA that combines low computational cost of a macroscopic simulation model with the focused use of separate individual microscopic features for all operational elements of the model, similar to an Agent-Based model (ABM). Moreover, an A* (A-star) based obstacle avoidance algorithm has been incorporated to the model aiming at the realistic representation of the travellers' moving tendencies. During the simulation, each entity is assigned with unique features that affect the person's behavior in the different areas of the airport terminal. It should be mentioned though that due to the fact that the density is restricted by the cell size, movement artifacts may arise because of the fixed footstep size. In Sect. 2, the proposed model is described providing all the parameters taken into consideration during the design and realisation process as well as the innovative elements that it incorporates. Section 3 presents the results of the simulation and a comparative listing of these for the various demand scenarios that may arise in the terminal of an airport during its operation. Finally, in Sect. 4 the conclusions are drawn, as well as the future perspectives of the model.

2 Model Description

This study presents a general simulation model for the final design of the airport passenger terminal using the computerized model of Cellular Automata (CA). The main and final objective is to develop an airport terminal design tool. This tool will allow the management of the terminal as well as the planning of either different designs or improvements for both existing and proposed terminals before construction. Simulation of a system of such a scale involves many complicated processes such as data collection, space modeling, experimentation, presentation and analysis of results, and proposals to be implemented according to these results. The model of an airport departure area was implemented, which is used both by passengers traveling on domestic flights and by passengers on international flights. Passengers enter the terminal after they have passed the corresponding check-in windows, depending on whether their flight is domestic or international. Then, passengers departing are characterized by freedom of movement among a number of options.

Initially, it is worth mentioning some basic principles governing the simulation model that has been developed with the usage of the MATLAB programming platform. In particular, the physical space represents the ground plan of an airport passenger terminal and is simulated by a cellular discrete mesh, each cell of which has a physical dimension of 60×60 cm, greater than 40×40 cm, which studies have shown to be the typical area occupied by an adult standing in crowded conditions [19], as the passenger terminal does not experience severe crowding and congestion. In addition, passengers may have to carry hand luggage, which increases the space they occupy in total.

Also, the neighborhood selected to realize the evolution rule is the Moore neighborhood. This means that the state $C^t_{i,j}$ of the cell (i, j) at time $t+1$ is affected by the states of its nine neighboring cells, including the cell i, j itself, at this time t according to the following equation. Therefore, the evolution rule that is applied is provided by Eq. (1):

$$\begin{aligned} C^{t+1}_{i,j} = C^t_{i,j} + C^t_{i-1,j} + C^t_{i+,j} + C^t_{i,j-1} + C^t_{i,j+1} + C^t_{i-1,j+1} \\ + C^t_{i-1,j-1} + C^t_{i+1,j-1} + C^t_{i+1,j+1} \end{aligned} \tag{1}$$

In this way, the diagonal movement in the grid is also allowed, which represents the human movement in a more realistic way [20,21]. Consequently, each agent can move no more than one cell within its neighborhood at each time step of the simulation. Moreover, it was assumed that all agents entering, leaving and moving within the airport terminal are characterized by the same speed, which is the average walking speed of an adult, calculated at 1.3 m/s [19], corresponding to 4.68 km/h. An initial description of the transition rule of the CA-based model M can take place according to the following relationship:

$$M = [S, t, L, D, T] \tag{2}$$

$$S = [F, G, P, d(F, t)] \tag{3}$$

where S stands for the schedule of the flights that is created separately and it is defined itself, by Eq. (3), with F describing the unique flight code, $G(F)$ the corresponding gate, $P(F)$ the total number of passengers of flight F, and $d(F)$ the departure time of flight F. Continuing the description of Eq. (2), t stands for the current time step and is the metric of time in the model. Since each agent has to cover an average distance of approximately $\frac{1}{2} \times (0.6 + \sqrt{2 \times (0.6)^2}) \cong 0.725$ m at every simulation time step and the average speed of movement of persons within the terminal equals 1.3 m/s, each of the time steps will be approximately 0.56 s [19]. Binary parameter L clarifies whether an individual is part of a group of passengers (0), such as a family, or travels alone (1). Parameter D corresponds to a finite set of k potential destinations that each agent can move towards, such as gates of terminals, duty-free shops, restaurants and cafes, resting seats, information benches, automatic cash dispensers, toilets. It can also describe the states of an individual that wanders in the terminal area without a specific destination, as well as the absence of movement. Finally, T describes the topology of the terminal station that is the exact location of all possible destinations within the terminal area.

According to the adopted modeling strategy, the services that are provided to the agents can be divided into different levels based on certain features in order to be more effective in managing them. In the context of this study, the first level refers to the check-in process and includes both the check-in windows and the queues that the passengers form when trying to approach the corresponding serving points. The generation of waiting queues in public places is a problem of great research concern [22]. In the case of airport checkpoints, it is more common to use a queue for multiple service windows, known as "snake-type" queue coupled with the so-called "fork-type" queue, where separate shorter queues are formed in front of each service window. The use of this type of queue is preferred when waiting at airports, because it allows longer queue lengths to take advantage of the space provided more effectively, and because people waiting in the queue maintain eye contact with the service windows, and thus the feeling of impatience is not increased as long as people wait [23]. Based on the airport scenario studied, the ticket control area is simulated coupling "snake-" and "fork-" type queues, ending in multiple ticket control windows [23].

In addition, the probability q of a new person to appear in the queue is adjusted by taking into account the S flight schedule. Specifically, it is inversely proportional to the time remaining until a flight departs (Eq. (4)):

$$q \propto \frac{1}{\prod_{i=1}^{n}[d(i,t)-t]} \tag{4}$$

where n is the maximum number of flights that can be served at the same time, with $n_{max} = |G|$, since n could not exceed the number of gates at the airport terminal. The model incorporates the options of increasing and/or decreasing the length of the queue, adding additional service windows, and changing the service times of each window.

As soon as the agents leave the check-points, they enter the second level. It represents the main area of the terminal and includes all the available points that an agent can visit until she/he is directed to the gate of boarding. As soon as an agent enters the main terminal area, she/he decides to move in one direction, according to the model description factors discussed previously. The factor being considered first is that of the remaining time until the departure of the flight, and whether or not it exceeds a predetermined limit. This, at a real airport terminal, is equivalent to whether the gate that corresponds to the flight to which each agent is going to fly is disclosed or not. In the event that the gateway has not yet been announced, the agent will move inside the 2^{nd} level, choosing a certain point among all available options that are expressed by parameter D in Eq. (2). The instantaneous density $p_{AoI,t}$ of the passengers in the individual areas of the main terminal depends on the flight schedule since the total number of persons using the terminal at the airport varies not only from season to season but also during the day, and it is calculated on the basis of the following relationship:

$$p_{AoI,t} = \frac{N_{AoI,t}}{AoI} \tag{5}$$

where AoI is the area of interest and N the number of people within the AoI. The model allows the topological parameterization of the main area of the terminal station that is the topological re-location of all available visiting points within the second level. Though, it should be pointed out that the measurement area does not always coincide with the topological area.

The space around the gates, although located within the terminal, should be considered as a separate level, since individuals behave completely differently in terms of their movement when they approach the gates in order to board. Once the boarding gateway is announced, the majority of the passengers is considered to be heading towards it. The proposed system provides the potentiality for the automated calling of passengers to the gate (call for flight), which is triggered when the following relationship is verified:

$$Remainingtime(F,t) = d(f,T) - t < P(F) \times (GateDelay(t) + 0.5) + \alpha \quad (6)$$

where $\alpha = 100$ an additional time parameter for security reasons and $GateDelay(t)$, the parameterized gate delay, i.e. the average number of time steps that each agent remains at the gate from the moment she/he arrives at the gate until she/he leaves it in order to board the airplane. In case that the boarding pass check takes place automatically then the minimum $GateDelay(t) = 1$ is considered, otherwise, $GateDelay(t) > 1$. Algorithmically, the gate opens when the following relationship is satisfied:

$$Remainingtime(F,t) = d(f,T) - t < P(F) \times (GateDelay(t) + 0.5) \quad (7)$$

Then the corresponding agent tries to leave the gate as soon as possible. At these points, there are phenomena of dislocation, which are absent in both the first and second level of the terminal. Naturally, these phenomena are not particularly intense, since there are no emergency conditions under normal circumstances. Thus, there is no reason for a rapid abandonment of the site through the gate. It is worth mentioning that the model description factors are reviewed for each individual, at each time step. Therefore, the desired destination for each agent can change at any time. In the case of obstacles, agents should have the ability to avoid obstacles that may be in their route while keeping their direction to the point they want to reach. In the context of this study, an obstacle avoidance algorithm, based on the optimal path finder algorithm A* (A-star) has been developed [24] in a CA environment. The algorithm takes into account the starting position of a person, the desired destination, and the topology of the obstacles as defined by the ground plan of the airport terminal. Then it is repeatedly trying to find the optimum path to the desired point, where the optimum term is the closest route, that is, the shortest path. Taking into account that variable x represents the agent's position at time t then the fact that the distance to the destination is minimized is represented mathematically by the following equation:

$$x^{t+1} = x^t + [a,b] \quad with \quad a,b \in -1,0,1 \quad (8)$$

where a and b are calculated so that Euclidean distance equals to:

$$d = \sqrt{(i_g - 1 + a)^2 + (j_g - 1 + a)^2} \quad (9)$$

with (i_g, j_g) referring to the coordinates of the desired destination, to be minimised. Potential paths to the desired position are then calculated by the cells-to-extend method [24]. In case that the optimal path that each person has to follow is found, then it is stored and the person moves according to it for each next step until it reaches the desired position. The algorithm is evolved that way provided that no other obstacle appears in the calculated optimal route and there is no need or desire for the agent to move to a place other than that originally considered as desirable; for example, in the case that an agent who is moving to a vacant seat and suddenly decides to use an automatic teller machine, or another that is wandering in the terminal's premises and she/he is informed that she/he has to move to the gate of her/his flight. In the event that one of the above conditions is not met, the algorithm is called to re-calculate either the optimal path to the same desired position taking into consideration the new obstacle that has appeared or the shortest path to the new desired position. In such a manner the computational complexity of the algorithm is lowered by the implementation of the proposed method.

3 Simulation Results

The cellular grid that simulates the physical space of the airport terminal equals 150×130 cells. Therefore, the total area of the physical system is described by Eq. (10), whereas the main area of the terminal is described by Eq. (11). Then taking into account walls and set places, the space left for agents to move is given by Eq. (12). Finally, the area of interest around each gate is provided by Eq. (13).

$$A_{total} = 150 \times 130\,(cells) \times \frac{0.6\,(\mathrm{m}) \times 0.6\,(\mathrm{m})}{cell} = 7,020\,\mathrm{m}^2 \tag{10}$$

$$A_{terminal} = 150 \times 100\,(cells) \times \frac{0.6\,(\mathrm{m}) \times 0.6\,(\mathrm{m})}{cell} = 5,400\,\mathrm{m}^2 \tag{11}$$

$$\begin{aligned} Appl_{term} &= A_{terminal} - seats - walls = \\ [148 \times 98 - 448\,(cells) &\times \frac{0.6\,(\mathrm{m}) \times 0.6\,(\mathrm{m})}{cell}] \cong 5,060\,\mathrm{m}^2 \end{aligned} \tag{12}$$

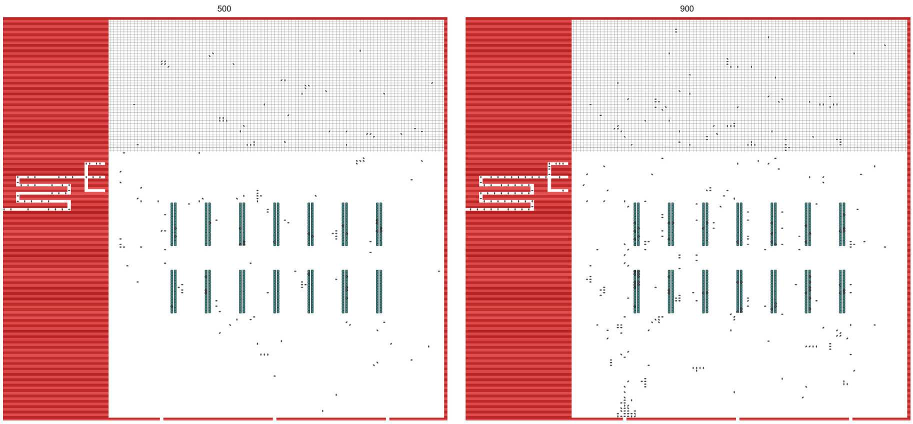
$$A_{gate} = 10 \times 10\,(cells) \times \frac{0.6\,(\mathrm{m}) \times 0.6\,(\mathrm{m})}{cell} = 36\,\mathrm{m}^2 \tag{13}$$

The scenario that is presented in the framework of this study is described by Table 1.

It is clear that the flight schedule determines how the airport terminal will operate, and any changes to it may result in various different scenarios of simulation. Figure 1 shows the evolution of the experiment based on the flight schedule of Table 1. Regarding Fig. 1(a), it is worth making two comments on that process. The first one refers to the queue that is formed before the boarding control windows; the density of people in the queue is relatively small. This is because a flight does not depart soon, thus as derived from Eq. (4), the probability q of

Table 1. The flights' schedule of the adopted scenario.

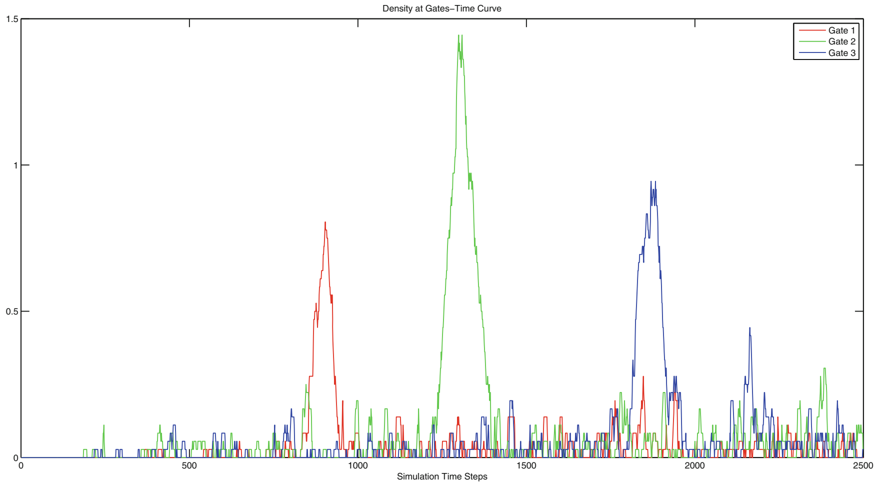
Number of flight (F)	Gate ($G(F)$)	Number of agents (Passengers) ($P(F)$)	Departure time ($d(F,t)$)
100	1	37	1,000
101	2	78	1,500
102	3	48	2,000



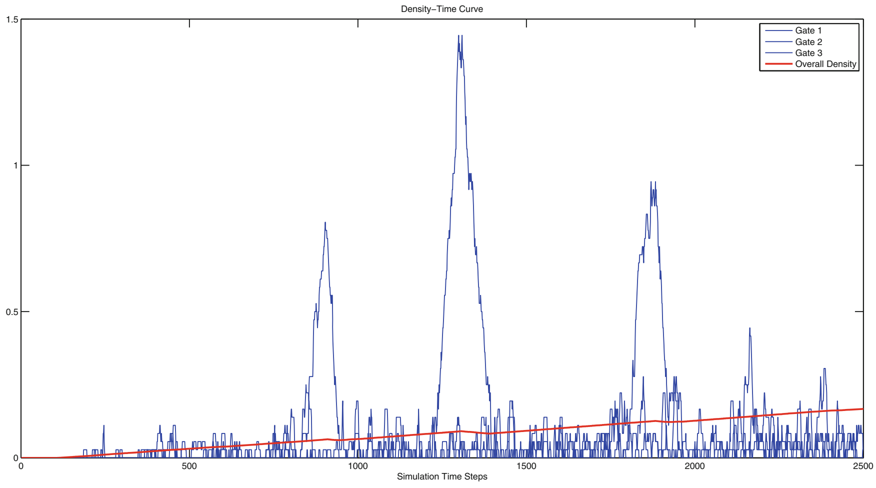
(a) (b)

Fig. 1. Top view of the terminal as simulated by the electronic system with an emphasis on some of its separated venue; the boarding pass control windows (left), the recreation and waiting areas (centre), as well as three terminal gates that the passengers leave to board the plane (down). (a) Time step 500; no boarding (b) Time step 900; boarding from Gate 1 has commenced.

a new person to appear in the queue is relatively small. The second comment refers to the groups that form some of the agents, with a size that varies. These groups remain inseparable throughout the wandering in the terminal area until the people leave the gate. In Fig. 1(b) we can observe that the density of agents has increased significantly (900-time step) since more flights are expected. Furthermore, the process of boarding from Gate 1 has started. Besides, this fact derives from the implementation of Eq. (6), when replacing the corresponding parameters of the equation with their current values of the time step, the number of agents expected to travel on the flight served by Gate 1 and the time step that corresponds to the departure of that flight. Figure 2 shows the graphs of crowd density in relation to the time resulting from conducting this experiment. We can observe that the densities in the area around each gate initially increase, then they form a maximum and finally decrease (Fig. 2(a)). The maximum density differs for the area around each gate and it is proportional to the number of agents that will be served by the corresponding gate. The time periods that



(a)



(b)

Fig. 2. (a) Recorded densities in the area around the gates as a function of time; Gate 1 (left - red), Gate 2 (center - green) and Gate 3 (right - blue). (b) The density in the terminal area (straight line with a small inclination at the bottom of the graph – red) compared to the crowd density around the gates (blue) depending on time. (Color figure online)

the density increases around the gates are identical to the periods before the scheduled departure of the flight. Finally, the moment that the density reaches its maximum value, it is the one that satisfies Eq. (6). Density is expressed in $1/\mathrm{m}^2$ and it is obtained by multiplying Eq. (5) with $p_{max} \cong 2.77778 \, \frac{persons}{\mathrm{m}^2}$, which is the maximum density for this electronic system, as the length of the side of each cell equals to 0.6 m. In Fig. 2(b), the comparisons of the densities around the gates with the densities that are observed at the rest of the terminal station take place. It is obvious that the densities reached around the gates, when agents approach them to board the planes, are much larger than those observed at the rest of the areas of the terminal station. Figure 2 highlights that the overall density has fluctuations that are strongly dependent on the flight schedule and what is happening at the terminal's gates. Initially, the total density is zero, as the first few people have not yet passed boarding documents checking. Subsequently, the density increases almost linearly with time, except for the time periods where one of the gates is evacuated, where it exhibits a downward trend.

4 Conclusions

An electronic system for the study and optimization of crowd behavior in the airport is proposed in this study. It is based on the computational tool of Cellular Automata (CA). Concerning the problem under study, CA present a number of extremely interesting features, such as local interactions, mass parallelism through the application of the rule, the flexibility of boundary conditions selection, the number of possible situations, the CA cells that form a simple structural element. Simulated experimental scenarios proved that the density of the crowd and its variations in time are directly related to the flight schedule according to which an airport operates for a given period of time. In order to avoid crowding and dissatisfaction of agents, the flight schedule must be appropriately designed so that the density does not increase beyond certain safety levels since it has a major impact on the speed at which people move of the terminal but also in the operation of the airport in general. In a physical system, both behavior and movement of people are affected by innumerable social and psychological factors. Thus, this feature could also be incorporated in the parameterization process of the proposed model. Finally, the model can be validated with the use of real data that could further enforce its efficiency.

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