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CHECK-IN PROCESSING: SIMULATION OF PASSENGERS WITH ADVANCED TRAITS

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ABSTRACT

In order to tackle the growth of air travelers in airports worldwide, it is important to simulate and understand passenger flows to predict future capacity constraints and levels of service. We discuss the ability of agent-based models to understand complicated pedestrian movement in built environments. In this paper we propose advanced passenger traits to enable more detailed modeling of behaviors in terminal buildings, particularly in the departure hall around the check-in facilities. To demonstrate the concepts, we perform a series of passenger agent simulations in a virtual airport terminal. In doing so, we generate a spatial distribution of passengers within the departure hall to ancillary facilities such as cafes, information kiosks and phone booths as well as common check-in facilities, and observe the effects this has on passenger check-in and departure hall dwell times, and facility utilization.

1 INTRODUCTION

The world-wide air industry has grown rapidly in the last two decades, especially in the Asia-Pacific area, where growth per year is above 5% annually (International Air Transport Association 2005). Large growth of air travel forces many airports to increase their capacity and optimize their processes. Increasing the efficiency of existing airport facilities requires a thorough understanding of passenger flows in airport terminals. This is further complicated by the fact that different stakeholders have different needs: airport operators want to distribute passengers evenly, airlines want to ensure that all passengers are at the correct gate on time to board the aircraft, and shop owners may want the system to re-route their specific focus groups towards their particular store to maximize revenues.

People movement is a highly complicated and even chaotic phenomenon. Passenger flow in airport terminal buildings outside of the mandatory processing steps is particularly hard to predict. Thanks to the advance of computer technology and the maturation of object-oriented programming, individuals can be treated as objects whose behavior and actions can be explicitly modeled. Moreover, the development of complexity theory provides a solid theoretical foundation for modeling individual behaviors.

Previous studies of passenger flows in airport systems mainly use macroscopic simulation tools (Ray and Claramunt 2003; Roanes-Lozano et al. 2004; Curcio et al. 2007), seldom addressing passengers' behavior at a microscopic level. Furthermore, these studies have only addressed evaluation of the mandatory passenger processing steps, lacking the capability to forecast and optimize individual passenger movement, particularly in regards to discretionary activities such as duty-free shopping or using the bathroom.

Agent-based models (ABM) are a useful tool in the exploration of space-time dynamics. In particular, agent-based modeling methods have the potential to detail individual passenger's behaviors and study emergent behaviors when large populations of passengers interact with each other. A major shortfall of previous applications of agent-based models to airport passenger simulation is the fact that only limited support is provided for discretionary activities. These activities can make up a considerable amount of the

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time spent in an airport (Takakuwa and Oyama 2003), with an important side effect being a reduced level of stress and increased comfort (Richter and Voss 2011). It is therefore becoming important to create more realistic passenger flow simulations through the inclusion of discretionary activities. This comes with the added complexity of mimicking human behaviors and decision making in these areas more accurately.

In this paper, we first demonstrate a lack of advanced passenger behavior in the airport terminal in previous airport simulation studies (Section 2), and argue the need for advanced passenger characteristics. In Section 3 we propose a simplified model of passenger characteristics which might dictate behavior in and around the check-in area of the terminal. In Section 4, we develop a simple case study which demonstrates the use of these passenger characteristics in passenger decision modeling, and perform simulations to see the added benefits this could have for analysis of existing airport systems. In Section 5, we summarize our conclusions and propose some future areas of research based on this advanced set of passenger characteristics.

2 AGENT-BASED MODEL APPLICATION TO AIRPORT PASSENGER SIMULATION

Agent-based models are flexible and able to capture emergent phenomena, and most importantly can provide a natural description of a system (Bonabeau 2002). Generally speaking, the computational agents in agent-based models can have a direct correspondence with real-world actors (in this case passengers). Agents themselves are not identical in most perspectives, standing for different actors in the world. They behave according to their own preferences or even according to their own rules of action.

Although interactions between agents can be complicated, ABM is able to simulate them. In the airport environment, these interactions include physical aspects (e.g., physical barriers to avoid, and route instructions to follow such as moving from security to immigration), the effects of other agents in the surrounding locality, and also the influence of factors such as queuing and crowding.

People's behavior are also guided by socio-economic factors and by short-term or long-term goals, for example buying a coffee or a bottle of water because of hunger or thirst or in preparation for boarding a flight that does not have in-flight service (e.g., on a low-cost carrier). People also have the ability to move and perceive different factors within the environment which will shape their future actions.

ABM are also able to simulate learning, both in individual agents and at the population level. For example, humans have cognitive ability. Through reading route instructions at various points in the airport terminal, humans can make an informed choice to go directly to the destination they desire. In general, learning can be modeled in any or all of three ways: as individual learning in which agents learn from their own experience; as evolutionary learning, in which the population of agents learn because some agents "perish" and are replaced by better agents, leading to improvements in the population average; and social learning, in which some agents imitate or are taught by other agents, leading to the sharing of experience gathered individually but distributed over the whole population (Gilbert 2008). All three learning models are likely to be applicable in the airport environment, but that is outside the scope of this paper.

Agent-based pedestrian models can be categorized into three levels: macroscopic, mesoscopic and microscopic. Macroscopic and mesoscopic simulations are commonly used in transportation modeling (Turner and Penn 2002). Microsimulation has to date focused mainly on granular-physics models; for example the crowding simulation performed by Helbing and Molnar (1997) using predetermined directional paths. These have led to observations of lifelike emergent phenomena based on simple rules such as lane forming simply by a predisposition to move left or right avoiding oncoming traffic (Helbing et al. 2001).

To date there have been few studies using microscopic simulation of passengers' movement in airport terminals, and have therefore not made full use of the capabilities of agent-based models. There have however been quite a few macroscopic simulations of passenger flow at airports to help identify key factors that affect passenger flow within airport terminals.

Ray and Claramunt (2003) did a case study of a transportation application by Atlas to simulate and analyze different passenger transportation schemes between different halls of an airport terminal. Roanes-Lozano, Laita, and Roanes-Macias (2004) simulated departing passenger flows, which can provide the number of passengers waiting in queue at any time. However, it lacks the study of instantaneous space occupancy at different sections of the airport terminal. Curcio et al. (2007) made a simulation model to investigate passengers' average waiting time before reaching the boarding gate area. It did not cater for other important outcomes such as passengers' queuing issues and space occupancy related problems.

Due to the macroscopic nature of these studies, it has not been necessary to have complex models of passenger behaviors. This is appropriate, since passenger behavior is very limited within the processing areas of check-in, security, immigration, and boarding. For example, once passengers enter a check-in queue, all they have to do is slowly move forward following the passengers in front until they reach the head of the queue. Once at the head of the queue, they proceed to a counter when it becomes available, and complete the formalities. Consequently, there is no need to consider any complex behaviors as queuing theory (as introduced by Lee (1966) for check-in processes) adequately describes this movement.

Unfortunately, the bulk of the passenger's time spent in the airport falls outside these mandatory processing areas (Takakuwa and Oyama 2003). Once passengers leave the compulsory processing areas, there is a myriad of activities that passengers can undertake, and a correspondingly large number of potential routes through the airport space can be pursued as depicted in Fig.1. Accordingly, passenger behavior becomes much more complicated and hard to predict. As such, it could be described that between processing points, passengers have full autonomy and we require a complex decision model to accurately describe their behavior. This is further complicated by the fact that the entire airport experience (at least in the departure path) is limited by time, which will also influence passenger behavior.

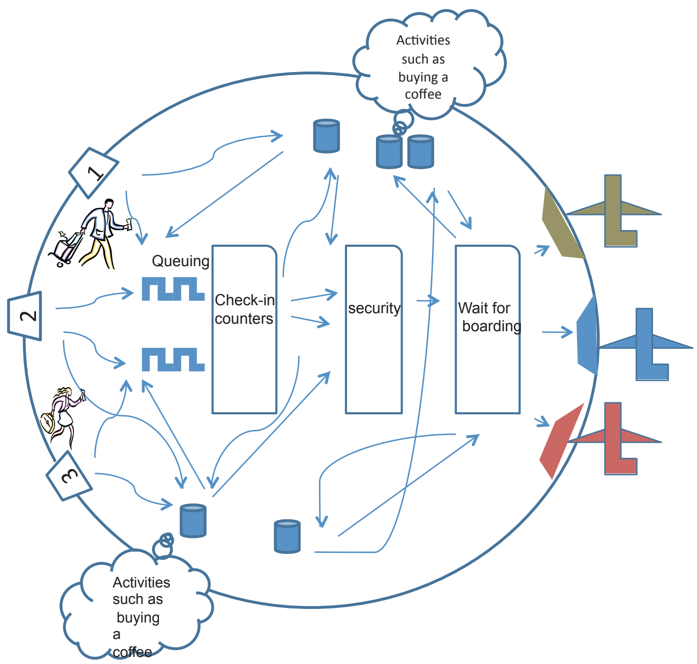


Figure 1: Whole-of-airport model showing complicated behaviors outside the mandatory processes.

The goal of this paper is to use microscopic simulation to extend airport passenger flow simulations to include the full range of activities. In Section 3, we propose an extension to basic passenger characteristics linked to flight schedules and class of travel in order to provide a platform upon which these complex decisions and agent learning can be incorporated into agent-based models. In this way, we can assume that no activity that passengers can undertake within the airport is excluded (as long as the decision model supports it).

3 ADVANCED PASSENGER CHARACTERISTICS FOR CHECK-IN

In order to enable more complicated passenger decision models to make passenger simulations in the airport more realistic, it is important to give a detailed set of characteristics to each agent. In this section we present a subset of the types of factors we see as important in guiding passenger behavior within the airport, particularly in regards to the check-in area. These characteristics not only influence the decision model, but also potentially the instantaneous walking speeds of each agent.

To do this, we divide traits into two categories. *Basic* traits (refer to Table 1) are related to the passenger's booking, and other easy to quantify characteristics. These types of characteristics are typically static for the period of time they are in the airport, and consist of characteristics which have been previously used in macroscopic simulations to some extent. These are the traits which direct passengers to specific check-in or immigration queues based on class of travel or nationality respectively.

Table 1: Basic factors which affect the passenger mobility and path navigation.

Influence	**Passenger Trait**	**Detailed factors**
Basic mobility	Gender	Male Female
	Age	< 20 20-30 30-45 45-60 > 60
	Baggage	Number of bags (checked and carry-on) Oversized/heavy bags
Value added mobility	Travel class	Economy, Business, First
	Frequency of travel in an airport (both this particular airport, or airports in general)	First time A few times Frequent flyer
	Travel group size	Single traveler A couple More than three
	Nationality	Native (e.g., AUS/NZ) Foreign

The traits also influence the walking behavior of each passenger. Although it is possible to model all passengers to walk at the same average speed (Young 1999), there are also some important variations which can be classified as basic or value added. Basic mobility indicates that the classifications by gender, age and baggage are applicable to all pedestrian simulation applications; the value added mobility aspect relates specifically to air travelers. For example, Finnis and Walton (2006) assessed walking speeds of large numbers of passengers, and showed some important variations in walking speeds, particularly influenced by the traits describing basic mobility in the airport environment.

Advanced traits are those which help to describe more complicated behaviors in airport terminals. These factors ensure that a passenger is not considered as a closed loop, but as an open loop which has the ability of perceiving and responding to their surroundings. In general, advanced traits can be used to explain which passengers will use shops, restaurants, information kiosks, internet or other forms of entertainment, make phone calls on in-airport telephones, or do more generic activities like using the restrooms (either for themselves or to change a baby's nappy) or having a nap between flights. The activities that result can describe how much time will be consumed performing these activities.

It is well understood that passengers will carry out certain actions based on their perception and prior knowledge (Kaplan 1983). The advanced traits we have identified for the check-in area are based on both these characteristics, and are outlined in Table 2. In particular, it was deemed important that passengers are: allowed to enter the terminal with a pre-conception of checking-in to their flight before doing anything else ("desire to check-in first"); characterized by travel experience ("frequency of travel"); are willing to ask for assistance; are hungry; or are generally comfortable with technology. How these traits are used to enable autonomous decision making in the passengers is described and demonstrated in the Section 4.

Table 2: Advanced passenger characteristics proposed for check-in area.

Characteristic	Data type	Example
Frequency of travel	Integer	0, 1, ..., 10
Pre check-in?	Boolean	True
Desire to check-in first	Boolean	True
Need to make phone call	Boolean	True
Willing to ask for assistance	Double	0 (not willing), 5 (very willing)
Level of hunger	Double	0 (not hungry), 5 (hungry)
Level of comfort with technology	Double	0 (uncomfortable), 5 (comfortable)

It should also be noted that a number of these traits are also dynamic within the time period of being in the terminal. Take the example of a passenger who is hungry. Their hunger will mean that cafes and restaurants will appear attractive, and increase the likelihood of the passenger buying something. Once they have finished however, their level of hunger will be reduced, and so this should be reflected to ensure they don't use every food outlet in the airport!

4 CASE STUDY

In order to demonstrate how the advanced traits presented in Section 3 enable more advanced passenger behavior in airport terminals, a hypothetical case study has been developed surrounding the flight check-in process. The physical environment which has been used in the simulations described in Section 4.1 is shown in Fig. 2. This scenario incorporates common check-in configurations with dedicated business and economy class check-in desks, as well as self-service check-in kiosks (SSK) and dedicated bag drop facilities for those checking-in prior to arrival or those who check-in using the kiosks. In addition to the check-in facilities, three other facilities have been included to demonstrate passengers undertaking discretionary activities; these facilities are a cafe, information booth and telephone. Whilst this set of facilities is on a small scale, and therefore not all-inclusive, it is still sufficient for validating the proposal.

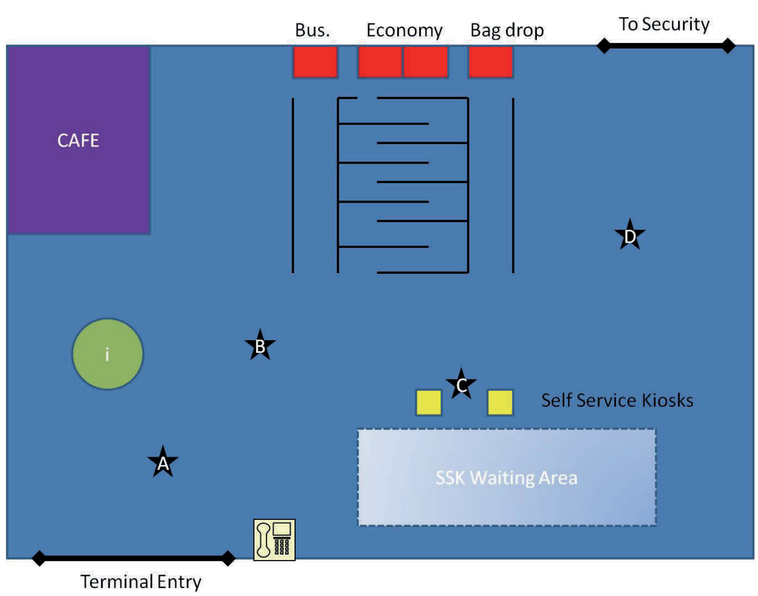


Figure 2: Spatial layout for hypothetical check-in case study.

Four main decision points have been created to demonstrate the necessity for both physical and non-physical passenger characteristics. A flow chart which describes the possible decisions that can be made at each of the points A, B, C and D is shown in Fig. 3.

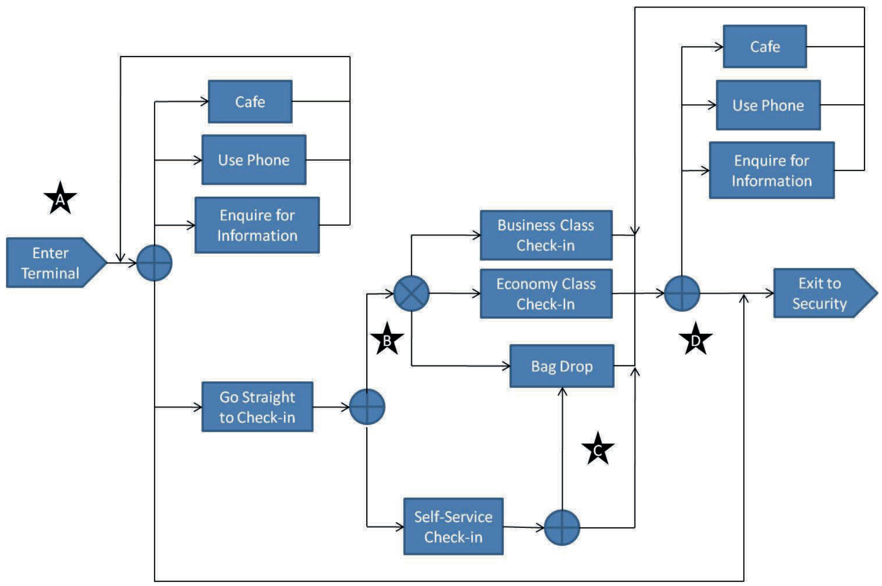


Figure 3: Decision flow chart to demonstrate the use of advanced passenger characteristics.

Decision point A represents a choice by which passengers can utilize any (or all) of the discretionary facilities, or proceed to check-in. This decision is related to the fact that some (arguably most) passengers will want to check-in prior to doing anything else to ensure that they have a boarding pass. Other passengers who arrive with lots of time to spare before boarding may make use of other facilities first, for instance to grab some lunch before flying. Passengers who have never traveled to the airport may decide to use the information booth first in order to find out where they need to go to check-in.

Decision point B is the point where passengers proceed to either the business or economy class check-in point, go straight to bag drop if they have checked in prior to arrival at the terminal, or to the SSK. Such a decision is based partly on passenger type (business versus economy) and also the passenger's level of comfort or familiarity with the SSK technology and also their individual frequency of travel.

Decision point C is included to ensure that passengers who use SSK are able to use the bag drop facilities (if necessary) or are able to clear the check-in process and proceed with their next action.

Decision point D dictates the next passenger movement. Having checked-in, passengers have the option of moving directly to security, or alternatively may proceed to any of the ancillary facilities. For instance, passengers with lots of spare time until boarding may choose to go to the cafe to have a coffee, or to phone a relative to let them know they made it to the airport and are departing on time. If the passenger is running short for time, they are then most likely to proceed directly to security. Details of how each of these decisions are simulated is discussed in Section 4.2.

4.1 Simulation

The physical environment has been set up as described in the previous section. In particular, there is one queue for each of the check-in areas, with single service counters for business class and bag drop, and two counters for economy and two self-service check-in kiosks.

The nine passenger characteristics described in Table 2 have been modeled for this case study. Only one flight has been modeled (i.e., all passengers have the same flight), however the time of this flight is used to determine the passenger's time to board. Passengers arrive at the terminal up to 3 hours before the flight is scheduled to board, through to 45 minutes prior.

Distribution of the passenger characteristics are as follows:

- Prob("Business") = 0.1
- Prob("Already checked in") = 0.25
- Prob("Need to check-in first") = 0.8
- Prob("Phone call") = 0.05
- Distribution of travel frequency = Triangular(0, 10, 1.5)
- Distribution of number of bags = Uniform(0, 2)
- Distributions of {willingness to seek assistance, level of hunger, level of comfort with technology} = Uniform(0, 5)

To demonstrate the use of advanced passenger characteristics, passenger decisions at the four points have been determined based on membership functions. At point A, passengers are able to either use the ancillary facilities or proceed directly to check-in (decision point B); 80% of passengers will proceed directly to check-in, whilst other passengers will use the phone (in 5% of cases). All remaining passengers will use the cafe or information booth based on the relationships shown in Fig. 4. In particular, passengers who are "hungry" and have sufficient time to board ($t_1 = 45mins$) will use the cafe (where $h_1 = 2$ and $h_2 = 3$), and passengers who are inexperienced at this particular airport ($f_1 = 2$ and $f_2 = 5$) and are willing to ask for assistance ($w_1 = 2.5$ and $w_2 = 4$) will use the information booth.

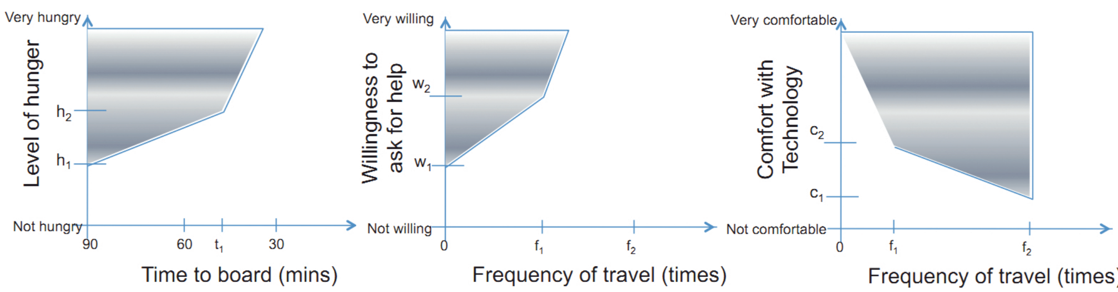


Figure 4: Membership functions used in simulations.

At decision point B, passengers will either choose to enter a check-in desk queue (or bag drop), or use the self-service kiosk. The willingness to use the self-service kiosk is based on the third membership function in Fig. 4; in particular, passengers who have traveled a sufficient amount ($f_1 = 3$, $f_2 = 8$) and are comfortable with technology ($c_1 = 1.5$, $c_2 = 3.5$) will choose to use the self-service (N.B. once they have checked in, they will proceed to the bag drop counter if they still have bags to check-in at decision point C). Passengers who have already checked-in but still have bags will proceed to the bag-drop queue, whilst the remaining passengers will choose the appropriate check-in queue based on their class of travel.

For simplicity, the final decision point (D) follows the same fuzzy rules as at point A with respect to using the ancillary facilities, or proceeding directly to security.

Using this configuration, three experiments were devised, each with 5 simulation runs over which the results are averaged in Section 4.2. *Scenario 1* simulated the case where passengers have no interaction at all with the ancillary facilities, thereby replicating what most airport passenger simulations currently do. In this instance, there is also no self-service kiosk utilization - all passengers proceed to either the business class, economy class or bag drop counter based on their pre-check-in status and class of travel.

Scenario 2 introduces some of the more advance passenger characteristics (namely comfort with technology) to demonstrate the choice to use self-service check-in. Again, no ancillary facilities are used, and passengers proceed directly to security once they have checked-in. *Scenario 3* introduces all of the fuzzy sets to enable passengers to utilize any (or all) of the ancillary facilities either pre- or post-check-in.

In all of the simulations, a constant arrival schedule has been used for consistency (refer to Fig. 5). Only a single flight has been simulated to demonstrate the concepts without the complexity of having multiple departing flights with overlapping arrival of passengers. During each of the simulations, statistics related to utilization of service facilities and time-spent within each service were collected. Analysis on each of these metrics for the three scenarios is presented in Section 4.2.

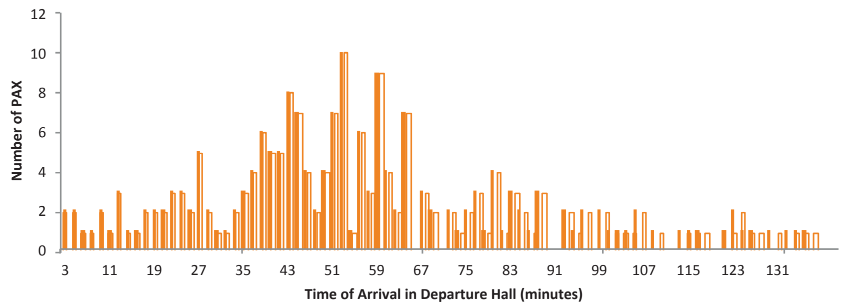


Figure 5: Departing passenger arrival schedule for a single flight.

4.2 Analysis

To verify the behavior of the simulation in the case of *Scenario 3*, Fig. 6 shows the average instantaneous utilization of each of the facilities in the case study departure hall. It can be observed that the utilization of the cafe is higher than either check-in option, and also that the information and phone booths do attract passengers (even if in very small numbers). This demonstrates that more passengers are concurrently in the departure hall, but are spread between a range of facilities, not just check-in as might be the case in traditional departure simulations.

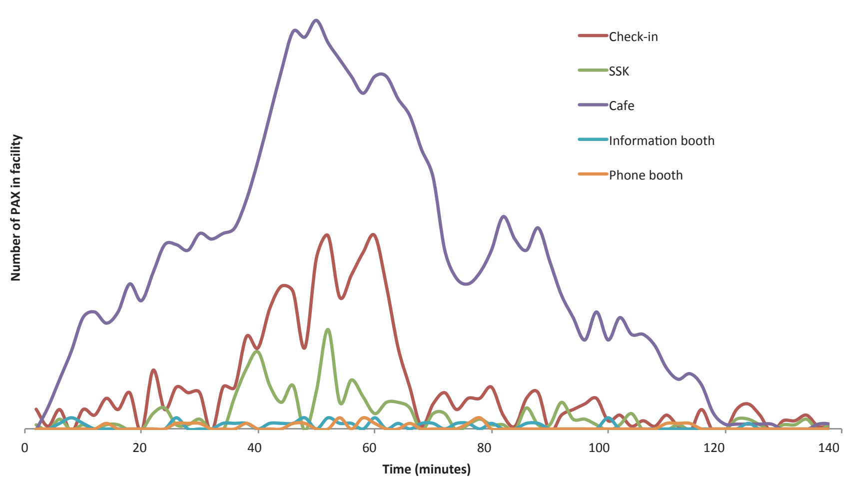
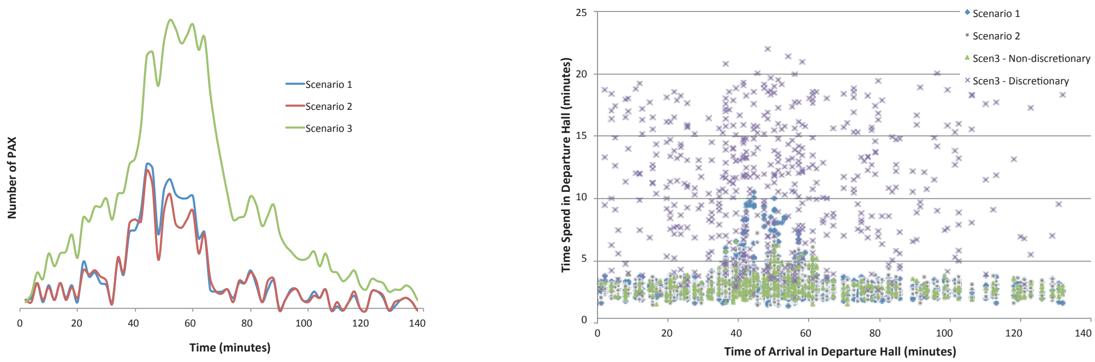


Figure 6: Utilization of check-in, SSK, cafe, phone booth and information desk.

Figure 7(a) demonstrates the utilization of the departure hall space by time. It is a representation of the number of passengers present in the departure hall at 2 minute sampling intervals. The peak utilization of the departure hall in *Scenario 3* is approximately two times greater than those in the other two scenarios which do not include discretionary activities. Since passengers now have advanced traits which dictate their preferences to use the various ancillary facilities, they will spend significantly more time in the departure hall (particularly those enjoying a coffee and some food in the cafe); therefore the overall departure hall utilization is significantly increased. This is important for designers as it provides a more accurate description of how the entire space is being utilized, not just the space dedicated to check-in.



(a) (b)

Figure 7: Comparisons of instantaneous utilization of departure hall (a), and overall dwell time (b).

To complement this result, and further understand how the advanced traits play a role in the overall departure hall dwell time, the passenger dwell time against the arrival into the departure hall was also visualized (Fig. 7(b)). For *Scenario 3*, we have separated passengers into two classes: one for passengers who used airport discretionary facilities, and one for those who did not. As could be expected, the general dwell time characteristics for check-in only passengers in *Scenario 3* is very similar to that for the other two scenarios. It should also be noted that the dwell time of passengers in *Scenario 1* is slightly longer than those in *Scenario 2* because of the addition of self-service check-in kiosks which reduce the queuing at the standard check-in desks.

Passengers in *Scenario 3* who choose to use the discretionary facilities have a fairly uniform distribution of dwell times within this simulation. The total dwell time typically varies from slightly longer than the check-in only passengers, up to 20 minutes (and in some cases more).

One of the key bottlenecks in airport operations is the time passengers spend in queues. It is therefore important to investigate the effects that adding advanced passenger traits and discretionary activities have on queues, particularly since the discretionary activities result in more passengers within the departure hall at the same time (as seen in Fig. 7(a)). Figure 8 shows the instantaneous utilization of the main check-in queues. It can be seen that, because passengers engage in discretionary activities prior to check-in, that this changes the instantaneous queue lengths. In this simulation, it is observed that these activities result in smaller peak queue lengths than the other two scenarios which only include check-in.

In order to demonstrate the impact of changing the membership functions which result from the advanced passenger traits, we ran a simulation based on *Scenario 2*, where the membership function was altered by changing the value of c_2 which relates to the level of comfort with technology (see Fig. 4). Figure 9 shows the cumulative usage of the self-service check-in kiosks for $c_2 = \{2.5, 3.5, 4.5\}$ which gradually decreases the number of passengers comfortable with using self-service check-in. As can be seen, the more passengers are comfortable with technology, the greater the utilization of the self-service kiosks. Further, according to the results shown in Fig. 8 which showed reduced check-in times due to the inclusion of more check-in modes. These two factors might be a driver for airlines to make the kiosks easier to use in order to reduce the traditional check-in queues.

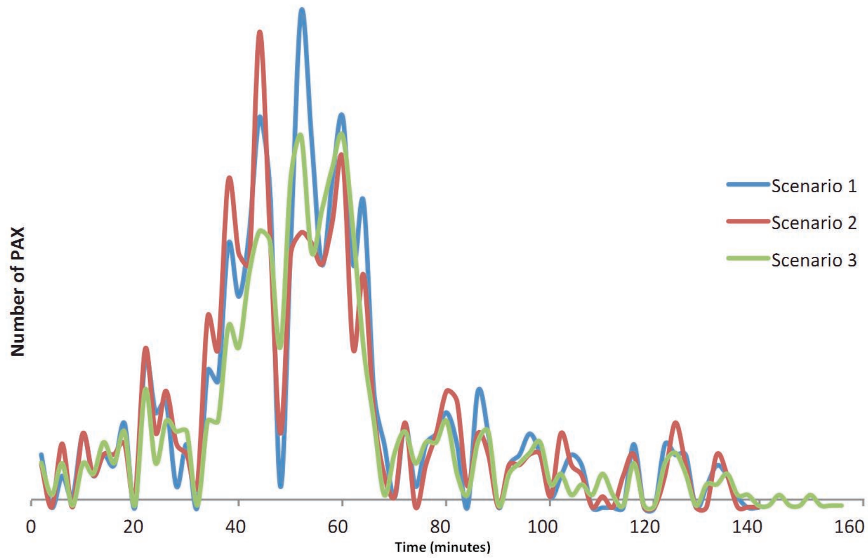


Figure 8: Check-in utilization for the three simulation scenarios.

In summary, the inclusion of the advanced passenger traits has the effect of distributing passengers within the space, resulting in greater dwell times in the departure hall, and shorter check-in queues and queuing times. We believe that by enabling these types of interactions, passenger simulation in airports (and other built environments) will be more realistic and reliable for use in planning exercises.

5 CONCLUSION & FUTURE WORK

A number of studies have performed passenger simulations in airport terminals for the purpose of analyzing current and future levels of service. Traditionally these studies have focused on the mandatory processing facilities such as check-in, security, immigration, airside boarding lounge and the boarding gates themselves. Unfortunately, passengers spend a significant portion of their time in the airport outside of these facilities, and it is therefore imperative to include these in the simulations.

To make passenger behavior more realistic, it is necessary to embed more advanced characteristics within the agent. Whilst it is easy to embed information related to the passenger's boarding pass and see how this relates to movement through the non-discretionary areas of the terminal, it is more complex to allow for interaction with other facilities. In this paper, we propose an initial set of advanced passenger traits which guide decisions around the utilization of discretionary facilities. We apply this to check-in, with the case study used to demonstrate this proposal based in the area around check-in where cafes, information booths and phone boxes may be located.

Three different scenarios were simulated to demonstrate the progression of adding in self-service check-in use based on passenger level of comfort with technology, through to use of the cafe, information and phone booths based on passenger hunger, travel frequency and desire to make a phone call. The simulations demonstrated the spread of passengers in the space, and showed that peak check-in queuing times which are produced by such simulations are reduced when distributing passengers amongst the full range of facilities. Passengers also spend a considerable amount of time in the departure hall area, allowing the instantaneous utilization of this space much higher than if only check-in is simulated.

Airports frequently improve passenger processing procedures through new technological or management approaches, such as fully automated counters and separate security lines for regular travelers. The model developed here can be used to study the benefits of new approaches. This initial set of characteristics will be extended to capture the entire airport and will also be used to develop advanced passenger walking and decision-making models.

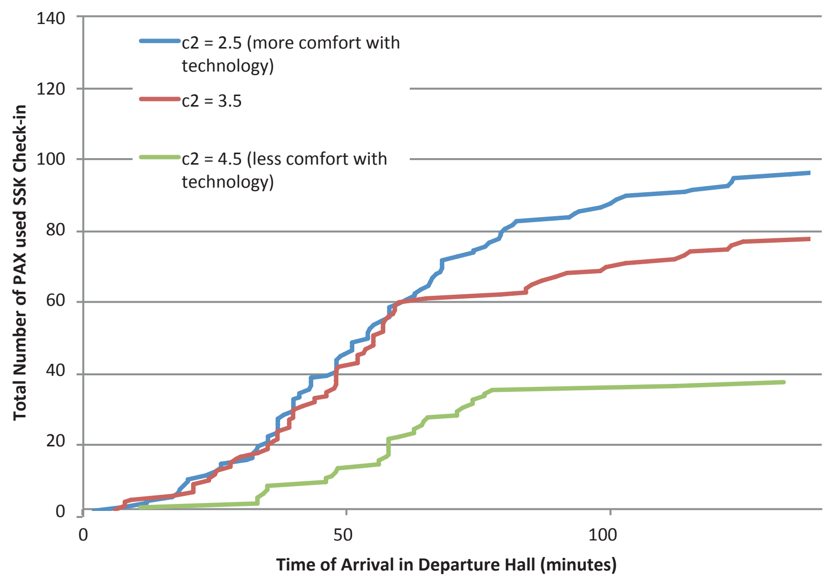


Figure 9: Demonstration of variation of comfort with technology on SSK utilization.

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