

Modelling Passengers Flow at Airport Terminals

Individual Agent Decision Model for Stochastic Passenger Behaviour

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Abstract: Airport system is complex. Passenger dynamics within it appear to be complicate as well. Passenger behaviours outside standard processes are regarded more significant in terms of public hazard and service rate issues. In this paper, we devised an individual agent decision model to simulate stochastic passenger behaviour in airport departure terminal. Bayesian networks are implemented into the decision making model to infer the probabilities that passengers choose to use any in-airport facilities. We aim to understand dynamics of the discretionary activities of passengers.

1 INTRODUCTION

Airport terminal is a particular built environment where there are large numbers of passengers travel through daily. It not only handles standard processes for departure and arrival but also provide in-airport discretionary services for passengers to use (Ma, Kleinschmidt et al. 2011). Airports have to satisfy a myriad of different tasks. Continual legal changes, security constraints, safety in public facilities and technological innovations always have a significant effect on handling passengers. Current models which mostly use aggregated approaches are hard to adapt to continuous changes (Gatersleben and Van der Weij 1999; Takakuwa and Oyama 2003; Andreatta, Brunetta et al. 2007). They seem only focus on standard processes and ignore discretionary components, i.e. duty-free shops, in-airport restaurants and telephones. Moreover, airports have been under growing pressure to be financially more self-sufficient since the early 1990s and bound to be less reliant on government support (IATA 1997). Airports rely increasingly on concession services to bring in more revenues (Fu and Zhang 2010). Concession services refer to the non-aircraft-related operations in terminals and on airport land, including activities such as running or leasing out shopping concessions of various kinds, car parking and rental, banking and catering, and so on. ATRS (2006) reports that most of the world major airports acquire anywhere between 45 and 80 percent of their

total revenues from non-aviation sectors, a major part of which is revenue from retail and parking. Since these operations depend greatly on passenger throughput of an airport, there is a complementarily between the demand for aviation services and the demand for concession services. In the passenger perspective, the escalating expectations of passengers make airport system become complicating. Passengers nowadays are accustomed to sophisticated, fast-changing technology environments at home and at work. They have grown to expect painless self-service and instant, unfettered access to resources and information. Like customers in other industries, passengers expect better, cheaper, and faster services from airlines and airports. They want real-time information about flight delays and demand streamlined processes for check-in, transit, and boarding, and want increasingly higher levels of personalized services. All in all, it is difficult to handle efficiency and security of airport processes and to balance all the stakeholders' interests.

Optimizing airport processes and infrastructure therefore becomes very important. Desired models are expected to be able to analyse the performance of an airport system, plan resources for a given future flight schedules, assist in planning changes and determine effects on the overall level of services. Individual-based models allow for a scientifically reliable and detailed evaluation of the behavioural processes, considering agent demands, environmental perception and individual

interactions. Agent-based models of human movement address that individual agent is autonomous. That is, surpassing conventional mathematical analysis, one simply instantiates a population having some distribution of initial states. Individual agents representing walking human with initial states are situated in a representation of an environment and interact with the environment and themselves, acting out possible macroscopic emergent behaviours. Agent-based models is “solved” merely by executing it, where results are dynamic at each simulation runs.

Modeling pedestrian dynamics gathers more and more attention because of safety issues in public facilities. However, current models hardly try to hypothesize complex passenger decision-making which would dictate the likelihood of individual agents entering discretionary areas (Kleinschmidt et al. 2011). In order to enable more intuitive stochastic passenger movements, Ma et al. (2011) tried to incorporate more detailed passenger information into the simulation model, and therefore provide airport operators with more realistic passenger flow models.

In this paper, we envisaged an individual agent decision model aiming to represent intuitive passenger behaviours. In section 2 we addressed the significance of studying stochastic passenger behaviours in air terminals. In Section 3 we propose Bayesian artificial intelligent for agent decision model. In section 4 we demonstrate the approach by have a Bays net simulation case study. In section 5, we summarize our conclusions and propose some future areas of research.

2 STOCHASTIC PASSENGER DYNAMICS

Airport is a complex system. It consists of many standard sub-systems such as Check-in, Security, Custom and Boarding. However among the intervals of them, passenger dynamics are regarded as stochastic and complex. Passengers might have difference preferences to use any (if all) in-airport facilities outside standard processes, for example duty-free shops, cafe, telephone and bank. We phrased such events as discretionary activities of passengers. Since passenger activities outside standard processing areas account for large significance regarding safety and airport revenue (Takakuwa and Oyama 2003, Ma et al. 2011), we found it is important to study the discretionary behaviours of passengers.

In order to understand the activities that passengers

use discretionary facilities, we first investigate what sorts of discretionary facilities an airport terminal might have and then investigate corresponding impact factors which have affection on passengers’ choice to use those facilities (Table 1).

Table 1: Discretionary facilities and corresponding impact factors.

Discretionary facilities	Impact factors
Relaxation facilities	Physical tired
Technological self-service kiosks	Technology preference
Information kiosks	New users
Currency service	Cash in need
Communication service	Business/entertaining purposes
Dietary places	Hunger level
Shopping places	Desire to shopping

Discretionary facilities can be categorised into the following parts according to utilities. They are relaxation facilities, technological self-service kiosks, information kiosks, currency service, communication service, dietary places and shopping places. It is true that passenger must use standard processing facilities to get access through airport. However, when utilising discretionary facilities, passengers would usually spend plenty more time.

Ma et al. (2011) use a revised social force model to simulate the basic motion of passengers in airport terminals. It enables passenger agents in the simulation can avoid collision by the repulsive forces.

Advance path choosing of each passenger agent are governed by one of the artificial intelligence decision theories. We choose Bayesian belief network as the tool for the study in this paper (Kevin B. K. and Ann E. N., 2011). Bayesian belief networks is used to generate the possibility that passengers choose to go to a certain service facility, which is an innovation comparing to conventional passenger flow models who pre-assign the probabilities. We aim to find the relationship between passenger traits and the possibility of using certain service facilities. Besides basic traits of passengers, such as age, gender, we also devise the advanced traits of passengers in Section 3. They can be inferred from basic traits within the graph model of Bayesian networks, and will be used for individual decision making in our simulation environment.

Bayesian inference computes the posterior probability by conditioning, according to the rule of Bayes. Advanced traits stand for mental preferences of passengers, which mean that passengers could

have sorts of probabilities to use different facilities when they need to make decision. To compute the posterior probabilities that a passenger would prefer to use a certain in-airport facility, we suppose a series of advanced trait which can be used to indicate preferences of passengers. The Bayesian network model is illustrated in detail at the next section.

3 AGENT DECISION MODEL

The supposed agent decision model was devised aiming to explain the complex stochastic behaviour of passenger’s motion. Fig 1 shows the model framework. In order to tackle the probabilities of passengers choosing to use specific sorts of in-airport facilities, we use Bayesian brief networks to infer certain types of passengers. For example, if a passenger who are a visitor and travel through the airport firstly, he/she would be regarded as a “desire shopping” passenger. Passengers who belong to this type have a great possibility to use duty-free shops as long as simulation-based components permit. Simulation-based components are currently defined as two parts: planned time and endurable walking distance. Planned time refer to the time left till boarding for departure process. Whether a passenger will go to duty-free shops depends on if there is enough time left to get on board. For inbound however passengers seem have no restriction on time. They may stay at airport any longer as they wish. Endurable walking distance is parameter which defines the normal longest distance a pedestrian can walk along. Currently very few study reveals walking distance issue at airport. We took a reference of a survey of walking distance guidelines used by North American companies, which addressed that the value is between 400m and 800m (Walking Distance Research – TOD Committee http://www.fairfaxcounty.gov/planning/tod_docs/walking_distance_abstracts.pdf accessed 2 March, 2012).

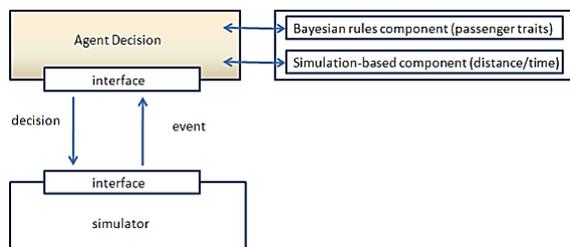


Figure 1: Agent decision model framework.

Passenger categories can be specified in terms of the six advanced traits (Fig 2). Different passenger categories are inferred through the devised Bayesian brief networks. Parent nodes are the basic traits of passengers which are not difficult to be found from the information of passengers’ air tickets. We investigated the ticket information and have the major seven so as to represent them as the seven basic trait nodes.

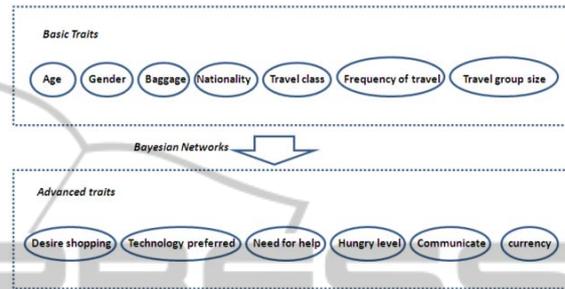


Figure 2: Inferring advanced traits of a passenger.

Table 1 explains the data type of the seven traits in our simulation. For example, the trait “Age” is calculated based on an equation that if the registration information on the air ticket is over than 60 we deem the passenger as old, otherwise we simply regard the passenger is young. We also can acquire information about whether a passenger is a frequent flyer who must use the airport more than three times. We give frequency of travel a Boolean data type. Other passengers who haven’t use the airport before or use the airport only a couple of times get the trait as non-frequent flyer. At this stage, generating the trait value for passenger agent in our simulation are due to the help of expert extrapolation and historical data.

Table 2: The basic traits of passengers.

Traits category	Data type	Example
Age	Boolean	Old/Young
Gender	Boolean	Male/Female
Baggage	Integer	0,1,2
Nationality	Boolean	Local/Foreigner
Travel Class	Boolean	Business/Economy
Frequency of Travel	Boolean	Frequent flyer/ non frequent flyer
Travel group size	Integer	0,1, ... , n (n >0, n is an integer)

Bayesian networks are used here to infer the six advanced traits for each passenger agent. Basically, it calculates the conditional probabilities of advanced traits. For example, in Fig 3, we select four major nodes of basic traits to infer the

conditional probabilities that a passenger would have this kind of proportion preference to use in-airport shop facilities. In the same theory, we also can acquire the conditional probabilities of the other five advanced traits of an individual passenger. All passenger agents can possess any or at least one type of the advanced traits. The whole value representing advanced traits of a passenger agent are calculated and stored at the first beginning when a passenger agent is generated in the simulation environment.

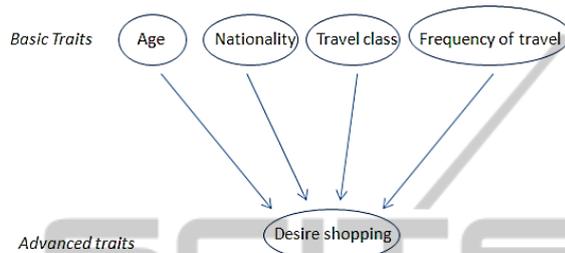


Figure 3: Bayesian network to infer desire shopping trait.

We also need to consider the utilities that a passenger agent makes a decision to use a series of service facilities. In order to make an intuitive simulation of passenger motion in an airport terminal, we add the components, planned time and endurable walking distance, into the agent decision model. Fig 4 illustrates the framework of the decision-making model. Bayesian network is used to infer the passenger preferences, which represent that a passenger is inclined to use certain service facilities. Simulation components part limits unreasonable behaviours of passenger in case passengers miss their flight. The decision graph calculates the utility that a passenger chooses to use a specific service facility. It provides the highest utility results for output to guild a passenger agent to execute the most feasible action.

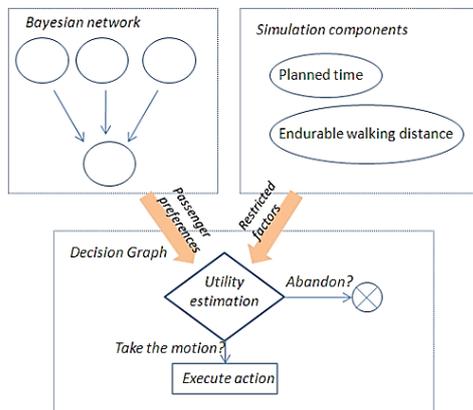


Figure 4: Decision making with utility estimation.

In the simulation, basically there are four major decision points where passenger would behave autonomously based on the results of their Bayesian network inferences. They are decision points before check-in process, after check-in and before security process, after security and before custom, and after custom and before gates. The higher results of utilities in the decision graph denote a passenger will choose to use a certain facility first. For example, at a decision point, as long as duty-free shops are contained in the following possible interval destinations, passengers who can fulfil their desire to shopping and also are able to board on time would choose to use duty-free shops first. They might walk as many shops as possible as long as the endurable walking distance is satisfied. Otherwise the passengers choose to rest on the lounge area.

4 CASE STUDY

Our simulation model takes the Brisbane international departure terminal as a case study. We aim to validate the devised agent decision model through the case study. Fig 5 shows parts of the simulation within the check-in hall. The blue areas stand for cafe and restaurants. The red areas represent shops. Passengers can behave discretionary activities before and after check-in process. The probabilities of using any discretionary are inferred through the devised agent-decision model.

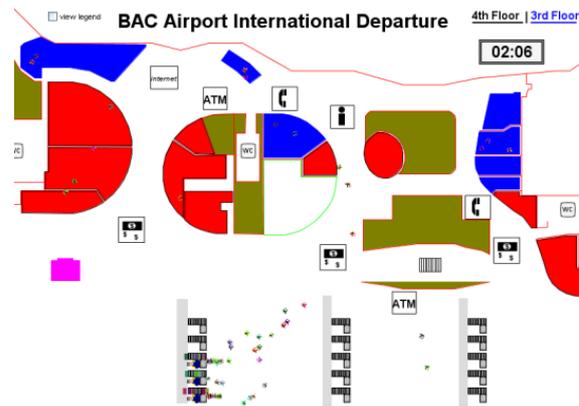


Figure 5: The simulation environment.

The simulation is able to simulate the whole departure process. Passengers' discretionary activities happen at both check-in hall and gate lounge. The dwell time that passenger stay at various discretionary facilities is calculated and put in a statistics graph (Fig 6). The longest dwell time in

discretionary facilities during the whole departure process is about one hour. The average value is a bit above 10 minutes.

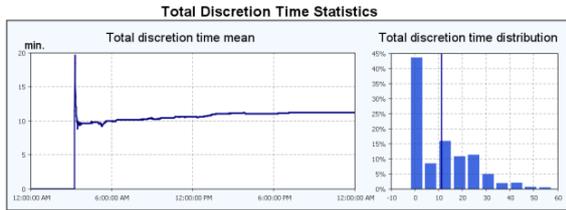


Figure 6: Average utilisation of discretionary facilities.

5 CONCLUSIONS

Passenger dynamics is becoming an important issue in the study of service rate within built environment such as transportation hub which includes airport terminals. The paper demonstrates a devised agent-decision model which can acquire the results of utilisation of discretionary facilities. For the future work, since individual passenger is programmed as single agent, it is also able to record other possible behaviours, such as how many shops passengers walked through and recording the walking routes so as to facilitate space design and estimation.

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