# AGENT-BASED MODEL OF PASSENGER FLOWS IN AIRPORT TERMINALS

A THESIS SUBMITTED TO

THE SCIENCE AND ENGINEERING FACULTY

OF QUEENSLAND UNIVERSITY OF TECHNOLOGY

IN FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF

DOCTOR OF PHILOSOPHY

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2012

**Statement of Original Authorship**

The work contained in this thesis has not been previously submitted to meet requirements for an award at this or any other higher education institution. To the best of my knowledge and belief, the thesis contains no material previously published or written by another person except where due reference is made.

**Signature:**

**Date:** **13th June, 2013**

*Dedicated to my parents, Jiqin Ma and Ping Jiang*

# Keywords

Agent-based model; simulation; airport; pedestrian flow; agent decision-making; Bayesian networks; influence diagram; routing decisions; route-choice decision-making.

# Abstract

Passenger flow studies in airport terminals have shown consistent statistical relationships between airport spatial layout and pedestrian movement, facilitating prediction of movement from terminal designs. However, these studies are done at an aggregate level and do not incorporate how individual passengers make decisions at a microscopic level. Therefore, they do not explain the formation of complex movement flows. In addition, existing models mostly focus on standard airport processing procedures such as immigration and security, but seldom consider discretionary activities of passengers, and thus are not able to truly describe the full range of passenger flows within airport terminals. As the route-choice decision-making of passengers involves many uncertain factors within the airport terminals, the mechanisms to fulfil the capacity of managing the route-choice have proven difficult to acquire and quantify.

Could the study of cognitive factors of passengers (i.e. human mental preferences of deciding which on-airport facility to use) be useful to tackle these issues? Assuming the movement in virtual simulated environments can be analogous to movement in real environments, passenger behaviour dynamics can be similar to those generated in virtual experiments. Three levels of dynamics have been devised for motion control: the localised field, tactical level, and strategic level. A localised field refers to basic motion capabilities, such as walking speed, direction and avoidance of obstacles. The other two fields represent cognitive route-choice decision-making. This research views passenger flow problems via a "bottom-up approach", regarding individual passengers as independent intelligent agents who can behave autonomously and are able to interact with others and the ambient environment. In this regard, passenger flow formation becomes an emergent phenomenon of large numbers of passengers interacting with others.

In the thesis, first, the passenger flow in airport terminals was investigated. Discretionary activities of passengers were integrated with standard processing procedures in the research. The localised field for passenger motion dynamics was constructed by a devised force-based model. Next, advanced traits of passengers (such as their *desire to shop*, their c*omfort with technology* and their w*illingness to*

*ask for assistance*) were formulated to facilitate tactical route-choice decision-making. The traits consist of quantified measures of mental preferences of passengers when they travel through airport terminals. Each category of the traits indicates a decision which passengers may take. They were inferred through a Bayesian network model by analysing the probabilities based on currently available data. Route-choice decision-making was finalised by calculating corresponding utility results based on those probabilities observed.

Three sorts of simulation outcomes were generated: namely, queuing length before checkpoints, average dwell time of passengers at service facilities, and instantaneous space utilisation. Queuing length reflects the number of passengers who are in a queue. Long queues no doubt cause significant delay in processing procedures. The dwell time of each passenger agent at the service facilities were recorded. The overall dwell time of passenger agents at typical facility areas were analysed so as to demonstrate portions of utilisation in the temporal aspect. For the spatial aspect, the number of passenger agents who were dwelling within specific terminal areas can be used to estimate service rates. All outcomes demonstrated specific results by typical simulated passenger flows. They directly reflect terminal capacity. The simulation results strongly suggest that integrating discretionary activities of passengers makes the passenger flows more intuitive, observing probabilities of mental preferences by inferring advanced traits make up an approach capable of carrying out tactical route-choice decision-making.

On the whole, the research studied passenger flows in airport terminals by an agent-based model, which investigated individual characteristics of passengers and their impact on psychological route-choice decisions of passengers. Finally, intuitive passenger flows in airport terminals were able to be realised in simulation.

# List of Publications

**Journal article**

- Wenbo Ma, Tristan Kleinschmidt, Clinton Fookes and Prasad K.D.V. Yarlagadda, "Micro-simulation of airport passengers with advanced traits: a case study of Brisbane Airport international departure terminal", Simulation Modelling Practice and Theory *(Under review)*

- Wenbo Ma, Tristan Kleinschmidt, Clinton Fookes and Prasad K.D.V. Yarlagadda, "A review: Pedestrian dynamics in the real and simulated world", Journal of Urban Planning and Development *(To be submitted)*

**Peer-reviewed conference papers**

- Wenbo Ma, Tristan Kleinschmidt, Clinton Fookes and Prasad K.D.V. Yarlagadda, (2011) Check-in processing: simulation of passengers with advanced traits. In Fu, Michael & White, K. Preston (Eds.) Proceedings of the 2011 Winter Simulation Conference, pp. 1783-1794, IEEE, Phoenix, AZ, USA.
- Tristan Kleinschmidt, Xufeng Guo, Wenbo Ma, and Prasad K.D.V. Yarlagadda (2011) Including airport duty-free shopping in arriving passenger simulation and the opportunities this presents. In Jain, S., Creasey, R. R., Himmelspach, J., White, K.P., &Fu, M. (Eds.) Proceedings of the 2011 Winter Simulation Conference, pp. 210-221, IEEE, Phoenix, AZ, USA.

- Wenbo Ma, Tristan Kleinschmidt, Clinton Fookes and Prasad K.D.V. Yarlagadda, (2012) Modelling Passengers Flow at Airport Terminals - Individual Agent Decision Model for Stochastic Passenger Behaviour. Proceedings of the 2th International Conference on Simulation and Modelling Methodologies, Technologies and Applications, pp.109-113, Rome, Italy.

- Wenbo Ma, Tristan Kleinschmidt, Clinton Fookes and Prasad K.D.V. Yarlagadda, (2012) A micro-simulation of airport passengers with advanced traits. Proceedings of 28th International Congress of Aeronautical Society, ICAS 2012 - 10.9.4, Brisbane, Australia.

- Wenbo Ma, Prasad K.D.V. Yarlagadda and Clinton Fookes, (2012) Using advanced traits of passengers to facilitate route-choice decision-making. To be presented in Proceedings of 4th International Conference on Computational Methods (ICCM), Gold Coast, Australia.

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# List of Abbreviations

| | |
|---|---|
| ABM | Agent-based Model |
| ABS | Agent-based Simulation |
| AI | Artificial Intelligence |
| ATM | Automatic Teller Machines |
| BDI | Belief-desire-intension |
| CA | Cellular Automata |
| CPD | Conditional Probability Distribution |
| CPT | Conditional Probability Tables |
| DES | Discrete-Event Simulation |
| ECP | Entry Control Point |
| IATA | International Air Transport Association |
| KPI | Key Performance Indicators |
| LOS | Level of Service |
| MCDM | Multi-criteria decision making |
| OAV | Object-attribute-value |
| PMM | Persons · Meter/Minute |
| PQA | Pedestrian Quality Attribute |
| SD | System Dynamics |
| SFM | Social Force Model |
| SSK | Self-Service Kiosks |

# Acknowledgments

I would like to thank Professor Prasad Yarlagadda for his advice and guidance throughout the course of this thesis. Thanks are also due to Associate Professor Clinton Fookes and Dr. Tristan Kleinschmidt for their valuable advice on my research and assistance in proofreading my papers, and to many colleagues who have contributed to this research.

I appreciate the financial support from Queensland University of Technology, China Scholarship Council, and the Airports of the Future project. With their generous support, I was able to concentrate on my PhD study without any financial distractions.

I thank the Airports of the Future project for providing a great platform to pursue collaboration among different disciplines, industry and government departments. My thanks are also due to the Brisbane Airport Corporation for permission to access their data to facilitate the simulation practice.

Lastly, thanks to all the people who have encouraged and helped me in my study, but who are not named here.

# Chapter 1: Introduction

The study presented in this thesis explores a new scope of modelling pedestrian flows in built environments. In particular, it investigates real scenarios of passenger flows in airport terminals. On the one hand, regulation policies and terminal layouts often change due to air transportation growth, security concerns and implementation of new technologies. As a result, the routes and patterns of passenger flows will change accordingly. On the other hand, standard processing facilities (such as check-in, security, immigration, customs, boarding, bag reclaim) and on-airport discretionary facilities (such as duty-free shops, restaurants and cafés, phone booths, Internet access, PC desks) are simultaneously used by passengers. Simply considering passengers through standard processing procedures does not seem to be comprehensive. So as to attain a realistic full-scale model of passenger flows, both the standard processing and discretionary types of activities are analysed in the study.

In airport terminals, passengers are considered to have strong cognitive ability. They watch and explore the environment within airport terminals and process way-finding information in the psychological aspect. This should be an approach to realise the route-choice decision-making of passengers. In this regard, a passenger is assumed to be an agent who is able to autonomously choose a direction and walk towards the next target. Such an agent-based model is utilised to tackle large numbers of passengers and study emergent outcomes of the formation of passenger flows in macroscopic detail. The agents within the proposed agent-based model could represent both passengers and on-airport facilities. Pedestrian localised dynamics are studied to cope with passenger motion. Advanced traits of passengers are devised in light of the cognitive preferences of passengers inside an airport terminal. Route-choice decision-making of passengers is executed by the devised agent decision-making module.

The background and motivation for this project is presented in Section 1.1. Section 1.2 sets out the research problems. The objectives are provided in Section 1.3 and the statement of contribution is presented in Section 1.4. The chapter concludes with an outline of the thesis structure in Section 1.5.

## 1.1 BACKGROUND AND MOTIVATION

The Australian airline industry is growing at a very high speed (National Aviation Policy White Paper, Australian Government, 2009). The role in transportation of people and goods served by airports has become much more important in the modern world. Due to the large growth of air travellers, many airports have to upgrade their capacities to fulfil their functions properly. The traditional way of dealing with passenger growth has been to add additional equivalent percentage of required capacity. However, airports face the problem of scarce land resources. In the neighbourhood of large cities, airports will not easily acquire enough land for new terminals, let alone the large costs required to build them. Therefore, building new airports is not often the best way to tackle growing passenger and cargo movements. In addition, low usage terminal capacities are often not included in airports' strategic capacity planning (Maaike van der Windt, Brisbane Airport Corporation, 2010).

Solutions that can increase capacity whilst not increasing the infrastructure and land use are optimal. Hence, increasing efficiency of the existing airport facilities and optimising passenger flows for full usage of the airport terminals are now the preferred viable solutions for the growth problem. In this regard, air passengers and the interactions with other passengers and airport processes, typically in the highly dynamic situations encountered at airport terminals, have a great significance upon airport passenger handling, although they are often very difficult to control and predict.

### 1.1.1 Passenger activities in airport terminals

In general, there are many different on-airport facility units which are for diverse functions. Moreover, there exists significant trade-offs regarding alternative operational policies and concepts of the physical terminal layout in airports. Hence, airport terminals can be considered as complex systems (Odoni and de Neufville, 1992; Fookes, 2009; Manataki and Zografos, 2009). The number of entities involved is in high volume, and the systems are in a continuous state of change. The processes in and around airport terminals are ideal for simulation studies.

Commonly the airport process includes airport access, parking, check-in, security, customs, shopping, eating and drinking, waiting, boarding, and baggage reclaim. Conventional studies (Babeliowsky, 1997; Gatersleen and Van der Weij, 1999; Joustra and Ban Dijk, 2001) have focused on macroscopic airport processes, simply regarding passengers as only passing through standard processing facilities such as check-in counters, security and customs counters. Little attention has been paid to discretionary activities of passengers outside standard processing procedures, which include activities at facilities such as duty-free shops, cafés and restaurants.

However, passengers have free will and do not always behave as airport terminal designers expect. There is a need to study the aspects of passengers' experience within airport terminals. Especially when there are delays or when the terminal capacity is near its capacity, to deal with boundary conditions such as these, simulation studies can be an advantage in terms of supporting decision-making for changes that will improve the airport's processes. Once the passengers are satisfied, the airlines, which are the other important customers of the airport, also benefit. Consequently, managing passenger flows is becoming an important issue for airport terminal operations.

People's walking behaviour is stochastic (Mayne, 1954; Ashford et al., 1976; Antonini et al., 2006), and can be very complex, since in reality people can stochastically change directions and speeds. Architects, planners and other social scientists have only endeavoured to accurately predict pedestrian movement in natural environments (Helbing, 2001; Scovanner and Tappen, 2009; Asahara et al., 2011). For passenger movement inside a particular airport terminal, however, few architects and airport planners have addressed the travel experience of passengers and how they utilise on-airport facilities. The need to make such predictions becomes particularly important when changes or interventions are being made to an existing terminal. Equally, this knowledge gap can also be a problem when designing large, complex terminal buildings (the larger or more complex a design problem is, the more probable it is that a designer's intuition will fail (Duuberly, 1995; Soo-Haeng and Eppinger, 2005). In order to be able to make these kinds of predictions, it is essential to strive to better understand how the airport terminal is currently being used by passengers and how to realistically reflect passengers' route-choice, dwell time and space occupancy at different sections of airport terminals.

### 1.1.2 Pedestrian movement and behaviours

The study of pedestrian movement in the built environment has recently been found of great interest in urban studies, transportation modelling and many other geographic-related fields (Verlander and Heydecker, 1997; Penn and Turner, 2002; Fuerstenberg et al., 2002; Hoogendoorn and Bovy, 2004; Teknomo and Gerilla, 2005; Kholshevnikov et al., 2008; Kulakowski et al., 2010; Beltaief et al., 2011). There is an increasing significance in considering pedestrian experience in architecture design. When changes and interventions are being made to an existing urban environment or building facility, the phenomenon of pedestrian movement within them should be taken into account. In order to accurately predict pedestrian movement in the built environment, it is necessary to better understand how the built environment is used by people and the local interaction laws underlying pedestrian dynamics. Transportation researchers, architects and social scientists are currently in urgent need of a decisive tool to understand and analyse human movement in different settings.

Pedestrians and human movements in general are topics which are worthy of thorough scientific inquiry. For studies of transportation in relation to the interactions between pedestrian and roads/cars (Shankar et al., 2003; Yang et al., 2006; Edward and Andre-Gilles, 2009) and for studies of architecture design in relation to social use of space (Penn and Turner, 2002; Penn, 2003), people are included for consideration. The studies would at last consider whether humans will be comfortable living and moving within the designed or created objects. In addition, from the point of view of pedestrian dynamics and evacuation, there is the more specific question of how a suddenly changed environment (for example, exits and building layouts are blocked or changed due to earthquake, fire or other events) can be included in large area evacuation modelling (Ratner and Brogan, 2005). Put simply, pedestrian simulation is a decisive tool to understand and analyse human movement in different settings.

There have been some advances in pedestrian dynamics studies. Moussaid et al. (2011) indicate that it is very possible for cognitive, heuristics-based models in pedestrian simulation to replace conventional physics and force-based models. This approach seems to be especially suitable for high density situations as, for example, the crowd disaster in Duisburg, Germany (Waldau, 2007), and other similar mass events. Technically, this is done by introducing a contact force that becomes active and effective in dense situations. The new heuristic approach is based on the vision dynamics of pedestrians – and in this way on the proactive behaviour – in contrast to physics-based models where pedestrians are passively influenced by forces. However, at this stage, this proposal is not yet proven to be able to intuitively capture collective pedestrian behavioural dynamics such as lane formation, although it seems very promising according to first results and validations.

### 1.1.3 Solution for passenger dynamics

Pedestrian walking behaviours can be very complex, since in reality people can stochastically change directions and speeds. Passengers in airport terminals, despite being goal-directed at both short-range and long-range scales, are no exception to this complex behaviour. For departing passengers, for example, the long-range goal is to board the correct aircraft on time. In this regard, high-level passenger flow in airport systems is not difficult to estimate; however, passengers' short-range goals change regularly and potentially very quickly, impacting short-range pedestrian flows. For example, passengers could suddenly find themselves lost, and need to locate some directional signage to assist them in finding their way. Another alternative is that on the way to the security control point, passengers could be suddenly side-tracked by a special offer in a duty-free shop which they had no initial intention to enter.

All the stochastic behaviours of passengers could be explained as results of the impact of physiological aspects of the passengers. Passengers are autonomous and intelligent, and have the ability to perceive the surrounding environment (Schultz et al., 2007). At the foremost, we investigate the behaviour, actions and decisions of each pedestrian and also their interactions with each other. We discover passengers have several different special characteristics and can take decisions following specific rules which congruously depend on their own characters. Some simple characteristics can be easily collected from a passenger such as gender, age and walking speed. Modelling individual people as computational agents in a virtual reality has become increasingly viable due to the advancement of computing technology. Significant aspects of pedestrian movement such as walking speed, obstacle avoidance and route planning can be realised by computer simulation. Several mathematical and physical mechanisms have came forth as bases to support this type of simulation, including cellular automata (Haklay, 2001; Burstedde, 2001), magnetic force theory (Matsushita, 1991; Okazaki et al., 1993), social force theory (Helbing, 1995), the benefit-cost cellular model (Gipps and Marksjö, 1985) and queuing networks (Lovas, 1994). All of these approaches attempt to model certain behaviours of humans whilst walking and interacting with each other and their environment.

Agent-based solutions to a decision-making problem explore agents as autonomous decision-making units and their interactions to achieve global goals. Agent-based models are most suitable to provide a natural description of the system and to capture emergent phenomena and complex human behaviours (Bonabeau, 2002). An individual agent incorporates the local function regarding time variable, motion speed, direction and path deviation to guide it to keep a tolerance distance with other agents, avoid collisions with an obstacle and calculate a feasible route choice. Medium-range control enables agents to act with environmental participation. This environmental participation includes normal airport system passengers' flow handling operation (mandatory processing procedures), infrastructure information (terminal layout and boundaries) and discretionary area positions (non-mandatory service facilities) where passengers undertake distinguishable, personalised activities. Modelling medium-range control functions allows for a valuable extension of the local movement function.

The agent-based model can explore space-time dynamics. It forms the foundation of this thesis. Computational agents can have a direct correspondence with real-world actors, which can be an animal in a flock, stock in the stock market, or a pedestrian walking down the street. Agents themselves are not identical in most perspectives but rather portray different actors in the world. On the other hand, pedestrian models are commonly used in transportation and traffic modelling (Turner and Penn, 2002). To date there are many granular-physics models focused on population flows; for example the crowding simulation performed by Helbing and Molnar (1998) using pre-determined directional paths. These have led to observations of life-like emergent phenomena based on simple rules such as lane forming simply by a predisposition to move to the left or right in the face of oncoming traffic (Helbing et al., 2001).

While much work has been conducted in airport passenger flow simulation, less work has focused on the impact of microscopic individual passenger behaviour leading to macro-emergent phenomenon. Only a limited number of studies have used microscopic simulation of passenger movement in airport terminals to date and the characteristics of the passengers in these studies have been based purely on physical aspects, such as age, gender, mobility and instantaneous position at airport (Richter et al., 2009). In terms of the decisions being made by passengers, only proportions of alternative route-choice decisions have been set for the simulation of passenger movement. The proportions are simply the percentage of passengers who go to different counters in airport terminals. Therefore, they have not made full use of the capabilities of agent-based models. In particular, we believe the personal preferences of a passenger can affect motion, path planning and also susceptibility to path-deviation. These types of preferences are regarded as *advanced traits* which assist in facilitating the decision-making of passengers in airport terminals.

## 1.2 RESEARCH PROBLEM

As pointed out in the above discussion, airports are growing, but the tools to support change are not yet optimal. The complex activity of passengers creates the requirement for models that are capable of expressing the variability of pedestrian movement in this environment. To solve this problem, a range of pedestrian movement theories were investigated in the thesis. The agent-based model was chosen as suitable tool because it is capable of capturing complex characteristics of passengers and therefore can express their individual movements more specifically.

There is a strong indication that the study of passenger flow for evaluating capacity efficiency and security issues is not effectively included in the operation of airports. One of the problematic conditions is that most of the current simulation tools cannot acquire highly accurate data compared to the real passenger flow at airport terminals, because of the unreliable input resources and the limitations of algorithm complexity. Input resources are sometimes based on surveys of airlines, airport staff and passengers. The obtained information is historical data and usually a partial truth of real operating conditions, not the whole picture of the airport. The limitation of this is not only due to the difficulty of collecting fine scale accurate information of a large number of passengers' processing time and dwell time at different facilities and places within the airport, but is also owing to the current simulation tools which do not have sufficient functions to handle such complex data. It usually appears that some simulation tools can only do one simulation of passenger processing at a time.

In order to solve such limitations, a joint view is needed to not only study passenger flow through standard processing checkpoints until boarding an airplane or exiting an airport but also to investigate passengers' interactions both amongst themselves and with airport service facilities minute by minute. Such a novel simulation method can help generate passenger flow and can plot histogram graphs of passenger numbers in different sections of the airport.

The above limitations can be crystallised into four major questions which need to be answered in this thesis:

- Is it possible to learn from the study of the simulated virtual environment to understand how passengers use airport terminals?
- Can passenger flow in an airport be defined as computational agent flow in a corresponding virtual world context?
- Can computational simulation accurately represent real interactions of passengers amongst themselves and with airport service facilities?
- Can the behaviour of passengers be inferred by the simulation of behaviour?

## 1.3 RESEARCH OBJECTIVES

The research aims to devise a novel solution to solve complex passenger flows in airport terminals. Passenger motion is stochastic and is rarely completely pre-determined. Conventional studies on passenger flows have typically only considered the standard processing procedures, such as check-in, security, immigration and boarding. Indeed, as long as there are no large numbers of passengers dwelling inside a terminal at any given time, such an approach is sufficient to facilitate air passenger terminal operations. However, with the growth of air transportation domestically and internationally, this is not the case in many large airports. Crowding and delays are common. Underlying public hazards, such as fires, natural calamity and terrorist attack, are also within the concern of airports. Furthermore, many stakeholders such as airlines and retailers deem passenger experience to be significant. For this reason, the discretionary activities of passengers outside standard processing procedures are in great need of closer examination.

Studies of pedestrian dynamics at present have been limited to symbolical force-based interactions and localised rules. However, humans are not just like cells and atoms. They have cognition and behave rationally most times. That is, a human undertakes an activity based on his/her cognition of the ambient environment. However, from the perspective of other people, for example, those who watch him/her, the activity may not be considered rational. Thus, localised physical and mathematical rules would never be able to capture intuitive pedestrian walking behaviour on the large scale. Other factors on macro scale should also be considered in modelling pedestrian dynamics, such as the impact of other environmental elements and user experience of built environments

The research has the following objectives to fill this knowledge gap:

1. Determine a feasible localised motion function for passengers walking within simulated airport terminals.

2. Identify the characteristics inside airport terminals that have an impact on passenger dwell preferences and path formation.

3. Devise advanced traits of passengers and build an agent-based model in which passengers are defined as individual intellectual computational agents. The agent is an epitome of a passenger in a simulation and has a series of rules to determine the interactions of passengers.

4. Carry out meaningful simulation scenarios of passenger flows inside airport terminals with the help of devised advanced traits of passengers and a novel agent decision-making model. The advanced traits are to be implemented into the proposed Bayesian network framework which aims to infer the

probabilities that passengers undertake respective routing decisions. The novel agent decision-making model is an influence diagram, which expands the Bayesian network to a decision-making model in order to finalise real-time routing decisions of individual passenger agents.

## 1.4 STATEMENT OF CONTRIBUTION

The study reported in this thesis extends existing knowledge on passenger flow simulation in airport terminals with a number of unique contributions as follows:

1) Discretionary activities of passengers were included in the study in order to have full-range intuitive passenger flows, that is, activities undertaken by passengers at on-airport discretionary facility areas such as duty-free shops. Surveyed data from other research about the time spent by passengers in both standard processing counters and discretionary facility areas are used in the simulation. Passengers in the simulation freely access discretionary facilities and decide to use standard processing counters and discretionary facilities by their own will. The devised decision-making model aims to work as the mental mechanism of passengers in the simulation. Discretionary activities have significant impact on both the overall utilisation of airport terminals and the interests of stakeholders inside airport terminals such as retailers and the airport itself.

2) The study takes passengers into account as individual intelligent agents and develops passenger flow simulation from the bottom up. The single passenger agent is constructed with the basic traits and the novel advanced traits. Walking capability and mental decision-making mechanisms can be constructed with both traits. Numbers of passengers are then populated in a specific simulated airport terminal environment. Through micro-simulation, passenger flow is studied by first investigating individual passengers' behaviours. The spatial and temporal dynamics of passenger flows can then be estimated through the agent-based approach.

3) A set of advanced traits of passengers is devised aiming to capture major interaction activities amongst passengers and with on-airport service facilities. Advanced traits are identified through tabulating passenger activities and discretionary facilities of major airports around the globe. In this thesis, ten

advanced traits are implemented into the tactical route-choice decision-making of passenger agents. They are developed by investigating various discretionary facilities at terminals of worldwide major airports.

4) Target and route choice decision-making of a passenger agent is carried out by the graphical models, Bayesian networks and influence diagram. They are devised to be able to conceive basic traits and advanced traits of passengers, and to infer the preferences of using an alternative on-airport facility in real time. Every trait of a passenger is incorporated into a node of the Bayesian networks. Values of probabilities the passenger would take regarding the respective activities can be obtained by the Bayesian networks. The influence diagram only expands the Bayesian network with a utility framework so as to finalise an alternative decision that a passenger agent undertakes an activity at a time inside the airport terminal. The utility framework assigns specific weighted values to every possible activity which has been inferred through the Bayesian networks. The final value of the probability of an activity with the weighted value represents the utility to take the activity. The one with highest utility denotes the true decision that the passenger agent makes regarding its routing choice.

## 1.5 OUTLINE OF THE THESIS

In Chapter 2, the phenomena of pedestrian flow in the built environment and related macroscopic and microscopic models are reviewed. Macroscopic models simply take into account the determined pathway of pedestrians, such as corridors or spare areas within built environments, and do not consider detailed interactions among pedestrians and building facilities. Microscopic models have more general usage and consider detailed pedestrian flow performance. Four major microscopic pedestrian flow models are addressed. They are the benefit-cost cellular model, magnetic model and social force model as well as a pedestrian flow concerning the psychological states of pedestrians in the emergence context. Since conventional studies focus on macroscopic aspects, the capabilities of microscopic pedestrian are not fully developed. Agent-based modelling is an important microscopic approach, which treats each individual as an independent agent with multiple traits.

In Chapter 3, airport business processes in terms of passenger flow are investigated. Over fifteen major airports around the world are selected for comparison, in order to acquire important elements which are most relevant to passenger movements and behaviours. According to the results, advanced traits of passengers are envisaged to represent passengers' mental preferences when they are travelling through airport terminals. The advanced traits of passengers are then measured as corresponding parameters, aiming to be implemented into models for simulation experiments.

In Chapter 4, a force-based walking model is used for devising the basic walking module of passengers. The modules simply consist of walking speeds, obstacle avoidance, attraction, bond force and repel force functions, in terms of the tactical/strategic function of walking which is for passenger cognitive behaviour regarding path choice and walking lane formation. Walking experiments are carried out to show basic passenger flow paths inside airport terminals.

In Chapter 5, the tactical functions of passengers walking inside airport terminals are devised and tested. First, envisaged virtual outbound airport terminal processes are set up. Passenger agents are assigned with the developed advanced traits and are populated into the simulation scenarios. The agent-based passenger flow model is successfully realised. The outcomes of the simulation results are proven to be more intuitive compared to conventional simulation. The model provides insights into the relations between different processes and passenger logistics, and between the presence of bottlenecks and their causes, and also can predict long-term situations along with passenger population growth.

In Chapter 6, the route-choice decisions of passengers within airport terminals are researched. Since passenger walking is stochastic, it is unwise to pre-determine the routes which passenger agents will move along. Bayesian networks deal with the uncertainty issues of objects. In the simulation, each passenger agent is an object in the Bayesian networks. Some basic information of passengers, such as age, gender, travel class and travel of frequency is recorded as basic definitions. Passenger objects are defined and composed accordingly.

In Chapter 7, case studies are carried out in collaboration with an airport in Australia. The agent-based passenger flow simulation of the international terminal of the airport generates general key performance indicators (KPI) which are compared to the regulated empirical and survey data, in order to confirm the capability and significance of the devised model.

In Chapter 8, the conclusions of the research are discussed in terms of the implications in a wider academic and application-based context. It concludes with recommendations for future research directions that could arise from the work forming this thesis.

# Chapter 2: Pedestrian Dynamics in the Real and Simulated World

This chapter focuses on the body of literature concerned with modelling pedestrian dynamics in the real and simulated world. It begins by discussing the significance of taking into account people's behaviour in the built environment. Next, in reviewing pedestrian walking in the real world, different methods of assessing pedestrian walking are presented and assessed. Through the illustration of relevant walking scenarios, this chapter distils a working theory of pedestrian interaction to be used throughout this thesis. Research works that focus on the effect of the environment on route formation mechanisms are then reviewed and their methods discussed.

After identifying problems around pedestrian walking research, most of which focuses on the assessment of behaviour and the effect of the environment, this chapter goes on to examine more recent work in the field. Recent work investigates pedestrian behaviour in real circumstances, and asks whether virtual environments can be considered adequate tools to investigate this phenomenon. A series of pedestrian walking experiments conducted in a virtual environment are then discussed, highlighting factors that led to a series of publications that investigate the effect of forced-based components (attractors, expel and bond effects) upon walking. Finally, a number of studies attempting to compare real and virtual pedestrian walking behaviour are compared, leading to the conclusion that, broadly speaking, the same approach is taken in all the research reviewed. Rather than basic walking behaviour, it is the mental preference of the pedestrian that is being analysed. Mental preference mainly refers to the mechanism which controls waking speeds and routing decisions of pedestrians. Assumptions of equivalence (that real walking correlates to virtual walking) are made based solely on this. This chapter concludes with the observation that more objective methods of measuring basic walking performance are needed, coupled with better analysis of environments, and that the degree to which real and virtual walking performance are analogous still needs to be established.

## 2.1 INTRODUCTION

The focus of this chapter is the examination of the body of knowledge of pedestrian walking, both in real scenarios, and from more recent years, in the virtual simulation realm. Since the research question underpinning this thesis is whether it is possible to learn from the study of virtual environments how people will behave in real environments, it is vital to first understand what is already known about behaviour in real environments. Besides the walking interaction among pedestrians, the real-world behaviour of greatest relevance to this thesis is the interaction between pedestrians and the built environment in which they are walking.

The study of pedestrian movement in the built environment has recently been of great interest in urban studies, transportation modelling and many other geographic-related fields (Penn and Turner, 2002; Fuerstenberg et al., 2002; Daamen and Hoogendoorn, 2003; Hoogendoorn and Bovy, 2004; Teknomo and Gerilla, 2005). As shown in Figure 2-1, in the research fields of built environment, architecture and geography, there are areas in pedestrian dynamics, multi-agent pedestrian models and some others which involve the modelling of people’s movements.

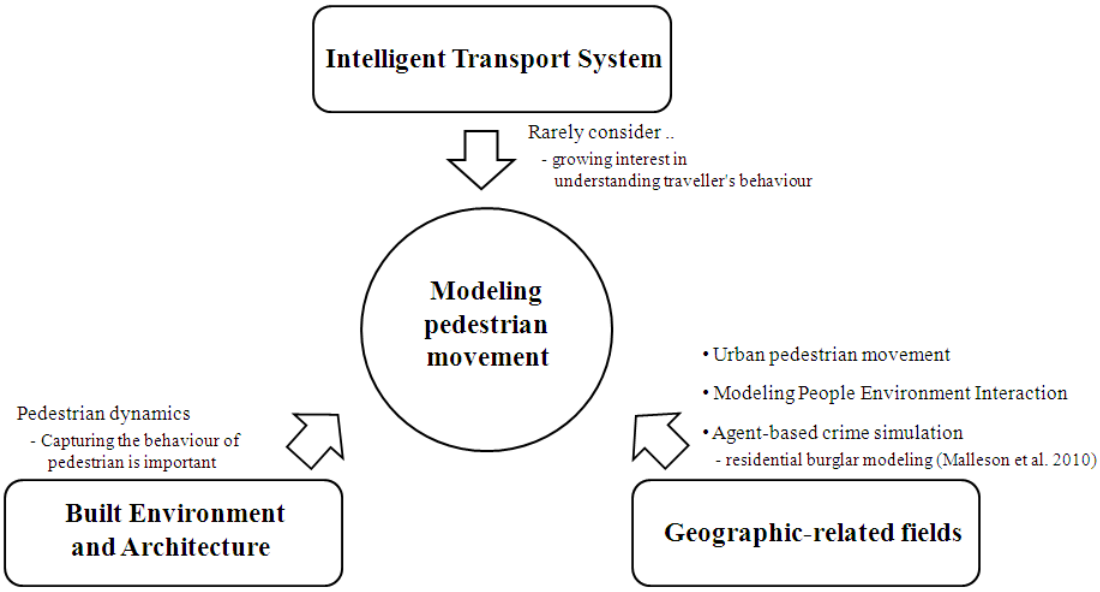



Figure 2-1: Pedestrian movement research fields

In built environment and architectural design, there is an increasing importance placed on the consideration of the pedestrian experience. Attractive appearance does not equal high efficiency in facilitating pedestrian flow; neat and ordered pathways or corridors may not cater for pedestrian walking experiences (Moussaid et al., 2009). Moreover, in emergency conditions, pedestrian flow would change dramatically to abnormal motion, such as stop-and-go waves and crowd turbulence (Helbing et al., 2007), which may cause serious trampling accidents. In this regard, it is crucial for pedestrian flow motion to be utilised to formulate a new urban design for safety considerations.

In particular, there is a great potential to carry out "crash tests" in emergency conditions for a proposed designed urban environment, in which pedestrians are injected and flow motion can be simulated and observed. Thus, in order to accurately analyse pedestrian movement in the built environment, it is necessary to better understand how the built environment is used by people and the local interaction laws underlying pedestrian dynamics.

Pedestrian movement research partly arises from the study and design of modern transportation systems, featuring a mix of automobiles, motorcycles, bicycles and pedestrians on constructed pathways. Pedestrians are an integral component of the transportation system. Their movements influence the design and operation of transportation terminals and the timing of traffic signals. In recent years, there have been several attempts to model pedestrian flow. For example, Smith et al. (1995)

modelled thousands of people's commuting behaviours in a city, where virtual traffic jams were observed and predicted. The model city in this case was populated with commuters according to detailed demographics and other data available to the modellers. The model showed how different plans of the current population of commuters were likely to produce congestion and other effects. The purpose of such a transportation system study is to predict traffic conditions and to guide transportation system design.

In non-vehicle passenger flow studies, methods derived from vehicle-based transportation systems have generated numerous applications and offered fruitful insights. Blue and Adler (2001) have applied cellular automata (CA) micro-simulation to model uni- and bi-pedestrian directional walkways and demonstrated that these models produce acceptable fundamental flow patterns. Hoogendoorn and Bovy (2004) have developed a model of pedestrian flows based on a gas-kinetic modelling paradigm widely applied for modelling vehicle flows. Gipps (1985), AlGahdi and Mahmassani (1991), Lovas et al. (1994), Helbing and Molnar (1995) and Li (2000) are among others who have worked toward developing pedestrian flow models. However, it is widely believed that vehicles and pedestrians behave differently in terms of speed control, obstacle avoidance and route choice in environments, thus exhibiting distinctive overall performance.

Research interest in pedestrian behaviour spans the retail industry, emergency services, urban planners and other agencies. Most models to simulate and model pedestrian movement can be distinguished on the basis of geographical scale, from the micro-scale movement of obstacle avoidance, through the meso-scale of individuals planning multi-stop shopping trips, to the macro-scale of overall flow of masses of people between places. In the STREETS model (Schelhorn et al., 1999), for instance, each entity in the model represents a single pedestrian. STREETS was built to enable the integration of various scales of movement in a modular way, and could incorporate any previous pedestrian models. Pedestrian activity has two distinct components, namely, the configuration of the street network and the location of building attractors (such as shops, offices, public buildings) on that network. Although the STREETS model is close in approach to TRANSIMS (Smith, 1995), it takes as its subject the activities of pedestrians in sub-regional, urban districts.

However, STREETS does not claim to imitate the cognitive behaviour of pedestrians, much less represent any particular psychological model of movement.

STREETS assigns socio-economic attributes to pedestrians in the first stage, calculates the routes and provides each pedestrian entity with “history” which encapsulates both long-term trends and short-term trends. A more realistic visualisation would be possible to develop modules that interact with pedestrian avatars to control the representation of physical movement in an urban space, such as the street network in this case.

Pedestrian movement in general is becoming a more important topic that is worth extensive scientific inquiry. There are studies on traffic regarding the interactions between pedestrian and cars (Retting et al., 2003; Shankar et al., 2003) and on architecture design regarding the social use of space (Penn and Turner, 2002), which include people in the plan and test whether humans will be comfortable living and moving within the designed or created objects. From the point of view of pedestrian dynamics and evacuation, there is the more specific question of how a shifting and moving ground can be included in large area evacuation modelling (Ratner and Brogan, 2005).

Transportation researchers, architects and social scientists are in urgent need of a decisive tool to understand and analyse human movement in different settings. Pedestrian simulation is an important approach to understand and analyse human movement. In a broad categorisation, pedestrian simulation can be divided into macroscopic simulation and microscopic simulation, in terms of the philosophies of the methodologies.

## 2.2 MACROSCOPIC MODELS

The major activity of human movement in built environments is walking or travelling through buildings or urban areas. Overall, it more or less like a fluid flow as a consequence of fluid molecules moving from one cross-section to another. Pedestrian flow is a result of the movement of many individuals. This is a simple definition of a macroscopic approach to analysing pedestrian flow. The macroscopic approach focuses on crowd behaviours as a whole.

In this regard, the characteristics of individual pedestrians are thought to be irrelevant to the overall motion flow. So, the space tolerance of individual pedestrians could be ignored. Pedestrians can be represented as particles in the model. Lovas (1994) introduced the basic phenomenon of pedestrian movement. The average flow was represented as:

$$F = S \cdot D, \tag{2-1}$$

where F is the average flow, denoting numbers of people (P) per meter second (P/ms); S (m/s) is the average walking speed and D (P/m$^2$) is the average density. Since the speed is a function of density too, F = F (D) is often considered to depend on the population density only. Illustration of the scenario described by Equation (2-1) is shown in Figure 2-2.

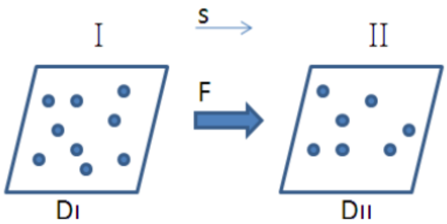



Figure 2-2: People flow equation (Lovas, 1994)

Hankin and Wright (1958) measured flow, taking into account that flow in a walkway is affected by what is happening on either side of the section under consideration, and obtained results similar to Figure 2-3. They predicted a formation of the arches, which might be formed approximately inversely proportional to the square of the exit width.

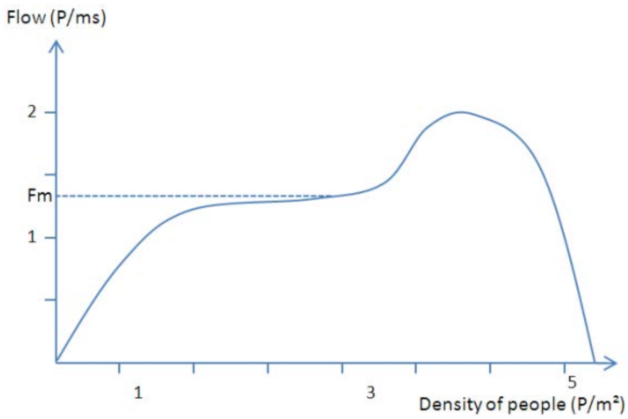



Figure 2-3: Graph of people flow density (Hankin & Wright, 1958)

The term pedestrian flow analysis can be further clarified. On one hand, it can be referred to as the study of densities at different locations inside large buildings such as airports (Ju et al., 2007), subway stations (Daamen, 2004) and religious places (AlGadhi and Mahmassani, 1991). This process-based research concerns the overall flow performance based on the statistics of dwelling at different spots. On the other hand, the term can be used to refer to intense crowd movement behaviour in a dense pathway in a short period of time. Under this circumstance, more precise physical and psychological factors are taken into account. For example, with a fixed width exit, how long does it take to evacuate a certain number of people? An example is given in Figure 2-4.

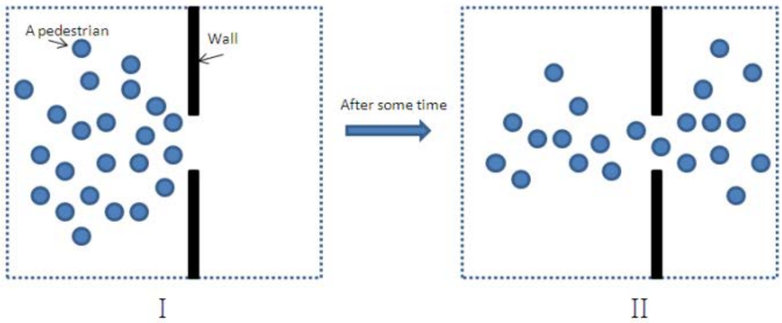



Figure 2-4: Illustration of pedestrians evacuating a fixed wide exit (Helbing & Molnar, 1995)

Fields that suit the pedestrian flow and crowd study are public spaces where crowds are likely to gather, especially in the location of evacuation routes. Physical aspects of built environments are the concern for studying pedestrian flow in a built environment. Basically, aiming to observe human movement in particular places, the pathways and corridors are first located to represent route trajectories where pedestrians are constrained and walk along (Seneviratne, 1989; Kretz et al., 2006). In many buildings such as offices, schools and hospitals, pedestrian flow is constrained to corridors, and pedestrians have little or no choice about the route they take between a particular origin and destination. In shopping malls or plazas, however, objects such as benches, fountains and kiosks or display stands frequently prevent pedestrians from following straight lines between their origins and destinations.

### 2.2.1 Physical characteristics of pedestrians

Besides involving physical aspects of built environments, the physical characteristics of pedestrians need to be considered in models as well. Fruin (1972) found that the fully clothed dimensions of the 95$^{th}$ percentile of the population (95% are less than this) are 33cm in body depth and 58cm in shoulder breadth. The average male human body occupies an area of approximately 0.14m$^2$. These figures could be helpful in determining the “buffer zone” between pedestrians required for comfortable use of a walkway. Fruin also reported that behavioural experiments involving personal space preferences showed minimum desirable occupancies ranging between 0.47 and 0.93m$^2$ per person, where physical contact with others is avoidable. People require a lateral space of 71 to 76cm for comfortable movement. The longitudinal spacing for walking would be 2.5 to 3m. This results in a minimum personal area of 1.9 to 2.8m$^2$ per person for relatively unimpeded walking in groups on level surfaces. Individual area occupancies of at least 3.3m$^2$ per person are required for pedestrians to attain normal walking speeds and to avoid conflict with others. In addition, Fruin found that unimpeded walking speed varies between 46 and 107 meters per minute, and the average is 82 meters per minute.

Fruin (1972) defined two types of queues: the linear/ordered queue, in which pedestrians line up and are served in their order of arrival; and the undisciplined or bulk queue, where there is more general, less ordered crowding. Fruin also stated that spacing between people in linear queues is generally 48 to 50cm; the recommended lateral single file width for railings or other dividers is 76cm.

### 2.2.2 Routing dynamics of pedestrians

Although the behaviour of pedestrians in the urban environment is sometimes stochastic and unpredictable, especially for crowds, there is good reason to believe it is governed by simple rules. At first glance, molecules in a liquid are presumed to epitomise the behaviour of people in a crowd, because they all behave in more or less the same way. Ciolek (1978) stated that pedestrian routes usually fulfil the following criteria:

(a) The route is the shortest one connecting the point of departure with the point of destination,

(b) The route should avoid physical objects or stationary groups of people,

(c) The route should not involve sharp and rapid changes in direction,

(d) The adopted route is the quickest and most convenient one to use,

(e) The route should not lead across areas where it is difficult to walk,

(f) The selected route should not involve rapid changes in elevation of the walking surface, especially for older people and those with luggage or pushing prams,

(g) The route is likely to provide interest such as shop windows,

(h) The importance of the location of the route in relation to the nearness of kerbs and walls.

Existing models of crowd behaviour tried to predict how a crowd will behave (Lovas, 1994; Hughes, 2003; Ali and Shah, 2008). They treat moving masses of humanity as though they were fluids. However, this approach usually cannot predict dynamics when pedestrian flow increases and becomes chaotic. There is a need to treat people as if they were truly human beings who can actively sense the environment, instead of treating them as molecules. In a desired approach, a pedestrian should be able to chart a path to a destination, such as an exit or the end of a corridor, while avoiding obstacles, including other pedestrians (Moussaid et al., 2009). The pedestrian could also make decisions according to some pre-defined rules. For example, he/she may possess a walking-speed variable and can adjust his/her speed according to his/her distance from such obstacles. All this can be realised by a computer model. Observations of pedestrian speed, density and flow relations have been carried out in previous studies (Fruin, 1972). Mōri and Tsukaguchi (1987) added a relation between speed and density as shown in Figure 2-5. Pedestrian area (square meter per pedestrian) was used instead of pedestrian density (pedestrians per square meter).

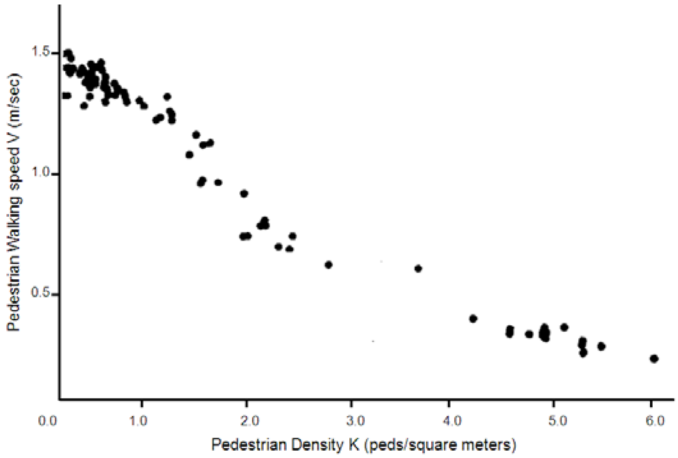



Figure 2-5: Pedestrian walking speed and density (Mōri and Tsukaguchi, 1987)

From Figure 2-5, it can be seen that speed is about 1.5m/sec for free-flow, decreasing gradually to a density of 1.5 peds/$m^2$, where the relation between pedestrian speed and density is shown as (Mōri and Tsukaguchi, 1987):

$$V = -0.204K + 1.48, \qquad (2\text{-}2)$$

after which speed drops sharply.

Because a pedestrian cannot necessarily see his final destination from his starting point, and may in any case choose to deviate from a direct path, route selection is based around the concept of intermediate destinations (or nodes) generated by the objects in the open area. Gipps and Marksjo (1985) used the physical layout to generate a number of nodes in their model. A pedestrian walking between his origin and destination moves from one node to another. When he is within a short distance of the node to which he is walking, he has to make a decision about the following node. The choice is limited by the requirement that the next node must not be hidden from his/her present position by a fixed obstacle. That is, a straight line between the present node and the next does not intersect any obstacle.

Besides physically assessable quality factors, various soft factors or social forces can also lead to either attracting or repelling pedestrian to parts of the network and influencing their routing decisions. These factors have in common that prior knowledge must be available to the individual pedestrian about their character and location (Czogalla and Herrmann, 2011). If these soft factors exist temporarily, an influence on a routing decision can only be assumed if it is visible to the individual at the point of decision. Examples of attractions are possibilities of social interaction such as groups of persons, street artists, street markets and temporary exhibitions or street festivals. Examples of repelling factors are socially insecure places such as known crime spots and areas known for loitering and begging, as well as alcohol and drug abuse. Czogalla and Herrmann (2011) indicated that the valuation of soft factors, as an increase or decrease of the *pedestrian quality attribute* (PQA), can be realised by estimating the *social force factor* $\mathrm{a_{SF}}$ for each concerned network element. The domain of $a_{SF}$ is defined as:

$$-1 < a_{SF} < 1, \tag{2-3}$$

valued from repulsion (-1) to attraction (1). The social force factor $a_{SF}$ is added to the evaluated link related PQA. As such, the social force factor serves as an additive measure for the further increase or decrease of the virtual distance between nodes of the network (Czogalla and Herrmann, 2011):

$$walkability\ attribute = \frac{1}{2}(PQA + a_{SF}). \tag{2-4}$$

The resulting attribute is denoted as the *walkability attribute* and measures the cost for travelling the network paths. Decisions for route choice are drawn during the routing process that determines the shortest virtual path.

The walkability attribute defines a measure for the virtual distance that is essential for a routing decision that takes into account the link quality and social factors. In the process of utility maximisation which is presumed as a basis for the routing decision, always the shortest virtual distance will be chosen by the pedestrian.

Apart from quality-related factors, there are important human factors that will have a strong impact on routing decisions at the tactical level. The trip purpose, personal fitness, as well as time constraints will have a significant influence on route choices. It is expected that these factors will not change during a trip. Hence, the individual factors are considered as additional input quantities for the utility maximisation process of route choice that will influence the decisions evenly over the entire network.

### 2.2.3 Limitation of macroscopic models

Particle representation theory is a good way to evaluate macro outcomes of pedestrian flows; for example, the total number of pedestrians who occupy a corridor or a building space. However, if more detailed information is required, such as how pedestrians react in a crowd or how pedestrians' interactions with building facilities impact on macro flow, the notion of pedestrian flow could be less useful.

The ability to predict the response of a pedestrian to the behaviour of his neighbours in a corridor or an open area is important in estimating the effect of changes in the walking environment (Greenwald, 2001; Landis, 2001; Saelens et al., 2003). While objects provide foci of interest around which people are likely to congregate, while talking or watching the passing traffic, they also involve pedestrians in a choice of route. From the viewpoint of management of such facilities, these objects fulfil a useful role in reducing the speed of pedestrians and dispersing them, as pedestrians who walk too quickly are unlikely to be attracted by window displays. If there are too many impediments in corridors, the mall may be unable to handle the crowds at times of peak usage. Thus, controlling pedestrian movements within and around buildings is an important facet of design.

In this regard, there exists a research opportunity to investigate the interactions among pedestrians and ambient environments so as to understand how a built environment impacts on pedestrian flow. For designers of buildings and other constructed facilities, it appears to be important to be able to predict how changes in the walking environment will affect the pedestrian flow. These changes can act on an individual pedestrian directly by diverting him/her from their preferred route, and indirectly through their effect on other pedestrians.

While the ability to predict pedestrian flows within and around constructed facilities is important, existing macroscopic models of pedestrian flow are, in the most part, limited to the quasi-steady state flow in corridors (Fruin, 1972). However, many buildings have pedestrian flows that are transient and vary over relatively short time intervals. Such variations in flows can arise from events such as a lift disgorging its passengers, or a set of traffic signals outside the building allowing pedestrians to cross the road and enter the building. Consequently, it is desirable to be able to model the behaviour of pedestrians in more detail than is provided by macroscopic models.

## 2.3 MICROSCOPIC MODELS

Pedestrian flow is categorised into macro-scale and micro-scale perspectives. Microscopic approaches separately concentrate on each individual's behaviour. The term "microscopic" here refers to the philosophy of the methodology rather than attributes of problems. It does not mean that microscopic approaches can be totally distinguished from macroscopic approaches in terms of applications. Normally, when pedestrians walk free of congestion in a sparse environment, the macro-scale side is more informative; when passengers aggregate into dense crowds, the micro-scale side is more determinative for integral performance (Xu and Duh, 2010).

A microscopic approach treats each individual as an independent entity which consists of multiple traits. Microscopic models have been evolving since the development of a pedestrian model based on fluid dynamics (Helbing, 1992). Later, some models of crowd behaviours were developed (Helbing and Molnar, 1995; Batty et al., 1999), and closely matched various observed pedestrian behaviours. In such models, pedestrians can spontaneously form lanes, for the purpose of avoiding collisions and quick movement.

Microscopic analysis has been made possible by the rapidly increasing speed of computation. A microscopic simulation of a micro-scale pedestrian flow problem is often computationally intensive.

Pedestrian flow is loose and free, and is more complex than vehicular flow which is constrained by "lanes" (Jian et al., 2005). From the standpoint of general principles for modelling, human flow is a complicated system, consisting of sets of interacting elements, namely, people. Performing a micro-simulation of pedestrian movements is a simple way to handle the stochastic nature of such pedestrian flows (Kholshevnikov et al., 2008). A microscopic pedestrian simulation model is a computer simulation model of pedestrian movement where every pedestrian in the model is treated individually (Teknomo et al., 2000).

### 2.3.1 Micro models of pedestrian dynamics

Pedestrian flow involves both the physical and the behavioural characteristics of crowds. It is perceived as a typical complex system (Helbing et al., 2001). Physical laws alone are considered insufficient to represent pedestrian walking dynamics. Therefore, experts from physics, applied mathematics, psychology, sociology and transportation engineering have been working on different aspects of the problem (Kholshevnikov et al., 2008).

Microscopic pedestrian flow models include the benefit-cost cellular model (Gipps and Marksjo, 1985), cellular automata model (Blue and Adler, 1999; Dijkstra et al., 2000), magnetic force model (Okazaki, 1979), social force model (Helbing et al., 1995), and models derived from other mature technologies such as game theory (Lo et al., 2006) (Figure 2-6). If the behaviour of individuals can be adequately modelled, and the appropriate distribution of pedestrian types is employed, their combined behaviour would be realistic.

The benefit-cost cellular model focused on the interactions between pedestrians which were intended to be used in graphical computer simulation. It simulated the pedestrian as a particle in a cell. The program used interactive colour graphics to display the operation of the model and assist in the validation and verification of the model. However, the model is limited by restricted computation capacity and as a result is not suitable for practical purposes.

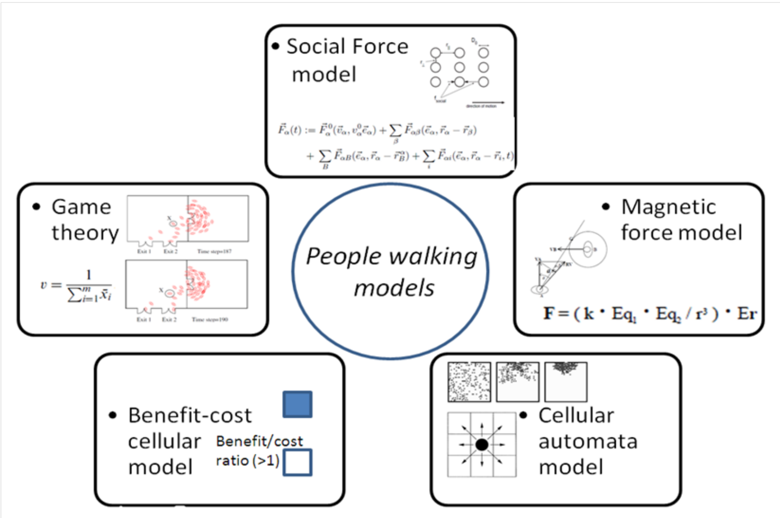



Figure 2-6: Current pedestrian walking models

In order to realise the interactions of pedestrians, pedestrians should be of a number of different types, and it should be possible to change their characteristics and numbers to suit the situation being investigated. The parameters in the model should correspond to obvious characteristics of pedestrians whenever possible (Gipps and Marksjo, 1985). However, little work has been done to conclude pedestrian characteristics until now. On the one hand, urban environments and building facilities are varied. It seems impossible to have a set of identical characteristics of pedestrians for all contexts. On the other hand, the interaction functions which link pedestrian characteristics and the action responses regarding the built environment are sophisticated.

In terms of the repulsive effect among pedestrians and obstacles, Gipps and Marksjo (1985) used simple arbitrary scores to assign cell occupation, which evidently lost physical meaning. To improve this, Okazaki (1993) developed the magnetic force model to apply to pedestrian movement. Each pedestrian and obstacle has a positive pole. The negative pole is assumed to be located at the goal of the pedestrian. Thus, the intensity of the magnetic load of a pedestrian and the distance between pedestrians bring about the magnetic force which leads pedestrians to move to their goals. Pedestrians move their goals and avoid collisions. Every pedestrian applies two forces: one is a magnetic force, which is assumed to be dependent on the intensity of the magnetic load of pedestrian and distance between pedestrians; the other one acts on a pedestrian to avoid collisions with other pedestrians or obstacles. As a consequence it will exert acceleration. Although the model involves certain physical meanings of real pedestrian movement, it still deviates from the true sense to some extent.

The cellular automata model is able to model pedestrians (Burstedde, 2001). In this model, space, time and state are discrete. The walkway is modelled as grid cells. Each pedestrian can only occupy one cell at a time, and at the next time the pedestrian will either move to or leave a cell. The occupancy of a cell is governed by localised neighbourhood rules. The movements of a pedestrian are lane changing and cell hopping. Although it is effective enough to estimate the probability that a certain direction and place will be chosen as a destination, the model cannot deal with each pedestrian movement in a more fine-scale environment. Pedestrian models which can be applied to the erratic movements of users in multi-purpose spaces, such as shopping malls and airport terminals, are strongly needed.

Helbing et al. (1991-99) developed the social force model which supposes a pedestrian is subjected to social forces that motivate the pedestrian. The model is based on the assumption that every pedestrian has the intention to reach a certain destination at a certain target time. The direction is a unit vector from a particular location to the destination point. The ideal speed is equal to the remaining distance per remaining time. It is the most popular microscopic pedestrian model up to now and has been implemented in many specific pedestrian simulations (Seyfried, 2005; Song and Duh, 2010). However, like the other two microscopic pedestrian simulation models reviewed above, there is no statistical guarantee that the parameters would be feasible for general cases.

Besides the above models, a queuing network model is also used in microscopic pedestrian simulation (Watts, 1987; Lovas, 1994; Thompson, 1995). The approach is a discrete-event Monte Carlo simulation. It suggested that each room is denoted as a node and the doors between rooms are links. Each person departs from one node, queues in a link and arrives at another node. A lot of pedestrians move from one node to another in search of the exit door. In one evacuation model, all people have to move from their present position to an exit as quickly and safely as possible. Walking route and evacuation time are recorded in each node. As soon as a pedestrian arrives in a node, it makes a weighted-random choice to choose a link among all possible links. The weight is a function of actual population density in the room, but a pedestrian may have to wait and find another route to follow when the current link cannot be used. In the source node, a pedestrian needs a limited time to react before movement begins, while in the final destination node it will stop.

The research in the present thesis considers pedestrian flow in normal conditions within airport terminals, so the sense of the reality of passenger flow is critical. In contrast with these microscopic models, the social force model is the most suitable for the research, since its variables have concrete physical meaning and can be explicitly measured. The variables in the social force model can also be easily adapted to real passenger walking behaviours. Table 2-1 gives a comparison of four applicable microscopic pedestrian simulation models. The other two are not sophisticated enough for the research in this thesis, either because of low capability (as in the benefit-cost cellular model) or because it is not applicable (game theory). Since the proposed passenger flows in an airport terminal will be envisaged by emergent phenomena of autonomous individual passenger behaviours, only the social force model meets the needs of the research.

Table 2-1: Comparison of microscopic pedestrian simulation models

| | *Cellular Automata* | *Magnetic Force* | *Queuing Network* | *Social Force* |
|---|---|---|---|---|
| **Movement to goal** | Min (gap, max speed) | Positive (negative) magnetic force | Weighted random choice | Intended velocity |
| **Repulsive** | Gap or occupied cell | Positive and negative magnetic forces | Priority rule | Interaction forces |
| **Value of the variables** | Binary | Arbitrary score | Physical meaning | Physical meaning |
| **Higher programming orientation in** | If-then rules (heuristic) | Heuristic | Queuing model | Dynamical system (continuous) |
| **Phenomena explained** | Macroscopic | Queuing, way finding in maze | Queuing, evacuation | Queuing, self-organisation |

Nevertheless, Moussaid et al. (2011) also indicated that cognitive, heuristics-based models in pedestrian simulation have the potential to replace conventional physics and force-based models. This approach seems to be especially suitable for high density situations as for example the crowd disaster in Duisburg, Germany, and other similar mass events. Technically, this is done by introducing a contact force that becomes active and effective in dense situations. The new heuristic approach is based on the vision dynamics of pedestrians – and in this way on the proactive behaviour – in contrast to physics-based models where pedestrians are passively influenced by forces. However, at this stage, this proposal is not yet proven to be able to intuitively capture collective pedestrian behaviours such as lane formation and dynamics in high density situations, although it seems very promising according to first results and validations.

### 2.3.2 Social force model

Based on the comparison of the models (Table 2-1), the social force model is very well suited for modelling pedestrian flow in the microscopic aspect. The social force model provides easy adaptation of real passenger behaviours. In this regard, it is envisaged that a newly devised model of pedestrian walking dynamics can utilise the social force model as a basic pedestrian walking model and then build its own tactical dynamic model for routing dynamics. In addition, since the social force model is restricted to walking interactions of pedestrians, it suits models based on other new physical built environments.

The mechanisms and capability of the social force model are provided in detail. Helbing et al. (2001) indicate that pedestrians can move freely only at small pedestrian densities, otherwise their motion is affected by repulsive interactions with other pedestrians, giving rise to the self-organisation phenomenon. They believed that the dynamics of pedestrian crowds are predictable, although pedestrians have individual preferences, aims and destinations. Since human behaviour is “chaotic” or at least very irregular, many have pointed out that individuals will usually not take complicated decisions in standard situations between various possible alternative behaviours, but apply an optimised behavioural strategy, which has been learned over time by trial and error. Therefore, a pedestrian will react to obstacles and other pedestrians in an automatic way.

The optimal pedestrian behaviour can be in principle determined by simulating the learning behaviour of pedestrians, which means pedestrians’ parameters can be changed randomly in the simulation, and the inverse travel times as well as the collision rates with different behavioural strategies can be compared with each other. Once successful strategies are replicated, they will be further refined over time. After several time cycles, it yields a parameter set which does not change anymore. The parameter set finally determines the optimal pedestrian behaviour in terms of interaction strength, acceleration behaviour and path choosing. Helbing (1995) also developed an approach to modelling behavioural changes and put it into mathematical terms.

As the position of the pedestrian $\alpha$ can be represented by points $r_\alpha(t)$ in space, which change continuously over time, pedestrian dynamics can be described by the following equation of motion (Helbing, 1995):

$$\frac{dr_\alpha(t)}{dt} = v_\alpha(t). \tag{2-5}$$

The functions delineating the temporal changes of the actual pedestrian velocities $v_\alpha(t)$ can be interpreted as the driving force of this motion, which are called behavioural forces or social forces.

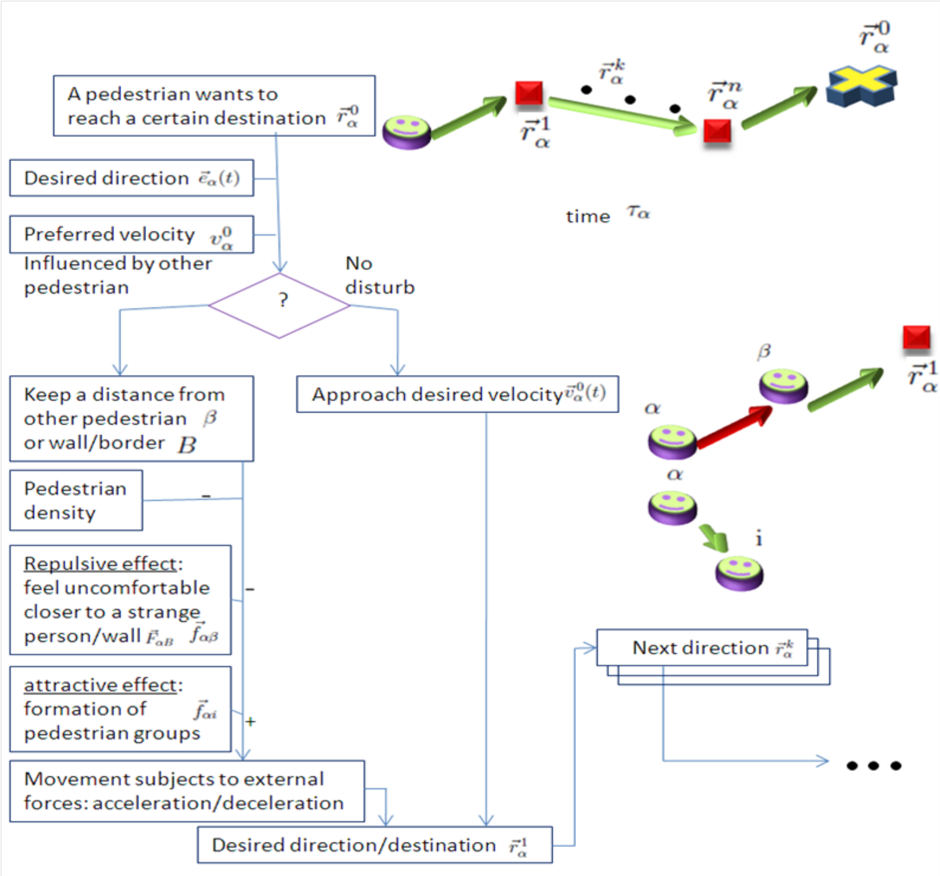



Figure 2-7: The social force model

Figure 2-7 shows a simple social force model of pedestrian motion (Helbing and Molnar, 1995). There are three force terms in the presented model of pedestrian behaviour (Equation 2-3):

- There is acceleration towards the desired velocity of motion.
- A pedestrian keeps a certain distance to other pedestrians and environmental obstacles.
- A pedestrian is distracted and walks to a specific attractive location.

The resulting equations of the motion are nonlinearly coupled LANGEVIN equations (Helbing and Molnar, 1995):

$$\vec{F_\alpha}(t) = \vec{F_\alpha^0}(\vec{v_\alpha}, v_\alpha^0\vec{e_\alpha}) + \sum_\beta \vec{F_{\alpha\beta}}(\vec{e_\alpha}, \vec{r_\alpha} - \vec{r_\beta}) + \sum_B \vec{F_{\alpha\beta}}(\vec{e_\alpha}, \vec{r_\alpha} - \vec{r_B^\alpha}) + \sum_i \vec{F_{\alpha\iota}}(\vec{e_\alpha}, \vec{r_\alpha} - \vec{r_\iota}, t), \tag{2-6}$$

$$\frac{dw_\alpha}{dt} = \vec{F_\alpha}(t) + fluctuations, \tag{2-7}$$

where,

- $\alpha$ and $\beta$ stand for two different pedestrians.

- B stands for an environmental obstacle in the model.
- $\overrightarrow{F_\alpha}(t)$ is interpreted as social force,
- $r_\alpha(t)$ represents the actual position of pedestrian α at time t,
- $\overrightarrow{v_\alpha}$ is the actual velocity of a pedestrian,
- $\overrightarrow{e_\alpha}$ represents passenger's desired direction,
- $\overrightarrow{v_\alpha^0}$ is the desired velocity, which equals to $v_\alpha^0\overrightarrow{e_\alpha}$,
- $\overrightarrow{r_B^\alpha}$ denotes the location of that piece of border B that is nearest to pedestrian α.
- $\overrightarrow{F_{\alpha\beta}}$, $\overrightarrow{F_{\alpha\beta}}$ and $\overrightarrow{F_{\alpha\iota}}$ represent repulsive effect that a pedestrian interacts with another pedestrian β, a border B and an attractor i.
- $\frac{d\overrightarrow{w_\alpha}}{dt}$ is the systematic temporal changes. It is of the preferred velocity $d\overrightarrow{w_\alpha}$ of a pedestrian α. It is described by a vectorial quantity $\overrightarrow{F_\alpha}(t)$. The fluctuation term considers random variations of the behaviour.

The social force model is capable of describing the self-organisation of several observed collective effects of pedestrian behaviour very realistically. The computer simulations of pedestrian groups not only demonstrate the development of lanes consisting of pedestrians who walk in the same direction, but also discover oscillatory changes of the walking direction at narrow passages.

The segregation effects of lane formation are not a result of the initial pedestrian configuration but a consequence of the pedestrians' interactions. Nevertheless, it normally leads to a more effective pedestrian flow since time-consuming avoidance manoeuvres occur less frequently. These spatio-temporal patterns arise due to non-linear interactions of pedestrians. They are not the effect of strategic considerations of the individual pedestrians since they were assumed to behave in a rather automatic way.

The social force model can be extended by a model for the route-choice behaviours of pedestrians. As soon as such a computer program is completed it would provide a feasible tool for pedestrian traffic planning.

Helbing et al. (2005) used video-based techniques (time-lapse recordings and single-frame analysis) to explore the effects of bottlenecks, obstacles and intersections. Their evaluations of video-recordings showed that the geometric boundary conditions were not only relevant for the capacity of the elements of pedestrian facilities; they also influence the time gap distribution of pedestrians, indicating the existence of the self-organisation phenomenon. Self-organisation means that these patterns are not externally planned, prescribed or organised by, for example, traffic signs, laws or behavioural conventions. Instead, the spatio-temporal patterns emerge due to the non-linear interactions of pedestrians. These interactions are more reactive and subconscious rather than being based on strategic considerations or communication. Early investigations of the self-organisation phenomenon in pedestrian crowds are based on qualitative empirical observations and simulation studies (Helbing, 1991; Helbing et al., 2001).

The great challenge for simulation models is the reproduction of the observed collective phenomena in pedestrian crowds. This includes lane formation in corridors and oscillations at bottlenecks in normal situations, while different kinds of blocked states are produced in panic situations. By means of micro-simulations based on a generalised force model of interactive pedestrian dynamics, the spatio-temporal patterns in pedestrian crowds can be successfully reproduced and interpreted as self-organised phenomena.

The advantage of the social force-based simulation approach is its simple form and its small number of parameters, which do not need to be calibrated for each new situation. Therefore, the model is suitable for the prediction of pedestrian streams in novel architectures and new situations.

### 2.3.3 Tactical routing models

Pedestrian flow was previously illustrated by representing it in terms of elementary flow models (Hankin and Wright, 1958; Lovas, 1994), namely, people moving in an orderly fashion in the same direction. Kholshevnikov et al. (2008) addressed the problem that the location of people within pedestrian flows can be quite random and stochastic. The spacing between people is variable. Local congestion occurs and dissipates within different parts of the flow. In their approach, travel speed was defined in terms of an average from data obtained from several sectors in a pedestrian flow when extended over many tens of metres. Travel speed in any interval of time, characterised by a particular, random density value depends on a number of factors. In this case, randomness is a characteristic of a real process and hence, in terms of a mathematical description, the relation between travel speed and density is a random function.

The value of the functioning parameter for each person depends on their individual properties (physiological and psychological characteristics of people in the flow) and it changes as interactions between people and common factors occur (emotional state, route type, and physiological reactions). Kholshevnikov et al. (2008) demonstrated, in a changing emergency context, that psychophysics and psychophysiology theory are able to establish rules to link the emotional state of persons to their travel speed and pedestrian flow density. Regarding pedestrian flow in normal conditions, their work did not address these aspects and there is still much work to be done in terms of considering not only physical influence factors but also psychological aspects.

Czogalla and Herrmann (2011) focused on the modelling of a decision process that takes place at the tactical level of a pedestrian's trip. The tactical level is defined in delimitation to the superior strategic level and subordinated operational level with respect to trip purpose and spatial relations. On the strategic level, the purpose, origin and destination, the choices for traffic mode and time of departure are set before the trip starts; whereas, on the tactical level, decisions are being made for the actual route or diversions within the pedestrian's network during the trip. At the tactical level, the decision-making process can be modelled by the minimisation problem of walking costs in a network that takes into account both the network-related quality and individual-related factors (Czogalla and Herrmann, 2011). For the tactical level, that is, on the trip during walking, the decision-making process for route choice can be modelled by minimising the problem of walking costs that take into account both the network-related quality and individual-related factors. It is assumed under the preconditions of acquired prior knowledge and assessment of the walking network by the pedestrian (Czogalla and Herrmann, 2011). Individual factors, such as time constraints and physical abilities, are incorporated in the model as they influence the weight of attributes used in the process of maximising the personal utility of the human individual.

### 2.3.4 Agent-based pedestrian models

Agent-based modelling offers a way to model social systems that are composed of agents who interact with and influence each other, learn from their experiences, and adapt their behaviours so they are better suited to their environment. Agent-based modelling is currently applied to model people walking at spatial scales and in city or urban areas.

Deadman and Gimblett (1994) introduced research on people-environment interactions using agent-based models, in which they simulated people deciding on taking a route during recreational trips in forest areas. Batty (2001) indicated that there was a dearth of work on pedestrian movement and introduced an agent-based method in modelling urban pedestrian movements. Teknomo and Gerilla (2005) presented a pedestrian movement model, which used a multi-agent system for pedestrian traffic analysis. The model captured the dynamic microscopic interaction between pedestrians, which cannot be addressed using the traditional macroscopic approach. The pedestrians were modelled as autonomous agents with non-linear system different equations. A critical issue for such multi-agent pedestrian models, however, is the validation of the model against real-world data.

Haklay et al. (2001) introduced recent advances and developments in modelling techniques and showcased an agent-based model, namely, the STREETS model, developed using the Swarm simulation toolkit and GIS. The STREETS model adopted a holistic, agent-based approach to pedestrian simulation, and as a result synthesised existing models and offered a test-bed for synergetic and cumulative influences between those models.

The traditional methods for observing and recording the movement of pedestrians in city streets are basically physical counts and time-lapse photography (Helbing et al., 2001). Gravity or spatial interaction techniques are rarely performed at the level of detail required for the prediction of pedestrian numbers, although they are able to distribute overall flow results across transport networks to predict the intensity of use of different routes. Thus, they are rarely successfully applied to modelling pedestrian movement at the scale of buildings and streets (Kurose et al., 2001). The reasons, to this extent, are the absence of adequate data at the level of detail and the limitation of the modelling capability. They are less applicable at small spatial scales, only suited to model general patterns of movement and can never be used to model the movement of individuals.

The STREETS model was initially loaded with pedestrians who have prescribed activity schedules or plans. These pedestrians are then modelled as agents who may choose to change their plans in response to their surroundings and the behaviour of other agents. Each agent has characteristics under two broad categories: socio-economic and behavioural. The socio-economic characteristics relate to income and gender, and are used to create a planned activity schedule for the agent. With the activity schedule, the agent autonomously decides a route that it intends to take in the model. Many other heuristic methods may also be used in this route planning.

Behavioural characteristics contribute to the detailed behaviour of agents. Factors include speed, visual range and fixation. In the dynamic operation of the model, agents have five programmed control modules to compute local movements. They are the Mover, the Helmsman, the Navigator, the Chooser and the Planner. Moreover, the more abstract goals of the upper levels can be decomposed to simple actions as control and target variables of the state of agents. All modules can access agent states. However, the STREETS model does not claim to imitate the behaviour of cognitive movement. So it hardly represents a particular psychological model of movement.

Emergence is generally seen as unidirectional, since agents are autonomous objects. The habitual, patterned, aggregate behaviours are the key drivers of change at more aggregate levels, and it takes time for actors in any socio-economic setting to recognise the patterns and adjust their individual and collective responses to those patterns. Emergence should be understood as occurring through social action via the cognitive processing of events by individuals over time.

The agent-based modelling approach is highly applicable to the pedestrian dynamics field. It is also clear that the application of socio-economic and other data to populate agent models with representative populations is viable and promises to enhance the prospects for this modelling approach in built environment planning more generally.

## 2.4 AGENT-BASED MODELLING AND SIMULATION

### 2.4.1 Agent

Regarding each individual's behaviours, the independent agent approach is feasible to represent each individual pedestrian as an independent pedestrian agent and construct a pedestrian flow model via a bottom-up approach. It is also described as the microscopic approach.

An agent can be thought of as an autonomous, goal-directed software entity. An agent's autonomy is constrained by the fact that it is constructed by human programmers and, in this context, this means that it pursues its goals in an open-ended manner. The definitive example of agent-based modelling technology is provided by the Santa Fe Institute's Swarm simulation toolkit (Minar et al., 1996). Agents incorporate sophisticated artificial intelligence techniques whereby they learn new ways to attain their goals (O'Sullivan and Haklay, 2000). For the proposed pedestrian agent in particular, it is possible for detailed traits of a pedestrian to be modelled. Together with advanced computational technologies, it provides a feasible way to tackle large crowds of pedestrian movement.

An agent-based model could have hundreds of agents or more interacting in an artificial virtual world, which represents a real-world environment. The modeller programs agents with proper rules governing their behaviour and examines simulation outcomes to obtain insight into real-world scenarios. It seems evident that built environment planners are well placed to investigate such models in both theoretical and substantive ways, contributing to the development of spatial dynamics in these models, and evaluating the assumptions which underlie them. In this sense, agent-based models of people walking regarding spatio-temporal dynamics are introduced.

Agent-based modelling and simulation is a relatively new approach to modelling complex systems composed of interacting, autonomous agents (Macal, 2010). Agents have behaviours, often described by simple rules, and interactions with other agents, which in turn influence their behaviours. By modelling agents individually, the full effects of the diversity that exists among agents in their attributes and behaviours can be observed and give rise to the behaviour of the system as a whole. By modelling systems from the ground up – agent-by-agent and interaction-by-interaction – self-organisation can often be observed in such models. Patterns, structures and behaviours emerge that were not explicitly programmed into the models, but arise through the agent interactions. The emphasis on modelling the heterogeneity of agents across a population and the emergence of self-organisation are two of the distinguishing features of agent-based simulation as compared to other simulation techniques such as discrete-event simulation and system dynamics.

A typical agent-based model has three elements (Macal, 2010):

1. A set of agents, their attributes and behaviours.

2. A set of agent relationships and methods of interaction – an underlying topology of connectedness defines how and with whom agents interact.

3. The agents' environment – agents interact with their environment in addition to other agents.

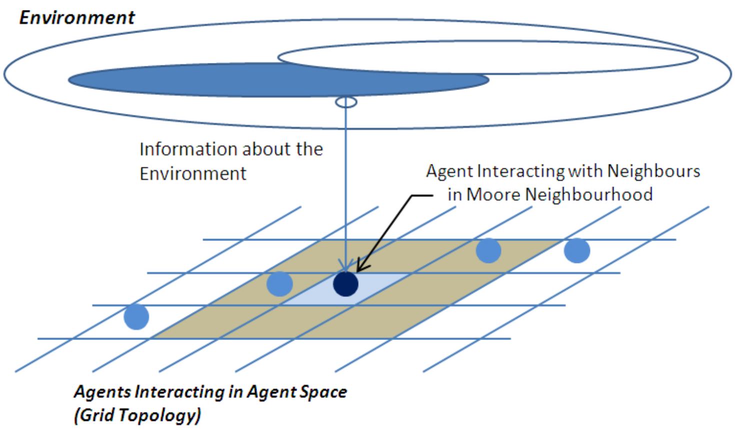



Figure 2-8: Structure of a typical agent-based model (Epstein and Axtell, 1996)

Most often agent-based modelling is used to model systems where outcomes have a high degree of dependency on the actions of humans. Common applications include the spread of diseases or information between populations, people or traffic movements, and the impact of marketing campaigns.

In the non-academic area, as suggested by the British Airport Association in terms of complex and comprehensive airport systems (in de Neufville and Odoni, 2003), there are no off-the-shelf tools that could meet all future requirements. Therefore, a skilful and comprehensive modelling solution for future complex airport systems is needed. The outcome of agent-based modelling and simulation for passenger flow could have a promising application.

From the comparison of the common features of the above models, several advantages of agent-based models are concluded:

(1) An agent is a discrete entity with its own goals and behaviours; it is also autonomous, with the ability to adapt and modify its behaviour.

(2) Agent-based models are inclined to perform methodological individualism.

(3) This commitment to individualism is accompanied by a one-way notion of emergence: the social can emerge only from the individual.

(4) Less behavioural complexity would be preferred; simplicity can help model and understand.

In summary, microscopic pedestrian models can deal with single passengers and allow the study of their interactive tendencies with each other and the neighbouring environment.

### 2.4.2 Agent-based model

An agent-based model is one in which the basic unit of activity is the agent. Agents represent actors at the individual level. An agent is an identifiable unit of computer program code which is autonomous and goal-directed (Hayes, 1999). An agent is an entity (either computer or human) that is capable of carrying out goals, and is part of a larger community of agents that have mutual influence on each other. Agents may co-exist on a single processor, or they may be constructed from physically separate but intercommunicating processors (such as a community of robots) (Hayes, 1999). The key concepts in this definition are that agents can act autonomously to some degree, and they are part of a community in which mutual influence occurs (Hayes, 1999). The outcomes of the model are determined by the interactions of many agents, usually tens or even thousands. However, physical spatial mobility in many models is not considered at all, because in most agent-based models the main concern is to understand how individual behaviour leads to global outcomes in a generic sense, rather than in the modelling of the real world.

A typical agent-based model is composed of agents who interact with each other and also with their environments (Castle and Crooks, 2008). Agent-based models are usually considered as forming a miniature laboratory where the attributes and behaviours of the agents and the environment in which they are housed can be altered. In turn, they can be experimented upon and the repercussions of such experimentation can be observed over the course of multiple simulation runs.

Agent-based models are good tools for studying the effects on process that operate at multiple scales and organisational levels, because they not only simulate the individual actions of many diverse agents but can also measure the resulting system behaviour and outcomes over time (Brown, 2006). Basically, agent-based models provide us with tools to tackle those change ideas which have emerged from complexity science, changing from the aggregate to disaggregate and from the static to the dynamic. It allows us to explore how individual decisions are made and how such decisions lead to emergent structures evolving (Crooks, 2009).

Agent-based modelling is derived from complexity science and complex systems. Because the world we live is increasingly complex, the systems that we need to analyse are consequently becoming more complex as well, particularly in terms of their interdependencies. Traditional models for some systems are not as applicable as they once were, for many human-made systems have been viewed as complex systems which cannot be adequately modelled by usual methods; large airport systems are a prime example.

Over the last three decades, simulation has become a frequently used modelling tool for supporting studies of complex systems. The simulation modelling paradigms used in this regard can be classified in three groups, as compared in Table 2-2:

(1) System dynamics modelling

(2) Discrete-event simulation modelling

(3) Agent-based simulation modelling.

Table 2-2: Comparison of system dynamics, discrete-event and agent-based simulation

| | System Dynamics | Discrete-Event Simulation | Agent-Based Simulation |
|---|---|---|---|
| Overall approach | Abstract, via state variables and equations that are solved to simulate behaviour over time | Randomness associated with interconnected events leads to system behaviour | Physical emulation of ‘agents’ whose rules for behaviour mirror the real world |
| Mathematics | Calculus; numerical integration of different equations | Statistical distributions to model the increments of simulation clock | Logic, algorithms, and simple probabilities |
| Representation | System represented as stocks and flows | System represented as queues and activities, schedules, processes, buffers | Autonomous, responsive and proactive agents which interact with each other to achieve their objectives |
| Problem key | The understanding of the problem lies in analysis of causal feedback effects | Randomness associated with interconnected processes and events | Individual agent classes with the rules for their interaction |
| Ease of communications | Very good for showing model structure and numerical results | True representation of system | Excellent for showing the behaviour of individual entities |
| Relationship | Interested in identification of non-linear relationships | Relationships can be non-linear but mostly are linear | Relationships are non-linear |
| Spatial relationship between entities | Spatial relationship is not represented because entities are aggregated | Distances between entities in the model cannot be calculated; discrete-event simulation model can take account of distance between entities and resources | Spatial relationship can be a key driver in the model. Individual agent behaviour can be influenced by spatial relationship |
| Accuracy of the model | Moderate in accuracy; the outcome of model is as learning laboratories | Due to its heavy reliance on data, the model produces accurate, statistically valid models | Models are much more difficult to construct compared to discrete-event simulation models and can have accurate models |
| Parameters | Model’s parameters are affected feedbacks loops with the system | Parameters are set after intensive research on historical data | The paradigm carefully considers the definition of agents and specifies their behavioural rules in the simplest possible fashion |
| Structure-determined performance | Based on the concept that performance of the model over time is determined by its structure | Based on the concept that performance of system over time is determined by randomness and by the internal structure of the system | Based on the concept that performance of system is the emergence of ordered structures independently of top-down planning |
| Role of computer simulation | Computer simulations are used as learning laboratories that allow managers to run models in the gaming environment | Models are less used as learning tools for non-technical people | The models are flexible; it is easy to add more agents to an agent-based model; a natural framework is provided for tuning the complexity of the agents. |
| Computer animation | Computer simulation is limited to graphs and equations | With its computer animation capabilities where entities can be shown moving across the system, can help more in visual understanding of process flow | With its computer animation capabilities, can display visual world environment for understanding operation process |

*(Wakeland et al., 2004; Borshchev and Filippov, 2004; Owen, 2008)

Agent-based modelling takes another perspective on simulation. Agent-based modelling is centred on interacting individuals with a view to assessing the system-wide effects of their individual behaviour and interactions, rather than system dynamics models which model from an overall picture of the flow in a system. Typically, thinking of a discrete-event simulation model of an airport, passengers are pushed or pulled between check-in and security processes and it works through to model several aspects of the airport: for example, some passengers might stop at a restaurant/café and then browse a gift/book shop. With an agent-based mindset, however, the passengers are in control and, like in real life, would make their own decisions on where to go and when. Instead of a centralised or global simulation control, agent-based modelling attaches rules of a system to individual agents. In discrete-event simulation, work-items are passive and actions are defined by activities that process them. Therefore, agent-based modelling is particularly suitable for modelling situations where large numbers of humans are present and each makes their own choice between many alternatives. It makes it easy to include individuality and see the impact on the overall system of the variations in different people's behaviours.

### 2.4.3 Applications of Agent-Based Simulation

Agent-based modelling can be viewed as a methodical advancement and generalisation of microscopic modelling styles in object-oriented and discrete-event simulation. Agent-based simulation is typically applied in microscopic modelling of systems where common actions of autonomously deciding actors (people) are represented (Page and Kruse, 2007).

Agent-based simulations can serve as artificial laboratories which will test ideas and hypotheses about phenomena which are not easy to explore in the real world. Crooks (2009) introduced a simulation and modelling system called Second Life, and demonstrated its usage for agent-based modelling, in particular illustrating the integration of symbolic models with iconic structures. Crooks made a basic 3D agent-based pedestrian evacuation model which combined both symbolic and iconic style models into a single form. Agents not only interact with each other but also interact with their surrounding environment. Crooks created a building in an artificial world, populated it with artificial people, started a fire and watched what happened. Agent-based models are quite suited to such topics where, with the help of simulations, modellers can identify potential problems such as bottlenecks and test numerous scenarios such as the way various room configurations can impact on evacuation time.

However, Second Life has a lot of disadvantages which limit its capability for the creation of agent-based models. In addition, Second Life is not free for use like most open source ones. The Second Life visual environment is only a demonstration of agent-based modelling application. Agent classes and rules for their interactions cannot be built for their specific own purposes.

In order to have our own agent classes and related rules, object-oriented programming techniques should be chosen to build agent-based models. The advanced computational technology helps populate large numbers of agents and calculate their interactions and emergence outcomes. In the last few years, the agent-based modelling community has developed several practical agent-based modelling toolkits that enable the development of agent-based applications. The toolkits have a variety of characteristics. Figure 2-9 shows their capacity for modelling complex and large-scale applications compared to the ease of developing a model.

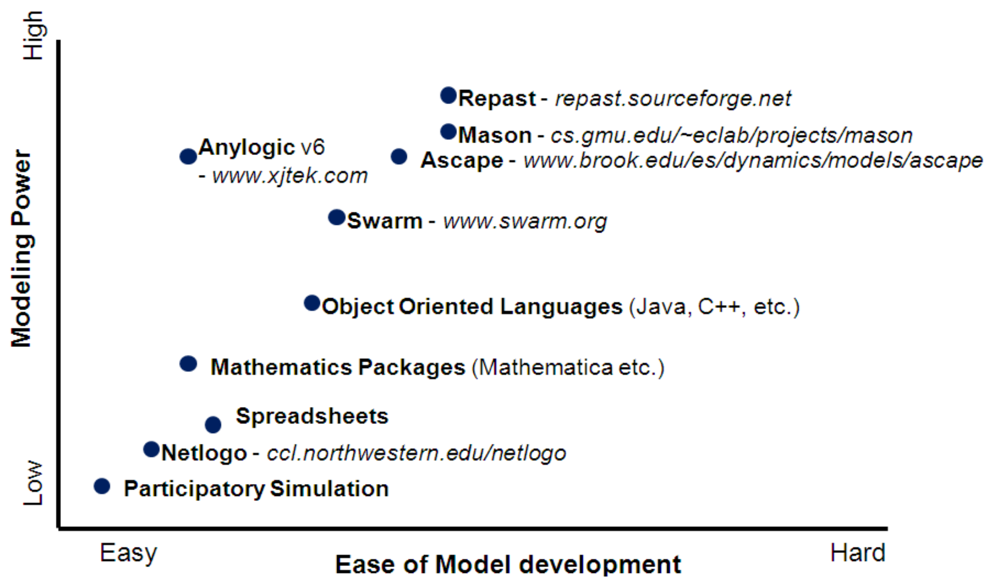



Figure 2-9: Agent-based modelling software (Macal and North, 2006)

The most popular tools to assist agent-based studies are the object-oriented languages Java, Repast symphony toolkit, NetLogo toolkit, Swarm toolkit and Anylogic v6. According to the specific application, an appropriate toolkit may be chosen (Table 2-3). It would need a myriad of programming work to build the visual simulation context (i.e. an airport terminal environment) in the Repast symphony toolkit before it can truly be implemented as an agent-based passenger flow simulation. NetLogo could be insufficient to model a large system due to its comparative low modelling power. Comparing the Swarm toolkit and other software, Anylogic is user-friendly and can be used to integrate agent-based concepts. Anylogic is used as the simulator platform to conduct modelling passengers flow in this thesis. Anylogic is a multi-paradigm/hybrid simulator capable of modelling systems as a combination of discrete-event, system dynamics and agent-based modelling. It is based on UML-RT and uses “hybrid state charts” to achieve this unique capability. It is based on Java and the models can also run on many other platforms. Anylogic supports agent-based modelling and can be efficiently combined with other modelling approaches. Anylogic has several embedded simulation libraries which can make building agent-based models easier. Its pedestrian library is convenient for setting up pedestrian walking in spatio-temporal circumstances.

Table 2-3: Comparison of agent-based modelling toolkits

| ***Platform*** | ***Primary Domain*** | ***License*** | ***Programming Language*** | ***GIS Capabilities*** | ***3D Capabilities*** | ***Model Power*** |
|---|---|---|---|---|---|---|
| **NetLogo** | Social and Natural Sciences | Free, not open source | NetLogo | Yes | Yes | Low |
| **MATLAB** | Simulation; programming; scientific and engineering math and computation; data analysis | Proprietary | Matrix-based data structures, m-language, and extensive catalogue of functions | N/A | Poor (SimuLink) | Moderate |
| **Swarm** | General purpose agent-based | General Public License | Java | N/A | N/A | Moderate |
| **Mason** | General purpose; social complexity; Physical modelling, abstract modelling, artificial intelligence/machine learning | Academic Free (open source) | Java | N/A | N/A | High |
| **Repast** | Social Sciences | Berkeley Software Distribution | Java(RepastS); Python(RepastPy); .Net, C++ | Yes | Yes | High |
| **Anylogic** | Agent-based; distributed simulation | Proprietary | Java; UML-RT (Unified Modelling language) | Yes | Yes | High |

Doing research on complex systems is a big challenge. However, it is becoming possible to take a more realistic view of these systems through agent-based modelling and simulation. Computational power is advancing rapidly, and such advances have made possible a growing number of agent-based applications in a variety of fields. Computing large-scale micro-simulation models is becoming plausible at present. Furthermore, data are becoming organised into databases at finer levels of granularity. Micro-data can now support micro-simulations. The invention of relational databases means that data can now be organised into databases at micro-data levels.

These findings can be used to improve design elements of pedestrian facilities and walking routes. Proper understanding of self-organisation phenomena allows modellers to change the patterns of motion and their efficiency by suitable specification of the boundary conditions. For example, Helbing et al. (2005) used suitably located "obstacles" to stabilise flow patterns and to make them more fluid. The flow pattern of people would behave "back and shock waves" in queues and crowds due to the impatience of some persons. It was suggested that long waiting time can be avoided by increasing the diameters of routes. In addition, zigzag-shaped geometries and columns could reduce the pressure in panicking crowds, if properly designed and placed. So, efficiency and safety of built environments could be increased accordingly. Furthermore, through parallel simulation of the social force model on PC clusters, it becomes possible to evaluate mass events within airport terminals and railway stations. Pedestrian flows in extended urban areas can also be simulated (Batty et al., 2003; Helbing et al., 2004). This allows access not only to information about the attractiveness of certain locations for new shops, but also the impact of new buildings like theatres or malls on overall pedestrian flows.

## 2.5 PEDESTRIAN FLOW SIMULATION

### 2.5.1 Models and simulation

Before constructing the model of passenger flow, it is important to firstly differentiate between modelling and simulation. Models are generally thought of as an idealised representation of reality, as some subject of inquiry that may be already in existence, or as a conceived idea awaiting execution. Because models are abstractions of an assumed real-world system that can identify pertinent relationships, models are used rather than the real system primarily because manipulating the real-world system would be costly or impossible. In most instances, models are constructed to be simpler than the real-world system because complex systems are difficult to implement and control (Maria, 1997).

To optimise the accuracy of the simplest possible model, the elements of the model are examined to determine the degree of representation of the real system. Finding the right variables and the correct relationships among the elements is the essence of good modelling. Although a large number of variables may be required to predict the phenomenon of a real system with perfect accuracy, only a small number of variables usually account for most of the real system. This rule is widely recognised and accepted in modelling – especially in regression. Nonetheless, the reliability of information obtained from a model eventually depends on the validity of the model in representing the assumed real-world system.

A simulation is a type of model. Iconic (physical), analogue, symbolic (abstract), and heuristic representations are other types of models (Rathindra, 2010). Simulations are models that use mathematical-logical representations of the real-world system to convert system descriptions, or input parameters, into an output that describes some features of the system.

Many scientists hold various interpretations of simulation. Taha (2007) regards simulation as behavioural imitation of the real-world system over time that seeks to replicate real-world behaviour by studying interactions among its components. Shannon (1998) interprets simulation as the process of designing a model of a real system and conducting experiments with this model for the purpose of understanding the behaviour of the system and /or evaluating various strategies for the operation of the system.

Biles (1987) described simulation as a valuable tool in the study of complex systems. It is the development of a mathematical-logical model of a system and the experimental manipulation of the model on a digital computer. There are two steps in simulation: (1) model development, and (2) experimentation. Model development involves the construction of a mathematical-logical representation of the system, and the preparation of a computer program that allows the model to mimic the behaviour of the system. Once we have a valid model of the system, the second phase of a simulation study takes place – experimentation with the model to determine how the system responds to changes in the levels of the several input variables.

Pritsker (1979) considers simulation models to be laboratory versions of systems on which experiments can be conducted as a first step in the design, analysis and assessment of the performance of real-world systems. Inferences can then be drawn about the real system without the need to physically build, disturb or destroy it.

*2.5.1.1 Simulation models*

There are three functional types of simulation models (Mumayiz, 1990):

(1) Analytic queuing models – probabilistic models that use mathematical expressions derived from queuing theory;

(2) Accounting models – models that are time-based and deterministic in nature that use pre-defined rules to describe the state of the system; and

(3) Time-dependent models – models that are event-based and stochastic in nature which use dynamic equations with mathematical-logical representations or Monte Carlo methods (Reuven and Dirk, 2008) for fast-time reproduction of the state of the system.

The first step in developing a simulation model is to select a conceptual framework to best describe the system to be modelled. Essentially, this involves defining a “world view” within which the real-world system’s functional relationships are perceived and described (Pritsker, 1979).

Simulation basically employs one of two world views: discrete or continuous. In discrete-event simulation, the system can be described by changes of its state that occur at discrete times (event times); between these times, the state of the system remains unchanged. In continuous-event simulation, the behaviour of the system is characterised by equations for a set of state variables whose dynamic behaviour simulates the real-world system (the state of the system if represented by dependent variables that change continuously over time). Discrete-event simulation is normally used for an airport terminal system because no set of equations can be derived to define the characteristics of the airport terminal and describe the nature of the system’s operation (Mumayiz, 1990).

Discrete-event simulation can be of three general types depending on the specific features of simulation. These are event-oriented, activity-oriented, and process-oriented simulations. Objects or basic units within the boundaries of a discrete system are called “entities”. Each entity has various characteristics called “attributes”. Attributes are characteristics common to groups of entities that engage in different kinds of “activities” (sometimes called “transactions”). A “process” is a time-ordered sequence of events that may encompass several activities (Mumayiz, 1990).

Model development consists of a highly modular approach used mostly in artificial intelligence and expert systems to provide simple, unifying programming and prevent extensive intertwined subroutine coding (Hu, 1987). The basic entities in object-oriented simulation are objects with attributes that have values, or object-attribute-value triplets. Each object has rules and procedures associated with the object-attribute-value triplets. These objects have the capacity to "communicate" with each other through "messages"; upon arrival of messages, the object-attribute-value rules and procedures process these messages and carry out their effects. This approach is believed to have great potential in simulation because it can considerably reduce the amount of programming and coding required for real-system representation (Mumayiz, 1990).

### 2.5.2 Conduct simulation study

The steps in a simulation study (Biles, 1987; Shannon, 1998) are as follows:

1. Problem formulation – formulating a statement of the problem that is to be solved. This includes a general description of the system to be studied and a preliminary definition of the boundaries of that system. A delineation is made of the questions that are to be answered by the simulation study, namely, why are we studying this problem and what questions do we hope to answer?

2. Project planning – being sure that we have sufficient and appropriate personnel, management support, computer hardware and software resources to do the job.

3. System definition – determining the boundaries and restrictions to be used in defining the system and investigating how the system works.

4. Conceptual model formulation – developing a preliminary model either graphically (e.g. block diagram or process flowchart) or in pseudo-code to define the components, descriptive variables and interactions (logic) which constitute the system.

5. Model building – capturing the essential features of a system in terms of its entities, the attributes of characteristics of each entity, the activities in which these entities engage, and the set of possible states in which the system can be found.

6. Data collection – gathering data and information which will allow the modeller to develop the essential description of each of the system entities, and developing probability distributions for the important system parameters.

7. Coding – translating the system model into a computer program which can be executed on an available processor.

8. Verification – confirming that the model operates the way the analyst intended (debugging).

9. Validation – ascertaining that the model mimics the real system, by comparing the behaviour of the model to that of the real system where the system can be observed, and altering the model to improve its ability to represent the real system. The combined steps of verification and validation are crucial to establishing the credibility of the model, so that decisions reached about the system on the basis of the simulation study can be supported with confidence.

10. Experiment design – designing an experiment that will yield the desired information and determining how each of the test runs specified in the experimental design is to be executed.

11. Production runs and analysis – assessing the effects of the chosen input variables on the selected measure(s) of system performance. This involves execution of the simulation to generate the desired data and to perform sensitivity analysis.

12. Simulation report – documenting the simulation program, reporting the results of the simulation study, and making commendations about the real system on the basis of the simulation study. The implementation of these recommendations is usually the result of a decision by the appropriate manager in the organisation.

*2.5.2.1 Simulation advantages and disadvantages*

Simulation has a number of advantages over analytical or mathematical models for analysing systems (Shannon, 1998). First of all, the basic concept of simulation is easy to comprehend and hence often easier to justify to management or customers than some of the analytical models. In addition, a simulation model may be more credible because its behaviour has been compared to that of the real system or because it requires fewer simplifying assumptions and hence captures more of the true characteristics of the system under study. Additional advantages include:

(1) New designs and layouts can be tested without committing resources to their implementation.

(2) It can be used to explore new staffing policies, operating procedures, decision rules, organisational structures and information flows without disrupting the ongoing operations.

(3) Bottlenecks in information and product flows are able to be identified and then can be used to test options for increasing the flow rates.

(4) Hypotheses about how or why certain phenomena occur in the system can be tested.

(5) Time can be controlled through simulation. Thus, the system for several months or years of experience can be operated in a matter of a day allowing us to quickly look at long time horizons or slow down phenomena for study.

(6) Insights can be gained into how a modelled system actually works and understanding which variables are of most importance to performance.

(7) New and unfamiliar situations can be experimented by simulation and "what if" questions can be answered.

Simulation also has drawbacks:

(1) Simulation modelling is an art that requires specialised training and therefore the skill levels of practitioners vary widely. The utility of the study depends upon the quality of the model and the skill of the modeller.

(2) Gathering highly reliable input data can be time consuming and the resulting data are sometimes highly questionable. Simulation cannot compensate for inadequate data or poor management decisions.

(3) Simulation models are input-output models. They yield the probable output of a system for a given input. They are therefore "run" rather than solved. They do not yield an optimal solution; rather, they serve as a tool for analysis of the behaviour of a system under conditions specified by the experimenter.

Increased awareness of environmental problems and the need for physical fitness encourage the demand for provision of better pedestrian facilities. Airport terminals consist of many on-airport facilities for passengers to use, such as elevators, escalators, flight info dashboard, way-finding signs and waiting lounges. To decide the appropriate standard and control of pedestrian facilities, pedestrian studies need to be carried out (Teknomo et al., 2001). Most of the pedestrian studies that have been carried out are at the macroscopic level. Macroscopic pedestrian analysis was first suggested by Fruin (1971), followed by the Highway Capacity Manual (1985). The Institute of Transportation Engineers (1994) recommended macroscopic pedestrian data collection in which all pedestrian movements in pedestrian facilities are aggregated into flow, average speed and area module. The main concern of a macroscopic pedestrian study is space allocation for pedestrians in the pedestrian facilities. It does not consider the interaction between pedestrians and is not well suited for the prediction of pedestrian flow performance in pedestrian areas or buildings with some objects (such as kiosks, seating, telephones, fountains).

Recently, with the development of microscopic pedestrian analysis, a paradigm shift to improve the quality of pedestrian movement has become a new goal (Lovas, 1994; Blue and Adler, 2000). Instead of merely allocating a space for pedestrians, the movement quality of pedestrians (such as comfort in walking and efficiency) is also considered. In macroscopic pedestrian studies, given a number of pedestrians and a level of service, the model may give the space allocation. At the microscopic level, however, given the same number of pedestrians and the same space, with a better set of rules and detailed design, more realistic indications of flow may be produced.

### 2.5.3 Measurement and control of pedestrian interaction

Pedestrian interaction is the repulsive and attractive effect among pedestrians and between pedestrians with their environment. Since the movement quality of pedestrians can be improved by controlling the interaction between pedestrians, better pedestrian interaction is the objective of this approach.

Pedestrian interaction can be measured and controlled. Pedestrian flow performance is defined as the indicators to measure the interaction between pedestrians. The pedestrian interaction can be controlled by time, space and direction. Pedestrians may be allowed to wait for some time, or walk to a particular space (e.g. door) or right of way (e.g. walkway), or in certain directions. Case studies using microscopic simulation as reported by Helbing and Molnar (1998) and Burstedde et al. (2001) show that the flow performance of pedestrians in the intersection of pedestrian malls and doors could be improved by introducing some controls such as roundabouts or direction rules. More efficient pedestrian flow can even be reached with less space. Those simulations have rejected the linearity assumption of space and flow at the macroscopic level. Analytical models for microscopic pedestrian model have been developed by Henderson (1974) and Helbing (1992), but the numerical solution of the model is very difficult and simulation is therefore favourable.

Therefore, microscopic pedestrian studies are needed to improve the quality of pedestrian movement. In microscopic pedestrian studies, every pedestrian is treated as an independent entity and the behaviour of pedestrian interaction is measured. It could be a third way of doing science besides deductive and inductive reasoning

(Macal and North, 2005). There are a few research works which tried to construct agent reasoning framework:

- The concept of *motivations* as the driving force that affects the reasoning of agents in satisfying their goals is considered as the underlying argument for agents to voluntarily comply with norms and to voluntarily enter and remain in a society (López et al., 2006).

- In the SMART agent framework (d'Inverno and Luck, 2003),

    - An *attribute* represents a perceivable feature of the agent's environment, which can be represented as a predicate or its negation.

    - A particular *state* in the environment is described by a set of attributes.

    - A *goal* represents situations that an agent wishes to bring about.

    - *Motivations* are desires or preferences that affect the outcome of the reasoning intended to satisfy an agent's goals.

    - *Actions* are discrete events that change the state of the environment when performed.

A model developer must identify, model and program these elements to create an agent-based model. The model should operate satisfactorily in a discrete formulation. Since decisions and movements in reality are being made in parallel in a continuous space-time framework, the errors generated by resorting to sequential decisions in a discrete or partially discrete framework should not be too gross. The model should be easy to upgrade to more detailed descriptions of behaviour if necessary. Approximations of real behaviour which are satisfactory in one context are not necessarily suitable for general use. Consequently, the basic model should be simple, but nevertheless relatively easy to modify or refine.

The operation of the simulation should be suitable for real-time graphical monitoring. Many potential users are more likely to be interested in 'seeing' what conditions certain layouts produce rather than reading tables of figures describing them. The simulation is implemented at the level of the individual pedestrian under the hypothesis that if the behaviour of individuals is modelled adequately, and the appropriate distribution of pedestrian types is employed, the behaviour of the simulated pedestrians will be realistic. Further, by working at the level of the individual it is possible to collect data on individual travel times and diversions, and subsequently to analyse the variability between different types of pedestrian.

However, in order to simulate pedestrian flows at the level of the individual, it is necessary to be able to model the way in which pedestrians select their routes and move along them. The present model separates these two aspects of pedestrian behaviour into independent sub-models which can be treated sequentially. That is, the pedestrian selects a route or part of a route, and then endeavours to follow it as consistently as possible. This separation of pedestrian behaviour into these two components permits the development of efficient mathematical criteria at later stages. Moreover, it is necessary to discuss the general principles of route selection so that the relationship between route selection and pedestrian interaction can be appreciated. Unless the relationship is understood, the criteria and behaviour associated with pedestrians while following their route may seem too limited.

### 2.5.4 Pedestrian flow validation

In computer modelling and simulation, validation is the process of determining the degree to which a model or simulation is an accurate representation of the real world from the perspective of the intended uses of the model or simulation. Often there is a trade-off between increasing confidence in the level of accuracy of the models and the cost of data collection and effort required to validate the models (Barton-Aschman Associates and Cambridge Systematics, 1997).

Model validation is a method of ensuring that the model replicates the observed conditions and produces reasonable forecasting results and to see whether there is an adequate agreement between a model and the system being modelled. The validation part concerns the determination of the numerical value of the parameters and the results of the simulation. Validation involves testing the model’s predictive capabilities. Pedestrian flow models need to be able to replicate observed conditions within reason before being used to produce future forecasts. As urban areas and built environments are not identical, the credibility of the pedestrian flow process will depend largely on the ability of analysts to properly validate the procedure and models used.

A critical issue for pedestrian models is the validation of the model against real-world data. Due to many factors being involved in the simulation of individual pedestrians and the large set of parameters in pedestrian models, the validation of a pedestrian model is very difficult (Teknomo and Gerilla, 2005). Only limited validations of pedestrian flow systems have been done. Lovas (1994) and Helbing and Molnar (1995) used simple observation methods to validate pedestrian flow. Blue and Adler (2001) validated a pedestrian multi-agent system by utilising matching speeds with *Highway Capacity Manual* standards. Teknomo and Gerilla (2005) conducted sensitivity analysis of control variables and parameters of the pedestrian multi-agents model and applied an automatic validation method. All in all, validations for pedestrian flow models require deep understanding of the behaviour of the factors and parameters.

The validation step ensures that the simulation model behaves as expected. The pedestrian flow model involves the issue of both space and time. Therefore, for pedestrian flow validation in general, individual pedestrian factors and model parameters all need to be considered. Typically, the radius of a pedestrian body is around 60cm and average speed is 1.34m/s (Teknomo and Gerilla, 2005). One way to inspect this behaviour is the decline of the average speed as the density increases. According to Teknomo and Gerilla (2005), data can be gathered manually or through video of a specific location where pedestrians are crossing. Manually collecting pedestrian flow data requires hard work and always takes plenty of time. For video data collection, each camera captures real pedestrian flow in one area. Sample video data can be collected in a uniform time-period or instead through consecutively capturing a constant number of pedestrians. Moreover, an image processing method need to be developed as well so as to track pedestrians and record the number of pedestrians passing the area. Analysis needs to be done in order to generate related data, namely, the speed and number of pedestrians in an area. Once real-world data is obtained, all the statistics are used for validation with pedestrian flow modelling/simulation results in certain aspects, such as speed of overall flow, instantaneous occupancy by pedestrians at a specific area and routing phenomena

## 2.6 CHAPTER SUMMARY

At the beginning of this chapter, the significance of the studies of pedestrian movement in built environments was discussed. Following that, two basic types of pedestrian flow studies within built environments were reviewed. Macroscopic models simply take into account the pre-determined pathways of pedestrians, such as corridors or vacant areas within built environments, and do not consider detailed interactions among pedestrians and building facilities. However, in fact, building facilities in general would occasionally divert the pedestrians' walking path, such as window displays that will attract certain pedestrians who are wandering around and looking for something interesting in a mall. Thus, macroscopic models are not well suited for the accurate prediction of pedestrian flow performance.

On the contrary, microscopic models have more general usage and consider detailed flow performance. Four major microscopic pedestrian flow models were addressed. The benefit-cost cellular model is limited by its physical representation and thus not convincing in its ability to solve all the relevant interaction issues, that is, walking speed, direction and avoidance with other pedestrians and obstacles. The magnetic and social force models have more variables with physical meaning and can better explain the behaviour of pedestrians. The pedestrian flow model of Kholshevnikov (2008) demonstrates that the emotional state of persons towards their travel speed can be affected by pedestrian flow density.

Next, two aspects of methods to model pedestrian flows were introduced and reviewed. Since conventional studies are based on macroscopic aspects, the capabilities of microscopic aspects are not fully developed. Agent-based modelling is an important microscopic approach, which treats each individual as an independent agent with multiple traits.

Agent-based modelling was illustrated to demonstrate applications of modelling people walking at spatial scales and in city or urban areas. Agent-based modelling is able to study interactions among pedestrians and ambient environment objects. The methodology for devising an agent-based model was introduced. As computing technology advances, pedestrians are modelled more realistically, not simply as a dot or rectangle. Consequently, the physical dimensions and walking route configurations can be modelled in detail, as well as speed, density of pedestrians and flow relations.

The detailed pedestrian dynamic studies were then reviewed. Force-based models were compared with the other three major microscopic models of pedestrian simulation. Recent trends of advanced pedestrian dynamic studies were also introduced as well as the limitations of these approaches. A more realistic and capable heuristic approach is needed for the study of the dynamics of pedestrians. Finally, literature on the calibration of pedestrian flow modelling was presented. This involves modelling the physical traits of a pedestrian agent and the function of interactions within crowds.

Gaps in the literature on pedestrian flow exist in relation to:

- Detailed physical interactions among pedestrians and building facilities
- Physiological and psychological traits of persons in pedestrian flow
- Correlation of the physical interactions and route-choice decisions.

In the next chapter, a specific built environment – the airport terminal – is taken into the pedestrian flow research. Since the objects within these environments are air passengers, a set of detailed traits of passengers is devised. This chapter concludes with the observation that better agent decision-making methods are required to intuitively generate different probabilities of each passenger's preferred targets.

# Chapter 3: Airport Characteristics and Advanced Traits of Air Passengers

This chapter will address general airport landside business processes and simulation techniques together with advanced traits of air passengers devised specifically for air passenger agents. It will begin by discussing universal airport terminal layouts and business processes. Through an example of domestic and international terminals of an airport in Australia, the processing procedures of three sorts of passengers – arriving, departing and transferring passengers – are shown. Next, in reviewing categories of modelling method and simulation techniques, a universal method of devising a simulation model is introduced. Modern airport systems not only consist of plenty of sub-modules, i.e. check-in counters, security inspection counters and catering facilities, which involve the interests of many stakeholders, such as airlines, immigration department, police, retailers and the airport itself, but also have to deal with large growth in the number of passengers who use the airport. As a consequence of this growth and complexity, many new regulations and technologies are frequently brought into airport operations. These could be restricted regulations for passenger inspection due to security concerns or new technological facilities implemented.

Because of the complexity of airport systems and three other issues to be concerned, i.e. changing operation policies, stricter security inspection regulations and implementation of new technologies, simulation is believed to be a desirable tool to manage to understand such scenarios and facilitate decision-making. Simulation methodologies for analysing airport capacity and passenger flows are reviewed, with the objective to select the most appropriate method to study passengers flow within airport terminals. A bottom-up research paradigm is considered as being suitable for this research. A series of airport terminal tools and experiments conducted in both academia and industry are then discussed, highlighting factors that have led to different outcomes.

Finally, by utilising information of basic traits of passengers, advanced traits are devised, which focus on the mental preferences of passengers. Rather than basic traits, they represent the possessed knowledge of each passenger that is to be inferred over time to determine the behaviours of passengers when they use airport facilities.

## 3.1 OVERVIEW OF AIRPORT PASSENGER FLOWS

Airport terminals are a good example of a built environment to apply simulation to as they have fixed and consecutive functions for passenger processing. Simulating passenger flow to evaluate passenger processing in airport terminals has a long history. Most passenger flow studies in airport scenarios are macroscopic. Although they can answer certain questions relating to airport operation, passengers' experiences are hard to be interpreted by this way. If we would like to know how passengers behave in real airport environments, then it is vital to first understand what affects passengers' walking and route choices. Many traits inhabited in passengers are envisaged to be those parameters which can react to ambient environment and help guide passengers' route choices.

Passenger flow in airport terminals typically have three different trajectories in terms of how passengers are processed when they proceed through terminals: arriving passengers, departing passengers and transferring passengers. Each category of passenger behaves differently in terms of how they use airport facilities. Hereby the terminals of an airport in Australia are taken as an example to illustrate a general layout of airport terminals. Figure 3-1 shows the layout of Domestic Terminal, and Figure 3-2 shows the layout of International Terminal.

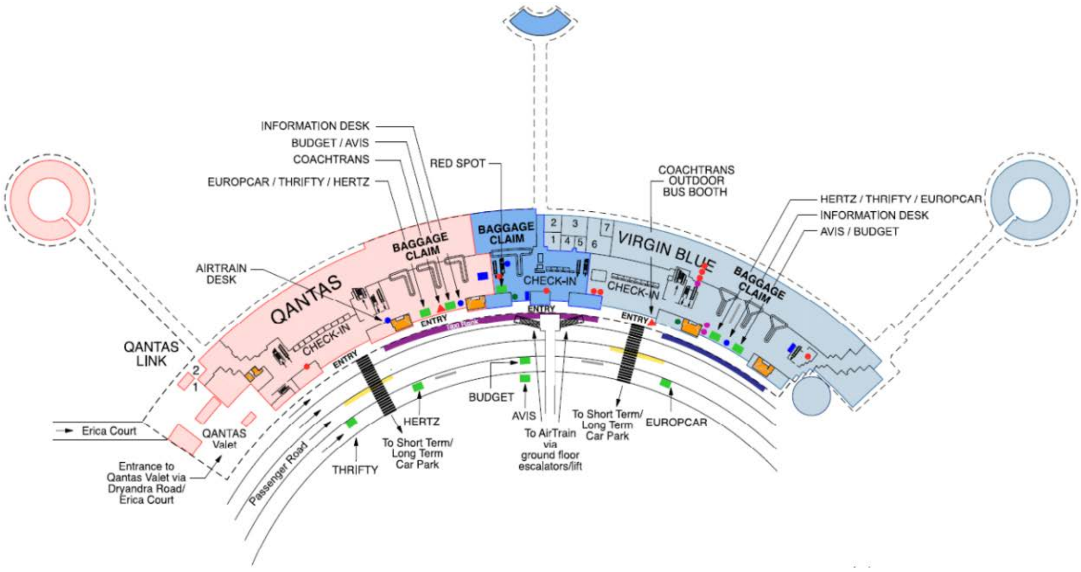



Figure 3-1: Domestic terminal

The domestic terminal is simply divided into three parts of check-in counters and baggage claim areas. They are operated by QANTAS (including Jet Star), VIRGIN Australia and Tiger Airlines respectively.

The international airport has five double-sided check-in rows. Some check-in areas are designated to specific airlines, and others are “common-use” based on flight schedule. In peak hour there could be over 1,500 passengers passing through these check-in counters. In the security check area, there are currently five security gates available to serve. In periods of low passenger numbers, only a few of these gates are used. For the border control point, the airport has both service counters and a smart-gate, which is only for the arrival process and helps expedite process customs control for Australia and New Zealand citizens over 18 years of age. Although the portion of usage of Smart-gate is not large till now by consulting the airport operators, it is believed that such technologies are good for smoothing passenger flows inside airport terminals.

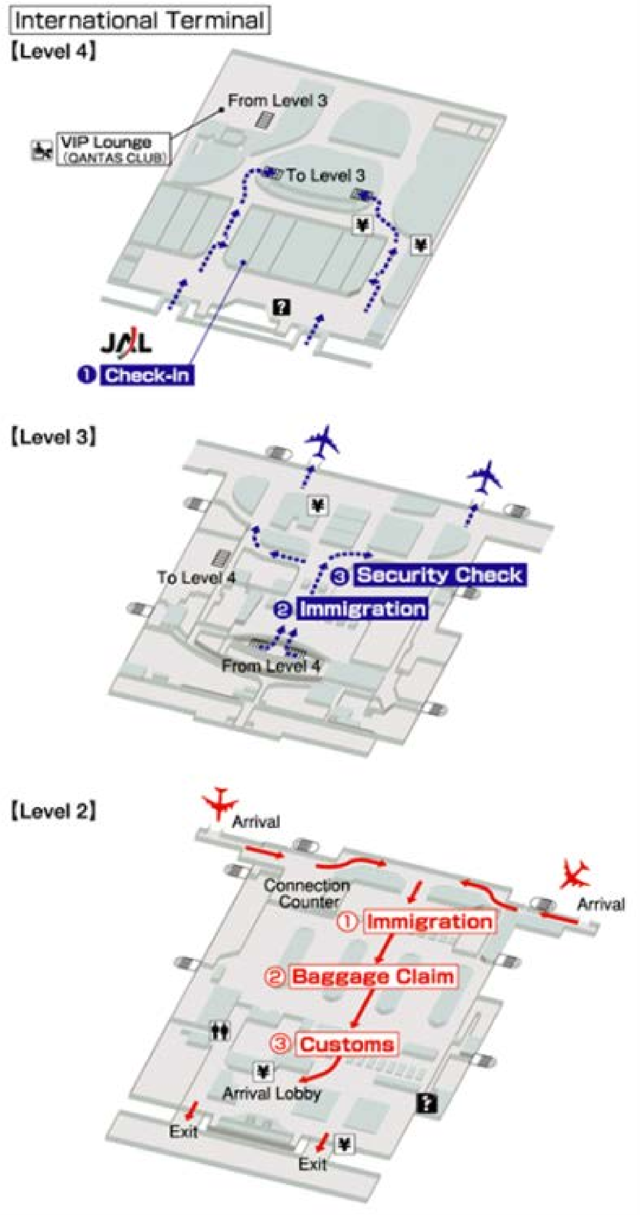



Figure 3-2: International terminal

### 3.1.1 Departing passengers

Departing passengers processing within airport terminals involves both passengers who start check-in process at the airport and who transfer aircraft at the same airport. An illustration of such processing procedures is shown in Figure 3-3. Passengers typically arrive at airport terminals a couple of hours before their aircraft departs, according to certain airline flight schedules. After three processes, check-in, security control and boarder control, passengers eventually wait in front of boarding gates in preparation for boarding. In the meantime, transferring passengers go through security control and arrive at the boarding gates. In Figure 3-3, the baggage flow was displayed in red, since baggage delivery is also an important aspect of airport passenger flow management.

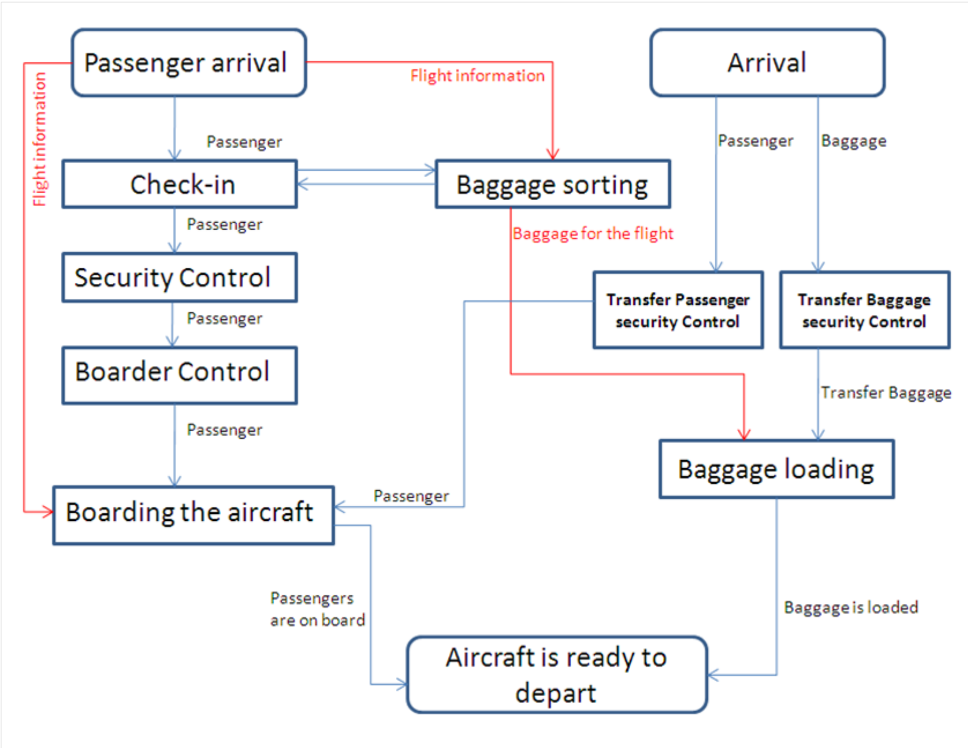



Figure 3-3: Departing passenger processing procedures

In peak hours, passenger check-in and security control processes are believed to be the most time consuming parts. Crowds and congestions are common in busy hours of a day. Though the overall check-in facility capacity may be sufficient, capacity limitations become prevalent when it comes to the peak time of many aircrafts departures.

Many airports also apply some methods to meliorate the condition, such as several airlines sharing their check-in counters and letting the economy class passengers use business class check-in counter to process check-in when economy class counters are too busy. Some airports have also installed self-service check-in counters and hope check-in time can be saved in this way. The usage of self-service check-in is envisaged to grow much more in the near future (Liljander et al., 2006).

For the part of security control, there are some technologies integrated in security inspection for passenger guidance. The International terminal implements queue-counting indicators which show the number of passengers who are currently waiting in different queues, so passengers arriving at the security counters can choose which queue to join.

Furthermore, for passengers who have more experiences in using airports, they normally are quite confident of travelling through the airport terminals and would feel much comfortable of using various on-airport facilities, such as Book shops, Café and Self-service kiosks. They know exactly what cannot be taken on the plane, and will typically proceed smoothly through security checks, unlike inexperienced passengers, who will go through security body check door multiple times, since they might forget to take out their phones, metal keys or remove belts in advance. For this reason, many airports have dedicated lanes for experienced passengers (but usually restricted to business/first class passengers) for faster processing. It will not only provide business passengers with a good experience but will also reduce the overall processing time.

### 3.1.2 Arriving passengers

At a certain time span of a day, right after aircrafts touch down, passengers come out of aircrafts and arrive at airport terminals. Arriving passenger processing is quite different from departing passenger processing in some ways. Figure 3-4 illustrates the arriving passenger processing procedure.

Passengers flow in the arrivals path is much smoother than that in departure path. However, if baggage is delivered slowly from aircraft to the baggage claim area, it can also bring about passenger flow delays. Further, for people travelling from one continent to another continent, some countries have strict restrictions on some food items. Baggage inspections at the border of these countries will also cost a lot of time through inspecting passengers' baggage.

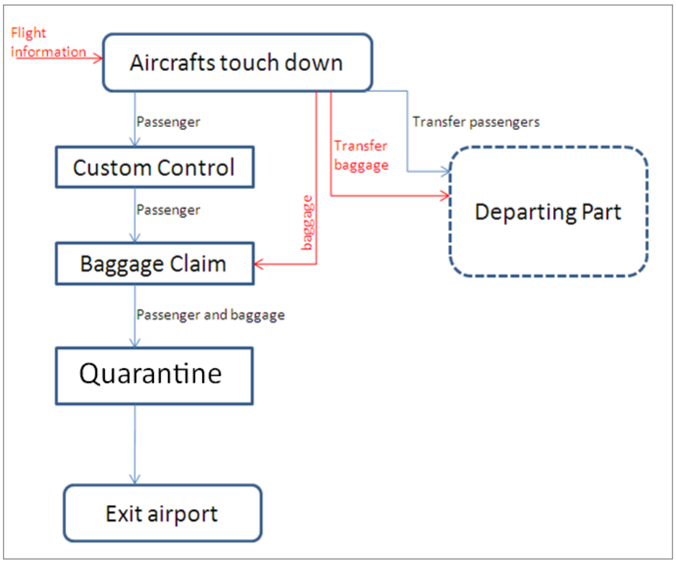



Figure 3-4: Arriving passenger processing procedures

### 3.1.3 Other forms of passenger flows

There is also some proportion of passengers who will transfer to another aircraft within the airport. They do not exit the airport but instead dwell in terminals until finally boarding another airplane and flying to their next destination. In mature airports, revenues are mostly from passengers rather than from airlines. In this regard, catering for passenger comfort is always an airport's main focus. For this kind of transferring passengers, their movement flow is also valuable for studying because they will use airport service facilities for enjoyment, such as restaurants, shops and bars.

Transferring passengers are involved in both departing and arriving processes. Commonly, transferring passengers do not need to claim their baggage – airports or airlines will help them to do so. Transferring passengers only need to take their belongings and go through certain security check procedures before proceeding to the waiting lounge.

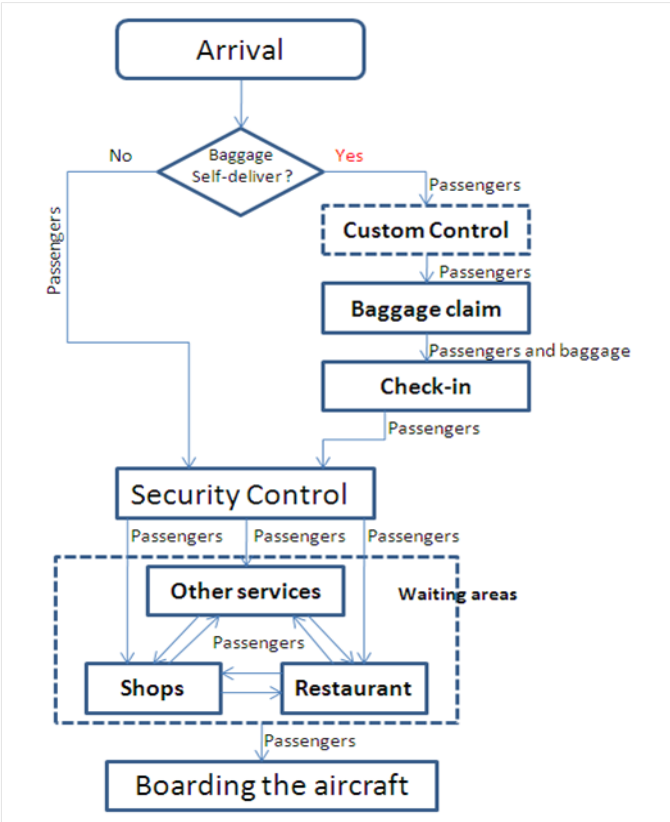



Figure 3-5: Transferring passenger processing procedures

Before boarding, transferring passengers, in the perspective of airport operators, would randomly move around the departure lounge. Restaurant, shops and other service areas will help them enjoy their lives in such short interval. However, due to the low number of transferring passengers, it typically is not considered significant, resulting in limited studies to date. Figure 3-5 shows transferring passenger flow at airport terminals.

## 3.2 SIMULATION AS A TOOL TO MODEL AIRPORTS

Simulation provides a cost effective decision making tool. It allows us to minimize risks by letting us discover the right decisions before we make the wrong ones (Shannon, 1998). For some large and busy airports worldwide, airport landside simulation is a preferred tool for airport capacity assessment (Mumayiz, 1990).

Airports are currently facing many problems of varying complexity and importance. Although most of these problems are not new, the long-term neglect and lack of action to find valid solutions have exacerbated the current situation of aviation and airport systems. Major problems include inadequate capacity and deterioration of quality of service, difficulties of financial planning and funding of new major airport development, political and environmental considerations that affect airport development and other specific issues related to planning, design, and operation of airports (de Neufville and Odoni, 2003). For airport terminals in particular, airport congestion, severe capacity shortages in the competitive deregulated environment, and airport security are major problems facing airport planners, designers, and managers (Smith, 2011). The status of airports is becoming a major concern, not only to airport operators who are struggling to accommodate passenger loads for which the designers did not plan, but also to federal, state, and local government officials, the airline industry, local communities, and the public at large.

Airport planners and managers need effective tools to assess the effects of these problems on airports. Techniques currently used for planning, design, and management of airport landside facilities appear inadequate to provide appropriate solutions. Empirical data, and rule-of-thumb approaches are overly simplistic, based mostly on gross and generalized assumptions, and unlikely to achieve effective solutions to complex problems in such a dynamic environment as the airport terminal (Lemer, 1988).

### 3.2.1 Overview of airport landside simulation

Landside-related research started in the late 1960s to investigate the problem of severe congestion and delay in airport terminals resulting from the substantial growth in air travel and the introduction of wide-bodied jets. Researchers in airport landside considered using simulation because of its convenience, reliability, and efficiency in analysis, and its capability in describing detailed activities in a manageable fashion (McCabe and Carberry, 1975). Airport organizations worldwide credited simulation as the most promising method of analysis, because it can efficiently cope with the time-varying nature of demand and the stochastic nature of the air travel system (McCabe and Gorstein, 1982).

Characteristics of simulation can vary depending on their features, specific approaches for modelling particular situations, and the objective of using simulation in analysis in airport planning. Basic properties of simulation could be static versus dynamic, analytic versus numeric, deterministic versus stochastic, discrete versus continuous, or interactive versus closed (Mumayiz, 1990). Low (1974) treats simulation as a technique for developing artificial historic (synthesized) data for situations described by the airport planner.

Mumayiz (1990) presented that Air terminal passenger flow model is an interactive event-oriented stochastic simulation model that simulates flow of passengers along pre-defined paths from curb to aircraft and vice versa. Mumayiz also indicated that the air terminal passenger flow model consists of three interactive segments: the airport terminal description data entry and edit module, the simulator module, and the statistic report generation module. Special data files are created using the data entry and editor module. Data required as input include the following:

1. Identification of carriers, sectors, terminal users, aircraft types, passenger types, and baggage claim;

2. Description of layout of air terminal building by identifying gates, links, processing facilities, separators and meeting areas, baggage dispensers, waiting, and holding rooms;

3. Arrival distribution tables;

4. Processing rate distributions;

5. Sequential lists of node numbers identifying paths used in the terminal;

6. Ratio tables of visitors to passengers by hour of day and by sector; and

7. Flight schedule

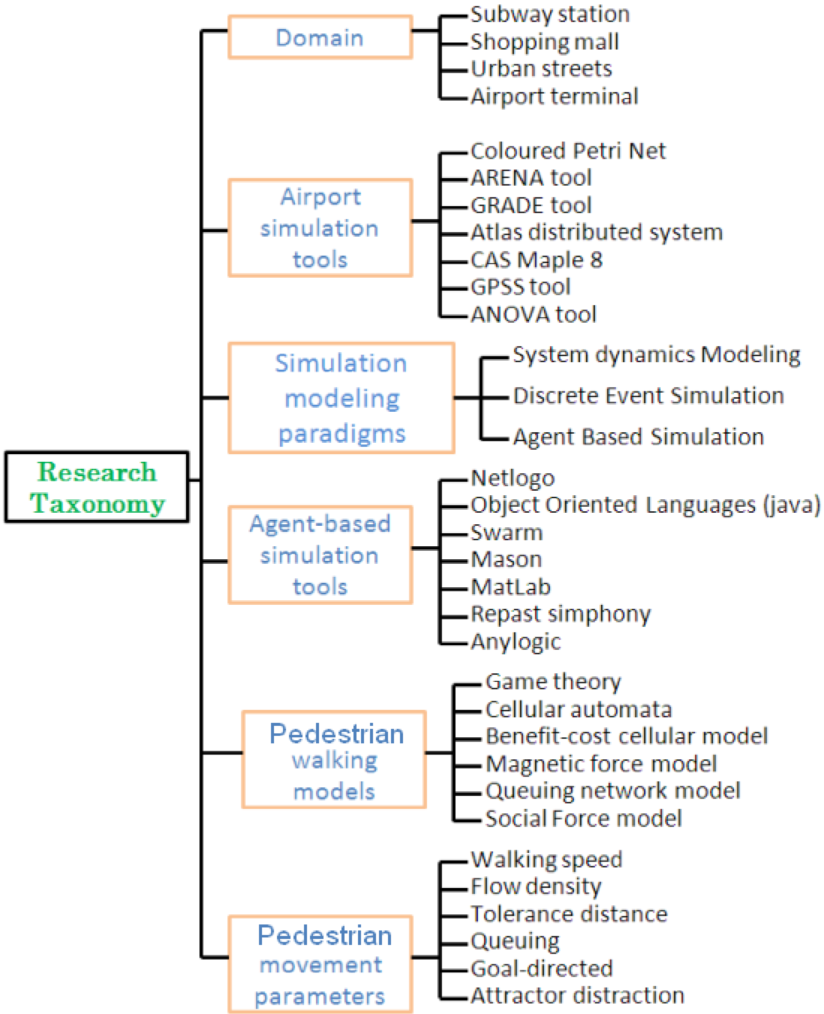



Figure 3-6: Overview of air passenger flow taxonomy

In order to clarify current research knowledge on airport passenger flow, the research taxonomy is given (Figure 3-6). It shows the different sub-branches that have be aggregated as the basis for this research.

Gatersleben and der Weij (1999) define a category of Key Performance Indicators (KPI) within the LOT project at Schiphol Airport, Amsterdam, Netherlands, which include resource utilisation, the number of passengers in waiting and shipping areas, processing times, waiting times, queue lengths, total travel time, the route length and the passenger flow rate per minute. The required throughput times are the addition of processing times and delays. Individual properties will cause different behaviours. The travel time is determined by the length the travel time among processes.

ARENA simulation environment was used to model Departures, Arrivals and Transfer processes. They first investigated the present airport resources and the flow related facilities, and then consulted experts' opinions and expertise on passenger handling during the modelling process. In addition, flight schedules and the number of passengers walking through terminal buildings are dynamic. The evaluation of supposed solutions and envisaged future scenarios is capable only by simulation. They also indicated that traditional methods of adding required additional capacity following the growth of passenger numbers is not an efficient way.

Curcio et al. (2007) made a simulation model to deal with passengers flow and security issues of the international airport of Lamezia Terme in Calabria, Italy. They analysed the system under different scenarios through a simulation model implemented in Anylogic. The simulation model investigated the passengers' average waiting time before reaching gate area. They used ANOVA (Analysis of Variance) method to generate an input-output model for correctly designing passengers flow into the airport and taking into consideration of security controls. However, the model did not cater for other important outcomes such as passengers' queuing issues and space occupancy related problems.

Roanes-Lozano et al. (2004) analysed the methodology and software on implementing a simulation of departing passengers flow in airport terminals. They chose the method of accelerated-time simulation and the software Computer Algebra System Maple to develop a package, which can simulate, in detail, passenger traffic minute by minute within the departure terminal of Malaga airport. The package has passenger attributes like the seating class, flight and destinations of each passenger, and can show plots or give details of queues in the terminals at any point in time. It can provide the number of passengers waiting in queue at any time, but it lacks the study of space occupancy at different sections of the airport terminal. It is evident that the computer algebra system Maple has limited capacity of space occupancy analysis.

Ray and Claramunt (2003) explained a disaggregated-based simulation system. They developed a modelling and simulation platform that replicates the static and dynamic properties of a real-world system modelled as a graph. Atlas is a distributed computing middleware that provides support for logical and physical management of a computing network and mobile objects on top of a distributed system. Atlas includes several functional levels from the logical representation of data structures and properties, to migration per group protocol and communication facilities.

The case study of a transportation application of Atlas modelled and simulated passengers flow within an airport terminal. Atlas provides an interactive simulation environment that supports analysis and assessment of different people transportation schemes between the different halls of an airport terminal. Atlas could be used for modelling large disaggregated data flows. However, it didn't consider autonomous behaviour at the object (passenger) level. It is also hard to study passenger groups and object interactions in detail by Atlas distributed computing.

Freivalde and Lace (2008) indicated there is always some extra unused capacity at airports, and described the ideas of modelling and simulation. He accentuated two simulation tools, GRADE and ARENA. He enumerated single process passenger flow study and a university airport simulation model using building blocks. He first did passenger flow observations and corresponding measurements at Riga airport, and then divided whole processes into several levels using the GRADE simulation environment. In this modelling process, he paid primary attention to baggage sorting delay, as small baggage sorting areas and insufficient space on baggage belts caused this and would also delay transfer passenger check-in process. Security control also faced delay problems in peak periods because there were not enough checkpoints in that context. The passenger flow study was limited as it only included the weakest and most measurable parts of Riga airport and the model was based on an even distribution of flights per hour.

Rauch and Kljajic (2006) constructed a discrete-event simulation model using the simulation programming language General Purpose Simulation System (GPSS). They studied the performance of the system in the present and forecasted future. They can evaluate the passenger flow; identify the system bottlenecks as well as the system capacities by the help of the simulation model. The developed model is flexible and allows easy modification of different parameters of the system. They accentuated the signification of the simulation applications in airport are that once a valid simulation model has been developed, new policies, operation procedures or methods without the expense and disruption of experimenting with the real system can be explored.

Table 3-1 compares the seven simulation tools in terms of theory background, theory method and application at airport.

Table 3-1: Comparison of macroscopic passenger flow simulation tools

| | ***Theory Background*** | ***Theory Method*** | ***Application at airport*** |
|---|---|---|---|
| **Coloured Petri Net** | Mathematical modelling language, bipartite graph | Estimate passenger trip time | Passenger trip delay, missed connections |
| **ARENA tool** | Simulation environment | Key Performance Indicators | Seek bottlenecks in future operation |
| **GRADE tool** | Simulation environment | Generate levels of simulation | Capacity limitation discovery |
| **Maple 8** | Computer Algebra System | Simulate passengers' traffic | Show plots and give details of queues |
| **Atlas distributed system** | Distributed computing middleware | Make graphs of real-world system | Simulate passenger flow |
| **GPSS tool** | Simulation programming language | Study system performance | Evaluate passenger flow, identify bottlenecks |
| **ANOVA tool** | Simulation environment | Build models together with Anylogic | Investigate passengers' average waiting time |

### 3.2.2 Significance of modelling airport system

Simulating passenger flow within airports is very important as it can provide an indication of queue lengths, bottlenecks, system capacity and overall level of service. To date, visual simulation tools have focused on processing formalities such as check-in, and do not incorporate discretionary activities such as duty-free shopping. However, airport retail not only contributes greatly to airport revenue generation (Graham, 2009), but potentially also has detrimental effects on facilitation efficiency benchmarks.

Airports are a perfect example of a system where a multitude of factors are in play, many of them undergoing continual change such as technological innovations and the need to provide a secure and safe travel experience in the face of malicious threats. Recent examples of such changes include the introduction of the Airbus A380 passenger jet, and the use of full-body security scanners. Each of these changes will have significant but different implications for the airport structure, the passenger facilitation process, the information and technologies required, and ultimately have an effect on passenger experience. All these changes have a significant impact on airport systems, but have rarely been addressed in detail (Kleinschmidt et al., 2010).

Coupled with this continual change is the large number of independent stakeholders, each having a different perspective on airport operations, and placing different criteria upon which successful airport operation is measured. For example, passengers want an efficient and pleasant travel experience, policing agencies want to ensure the terminal and aircraft are at low risk of malicious attacks, whilst the airlines, airport and retail firms want to increase passenger throughput and to generate increasing revenues.

Modelling airport systems therefore becomes very important to:

(a) analyse the performance or level of service of an existing system; Within an airport, it includes several stakeholders which concerns different interests of their own as addressed above. An airport system, which consists of passengers, policing agencies, airline, airport, retail firms etc., needs to be modelled as a whole so as to investigate the relations among existing stokeholds and analysis system performance.

(b) plan resourcing requirements for a given future flight schedule; By analysing a given future flight schedule, numbers of passengers using the airport can be estimated. In busy season or peak hours of a day, all service facilities and staffs can be arranged accordingly to meet the requirements. For example, through modelling the amount of security counters opened for passenger processing in morning peak, the level of service in security section can be evaluated and compared. The number of security counters can be determined eventually so as to maintain a good service level.

(c) assist in planning changes prior to their implementation and determine what effects (if any) these have on the overall level of service. The growth of populations of air passengers transit form airports and larger aircrafts make current airport realise its capacity would not meet future needs. Modelling is well capable to deal with the likely changes of airport systems in future. Without truly built new terminal or expend current terminal, new terminal building can be built virtually in simulations and the outcomes of the simulations can explore that if planned changes are optimum.

Simulation models are particularly important in the latter case since it is extremely impractical to manipulate the live airport system.

There are a number of different methods which have been used for airport modelling, and are broadly divided into macroscopic and microscopic models (de Neufville and Odoni, 2003). Tosic (1992) provides an early review of airport system models. Due to the presence of mandatory checkpoints throughout the airport terminal (such as check-in, security screening, immigration, customs, quarantine inspection and boarding), it is no surprise that queue-based models (such as that initiated by Lee (1966) dominate these reviews.

Significant examples of airport terminal simulation include the *Simple Landside Airport Model* proposed by Brunetta et al. (1999). This model estimates the terminal capacity and passenger delays by analysing different spatial configurations of various checkpoint facilities. Manataki and Zografos (2009) present a generic mesoscopic simulation based approach using system dynamics and demonstrate on a model for the Athens International Airport for departing passengers. Wang et al. (2008) describes a passenger flow simulation through the use of coloured Petri nets, which captures passenger delays related to air transportation network cancellations or delays.

All of these models are used to evaluate aspects of passenger flows throughout the terminal based on what-if scenarios, but do not provide visual simulation of passengers moving through the terminal. Through the interactions with industry practitioners, this is believed to be a very useful feature for airport passenger simulation as it helps to visually identify bottlenecks and crowding which can be related to the real-time operation with which they are familiar.

Agent-based models (where passengers are the agents) are a useful tool for studying passenger systems since they are able to simulate both the individual actions of passengers, but also the aggregated system behaviour, and importantly provide a visual representation of the system. In this way, agent-based models are a good fit for the needs of industry practitioners, and as a consequence, agent-based model is chosen as the simulation tool for the study in this thesis.

In airport environments, it is important to recognize that passengers not only interact amongst themselves, but also with all the service facilities within the terminal such as check-in, security screening, boarding and even discretionary facilities such as duty-free outlets and restaurants. The models described above focus primarily on mandatory activities through which passengers must proceed (e.g. security), typically excluding simulation of discretionary activities. This is a major shortfall of existing models particularly since retail sales account for large amounts of revenue generation for airports (Torres et al., 2005), but they can also significantly influence passenger facilitation, particularly for arriving passengers.

In the thesis, agent-based model is utilised to simulate passenger flow in the airport terminal. Agent-based models provide a model of agent interaction with other agents and the environment (Reynolds, 1999), and importantly provide a sense of agent autonomy which is not present in entity-based models. Entities are normally controlled by processes within the system, and not by decisions of the individual agent (Johnstone et al., 2009). For this reason, an agent-based model is more suited to modelling areas of the airport which are not as process-driven such as duty-free shopping.

## 3.3 AIR PASSENGER CHARACTERISTICS

In an airport environment, passengers interact with physical elements (e.g. physical barriers, or queue ropes at check-in or immigration), other passengers in the surrounding locality, and are also subject to the influence of factors such as queues and crowding. Passenger behaviour is also guided by socio-economic factors and by short-term and long-term goals, for example buying a coffee or a bottle of water because of thirst or in preparation for boarding a flight that does not have in-flight service (e.g. on a low-cost carrier).

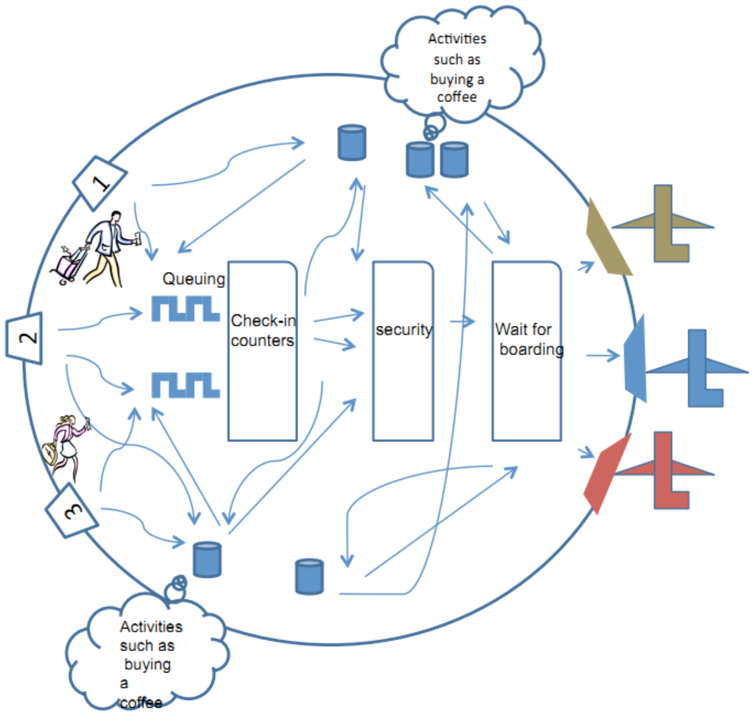



Figure 3-7: Whole-of-airport model showing complicated behaviours outside the mandatory process

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 Figure 3-7. Accordingly, passenger behaviour becomes much more complicated and hard to predict. As such, it could be described that between processing points, passengers have full autonomy and a complex decision model is required to accurately describe their behaviour. 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 behaviour.

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

There has been scarce attention to identify what are the passenger characteristics (age, gender, travel class, etc.) that affect passenger propensity to routing behaviour. According to above literature, models of passengers flow are almost simply restricted to standard processing procedures, i.e. check-in, security, customs, and immigration. It is evidently that air passengers in terminals are goal-directed. The major function of airport terminal is to efficiently facilitate passenger travelling from landside through airside to boarding. As a consequence, characteristics of air passengers have not been considered in detail in related models and simulation. Implicitly, researchers may have assumed that these variables are not relevant or their effects can be neutralized by proper randomization.

However, people also have the ability to move and perceive different factors within the environment which will shape their future actions. For the departure process, passengers might wish to make a phone call to their relatives to inform them they arrived safely at the airport and will board on time. Alternatively, they might want to have a drink and something to eat at a café prior to check-in opening. These are just a couple of examples of a wide range of activities passengers can undertake in modern-day airports. These activities are assumed as discretionary activities. Standard processes are as the mandatory, such as check-in, security, immigration and boarding. All passengers must go through them. To the contrary, maybe only a certain portion of passengers behave discretionary activities (e.g. go to phone booth to make a phone call, go to café to buy a drink).

In this thesis, modelling the profile of a passenger – i.e. detecting the characteristics of who is more likely to make a phone call or buy a drink – is believed to be crucial, because identifying what variables affect the probability of routing decisions will allow future research to design more controlled experiments and check if the randomization works properly.

Basically, statistical information on air passenger characteristics can be collected from airlines, airport and national aviation regulatory authorities (Parliamentary Office of Science and Technology, UK). Demographic, socio-economic and other relevant data can be obtained from surveys conducted by airport operators or regulatory authorities. The surveys are important for airport planning. For the purpose of this thesis, air passenger characteristics can be envisaged to be utilised to model different profiles of passengers.

Demographic and socio-economic characteristics of air passengers are *Age structure*, *Socio-economic group* and *Ticket types* (Parliamentary Office of Science and Technology, UK). Detailed characteristics devised for modelling routing selections of air passengers are hardly studied. However, they are important for airport planning and should be significant to design more advanced models of passengers flow model in airport environments. Thus, air passenger characteristics are studied initially in order to have a more controlled model for passengers flow in airport terminal scenario.

Passengers' traits from other transportation scenario can be referred for the study. In a similar field – public transportation, a report provides two categories of characteristics of passengers (Neff and Pham, 2007). They are *demographic characteristics* and *travel characteristics*, which contain *Age, Ethnicity, Gender, Occupation, Frequency of Transit travel, Trip Purpose*, etc. Yaakub and Napiah (2011) studied city buses services to assess passengers' demographic and travel characteristics and to determine the passenger's preference in transportation mode. Given the methods in literature, basics traits of passengers are first devised.

### 3.3.1 Basic traits of air passenger

A series of the types of factors are set out, which are believed to be significant in describing various passenger behaviours within an airport. Basic traits are those that are typically static for the entire period of time passengers spend in airport terminals. They are implemented to guide passengers to specific check-in, security and immigration queues based on class of travel and nationality. In addition, the traits also influence the walking behaviour of each passenger. Walking speed can be generated automatically by some important variations which can be classified as basic or value added. Finnis and Walton (2006) assessed the walking speeds of large numbers of passengers, and showed the important variations (e.g. age) in walking speeds, particularly influenced by the traits describing basic mobility in airport environments. Based on them, the basic factors are concluded in Table 3-2.

Basic mobility indicates that the classifications by gender, age and baggage are applicable to all pedestrian simulation applications. Other than the classifications by Richter et al. (2009), for simplicity, the trait *Age* is only distinguished as two categories, since walking speed of passengers whose ages are less than 65 vary only a little bit (Young, 1999). Those over 65 walk much slower. In addition, characteristics such as *Travel class* and *Frequency of travel* have impact on mobility and path selection as well. They are included in to the influence factor –Value added mobility. It relates specific ticket information to air travellers.

Table 3-2: Basic factors which affect passenger mobility and path selection

| Influence | Passenger Trait | Detailed factors |
|---|---|---|
| Basic mobility | Gender | Male<br>Female |
| | Age | =< 65<br>> 65 (old passenger) |
| | Baggage | Number of bags (checked and carry-on)<br>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<br>A few times<br>Frequent flyer |
| | Travel group size | Single traveller<br>A couple<br>More than three |
| | Nationality | Native (e.g. AUS/NZ)<br>Foreign |

## 3.4 ADVANCED PASSENGER CHARACTERISTICS

In order to gain an understanding of all potential mandatory processing activities and discretionary activities in airport terminals, service facilities provided by 15 major airports around the world are investigated. This review included airports in

- Europe (London Heathrow, Amsterdam Schiphol and Frankfurt)
- United States (Atlanta, Chicago O'Hare and Los Angeles)
- Asia (Singapore Changi, Hong Kong and Tokyo Haneda)
- Australia (Melbourne and Brisbane)
- Middle East (Dubai)

and a few limited examples in other parts of the world. By making this selection, it is convinced that any cultural/regional variability is able to be represented.

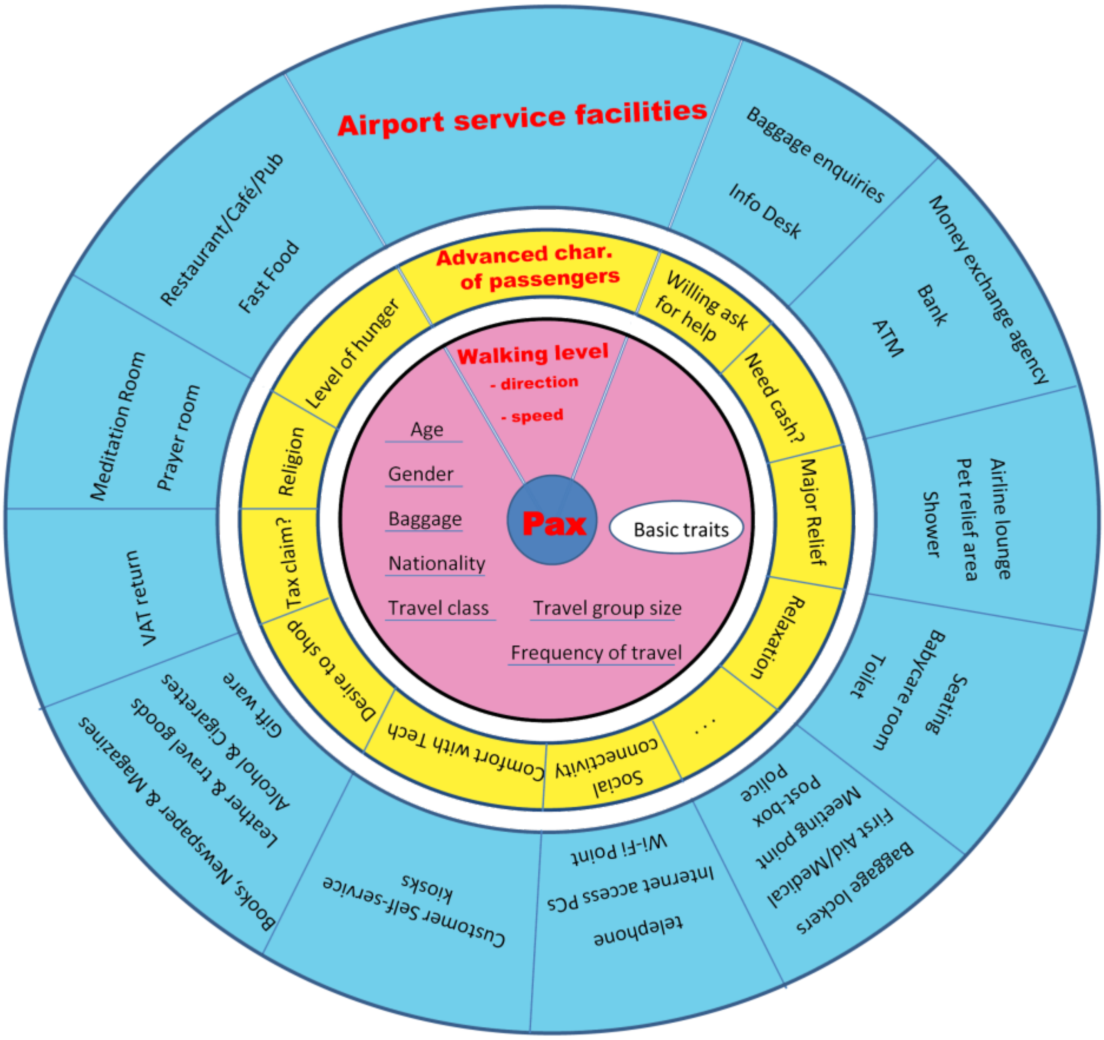



Figure 3-8: Relationship between airport ancillary facilities and the activities that passengers undertake

Following this review, eleven major categories of airport ancillary facilities were able to be categorised. Figure 3-8 shows the eleven categories of airport ancillary facilities and their relations with passenger activities. The outer ring shows the airport facilities, the middle ring describes some characteristics which influence a passenger's use of a particular facility, and the inner ring shows the basic traits of a passenger. These characteristics form the basis of our proposed advanced passenger characteristics.

Facilities in every category cater to a particular purpose. Restaurant, Café, Pub and Fast Food facilities are formed as a group because they provide food for passengers. Similarly, Baggage enquires and Information Desks provide information services and so that they are categorized into one group. Except standard processing, services being provided to passengers can be concluded as ten major fields in this way. They are food services, information services, cash services, VIP lounge, basic relaxation, social connectivity, customs self-service kiosks, shops, tax return and religion-related services. Advanced characteristics of passengers are devised according to the ten sorts of services.

For example, consider food and beverage outlets. Depending on time of day (e.g. lunch time) and other factors, passengers who arrive at an airport terminal may be feeling hungry and would like to use a terminal’s eateries. The activities are driven through some “Level of hunger” in the characteristics circle (Figure 3-8). The types of facilities which relate to this particular characteristic are listed in the adjacent cell in the outer circle. Specific examples include (but are not limited to) fast food outlets, restaurants, cafés and bars. If a passenger who is young and travel smart, he/she would most likely are comfortable with using technology facilities and use self-service check-in facilities all by himself/herself in order to quickly obtain a boarding pass. Or if passengers who are foreign visitors and happen to wish to take some gifts home, they will likely go to Gift ware shops. Characteristics of “Comfort with Technology” and “Desire to shop” indicate passengers would use customs self-service kiosks and duty-free shops respectively. The motivation traits of passengers will therefore influence passengers’ route choice and other behaviours.

The possibility of using service facilities by air passengers are determined by passenger traits, which contains basic traits and advanced traits. Basic traits facilitate walking function of an individual agent – avoiding obstacles, maintaining a tolerance distance with other passengers and walls, walking speed and walking direction. Advanced traits are used for decision-making of individual passengers – medium- and long-range rout choice, service facilities selection, and time spent at different facilities. Advanced traits evidently can impact on the most inner circle – i.e. the walking level.

Advanced traits are significant outcomes in the thesis. Simply, they are personal activity motivation characteristics, which facilitate route-choice decision-making and help describe more complicated behaviours in airport terminals.

Table 3-3: Discretionary behaviours

| **Behaviours** | **Demographic** | **Time expenditure** | **Venue(s)** | **Frequency of occurrence** |
|---|---|---|---|---|
| Shopping | All passengers | Short or Long | Newsagent<br>Gifts/Souvenir<br>Clothing/Accessories<br>Shops | Very often |
| Eating & Drinking | All passengers | Short or Long | Take-away<br>Café<br>Restaurant<br>vending machines | Very often |
| Meet & interact with other people | All passengers | Long | Meeting point<br>Waiting area<br>Shops<br>Restaurant | Often |
| Go to restroom | All passengers | Quick | Restroom | Almost always |
| Snooze | Tired passengers | Long | Coach rooms<br>Airport hotel | Average |
| Entertainment | All passengers | Long | Areas with TV<br>Wi-Fi access<br>free Internet surfing | Average |
| Pray | Religious people | Average | Prayer room | Often |
| Make a phone call | All passengers | Average | Phone booth<br>Cell phone charger facilities | Often |
| Baby caring | Baby, mother, others | Average | Baby caring facilities | Seldom |
| Buy any medicine, go for a doctor | Keeper<br>Sick passengers | Short or Long | Medicines<br>Clinic in airports | Very seldom |
| Inquiry | All passengers | Quick | Information kiosk | Very often |
| Take shuttle train to other terminal | Transit passengers | Average | Shuttle train stops | Average |
| Baggage left | Transit passengers | Quick | Baggage left place | Average |
| Cash machine | Some passengers | Average | Cash vending<br>Money exchange | Average |
| Other unspecified | All passengers | Average | Other possible places | Average |

Advanced traits are those which help to describe the more complicated behaviours in airport terminals which are to be captured in future simulation models. These factors ensure that a passenger is not considered as a closed loop (passengers' walking behaviour only governed by pre-defined parameters), but as a truly intelligent agent with the ability to perceive and respond to their surroundings. In short, 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 have a nap between flights. The activities that result can describe how much time will be consumed performing these activities.

Passengers will behave accordingly to their perception and prior knowledge, and the advanced traits identified in this thesis are based on both of these aspects (Table 3-3). 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");
- characterised by travel experience ("frequency of travel");
- are willing to ask for assistance; are hungry; have a desire to shop;
- or are generally comfortable with technology.

How these traits are used to enable autonomous routing decisions of passengers is described and demonstrated in the Chapter 4. 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 take-away, cafes and restaurants will appear attractive (at that point in time), and increase the likelihood of the passenger buying something and consuming it. Once they have finished their food however, their level of hunger will be reduced, and so this should mean that food outlets become less attractive than previously.

## 3.5 CHAPTER SUMMARY

At the beginning of this chapter, passengers processing procedures within airport terminals were examined. Three different processes of passengers were illustrated – departure, arrival and transfer processes. The three processes ideally indicate three forms of passenger flows. Due to the specific business processes, airports are a prime application for simulation. The methodology of utilising simulation to solve system problems, including airport system, was addressed. The steps to study a simulation were also discussed.

By analysing current airport simulation research, including both macro- and microscopic models, a bottom-up approach was outlined as the most suitable one to undertake the research addressed by this thesis. It is the agent-based microscopic simulation of passenger dynamics with advanced passenger traits. The bottom-up approach has an advantage over conventional macroscopic models in terms of modelling individual dynamics of passengers and also can study the interactions among passengers and the terminal building. Basic traits of passengers, which are most commonly used characteristics during a simulation, were extended by adding devised advanced traits so as to tackle decision-making problems of passengers when they are about to make route choices at a decision point.

In the next chapter, the opportunity of including discretionary activities of passengers into airport simulation is to be addressed. The case study for implementing advanced traits of passengers into a simulation model will then be conducted. Advanced traits of passengers are devised in this regard to carry out further experiments regarding route-choice decision making of passenger agents.

# Chapter 4: Including Discretionary Activities in Airport Simulation

In *Chapter 3*, advanced traits of passenger were devised so as to tackle decision-making problems of passengers when they are about to make route choices at a decision point. The decision points are defined in this thesis as places before and after a standard processing procedure, where passengers have free will to make route-choice decisions. During the intervals between standard processing procedures, passengers would have certain possibility to leave standard checkpoints, such as check-in and security counters, and behave discretionary activities, i.e. using on-airport shops and restaurants. This kind of activities of passengers is addressed in this chapter.

With a clear idea of passenger flows through standard processing procedures in airport terminals and the proposed air passenger characteristics presented in Chapter 3, this chapter will extend the research to include discretionary activities into modelling airport system, such as duty-free purchasing, and then develop an airport passenger flow model with high-level behaviours of passengers. A model of such is argued to enable more realistic simulation of passenger facilitation, and provides a platform for simulating more complex passenger behaviours within the airport. Probabilistic distributions of passengers within the departure hall are generated to ancillary facilities such as cafés, information kiosks and phone booths as well as common check-in facilities. The effects and outcomes which have impact on passengers' check-in processing, dwell times and facility utilization at departure hall are observed.

## 4.1 INPLEMENTATION OF DISCRETIONARY ACTIVITIES

A high-level description of arrivals process model for Australia airports is presented graphically in Figure 4-1. Dotted lines indicate optional activities/transitions between activities. The major processing points are aircraft disembarkation, immigration and the secondary examination area which incorporates both customs and quarantine (biosecurity) checks. Baggage reclaim is regarded as optional as not all passengers will have checked baggage to collect.

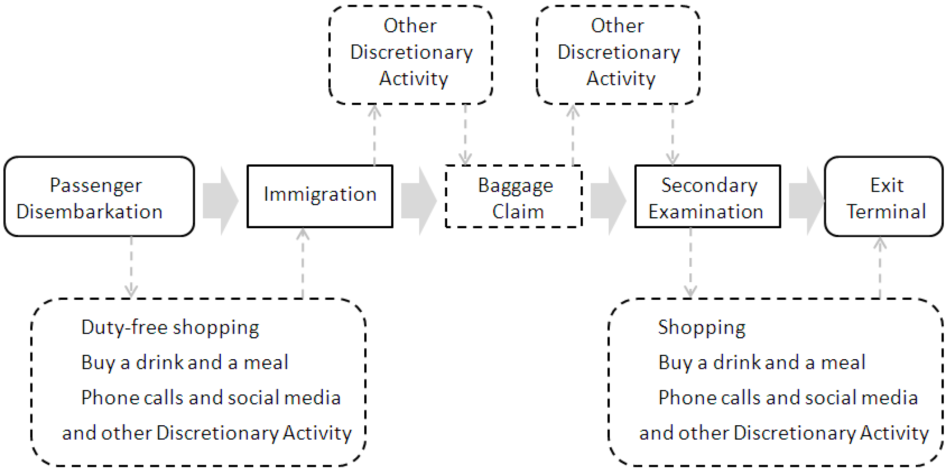



Figure 4-1: International passenger arrivals process common to Australian airports

As can be seen, there are a number of areas in which passengers can undertake discretionary activities between the necessary formalities, including duty-free shopping, going to the bathroom, depositing prohibited items in the quarantine bins and obtaining luggage trolleys (among others).

Take duty-free shopping activities as an example, since airport retail contributes greatly to airport revenue generation (Graham, 2009), a model with duty-free retail at airports would have a number of benefits for airport operators over previous models.

It can increase accuracy for passenger flow assessment, and have an ability to assess revenue generation based on a particular flight schedule. It opens to way to incorporate more advanced passenger behaviour characteristics to make agents more autonomous. It also provides a platform for researching methods by which passenger experience is encapsulated within an agent-based model. These benefits increase the accuracy of passenger flows model.

Similarly, departure process model for Australia airports can be illustrated in Figure 4-2. Passengers can undertake discretionary activities between the necessary formalities, such as check-in, security and customs.

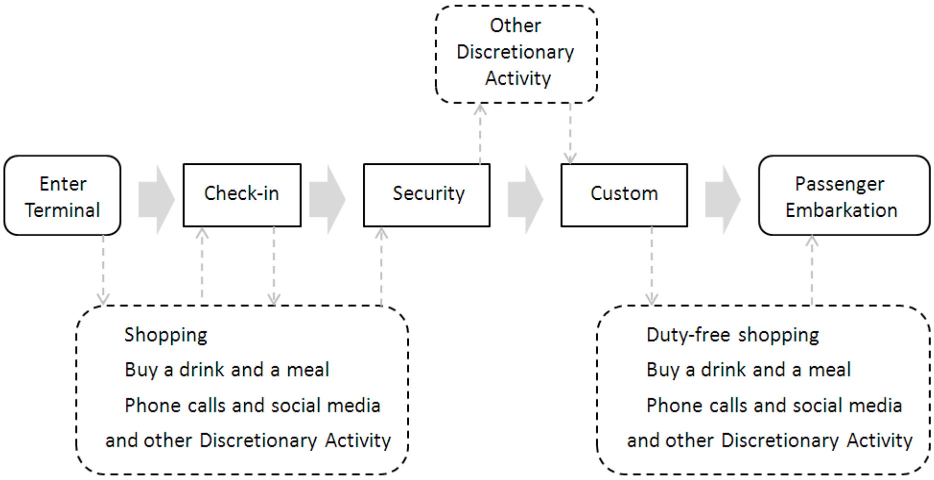



Figure 4-2: International passenger departure process common to Australian airports

Agent-based models have been used extensively to measure aspects of passenger flow, in particular to identify passenger dwell times, queue waiting times, and locating bottlenecks within the airport system (Gatersleben and van der Weij, 1999; Kiran et al., 2000; Takakuwa and Oyama, 2003). In many cases however this has neglected to include passenger utilization of on-airport discretionary facilities, such as retail opportunities and other discretionary activities.

In Australia, airports are encouraged to meet the recommended practice for arrivals procedures outlined in Annex 9 on facilitation provided by the International Civil Aviation Organisation (2005), which states:

*Definition 1*: Contracting States, with the cooperation of aircraft operators and airport operators, should establish as a goal the clearance within 45 minutes of disembarkation from the aircraft of all passengers requiring not more than normal inspection, regardless of aircraft size and scheduled arrival time.

Unlike the recommendation for departing procedures, this recommendation does not limit the performance standard to the mandatory processing requirements. Since there are often retail facilities in this area, the measured 45 minute benchmark will also include time spent in retail. As such, it is imperative to include these facilities in any arriving passenger flow model.

Table 4-1: Impact of utilising retail for passenger clearance times through international arrivals in Australia

| *Airport* | *Time to ECP* | | *Clearance Time* | *% Time in Retail* |
|---|---|---|---|---|
| | Retail | No Retail | (Retail Only) | |
| Brisbane | 7’00’’ | 3’30’’ | 27’15’’ | 12.8% |
| Darwin | 8’30’’ | 1’15’’ | 32’30’’ | 22.3% |
| Melbourne | 10’15’’ | 4’30’’ | 35’30’’ | 16.2% |
| Perth | 8’00’’ | 2’45’’ | 37’30’’ | 14.0% |

To demonstrate the influence of time spent in retail in the arrivals facilitation path, consider the mean facilitation times shown in Table 4-1 for passengers in four Australian international airports involved in the “Airports of the Future” project. These summary statistics are based on data provided to the research team by the Australian Customs & Border Protection Service where selected passengers were time-stamped as they moved between points of interest.

In this instance, the four airports have been chosen as they each have duty-free outlets between the point of aircraft disembarkation and the Entry Control Point (ECP) where immigration checks are undertaken. To understand how much time passengers spend in retail between disembarkation and the ECP (as a percentage of their total clearance time), mean times are shown for both passengers who use retail and those who go directly to the ECP. It can be seen for all airports that the time to ECP via retail is more than double the time when proceeding directly to immigration. As a percentage of total clearance time, passengers spend at least one eighth (i.e. 12.5%) of their total time in the duty-free shops, and in the case of Darwin International Airport, almost one quarter of their time.

It is therefore important to appreciate that a significant proportion of the overall clearance time (which is also affected by government agencies conducting arrival formalities, and baggage handlers delivering luggage to carousels) is consumed by passengers in retail. Consequently, changes to these retail stores (e.g. by changing purchasing opportunities) will have a noticeable impact on passenger flow and passenger clearance times against which stakeholders often measure airport performance.

To some extent, passenger behaviour in airports is still not well understood, particularly in relation to discretionary activities. A number of key aspects which will allow for additional layers of passenger behaviour simulation can be added, in particular the presence of multiple decision points around discretionary facilities. Take the duty-free shop for instance, decision points could be used to simulate three different types of passenger in respect to their willingness to use airport retail. The first type could include passengers who had decided prior to leaving the aircraft that they wished to entry the duty-free shop, either with the view to make a purchase, or to collect pre-purchased goods. At the other end of the scale are passengers who have no intention of entering duty-free, particularly those business travellers who wish to get out of the airport as quickly as possible. The third passenger type would then be somewhere in between these two extremes; such passengers might be persuaded to enter the duty-free shop because of advertising around the store, or seeing a product that they like. This demographic of passenger may also describe those who are most likely to enter duty-free upon seeing long queues at the immigration checkpoint.

In such a way, the ability to increase the autonomy of the passenger by incorporating more detailed passenger information into the simulation model will enable more complex passenger movements, and will therefore provide airport operators with more realistic passenger flow models.

## 4.2 SIMULATION OF PASSENGERS WITH ADVANCED TRAITS

Due to the macroscopic nature of these studies, it has not been necessary to have complex models of passenger behaviours. This is appropriate, since passenger behaviour 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 behaviours as queuing theory (as introduced by Lee (1966) for check-in processes) adequately describes this movement.

### 4.2.1 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, a subset of the types of factors that are regarded as important in guiding passenger behaviour within the airport are presented, 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.

It should be noted however that the current model (and associated simulation) does not try to hypothesize complex passenger decision-making which would dictate the likelihood of individual agents entering on-airport discretionary facilities; proportions are simply applied to demonstrate passengers moving through the respective decision points to demonstrate the concepts.

The traits of passenger agents are divided into two categories. *Basic traits* 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.

The traits also influence the walking behaviour 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 travellers. 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 behaviours 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 that identified for the check-in area are based on both these characteristics, and are outlined in Table 4-2. 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");
- have pre checked-in or not;
- are characterised by travel experience ("frequency of travel");
- are willing to ask for assistance or not;
- are hungry or not ("Level of hunger");
- are generally comfortable with technology or not.

How these traits are used to enable autonomous decision making in the passengers is described and demonstrated.

Table 4-2: Advanced passenger characteristics proposed for check-in area

| *Characteristics* | *Data Type* | *Example* |
|---|---|---|
| Desire to check-in first | Boolean | True |
| Pre check-in? | Boolean | True |
| Frequency of travel | Integer | 0, 1, …, 10 |
| 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 hunger), 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 cafés 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.

### 4.2.2 Check-in processing simulation

In order to demonstrate how the advanced traits enable more advanced passenger behaviour 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 is shown in Figure 4-3. 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 café, 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.

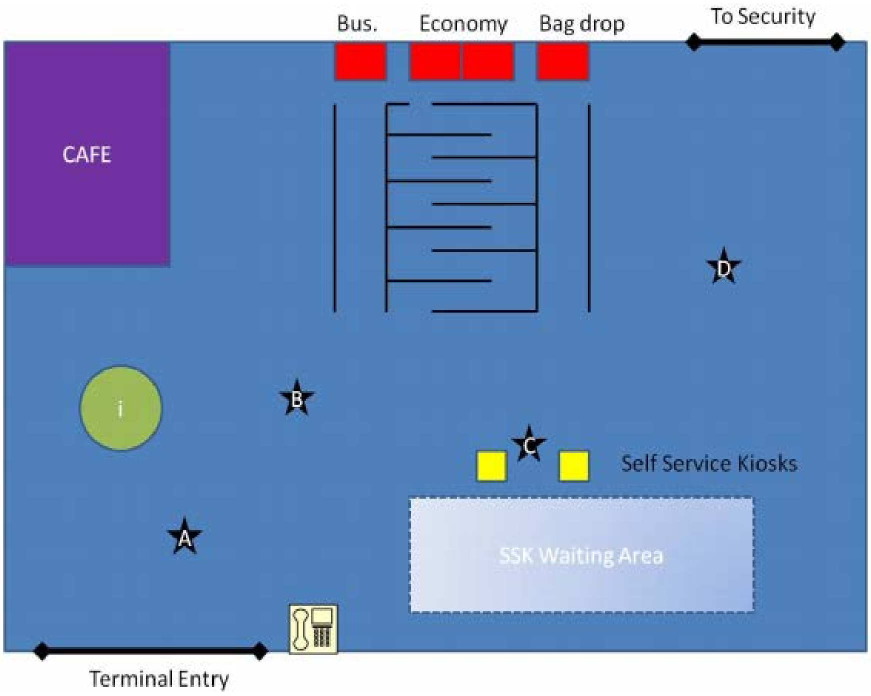



Figure 4-3: Spatial layout for hypothetical check-in case study

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 Figure 4-4.

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 travelled 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.

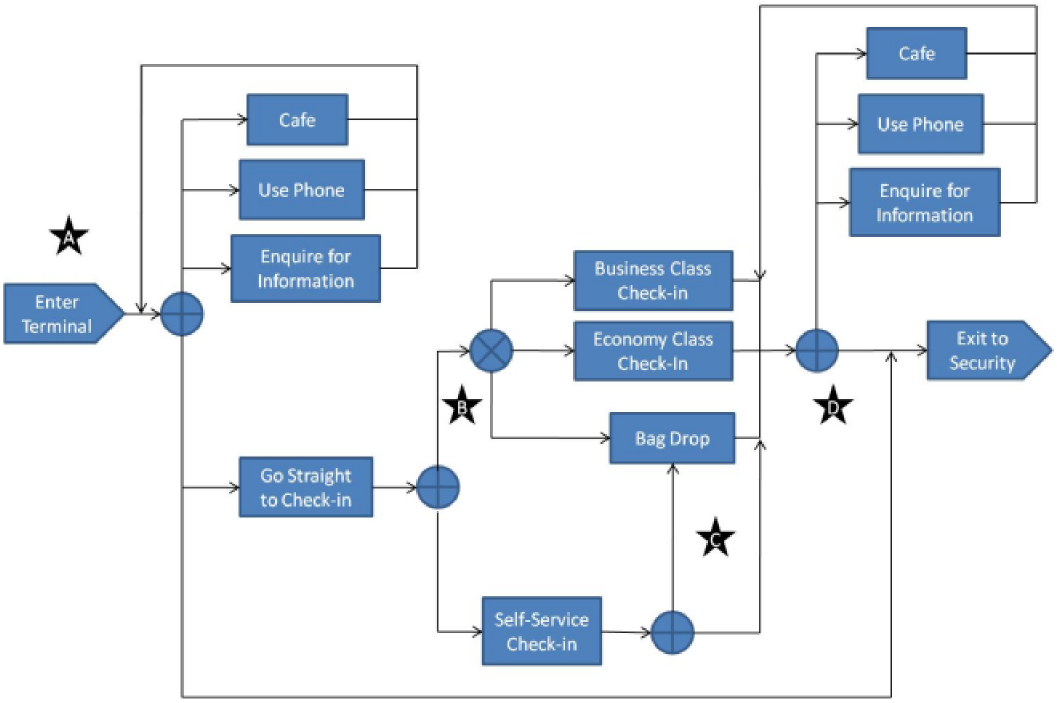



Figure 4-4: Decision flowchart to demonstrate the use of advanced passenger characteristics

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.

### 4.2.3 Setting up 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 modelled for this case study. Only one flight has been modelled (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 Figure 4-5. In particular, passengers who are "hungry" and have sufficient time to board (t1 = 45mins) will use the cafe (where h1 = 2 and h2 = 3), and passengers who are inexperienced at this particular airport (f1 = 2 and f2 = 5) and are willing to ask for assistance (w1 = 2.5 and w2 = 4) will use the information booth.

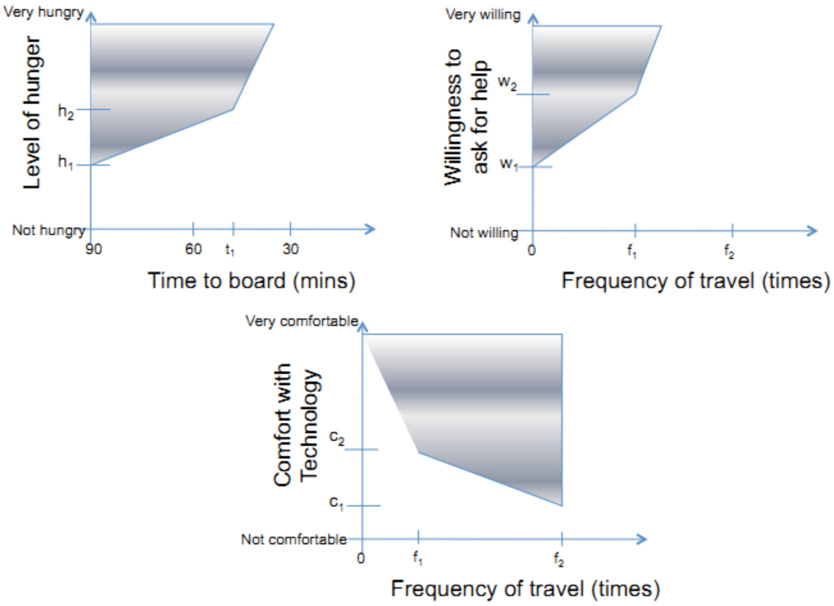



Figure 4-5: Membership functions used in simulations

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 Figure 4-5; in particular, passengers who have travelled a sufficient amount (f1 = 3, f2 = 8) and are comfortable with technology (c1 = 1.5, c2 = 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.

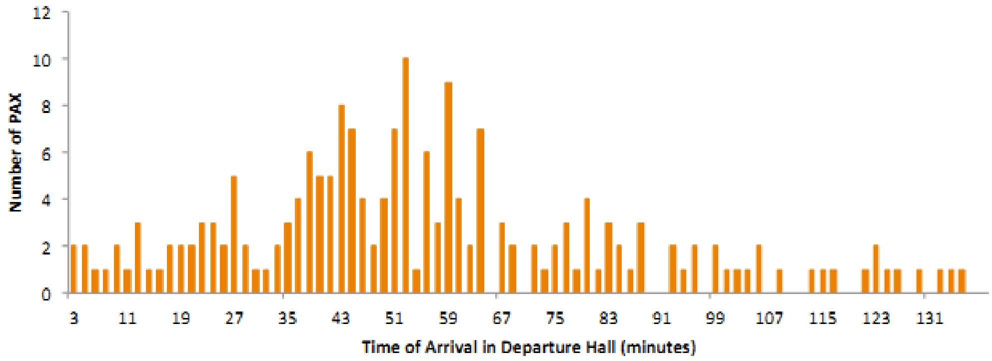



Figure 4-6: Departing passenger arrival schedule for a single flight

In all of the simulations, a constant arrival schedule has been used for consistency (refer to Figure 4-6). 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 next.

### 4.2.4 Results of simulation and analysis

To verify the behaviour of the simulation in the case of Scenario 3, Figure 4-7 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.

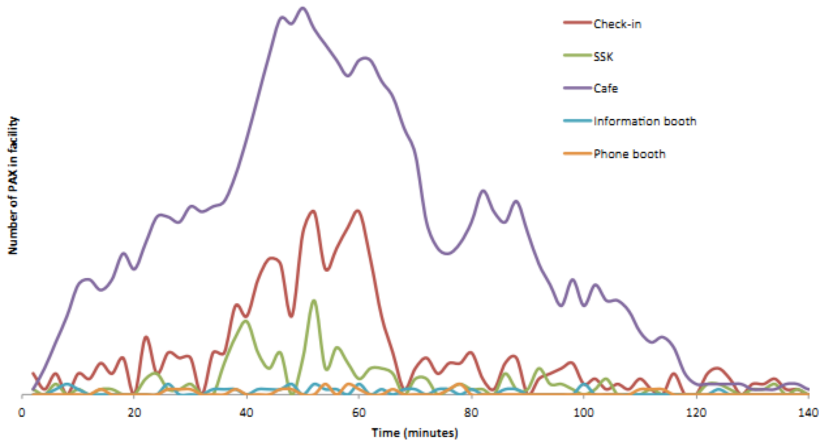



Figure 4-7: Utilisation of check-in, SSK, café, phone booth and information desk

Figure 4-8 demonstrates the utilisation 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 utilisation 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 utilisation is significantly increased. This is important for designers as it provides a more accurate description of how the entire space is being utilised, not just the space dedicated to check-in.

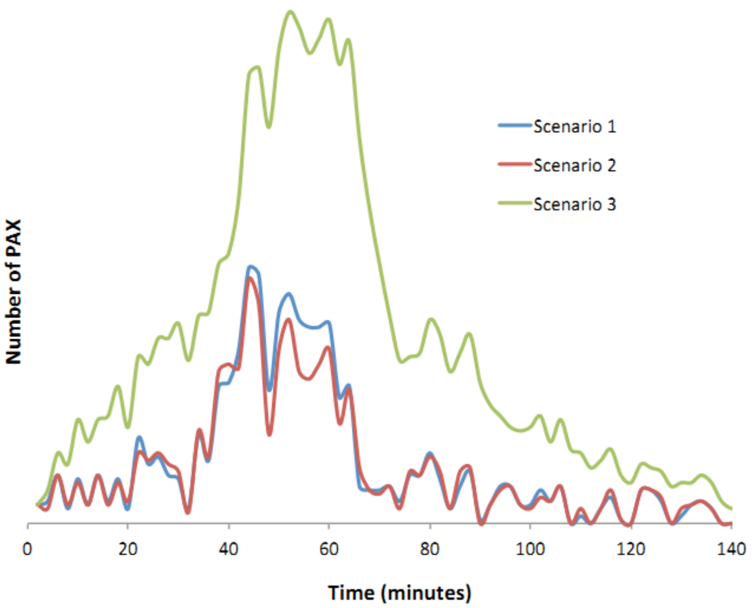



Figure 4-8: Comparisons of instantaneous utilisation of departure hall

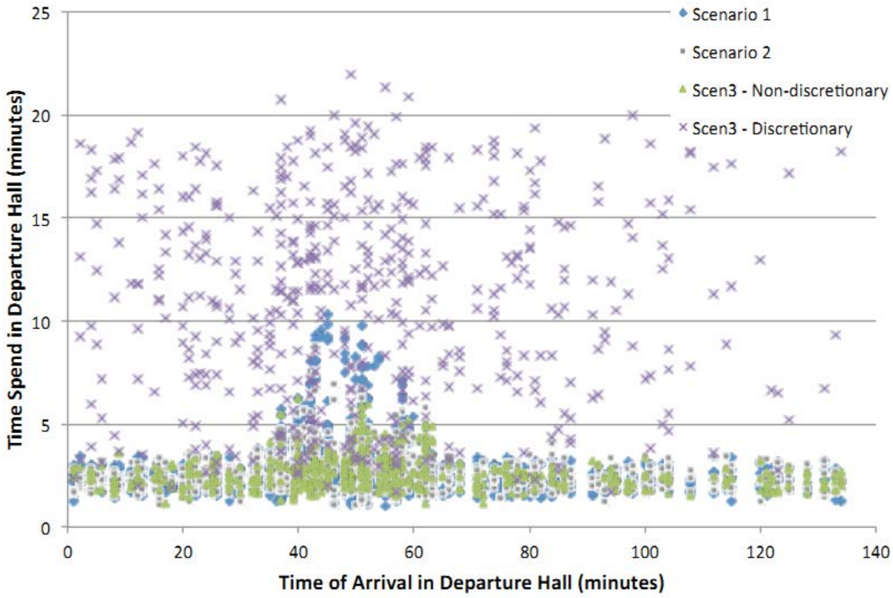



Figure 4-9: Comparisons of instantaneous utilisation of overall dwell time

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 (Figure 4-9). For Scenario 3, passengers are distinguished 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 characteristic 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 Figure 4-8). Figure 4-10 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.

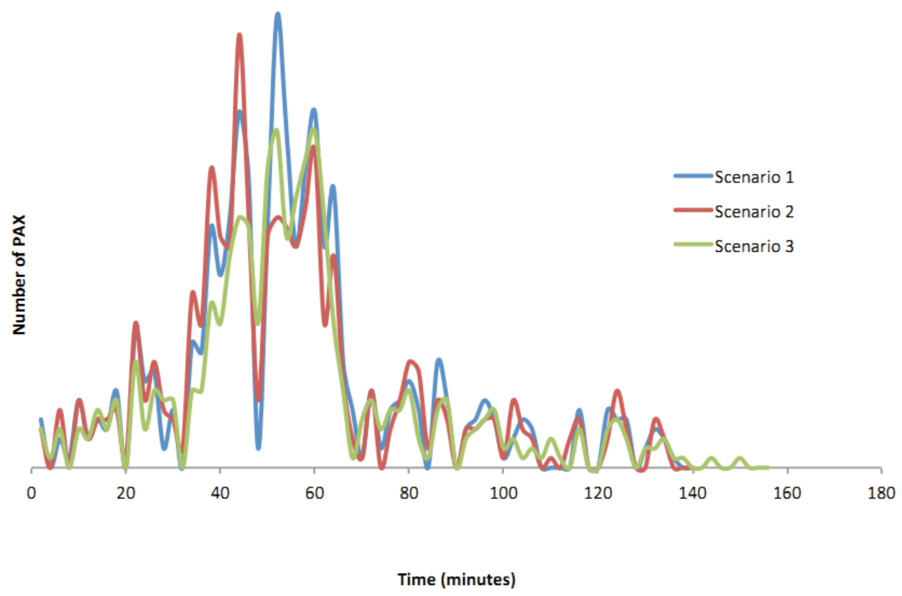



Figure 4-10: Check-in utilisation for the three simulation scenarios

In order to demonstrate the impact of changing the membership functions which result from the advanced passenger traits, a simulation was ran based on Scenario 2, where the membership function was altered by changing the value of c2 which relates to the level of comfort with technology. Figure 4-11 shows the cumulative usage of the self-service check-in kiosks for c2 = 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, the results shown in Figure 4-10 also 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.

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. 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. Whole outbound passenger flow simulation can be constructed in this way. The simulation results in terms of the three devised scenarios are also displayed in Appendix D.

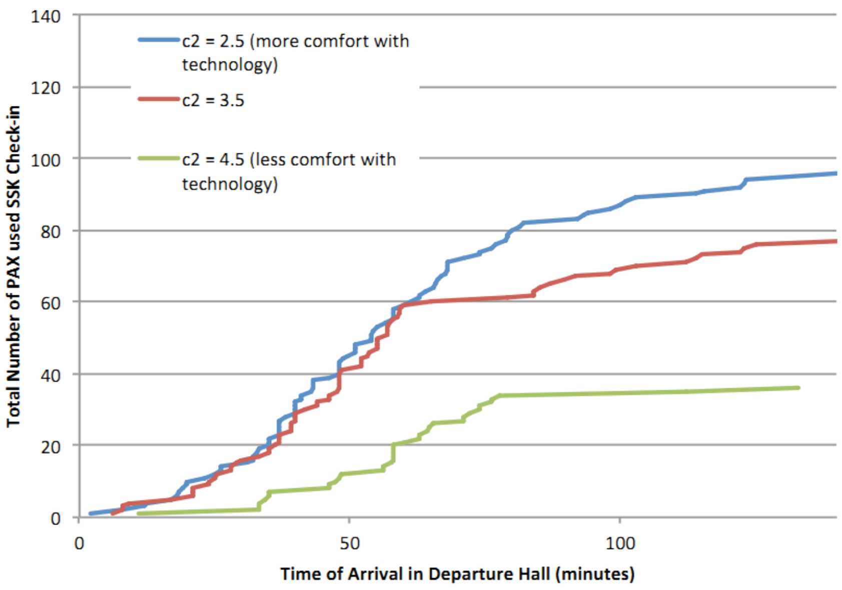



Figure 4-11: Demonstration of variation of comfort with technology on SSK utilisation

## 4.3 CHAPTER SUMMARY

Airport passenger flow modelling is very important for understanding airport level of service based on passenger delays, queue lengths, and number of passengers occupying particular spaces. A number of studies have been completed previously in this area – these have focused on the formalities associated with departures and arrivals, and not on passenger interaction with ancillary facilities such as duty-free shops. In this chapter, the opportunity of research to include discretionary activities was demonstrated to model airport system.

*Advanced traits* of passengers were implemented into the passenger flow simulation in check-in hall. An initial set of advanced passenger traits was proposed, which guide decisions around the utilization of discretionary facilities. The traits were applied 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.

In next chapter, the spatial and temporal criteria for conducting intuitive passenger flow simulation are to be investigated. In order to have a more accurate and meaningful model, the methodology of modelling route-choice decision-making of passenger agents will be reviewed.

# Chapter 5: Approaches for Meaningful Passenger Flow Simulation

This chapter explores the knowledge and methods for capturing real scenarios of passenger flow and individual behaviours. The airport terminal environment is a dynamic facility to cater for passengers. The dynamic capacity is classified as sustained and maximum dynamic capacity respectively. The proposed simulation outcomes are presented with accompanying explanation of spatial and temporal criteria, which are used for estimating passengers' experience and service standard in airport terminals. Included in this chapter are probability graphical models, which are presented here to demonstrate their capabilities and advantages as they will be utilised later in the thesis to model various likely route-choice activities of passengers. Since sophisticated small-scale pedestrian activities cannot be modelled practically at this moment, the method of estimating the probabilities of passengers sequentially choosing targets to walk to is demonstrated aiming to accomplish route-choice decision-making of passengers. The initial results of the simulation experiment are discussed in the light of what is already known about airport operational regulation and criteria around passenger activities. So as to have intuitive and meaningful passenger flow simulation experiments, this chapter presents the spatial and temporal criteria for the proposed agent-based passenger flow simulation experiments. Probability graph models for devising the route-choice decision-making model are also reviewed.

## 5.1 OUTLINE OF THE PASSENGER FLOW SIMULATION

The results of the previous pilot-study were encouraging since they suggested that the discretionary activities of passengers have a significant impact on the overall operation of airport system. The static capacity of an airport terminal represents the storage potential of facility. The dynamic capacity of an airport terminal denotes the ability of facility to process passenger and cargo flows (Brunetta et al., 1999; de Neufvilleand and Odoni, 2003; de Neufvilleand, 2004). It is the central concept for the design of airport buildings, since passengers, bags and cargo always queue for and move through services, namely, check-in, security inspection, customs/immigration, and boarding gate.

Dynamic capacity can be either sustained or maximum capacity. Sustained dynamic capacity refers to maximum flow over a significant period, e.g. a morning arrival period. Maximum dynamic capacity quantifies the maximum flow for a brief period. The criteria of design for dynamic flows regard the trade-off between delays and cost of service and space.

Furthermore, it is difficult to model the exact flows comparing with real passengers' activities, since passengers behave kind of stochastically which cannot be replayed totally as the same. In microscopic, sophisticated small-scale pedestrian activities are proposed to be modelled more practically in future by collecting individual movement data and setting up statistical procedures for calibration (Teknomo et al., 2000). However in this thesis, a method of estimating the probabilities of passengers sequentially choosing targets to walk to is demonstrated as a feasible method to accomplish route-choice decision-making of passengers.

In the field of computer science, probabilistic methods lie primarily in the realm of artificial intelligence. The artificial intelligence community first encountered these methods in the endeavour of building *expert systems*, computerised systems designed to perform difficult tasks, such as oil-well location or medical diagnosis, at an expert level (Russell, 2010). Researchers in this field quickly realized the need for methods that allow the integration of multiple pieces of evidence, and that provide support for making decisions under uncertainty.

In order to satisfy simulation accuracy, the proposed agent-based simulation model has to be verified at first. There are two aspects of verification: easy-to-record constant state of passengers (related to static capacity of an airport terminal) and dynamics of interactions of passengers (related to walking movements). The easy-to-record constant state of passengers refers to both spatial and temporal criteria. The spatial criteria can denote as dimensions of a single passenger, the tolerance distances among passengers and the Level of Service (LOS) published by the international Air Transport Association (IATA) for airport landside terminal service rate evaluation. The temporal criteria represents the average service time at various checkpoints inside landside terminals, arrival time of passengers and average dwell time of passengers within every space of airports.

The dynamics of interactions of passengers refer to physical reactions of passengers' walking capability and cognitive criteria of passengers to make route-choice decisions. To tackle this sort of uncertainty issue, Bayesian networks provide a feasible tool. Bayesian Networks is a graph model. It shows clear causal relationships among significant factors or nodes. To execute a decision, Bayesian Networks can be extended to *Influence Diagram* by including Utility and Decision portions. Probability graph models are used for devising the model of route-choice decision-making of passenger agents.

## 5.2 CONSTANT STATES OF PASSENGERS

### 5.2.1 Spatial criteria

The space occupancy of a single passenger is regarded as two parts. The first one is the static dimensions of a single passenger. It has be found that the average body depth is 33cm and shoulder breadth is 58cm (Fruin, 1972). The average male human body occupies an area of approximately 0.14 square metres. In order to make physical contact with others avoidable, minimum desirable occupancies range between 0.47 and 0.93 $m^2$ per person.

The other aspect is the dimensions among passengers for comfortable movement. The lateral space is between 71 to 76 cm and the longitudinal spacing for walking is from 2.5 to 3 m (Fruin, 1972). A minimum personal area of 1.9 to 2.8 $m^2$

per person can then be calculated for relatively unimpeded walking in groups on level surfaces. In order to attain normal walking speeds and to avoid conflicts with other passengers, the individual area occupancies would be at least 3.3 $m^2$ per person.

Level C Level E

Figure 5-1: Scenario comparisons of Levels C and E of IATA LOS Space Standards (de Neufville, 2003)

In addition, for passengers who are being processed through airport facilities in particular, desirable dimensions of passengers in queuing spaces have to be considered as well. The spacing between people in linear queues is generally 48 to 50 cm and the recommended lateral single-file width for railings or other dividers is 76 cm.

Table 5-1: IATA LOS Space Standards for airport passenger terminal based on busy hour ($m^2$/pax) (IATA LOS Space Standards, old version: Airport Development Manual, 8th ed., 1995)

| ***Level of Service*** | ***A*** | ***B*** | ***C*** | ***D*** | ***E*** |
|---|---|---|---|---|---|
| Check-in Queue | 1.8 | 1.6 | 1.4 | 1.2 | 1.0 |
| Wait/Circulate | 2.7 | 2.3 | 1.9 | 1.5 | 1.0 |
| Hold Room | 1.4 | 1.2 | 1.0 | 0.8 | 0.6 |
| Bag Claim Area | 2.0 | 1.8 | 1.6 | 1.4 | 1.2 |
| Government Inspection | 1.4 | 1.2 | 1.0 | 0.8 | 0.6 |

For the airport terminal environment where passengers are present, the International Air Transport Association (IATA) has published Space Design Standards based on a Level of Service (LOS) concept (de Neufville, 2003), where A is Excellent. Level F is the point of system breakdown or congestion. These standards have been adopted for terminal planning and are shown at Table 5-1. Level C is regarded as the standard minimum quality of service. An ordinary airport usually chooses Level C for planning purposes. However, more space will be needed for movement if passengers are with bags. Figure 5-1 shows the example scenarios of Level C and E.

Table 5-2: IATA LOS Space Standards (New version: Airport Development Manual, 9th ed., 2004)

<table>
<tr><td rowspan="6">Check-in Area</td><td rowspan="2">Row width</td><td rowspan="2">Carts bags</td><td colspan="5">Square meters ($m^2$) / Passenger for Level of Service</td></tr>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td></tr>
<tr><td>1.2m</td><td>few</td><td>1.7</td><td>1.4</td><td>1.2</td><td>1.1</td><td>0.9</td></tr>
<tr><td></td><td>more</td><td>1.8</td><td>1.5</td><td>1.3</td><td>1.2</td><td>1.1</td></tr>
<tr><td>1.4m</td><td>high</td><td>2.3</td><td>1.9</td><td>1.7</td><td>1.6</td><td>1.5</td></tr>
<tr><td></td><td>heavy</td><td>2.6</td><td>2.3</td><td>2.0</td><td>1.9</td><td>1.8</td></tr>
<tr><td rowspan="4">Wait/Circulate</td><td colspan="2">Location</td><td>Carts</td><td colspan="2">Space $m^2$/pax</td><td colspan="2">Speed m/sec</td></tr>
<tr><td colspan="2">Airside</td><td>None</td><td colspan="2">1.5</td><td colspan="2">1.3</td></tr>
<tr><td colspan="2">After check-in</td><td>Few</td><td colspan="2">1.8</td><td colspan="2">1.1</td></tr>
<tr><td colspan="2">Departure area</td><td>Many</td><td colspan="2">2.3</td><td colspan="2">0.9</td></tr>
<tr><td rowspan="3">Hold Rooms</td><td colspan="2" rowspan="3">Assumes 1.7 $m^2$/pax, 1.2 $m^2$/standee</td><td colspan="5">Maximum Occupancy Rate (% of Capacity)</td></tr>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td></tr>
<tr><td>40</td><td>50</td><td>65</td><td>80</td><td>95</td></tr>
<tr><td rowspan="3">Bag Claim Area</td><td colspan="2" rowspan="3">Assumes 40% of passengers use carts</td><td colspan="5">Square meters ($m^2$) / Passenger for Level of Service</td></tr>
<tr><td>A</td><td>B</td><td>C</td><td>D</td><td>E</td></tr>
<tr><td>2.6</td><td>2.0</td><td>1.7</td><td>1.3</td><td>1.0</td></tr>
</table>

The spatial allocation required for a space or process can be determined by a formula (de Neufville, 2003),

$$Area = [ArrivalRate(t) - DepartRate(t)] \times SpaceStd(m^2) \times DwellTime, \qquad (5\text{-}1)$$

$$DepartRate(t) = NumCounters \times ProcessRate(t), \qquad (5\text{-}2)$$

where $ArrivalRate(t)$ denotes a distribution of the number of passengers who go to a space or a process point along a time period. Similarly, $DepartRate(t)$ represents a distribution of the passengers who depart from the space or the process point. It is the sum of $ProcessRate(t)$ at all single counters, where $ProcessRate(t)$ is the processing time at each counter.

A simple example around this is: What space is required for passport inspection of 2000 passengers per hour when maximum queuing time is 20 minutes, where it has 10 counters and processing time at each counter is 71 second per passenger? The space required is calculated as,

$$Area = \left[2000 - 10 \times (\tfrac{3600}{71})\right] \times (1.0) \times \left(\tfrac{1}{3}\right) = 498\, m^2, \qquad (5\text{-}3)$$

A recommended Arrival Rate of passengers is also calculated, when the space or processing area is fixed, by selecting an IATA LOS space standard of Level C and substituting it into Equation 5-4,

$$ArrivalRate(t) = \frac{Area}{SpaceStd(m^2) \times DwellTime} + DepartRate(t). \tag{5-4}$$

On the other hand, the *Flow* standard is defined as, in a meter distance, the numbers of passengers passing through per minute (de Neufville, 2003). In Table 5-3, the Level of Service standards of passenger flow are defined in terms of Persons· Meter/Minute (PMM).

Table 5-3: Flow standards

| *Type of Passageway* | *Level of Service Standard* | | | | | |
|---|---|---|---|---|---|---|
| | A | B | C | D | E | F |
| Corridor | 10 | 12.5 | 20 | 28 | 37 | More |
| Stairs | 8 | 10 | 12.5 | 20 | 20 | More |

Figure 5-2 shows the level of service diagram for passenger flows. Assumptions of flow standards include two factors: Space per Person and Walking Speed.

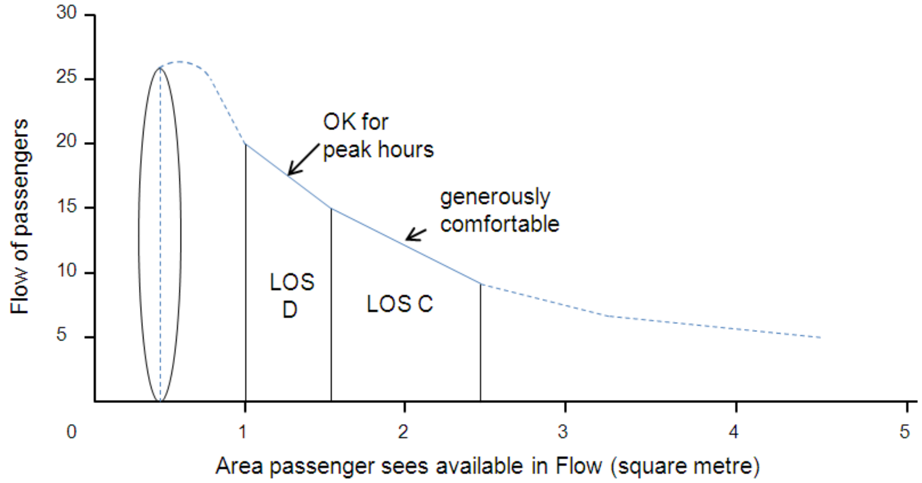



Figure 5-2: Level of service diagram for passenger flows (de Neufville, 2003)

### 5.2.2 Temporal criteria

The average time passengers spend at both standard checkpoints and ancillary facilities are attained by surveys executed at an airport in Australia (Airports of the Future project, QUT). Dwell time is the average time a person spends in a particular space or process. To some extent this help determine capacity of any space or process. When a passenger leaves a space, another passenger can then use it. As passengers move faster, the dwell time would be shorter and more passengers can use the space. The data of average dwell time distributions are selected and calibrated in Table 5-4.

Table 5-4: Average dwell time that passengers spend at standard checkpoints and ancillary facilities

| ***Standard Checkpoints*** | ***Dwell time (minutes)*** | ***Processing time (seconds)*** |
|---|---|---|
| Check-in | 1020s – 1200s | 22s |
| Security | 420s – 1140s | 71s |
| Customs | 240s – 300s | 17s |
| Departure gate | 1440s – 1980s | 2s |
| **Ancillary facility** | **Dwell time (seconds)** | **Distribution** |
| Shop | 300s – 450s landside | Normal distribution, alpha = 371s |
| | 600s – 750s airside | Normal distribution, alpha = 685s |
| Take-away | 30s – 120s | uniform |
| Café | 1650s – 1750s landside | Normal distribution, alpha = 1709s |
| | 1300s – 1400s airside | Normal distribution, alpha = 1333s |
| Internet | 1600s – 1700s | uniform |
| Restroom/Baby care | 160s – 230s | uniform |
| ATM (cash withdraw) | 60s – 70s | uniform |
| Money exchange | 140s – 190s | uniform |
| Information kiosk | 5s – 60s | uniform |
| Phone booth | 60s – 300s | uniform |
| Prayer room | 780s – 900s | uniform |

With the authentic flight schedules of an airport daily, passenger arrival rate of a certain period of a day can be generated by overlapping the passenger arrival rates of individual flight. The check-in counters normally would close about 30 minutes before departure. Passengers are encouraged to arrive at the airport at least one hour earlier before departure, because there are a series of checkpoints which passengers must pass till prior to arriving at their specific boarding gate and these formalities require certain amounts of time. If it is a busy airport or a typical international airport, passengers must arrive much earlier than expected, just in case crowding and long queues occur.

## 5.3 INTERACTION DYNAMICS OF PASSENGERS

Interaction dynamics of passengers refer to physical rules of passengers' walking capability and mental preferences of passengers to make decision-making of route choices. Regarding mental criteria of passengers, they have rarely been considered. Norling (2004) extended the *belief-desire-intension* (BDI) agent framework to develop a simple approach to integer folk psychology for human modelling. The folk psychological model basically represents the reasoning of what the agent *intending* to do in terms of achieving its *desires*, given its *beliefs* about the world. However, it cannot implement detailed human characteristics for modelling interaction dynamics of pedestrian, since BDI agent framework is not for the purpose in nature. Moreover, mental criteria are hard to verify because human behaviours sometimes are seen as stochastic (Kholshevnikov et al., 2008).

In general, the route-choice decision-making is influenced by both our own knowledge and the attained information of an ambient environment. To tackle this kind of uncertainty issue, Bayesian Networks provide us a feasible tool (see Appendix A for detail). It can show clear causal relationships among significant factors and parameters. To execute the decisions, Bayesian Networks can be extended to *Influence Diagrams* by including Utility and Decision portions (see Appendix B for detail). An agent-decision model is devised so as to carry out the route-choice decision-making of passengers in the simulation.

### 5.3.1 Walking model with physical meaning

There is opportunity for further devised psychological traits of pedestrian to be used to expend the social force model to a more competent model. Modelling the individual movements of pedestrians can provide a description of macroscopic pedestrian flow through a bottom-up approach. It has the advantage of evaluating designs of pedestrian facilities at a more detailed level. Microscopic pedestrian dynamic models can be categorised as the cellular automata models and models in a continuous space (Gershenfeld, 1999; Kirchner, 2004). For cellular automata models, pedestrians are set to be able to occupy a cell at a time and move simply by occupying another cell. Cells are at best assigned with attributes and values, on which pedestrian can act so as to decide which cell to occupy at next. They are not the same physical meaning with real walking behaviours of pedestrians.

Models in a continuous space however can to a large extent reflect realistic walking behaviours of pedestrians. They have different mechanisms to describe the ‘interaction’ between pedestrians. Take an example of the social force model, repulsive and attractive forces are envisaged to impact on the interaction between pedestrians (Helbing and Molnar, 1995). The repulsive and attractive forces have their true physical meaning as keeping *tolerance distance* between other pedestrian and obstacles as well as avoiding collision. Some other models implement a minimum inter-person distance between pedestrians (Thompson and Marchant, 1995) or study the local interaction laws underlying collective crowd dynamics in terms of group density and walking behaviour (Seyfried, 2005; Moussaid et al., 2010).

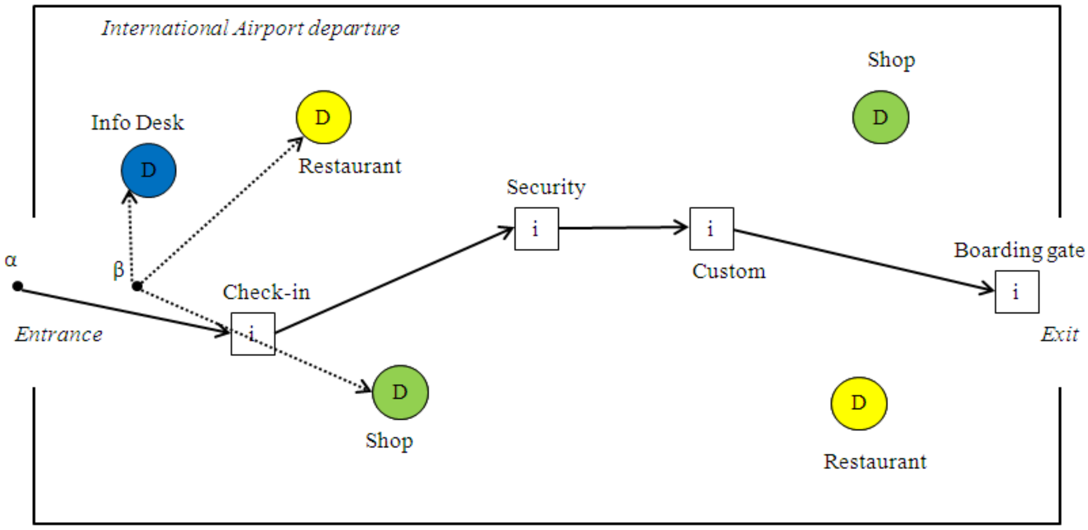



Figure 5-3: Illustration of destination-choice of passengers in the force model

In this research, the social force model is re-developed and calibrated for capturing passenger dynamics in the specific airport terminal scenario. In comparison with Equation 2-6, a new form of social force model is built and calibrated as follows:

$$
\begin{aligned}
\vec{F}_\alpha(t) &= \vec{F}_\alpha^0(\vec{v}_\alpha, v_\alpha^0 \vec{e}_\alpha) && \rightarrow \text{ The initial desired speed and direction of a passenger;} \\
&+ \sum_\beta \vec{F}_{\alpha\beta}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_\beta) && \rightarrow \text{ The tolerance distance with other passenger;} \\
&+ \sum_B \vec{F}_{\alpha B}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_B^\alpha) && \rightarrow \text{ The tolerance distance with obstacles/walls;} \\
&+ \sum_i \vec{F}_{\alpha i}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_i, t) && \rightarrow \text{ Attract force by standard processing check points;} \\
&+ \sum_D \vec{F}_{\alpha D}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_D, t, \Pi) && \rightarrow \text{ Distract force by on-airport discretionary facilities,}
\end{aligned}
\tag{5-5}
$$

where $\Pi$ refers to the type of things which would attract passengers, e.g. Info Desk, restaurants, shops, etc.; and $\vec{r}_\alpha - \vec{r}_i$ is a visual proximity. The revised social force model has similar physical meaning as that in Equation 2-6. However, for airport terminal passenger flow studies in particular, since passengers are goal-directed (either to get on board aircraft or exit from landside of terminal), the influence of attractors and distracters are easily envisaged to represent the attractive and distractive force by standard checkpoints and discretionary facilities respectively (Figure 5-4).

The motion of passengers that determined by the force model is introduced in the instance of Figure 5-4:

1. A passenger has four goals to reach, i.e. check-in, security, customs and boarding gate. Each one stands for an attract force in the fourth item in Equation 5-5. Thus, at *Entrance*, the initial destination is $\vec{r}_{Check-in}$. The passenger normally takes the shortest possible way to reach $\vec{r}_{Check-in}$ without detours. This way has the shape of a polygon with edges, $\vec{r}_{\alpha}^{1} \ldots, \vec{r}_{\alpha}^{n} := \vec{r}_{Check-in}$. If $\vec{r}_{\alpha}^{k}$ is the next edge of this polygon to reach, the desired direction $\vec{e}_{\alpha}(t)$ of motion will be,

$$\vec{e}_{\alpha}(t) := \frac{\vec{r}_{\alpha}^{k} - \vec{r}_{\alpha}(t)}{\|\vec{r}_{\alpha}^{k} - \vec{r}_{\alpha}(t)\|}, \quad (5\text{-}6)$$

where $\vec{r}_{\alpha}(t)$ denotes the *actual position* of passenger $\alpha$ at time *t*.

If a passenger's motion is not disturbed, he will walk towards $\vec{r}_{Check-in}$. With the desired direction $\vec{e}_{\alpha}(t)$ and a certain desired speed $v_{\alpha}^{0}$. Once $\vec{r}_{Check-in}$ is reached, the passenger wants to reach $\vec{r}_{Security}$, then similarly go to $\vec{r}_{Custom}$ and $\vec{r}_{Boarding\ gate}$.

2. The motion of a passenger $\alpha$ is affected by obstacles and other passengers. A passenger would feel uncomfortable when he gets too closer to a strange person. It is assumed, therefore, that he may react into a *repulsive effect* and maintain a *tolerance distance* with others. The results in repulsive effects of other passenger $\beta$ can be represented by vectorial quantities,

$$\vec{f}_{\alpha\beta}(\vec{r}_{\alpha\beta}) := -\nabla_{\vec{r}_{\alpha\beta}} \mathrm{V}_{\alpha\beta}[b(\vec{r}_{\alpha\beta})]. \quad (5\text{-}7)$$

The repulsive potential $\mathrm{V}_{\alpha\beta}(b)$ is a monotonic decreasing function of *b* with equipotential line having the form of an ellipse that is directed into the direction of motion (Helbing and Molnar, 1995). *b* denotes the semi-minor axis of the ellipse and is given by,

$$2b := \sqrt{(\|\vec{r}_{\alpha\beta}\| + \|\vec{r}_{\alpha\beta} - v_{\beta}\Delta t\vec{e}_{\beta}\|)^2 - (v_{\beta}\Delta t)^2}, \quad (5\text{-}8)$$

where $\vec{r}_{\alpha\beta} := \vec{r}_{\alpha} - \vec{r}_{\beta}$. $s_{\beta} := v_{\beta}\Delta t$ is of the order of the step width of passenger $\beta$.

$$\vec{F}_{\alpha B}(\vec{r}_{\alpha B}) := -\nabla_{\vec{r}_{\alpha B}} U_{\alpha B}(\|\vec{r}_{\alpha B}\|), \quad (5\text{-}9)$$

represents the repulsive force evoked by obstacles. $U_{\alpha\beta}(\|\vec{r}_{\alpha B}\|)$ is monotonic decreasing potential.

3. Passengers are sometimes distracted by other on-airport facilities, i.e. shops, restaurants and Info desk. These *distract force* at places $\vec{r}_D$ can be modelled by monotonic increasing potential $\mathrm{W}_{\alpha\mathrm{D}}(\|\vec{r}_{\alpha D}\|, t)$,

$$\vec{f}_{\alpha D}(\|\vec{r}_{\alpha D}\|, t) := -\nabla_{\vec{r}_{\alpha D}} \mathrm{W}_{\alpha\mathrm{D}}(\|\vec{r}_{\alpha D}\|, t), \tag{5-10}$$

where the attractiveness $\|\vec{f}_{\alpha D}\|$ is usually decreasing with time *t* because boarding time is impending and the interest to use discretionary facilities is declining. In addition, in order to take this effect of preference into account, the utilities of passenger utilising a certain type of discretionary facilities (Info desk, shops and restaurants) is presented as *Π*. The distract force can be given by,

$$\vec{F}_{\alpha D}(\vec{e}_\alpha, \vec{r}_\alpha - \vec{r}_D, t, \Pi) = \Pi \cdot \vec{f}_{\alpha D}(\vec{r}_\alpha - \vec{r}_D, t). \tag{5-11}$$

The revised social force model reflects major motion function. Numerical parameters for a simulation based on the force model are summarized in Table 5-5. For simplicity, the dimension of the simulation layout is as the same as that in Figure 5-4. The numerical values are illustrative. Simulation focuses on a period of T = 5 minutes (300 seconds). The distract force are set to be zero at time *t*=3 minutes. It is assumed that passengers are about to boarding and have no distraction by discretionary facilities, i.e. Info desk, shops and restaurants. Figure 5-4 shows the simulation scenario. Passengers are simply represented as black circles. The back circle at Entrance was chosen to show the next destination to which it is about to go at the time step, which represents a passenger has the initial goal, i.e. Check-in.

Table 5-5 Numberical parameters for a simulation of the force model

| ***Numerical parameters*** | ***Indications*** | ***Values and distributions*** |
|---|---|---|
| $v_\alpha^0$ | Desire speed | Gaussian distribution: mean=1.34$ms^{-1}$, standard deviation$\sqrt{\theta}$=0.26$ms^{-1}$. |
| $\vec{v}_\alpha$ | Actual speed | $v_\alpha^0 \vec{e}_\alpha(t)$ |
| $\mathrm{V}_{\alpha\beta}(b)$ | The repulsive potential | $V_{\alpha\beta}^0 e^{-b/\sigma} = 2.1e^{-b/0.3}$ |
| $U_{\alpha B}(\|\vec{r}_{\alpha B}\|)$ | The repulsive potential | $U_{\alpha B}^0 e^{-\|\vec{r}_{\alpha B}\|/R} = 10e^{-\|\vec{r}_{\alpha B}\|/0.2}$ |
| $\mathrm{W}_{\alpha\mathrm{D}}(\|\vec{r}_{\alpha D}\|, t)$ | The distractive potential | $W_{\alpha D}^0 e^{-\|\vec{r}_{\alpha D}\|/R} \cos[\varphi(t)] = 6.1e^{-\|\vec{r}_{\alpha D}\|/0.2} \cos\left[\min\left(\frac{\pi \cdot t}{360}, \frac{\pi}{2}\right)\right]$ |
| $\Delta t$ | Time step | 2s |
| Π | Distraction utility | Uniform (0,1) |

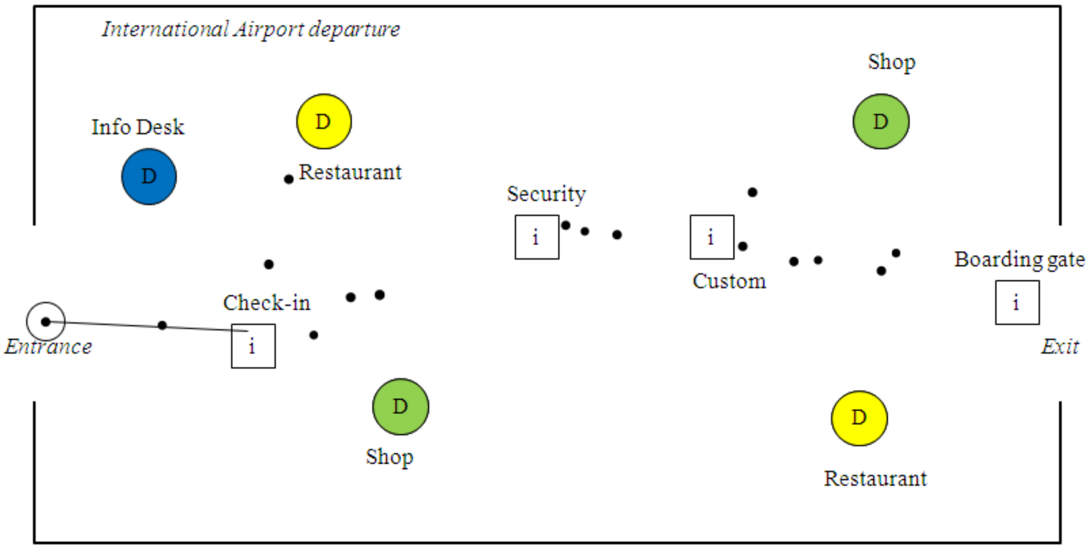



Figure 5-4: Screenshot of the force-based model simulation

The benefit of the force-based model is that it is capable to model the localised motion and interactions of passengers. The goal-directed walking activities of passengers by this force-based model have intuitive physical meaning and seem realistic. However, in the aspect of distraction activities at the three places, i.e. Info desk, restaurants and shops, they are hardly meaningful with respect to real distraction scenarios. It is usually the case that passengers who have certain psychological preference would use one of the discretionary facilities. For example, a passenger who is very hungry would buy a food before he processes Check-in. Clearly the localised motion model cannot tackle real psychological route-choice decision-makings.

Although pedestrian walking behaviour is difficult to study due to the complexity, modern computing technologies are able to provide feasible tools to tackle it. By capturing each frame of digital cameras, the dynamics interactions of pedestrian walking between speed and density can be calibrated, distance. With advanced programming language, the local laws of interactions between pedestrians can be modelled in detailed level. Graphical techniques enable us to simulate pedestrian flow in real-time. All these make models of pedestrian dynamics be more intuitive and realistic than before.

Validation of microscopic models can be promising in terms of authentic by the help of computing technologies. Usage frequency on walking floor and dwell time of pedestrians at a space, among other outcomes of pedestrian flow models, is able to be captured with a comparison with true scenarios.

### 5.3.2 Theory of route-choice decision making

At the initial work by Helbing and Molnar (1995), they agreed that behaviour change of a pedestrian is due to the psychological/mental processes. The psychological process is a course through *Information processing* (i.e. Perception of the environment and Personal interests) to the *Motivation to act*. Similarly, it is feasible to deliver an idea of passengers travelling within airport terminals (Figure 5-5).

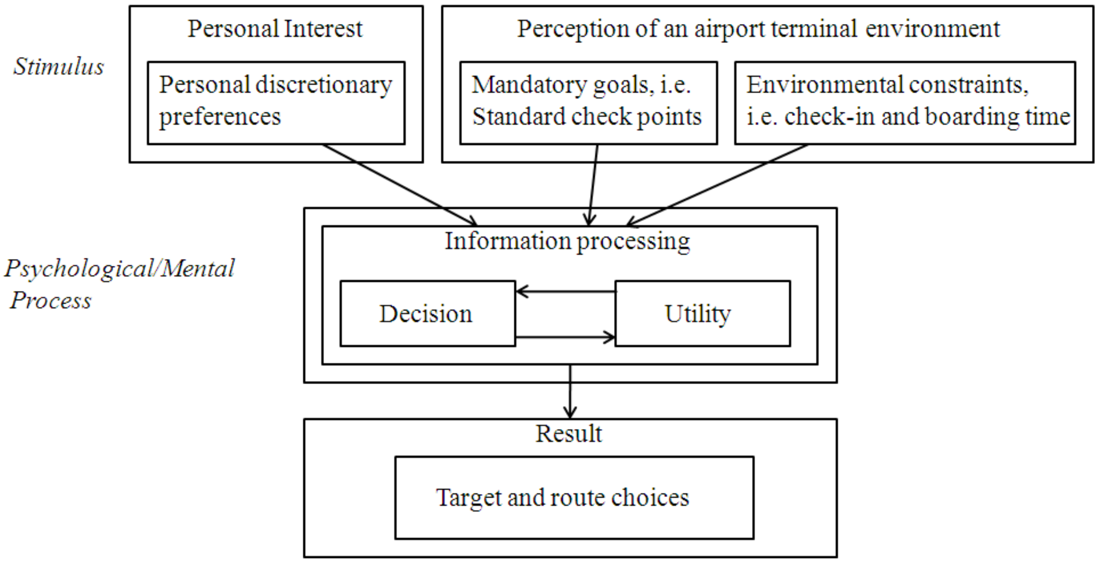



Figure 5-5: Schematic representation of processes leading to route-choice decisions

Passenger target and route choices within an airport terminal are conceptualized as: passengers arrive at entry points – either arrival entrance or touch-down aircraft in terms of outbound and inbound passengers respectively. Then they are faced with the problem of choosing a number of destinations in sequences, given their decision to utilise sequential checkpoints as well as a set of discretionary facilities, i.e. restaurants, café, duty-free shops, or waiting lounge (to name a few). Passengers would select different routes to travel through the terminal for multiple purposes.

The choice itself is regarded as the result of a decision-making process through which passengers evaluate each of large number of choice alternatives on the basis of a set of attributes relevant to their decision-making task and select the alternative that receives the most optimal outcomes. The set of attributes is assumed to consist of both local and nonlocal attributes. Local attributes stand for basic traits of passengers, i.e. travel class, frequency of travel, gender, age, nationality and walk speed. Nonlocal attributes are other attributes related to *Advanced Traits of Passengers* (Chapter 4), i.e. mental preferences of passengers of using different sets of on-airport facilities, and environment factors, e.g. flight time and maximum walking distance of a passenger.

There are also some scenario factors of experiment that need to be considered in a passenger flow simulation. Flight time is the scheduled departure time of flights at an airport. Maximum walking distance of a passenger denotes the longest tolerant distance a passenger would walk continuously without rest. Since airport are becoming larger than before due to high growth in the couple of decades, walking distances from entry to exit gates inside a terminal usually are quite far. Hence, it is a significant factor which has impact on experiences of passengers using an airport.

Suppose now that passengers enter in an airport terminal, they would select the first target. They could go directly to checkpoints or perform other activities, i.e. buying a coffee. It is the first stop in the travel and passengers make their decisions for which target to go. The stop is called as a decision point. It is also hypothesised that the choice of the next target is a result of an evaluation – maximising process in which passengers trade off the local and non-local attributes of potential choice alternatives and arrive at a decision. This process is assumed to continue until all decision points have been traversed.

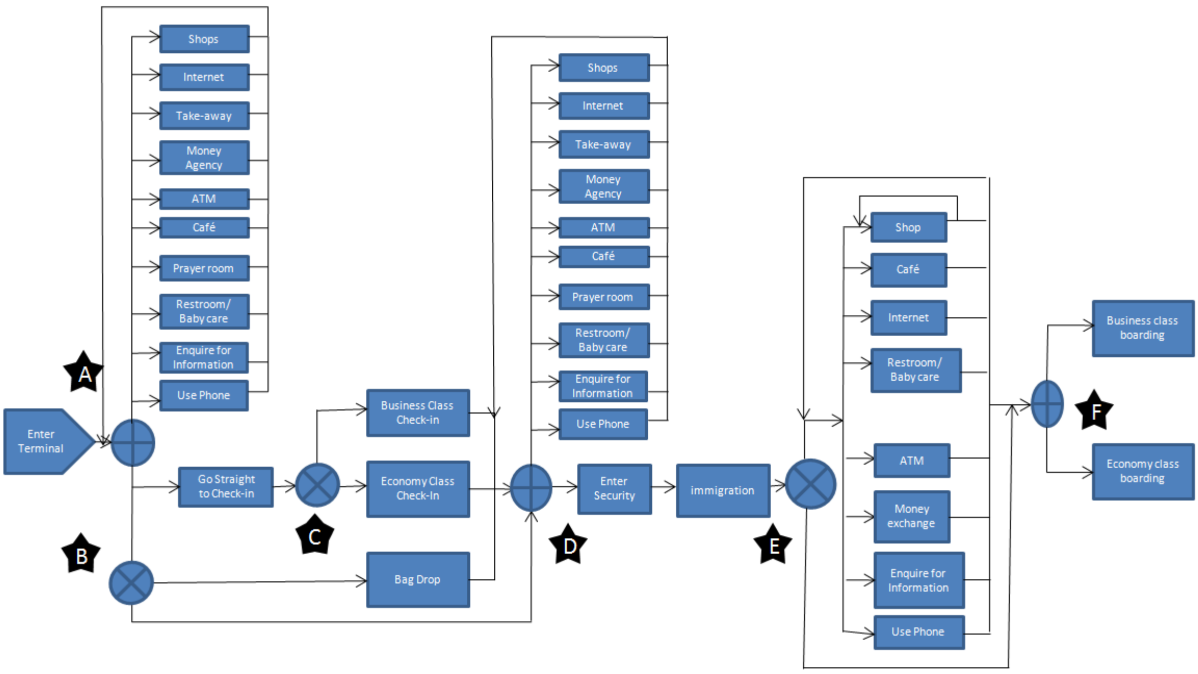



Figure 5-6: Outbound passenger flowchart

Figure 5-6 illustrates the decision points diagram for outbound passenger flow. There are at least six key decision points along the whole outbound process. At each decision points (stop), passengers themselves have to infer/deduce a maximum utility by potential choice alternatives and make the most rational choice at the decision point. Therefore, the target choice process can be regarded as a multistep decision-making process in which utilities are sequentially maximised.

The result of the target choice process is a set of targets where the preferences of passengers are fulfilled and satisfied. Then, the route choice process is that passengers choose a route that connects two successive targets in a terminal from among all possible routes. In this sense, route choice is assumed as the result of a decision-making process in which passengers integrate their utilities, defined on the attribute levels of the choice alternatives, into some overall utility measure and then choose the alternative that receives the highest utility.

Finally, terminal travel itself would give passengers stochastic attractions, since airport terminals are also designed for catering for different stakeholders as well, e.g. retailers and airlines. That is, additional targets may be visited by passengers along their routes. It is regarded as conditional stochastic stops upon passenger targets and route choice behaviour. All together, the regular stops and stochastic stops consist of major significant route choice activities.

Thus, passenger choice behaviour inside airport terminal building can be represented as a multiple purpose travel. It consists of both intended and stochastic stops. The intended stops are assumed to be the result of a multistep target-choice decision-making process, in which utilities are sequentially maximised. The stochastic stops are a function of route-choice behaviour, which, in turn, is conditional upon passengers' target-choice. Therefore supposed models should consist of target-choice, route choice and stochastic stops.

### 5.3.3 Devise graphical model

Target choice, route choice and stochastic stops are all random events to some extent, though a utility evaluation method can be envisaged to attain a maximum probability of an alternative act. So as to tackle randomness of a complex system, normally tools that can facilitate decision-making processes are utilised, i.e. probabilistic graphical models. Systems with uncertainty can be solved by the help of Bayesian networks in terms of inferring the probabilities of every child node (Heckerman and Wellman, 1995). In this case, passengers who travel through airport terminals can be classified into several categories in the light of purposes of using the airport terminals.

Complex systems can be characterised by the presence of multiple interrelated aspects, many of which relate to the reasoning task (Koller and Friedman, 2009). By discovering a complex system, it always has limited observation and limited knowledge or even with noise interrupt. For instance, pedestrian route-choice is almost impossible to be accurately predicted. So, the task is to reason probabilistically about values of one or more of the variables, given observation about some others. In order to do this, principle probabilistic reasoning is applied. Foremost, a *joint distribution* over the space of possible assignments to some set of random variables need to be constructed. This type of model allows us to answer a broad range of interesting queries. For example, observation can be made that a variable $X_i$ take on the specific value $x_i$ , and ask, in the resulting *posterior distribution*, what the probability distribution is over values of another variable $X_j$.

The framework of probabilistic graphical models provide a mechanism for exploiting structure in complex distributions and describing them compactly, and in a way that allows them to be constructed and utilised effectively. Probabilistic graphical models use a graph-based representation as the basis for compactly encoding a complex distribution over a high-dimensional space. In this graphical representation, the nodes (or ovals) correspond to the variables in the domain, and the edges correspond to direct probabilistic interactions between them.

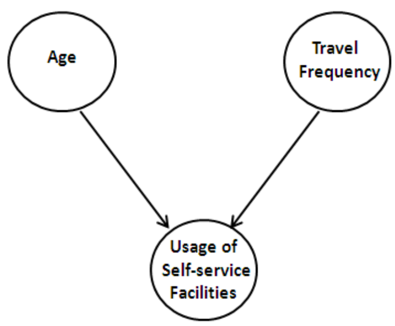



Figure 5-7: Bayesian networks of usage of self-service facilities

There is a dual perspective that one can use to interpret the structure of this graph. From one perspective, the graph is a compact representation of a set of *independencies* that hold in the distribution: these properties take the form X is independent of Y given Z, denoted (X⊥Y|Z), for some subsets of variables X, Y, Z.

In Figure 5-7, the distributions encoding the beliefs about a passenger use self-service facilities may satisfy the conditional independence (Age ⊥ Travel Frequency | Usage of Self-service Facilities).

The other perspective is that the graph defines a skeleton for compactly representing a high-dimensional distribution: Rather than encoding the probability of every possible assignment to all of the variables in the domain, the distribution can be “break up” into smaller *factors*, each over a much smaller space of possibilities. It is then able to define the overall joint distribution as a product of these factors.

It turns out that these two perspectives – the graph as a representation of a set of *independencies*, and the graph as a skeleton for factorizing a distribution – are, in a deep sense, equivalent. The independence properties of the distribution are precisely what allow it to be represented compactly in a factorized form. Conversely, a particular factorization of the distribution guarantees that certain independencies hold.

There are two families of graphical representations of distributions. One is called Bayesian Networks, which uses a directed graph (where the edges have a source and a target), as shown in Figure 5-7. The second one is Markov networks (Asahara et al., 2011), which uses an undirected graph. It can also be viewed as defining a set of independent assertions or as encoding a compact factorization of the distribution. Both the representations provide the duality of independencies and factorization, but they differ in the set of independencies they can encode and in the factorization of the distribution that they induce.

These three components – representation, inference, and learning – are critical components in constructing an intelligent system (see Appendix A). A declarative representation is needed as a reasonable encoding of the world model. This representation is also to be able to be used effectively to answer a broad range of questions that are of interest. And this distribution is needed to be acquired as well, combing expert knowledge and accumulated data. Probabilistic graphical models are one of a small handful of frameworks that support all three capabilities for a broad range of problems.

### 5.3.4 Utilities and decisions

The task of simply reasoning under uncertainty – reaching conclusions about the current situation from partial evidence – is now moved to the task of deciding how to act in the world. In a decision-making setting, an agent has a set of possible actions and has to choose one of them. Each action can lead to a specific one of several outcomes, which the agent can prefer to different degrees. Most simply, the outcome of each action is known with certainty.

In this case the agent must simply select the action that leads to the outcome that is most preferred. Even this problem is far from trivial, since the set of outcomes can be large and complex and the agent must weigh different factors in determining which of the possible outcomes is most preferred. For example, when deciding which target to go to, a passenger agent at a decision point inside airport terminal must take into consideration the time left till boarding, whether use self-service kiosks or not, go to standard checkpoints, such as check-in, security inspection, customs, boarding gate, immigration and bag claim, or discretionary areas, such as restaurant/café, duty-free shops and lounges. All these factors are related to the mental preferences of target and route choices of passengers. Deciding which of the possible configurations a passenger mostly prefers can be quite difficult.

In the decision-making task the outcome of an action is not fully determined. Both the probabilities of various outcomes and the preferences of the passenger agent corresponding to these outcomes have to be taken into account. Preferences to complex scenarios involving probability distributions over possible outcomes must be ascribed. The framework of *decision theory* provides a formal foundation for this type of reasoning. This framework requires that numerical utilities to the various possible outcomes are assigned, encoding the agent's preferences. *Maximum expected utility* is the foundation for decision making under uncertainty. It is the basic principle of decision-making under uncertainty.

Structured representations for decision-making problems and algorithms exploit this structure when addressing the computational task of finding the decision that maximized the expected utility. A *decision tree* is a simple yet intuitive representation that describes a decision-making situation in terms of the scenarios that the decision maker might encounter. It represents different scenarios that might be encountered by the decision maker in the context of a particular decision problem.

Decision trees provide a structured representation for complex decision problems, potentially involving multiple decisions, taken in sequence, and interleaved with choices of nature. However, they are still instances of the *abstract framework*. Specifically, the outcomes are the leaves in the tree, each of which is annotated with a utility; the set of agent actions is the set of all strategies; and the probabilistic outcome model is the distribution over leaves induced by nature's random choices given a strategy (actions) for the agent.

The decision-tree representation is a significant improvement over representing the problem as a set of abstract outcomes; however, much of the structure of the problem is still not made explicit. Some interactions between these different parameters are obscured by the decision-tree representation.

Decision trees and the influence diagrams are complementary views of a decision problem: Decision trees display the set of alternative values for each decision and chance variable as branches coming out of each node. The influence diagram shows the dependencies among the variables more clearly than the decision tree. The decision tree shows more details of possible paths or scenarios as sequences of branches from left to right. The influence diagram is a much more compact representation.

## 5.4 CHAPTER SUMMARY

This chapter began by introducing the dynamic capacity of airport terminals. The spatial and temporal criteria are as the empirical basis for this thesis. Spatial criteria demonstrate the correlation between space utilisation by passengers and service evaluation. Time criteria consider realistic dwell time of passengers at various on-airport facilities.

The dynamics of passengers in terms of airport terminal scenarios were presented. Regarding the particular passenger flow scenario in airport, the specific force-based model for localised interactions of passengers was addressed. Devised theory of route-choice decision-making of passengers was also illustrated to show the approach to conduct choosing alternative targets for passenger agents. Furthermore, the two probability graphical models – Bayesian networks and Influence diagram – were investigated and demonstrated the capability and advantage to solve complex uncertainty problems.

In summary, the chapter outlined the concrete procedures of conducting meaningful passenger flow simulation in airport terminal scenarios. The objective is to have passenger agents in the proposed model behave autonomously and to some degree generate realistic passenger flow context. Thus, airport operational criteria from passenger perspectives and personal route-choice decisions should be integrated within the system model for the sake of modelling intuitive and meaning passenger flows. It would be extremely promising to be able to combine sufficient details from the both aspects.

Therefore, the following chapters of this thesis will apply airport capacity criteria to calibrate the utilisation of on-airport felicities by passengers in simulations. Probabilistic graph models are to be implemented into the agent decision making model for passengers in next chapter.

# Chapter 6: Tactical Routing Choices of Passenger Agents

It is hard to predict passenger activities in psychological, environmental and social impact aspects, due to mental criteria of human are hard to verify. In order to model intuitive passenger flows inside airport terminals, tools of artificial intelligence are to be used to evaluate uncertainties of human psychological preferences and to facilitate executing the agent-based model of passenger flows. This chapter explores a method for accomplishing tactical route-choice decisions of passengers by using probabilistic graph models.

The probabilistic graph models used in the thesis are *Bayesian networks* and *Influence diagrams*. Bayesian networks captures probabilities of passengers choosing different targets or routes when they are travelling through airport terminals. Influence deprograms is an expansion of the devised Bayesian networks. With incremented *Utility* and *Decision* nodes, influence diagram can finalise a routing decision through the utility evaluation. All information and evidence which facilitate inference functions in both *Bayesian networks* and *Influence diagrams* are *basic/advanced traits* of passengers and devised utility table respectively.

Both basic traits and advanced traits devised in Chapter 3 are stored into corresponding nodes of the devised Bayesian networks accordingly. The causal relationships between basic traits and advanced traits are realised in this way: advanced traits are inferred through basic traits with the approach of the devised Bayesian networks. Regarding route choices of passenger agents in the simulation, utility evaluation process is involved in the decision-making process. Influence diagram extended the Bayesian network by adding two other types of nodes – utility node and decision node. Thus, it is feasible to compare a set of target-choices or routing decisions in terms of chance and utility. The results of these probability inferences and utility tests at every decision points are able to provide the ultimate route-choice decisions of a passenger agent during simulations.

## 6.1 DECISION-MAKING STRATEGY OF PASSENGERS

In this thesis, the domain of interest involves passengers entering an airport terminal, travelling through it and exiting. Basically there are two major types of passenger flows inside airport terminals: outbound and inbound. Outbound passenger flow represents that departure passengers enter Check-in hall of an airport terminal, behave some discretionary activities, go through check-in, security and customs checkpoints and get on board. Inbound passenger flow is in similar way, which are illustrated in Chapter 3.

The decision making of passengers making their way through the airport terminal environment is a main concern in the thesis. The system involves an open environment where there are plenty of uncertainty factors which have impact on activities of passengers. Several discretionary targets were located on the way through the airport terminal, such as restaurant, café, duty-free shops and money exchange agency. The airport terminal environment would contain a large number of passengers in the enclosed spaces. Passengers would also have plenty of activities within the enclosed spaces environments, e.g. walking around duty-free shops, queuing at checkpoints and possibly longer stops at restaurants and waiting lounges.

### 6.1.1 Key behaviours of passengers in airport

Several key behaviours of passengers in airport terminals are to be considered in the model. Regarding different categories of passengers in terms of frequent flyer and travel class, passengers would behave differently in both spatial and temporal aspects. Frequent flyers who have travelled through an airport several times would be familiar with the airport (or generally familiar with airports). Thus their activities are performed with greater purpose. The notion of purpose can refer to cognitive or mental map. They know where they are going, how to get there. In contrast, although non-frequent flyer passengers know where they want to go, they are not sure how to get to their targets and have to rely more on way-finding activities. They have a certain possibility of getting lost or at least distracted along the way.

In addition, there are several environment factors which are out of the control of passengers. The first is queuing, an activity very common inside airport terminals. At all checkpoints, passengers have to wait for an action to happen before they can continue. Take check-in for example, they have to wait in a queue to acquire their boarding pass or deliver their checked-in bags, but they have no control over the queue.

The next are temporal constraints (Ronald et al., 2007). The flight leaves at a scheduled time and departing passengers must get on board on time. Passengers for international travel normally arrive at an airport two hours earlier before the boarding time. In contrast, one hour may be enough for passengers who are taking a domestic flight. On the way through an airport terminal, passengers can also behave in wandering mode in discretionary spaces as long as the factor of temporal constraint permits. Otherwise passengers have to proceed to the mandatory checkpoints as quickly as possible.

### 6.1.2 Agent decisions

There are several architectures to model human behaviour, such as the BDI architecture (Norling, 2004). However, they are less informative about the characteristics of a person. More of the basic characteristics of human behaviour a framework includes, more powerful modelling tool it would be, because the model builders could then focus on the domain-specific aspects of the model being built, reducing their overall workload. For passenger agents in particular, agent decisions involve all aspects of psychological, environmental and social factors. In other words, there are a myriad of passenger characteristics that would have impact on routing decisions in airport terminals. According to the devised basic traits and advanced traits of passengers in Chapter 3, *influence diagram* architecture is proposed to be able to model the mental decisions of a single passenger agent. In theory, the supposed agents use a utility-based decision strategy, where decisions are made to maximise the expected utility of the selected course of action.

However, passengers will use different strategies and will act differently even given the same situation. Therefore, capturing a full range of passenger decision making is the first step. In the airport terminal domain, three environmental characteristics are devised to have impact on the decision-making process. They are *Uncertain Dynamic Facilities, Time Stress, Distance Stress*. The three characteristics are important for modelling passenger behaviours inside the environment of airport terminals. *Uncertain Dynamic Facilities* capture the fact that airport terminal environments can change dynamically and contain many uncertain factors that cannot be known exactly during a course of passengers travelling through an airport terminal. For example, the numbers of counters at a checkpoint could change accordingly due to the load of the airport at a given period of time, or a particular facility is open or shut down for catering a certain category of passengers, such as “Smart Gate” in Brisbane international airport, which is a fast self-service customs checkpoint only for Australian and New Zealand citizens.

*Time Stress* represents the temporal constrains discussed previously in Chapter 5. It is assumed that passengers are generally susceptible to distractions during the course of travelling through airport terminals. For example, they would visit shops in duty-free. If time is tight and limited, passengers are less likely to be distracted by other facilities and will simply proceed directly through the mandatory checkpoints as fast as possible so as to not be late. Basically, outbound passengers have to catch up and board the correct flight on time, and inbound passengers would likely want to accomplish all standard checkpoints and claim their bags as quickly as possible.

*Distance stress* denotes the distances passengers within airport terminals can walk at a time before they need a rest. This is particularly the case when passengers are wondering around Duty-free shops. It is intuitive that passengers visit a few shops and then buy a drink and snack and stop at a place, such as waiting lounge.

## 6.2 OVERVIEW OF PASSENGER AGENT DECISION-MAKING

Within current pedestrian models, path evaluation is based on calibration from observed data or on sophisticated but deterministic route-choice mechanisms; there is little open-ended behavioural modelling of human-movement patterns. In order to make human movement simulation more intuitive and realistic, it is necessary to consider dynamic decision-making of path deviation when people are walking in an environment context. This could be based on many factors, e.g. human visual range, sidewalks, signage. People autonomously interact with the environment through certain logic rules which normally are vision-based in reality. In the airport terminal context, humans behave as outbound, inbound or transferring passengers with different initial preferences. Such initial states of human agents together with a devised visual scheme would generate aggregate movement levels very similar to those found in actual contexts. The supposed rules connecting states of human agents and the visual scheme mostly rely on parameters such as destination selection, field of view, and steps taken between decision points.

One advantage of implementing agent-based models for human movement is that, surpassing conventional mathematical analysis, one can simply instantiate a population having some distribution of initial states, e.g. initial knowledge, mental preferences. There is no need to appeal to representative agents in highly stylized ways. Individual agents representing walking humans with initial states are situated in a representation of an environment and interact with the environment and with one another, acting out possible macroscopic emergent behaviours. Agent-based models are “solved” merely by executing it, where results are dynamic for each simulation run.

Autonomous rules regarding the control of individual agents are the key. The supposed passenger agents are autonomous and can walk according to equations of motion and devised decision making processes. The space and time is taken to be continuous. Inside an airport terminal, the assigned states of an agent would change as the space changes as well as the time passes. To consider such changing states, a decision-making graph model is needed, which will take into account all possible factors which influence passengers’ behaviours. The two key behaviours of them are *target* and *route* choices. When agents are non-deterministic, they automatically make decisions according to pre-devised decision-making rules. Basically, such rules of decision are based on facts or psychology or both.

Multi-criteria decision-making is one of the simple decision rules. More advanced multi-criteria decision-making tools include neural networks, genetic algorithms and artificial intelligence. Since the cumulative effects of agent to agent interactions are to be concerned, *influence diagram* suits the proposed agent-based model as decision making tool. *Influence diagram* is the expansion of Bayesian networks. Bayesian Networks will be used here primarily for calculating initial probabilities of walking speed and direction, then to continually update all categories of probabilities based on incoming information about the immediate situation.

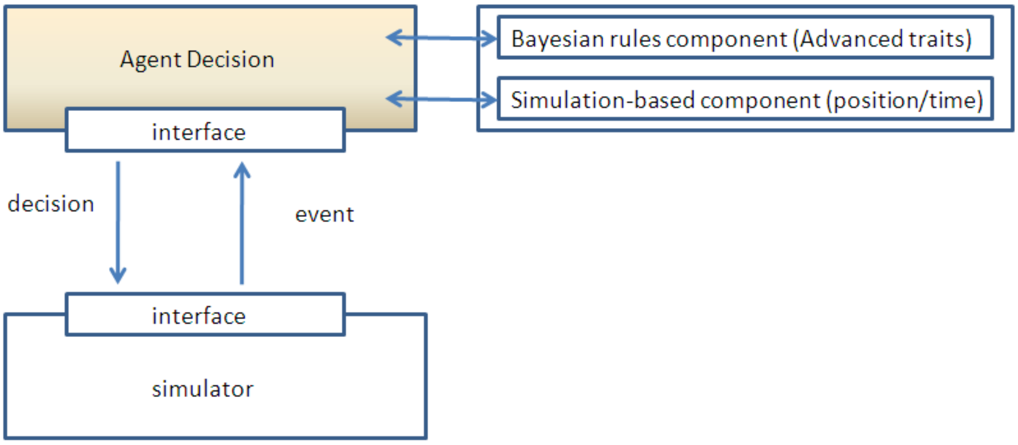



Figure 6-1: Framework of agent-decision model

Figure 6-1 shows the framework for an interface to connect a Bayesian network model with an agent-based passenger flow model. With all the available basic traits of air passengers, a series of beliefs about passengers' psychological preferences can be acquired. Psychological preferences can be encapsulated into the advanced traits, i.e., comfort with technology, willingness to ask for assistance, Need for obtaining foreign currency, desire to shopping and need for cash withdrawal.

Bayesian networks are graphical representations which are useful to visualize the variables in a system and the relationships between them (Rother, 2008). Bayesian networks are one formal framework used to deal with uncertainty. Applying Bayesian Networks to real-world domains requires modelling large, complex, systems. An ordinary BN is made up of ordinary nodes, representing random variables (Korb and Nicholson, 2011). In order to make the probability elicitation task easier and to simplify belief updating, we would like to minimize the number of nodes and parameters. These goals suggest fewer nodes, fewer arcs and smaller spaces. On the other hand, we would have to maximize the fidelity of the model, which sometimes requires more nodes, arcs and states (although excess detail can also decrease accuracy). A trade-off must be made between building a more accurate model and the cost of additional modelling.

In a nutshell, Bayesian networks are used in the thesis to inference the likelihood that passengers autonomously choose to go to preferred targets and decide route choices. Based on the rules set up by Bayesian networks, they give every passenger agent certain intelligence to fulfil its goals. Moreover, utilities that an agent chooses to go to different targets and have identical route choice are incremented on the proposed Bayesian network model. They help finalise detailed decision-making of agents.

### 6.2.1 Categories of air passengers

Basic characteristics of passengers in airport terminals consist of at least seven elements, i.e. age, gender, nationality, travel class, numbers of carried baggage, group size and frequency of travelling through the airport. Passengers would behave differently in the light of such elements. For example, young passengers who travel through the airport more than a couple of times would most possibly use self-service kiosks to proceed through check-in (and other) operations. In contrast, elderly passengers who use the airport for the first time or are not familiar with the airport terminal would most possibly ask airport staff for assistance.

In addition, advanced characteristics are envisaged to represent mental preferences of passengers at every decision point. They can be inferred in the light of basic characteristics of passenger mentioned above. How passengers are likely to behave at every decision point can be accurately attained, as long as categories of advanced characteristics of passengers concluded are enough. The more categories of passengers, the more possible activities they can represent. All these could not even be formulated previously can now be considered and solved by a subjective probability approach to decision processes.

Categories of passengers are devised according to both *basic traits* and the *advanced traits* of passengers. Ten advanced traits are envisaged for the major mental preferences of passengers. They are “Willing ask for help”, “Need cash”, “VIP lounge”, “Relaxation”, “Social connectivity”, “Comfort with technology”, "Desire to shop", "Tax claim", "Religion" and "Level of hunger". Hence ten categories of passengers can be devised. They denote passengers who would behave differently and use different facilities inside airport terminals. Table 6-1 shows the ten categories of passengers. Take the category of "Willing to ask for help (WH)" for instance, passengers who might belong to this category will ask airport or airline staff to assist their travel processes. So, in terms of target and route choices for the dynamic walking behaviour of passengers, facilities like Enquiry Counter and Information Desk are denoted as targets in this case.

Table 6-1: Categories of air passengers

| ***Categories of Passengers*** | ***Activities*** | ***Usage of Facilities*** |
|---|---|---|
| Willing to ask for help (WH) | Inquire and ask for assistance | Enquiry counter, Info Desk |
| Need cash (NC) | Withdraw money | Bank, ATM, money exchange agency |
| VIP lounge (VL) | High level catering | Airline lounge, pet relief area, shower |
| Relaxation (RX) | Have a rest | Seating, baby care room, toilet |
| Social connectivity (SC) | Emails, Phone calls and Social Media | Telephone, Internet access points, |
| Comfort with technology (CT) | Use self-service kiosks | Customer self-service kiosks |
| Desire to shop (DS) | Shopping | Giftware, newsagent, duty-free shops |
| Tax claim (TC) | Claim tax | Tax return |
| Religion (RG) | Pray and meditate | Prayer room, meditation room |
| Hungry and Thirsty (HT) | Buy a drink and a meal | Restaurant, Café, Pub, Fast Food |

(Note: a few facilities such as *Pet relief area* are not compulsory ones in most airports)

With the ten categories of passengers, the general structure of experimental decisions can now be considered. Firstly, passengers need to conclude which categories of the ten it belongs to. Once at a decision point, the current states of a passenger are provided so as to calculate the probabilistic results by using *Bayes' Rule*. The states of information consist of both the basic traits of passengers and airport environmental factors.

Then the corresponding action is executed by the passenger agent. The process relies not only on categories to which the passenger agent belongs, but also on initial states of the passenger agent. It considers *Uncertain Dynamic Facilities*, *Time Stress* and *Distance Stress*. For example, a passenger agent who belongs to "WH" category would not go to *Information Desk* simply because it is not available. Or instead the passenger goes to a restaurant since he/she is in great hunger level. In other words, passengers can be held into several categories at a time, since the devised ten categories are not exclusive. Moreover, the quantification of each category feature is both time-variant and location-variant, and is dependent upon the history of the passenger within the simulation. All probabilities and utilities need to be evaluated so as to decide what action a passenger most likely take.

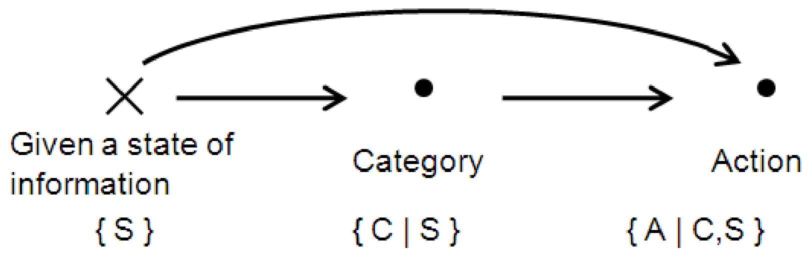



Figure 6-2: Decision tree of the general structure of experimental decisions

Thus every passenger possesses a greatest likelihood value and decides "intelligently" to take a corresponding action "A" from a set of alternatives open within the decision problem. In Figure 6-2, it shows the basic structure of experimental decisions. First a state of information was selected to infer categories out of ten sets of categories. Next, plus considering environmental factors (e.g. *Time Stress*), an action can be decided based on the resultant *category*. The crosses indicate an instantaneous time and location in simulation for passenger agent making route-choice decisions. The dots represent that inferred categories are quantified by chance. It is a basic Bayesian inference mechanism to attain values of probabilities of categories based on the current state of information – basic traits of passengers in this case. The problem for passenger agent is to select the category C and action A that will maximise his expected profit based on prior state $S$. The numbers $\{C|S\}$, $\{A|C,S\}$ are the probabilities to be assigned to the portions of in the decision diagram. $\{A|C,S\}$ is at the command of the decision maker. The agent will find it to their advantage to choose with certainty the category $C$ and action $A$, given the highest expected utility a priori. The theory of expected utility is addressed on section 6.2.3.

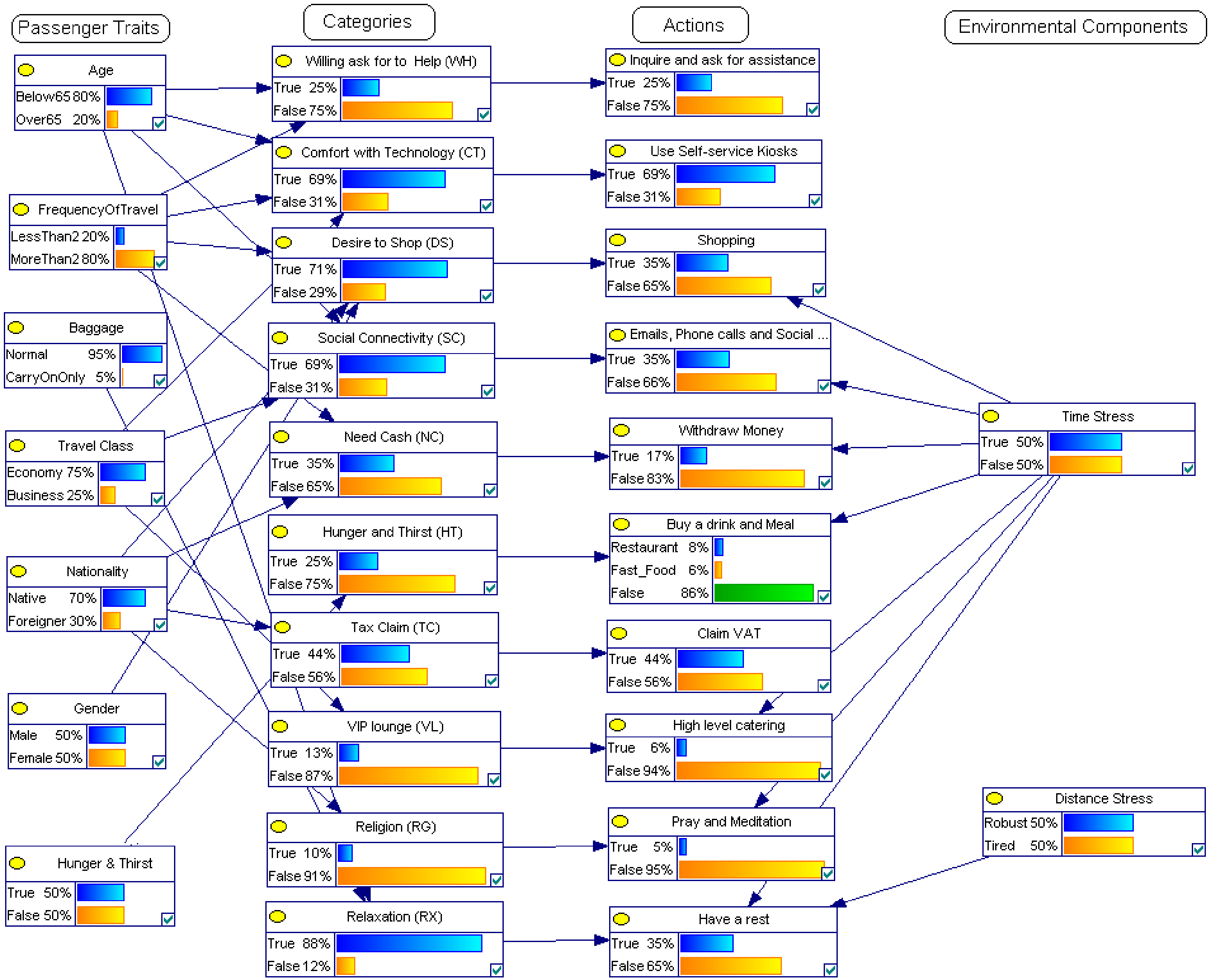



Figure 6-3: State and inference model for passenger agent discretionary activity decision-making

### 6.2.2 Bayesian network decision-making approach

Passenger flows in airport terminals in which the decisions of target choosing and route choices of passengers are often difficult to predict. The phsycological, subjective and social aspects of passengers are complex and it is impossible to account for all this complexity in a decision support tool. This chapter shows how passenger behaviour dynamics can be modelled by using Bayesian network. It provides simple graphical models describing passenger decision variations in relation to personal preferences and environmental events. It can be used for scenario analysis to answer “what-if” and “how” questions. The method aims to be utilised in such areas where empirical data are scarce (as is the case in pedestrian simulation in airport terminals). Experiential knowledge and empirical data where available to accommondate uncertainty can be applied. Figure 6-3 illustrates the passenger discretionary activities decision-making framework by utilising Bayesian network.

Relationships between nodes within a Bayesian network are defined using conditional probability tables (CPT). These CPTs store the probabilities of outcomes under particular scenarios and these probabilities allow uncertainty and variability to be accommodated in model predictions. The probabilities of *basic traits* are possible to be acquired from airlines and airports. Basic information could be found on ticket registration data of passengers and other experiential knowledge, if cooresponding data collections are conducted. However, measured probabilities for proposed passenger categories can only be obtained from long-term studies. Thus, at this stage, in the absence of measured probabilities, subjective probability estimations were obtained from airport corporations and scientists.

The difficulties in populating large probability tables mean that when constructing the cleared passenger agent decision-making Bayesian network, it is necessary to summarize the many factors that influence passenger activities into a few nodes with as few classes as possible. Hence, the Bayesian network modelling approach has similar limitations to other modelling approaches, in that all possible factors that may contribute to outcomes cannot be accommodated.

Databases, scientific literature, and other models can be used to determine the probabilities in a Bayesian network model. Table 6-2 show the Conditional probability table (CPT) for the node “Comfort with Technology” as an example.

Probabilities that passengers belong to "Comfort with Technology" category are related to three factors: *Age*, *Frequency of Travel* and *Travel Class*.

Table 6-2 Conditional probability table for the node "Comfort of Technology"

| *Factors influencing "Comfort with Technology" category* | | | *Probability of belonging to "Comfort with Technology" category* | |
|---|---|---|---|---|
| Age | Frequency of Travel | Travel Class | TRUE | FALSE |
| Below 65 | More than twice | Economy | 95 | 5 |
| | | Business | 100 | 0 |
| | Once or twice | Economy | 10 | 90 |
| | | Business | 60 | 40 |
| Over 65 | More than twice | Economy | 20 | 80 |
| | | Business | 40 | 60 |
| | Once or twice | Economy | 0 | 100 |
| | | Business | 10 | 90 |

Several other uncertain elements which are significant for modelling intuitive passenger flows also need to be included in the agent-based passenger flows model. These elements either are the empirical regulations of the supposed airport terminal environments or are probabilities of route choices which, in deterministic terms, are hard to be verified by basic traits of passengers. However, these elements can be inferred through long terms observations and scientific statistics. For simplicity, only "Pre Check-in" is considered for this regard.

Some intuitive activities of passengers need to be taken into account as well. Most departing passengers who enter into check-in hall of airport terminals will firstly need to be processed at check-in. It is because commonly the more travel experiences a passenger has, the less probability that the passenger will do check-in firstly, as long as there is enough time left for behaving any discretionary activity before Check-in desks are closed. Although the probability of having check-in processing prior to other discretionary activities can be done by inferring in the light of the trait *Frequency of Travel*, some passengers could just prefer to do check-in first, no matter how many times they used the airport. It is purely a personal habit.

### 6.2.3 Influence diagram of agent decision-making

Since passengers can belong to several categories at a time with varying levels of membership, the goal of influence diagrams will be to choose an alternative decision that has the highest expected utility. While *Bayesian networks* allow us to quantify uncertain interactions among random variables and use this quantification to determine the impact of observations, *influence diagrams* allow us to quantify a decision maker's decision options and preferences and use these to determine the optimal decision policy. In order to build a decision model, both the problem and the decision to be made need to be clearly framed.

It is relatively easy for humans to specify elements of decisions, such as available decision options, relevant factors, and payoffs: it is much harder to combine these elements into an optimal decision. Thus a utility model to facilitate the decision making of passenger agents is devised. The model supports a decision by computing the expected utility of each decision alternative. The decision alternative with the highest expected gain is by definition the best probable choice and should be chosen by the decision maker. Bayesian network is extended for a passenger agent's discretionary activity decisions to an influence diagram to guide a passenger agent to execute the most optimal decision.

A passenger agent is initially assigned a set of states. Multiple categories can then be inferred through the initial states for the passenger agent. Given different categories of passengers would carry out different activities, a passenger agent needs to decide when and where he/she should choose which alternative decision that best for him/her. That is, the utilities for each decision which could be selected needs to be evaluated.

The diagrams are built for both inbound and outbound passengers. Take international outbound passengers for example, the major processing points are Check-in, Security Inspection and Immigration checks. As for major Australian airports, there are a number of areas in which passengers can undertake discretionary activities between the necessary formalities, including duty-free shopping, buying a drink, making phone calls and Internet access. The parallel decisions are located in two major portions, from "Enter Terminal" to "Security" and also from "Immigration" to "Passenger Embarkation". By investigating the first portion, possible parallel discretionary activities are "Shopping", "Emails, Phone calls and Social Media", "Buy a drink and a meal" and "Withdraw Money".

The Influence diagram extends current Bayesian network by introducing decision and utility nodes. It is a directed acyclic graph representing a target choosing problem under uncertainty. The influence diagram models the subjective beliefs, preferences and available actions from the perspective of a single passenger agent. The passenger agent considers its current states and environmental components circumstances, and then uses an algorithm to determine an action which fulfils the highest utility.

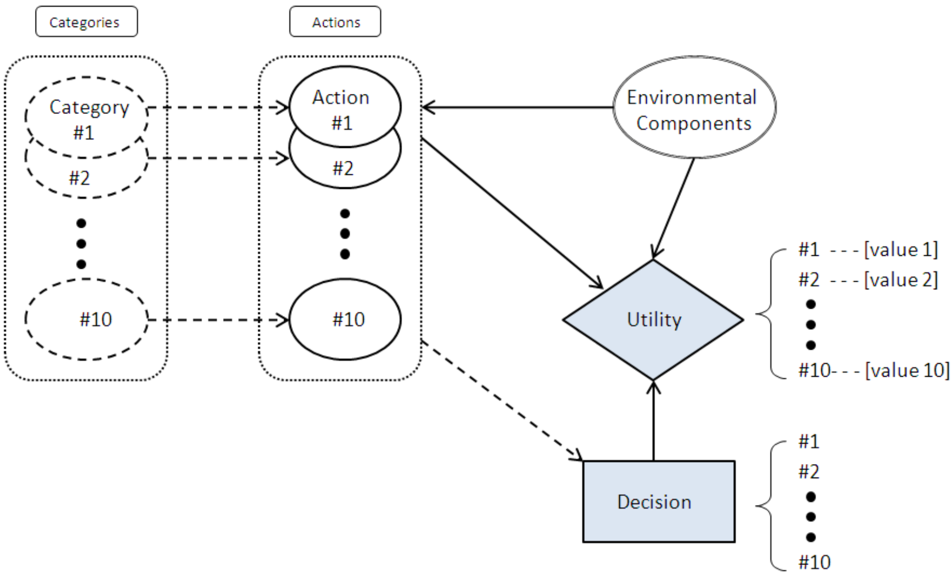



Figure 6-4: Influence diagram

The general graph model by influence diagram is presented in Figure 6-4. An arc in the influence diagram denotes an influence, i.e. the fact that the node at the tail of the arc influences the value of node at the head of the arc. Obviously most arcs in the influence diagrams are on behalf of causal relationships. The dashed arc coming into the *Decision* node has a different meaning. It is called informational arc. It denotes the fact that a passenger agent will know which action that he expects at a moment at the tail of the informational arc before he makes the decision. A passenger agent knows his preferred action is of advantage. He then can estimate facts of “Environmental Component” and Utility values to decide an appropriate and applicable action, and so may change his prior alternative decision. As stated, *Decision* nodes are under the decision maker’s control, the arcs do not denote influences but rather temporal precedence (in the sense of flow of information). The outcomes of all nodes at the tail of informational arcs will be known before the decision is made. In particular, if there are multiple decision nodes, they all need to be connected by informational arcs. This reflects the fact that the decisions are made in a sequence and the outcome of each decision is known before the next decision is made.

*Utility* nodes are implemented in the model to facilitate passenger agents to make their real-time routing decision. In the model, *Actions* group presents several possible actions that a passenger agent could undertake. Certainly the passenger agent needs to make the final action according to other impact factors. The *Utility* node works in this respect. First passenger activities in *Action* group that could conflict with each other in real time need to be resolved. In *Actions* group, "Inquire and ask for assistance" and "Use Self-service kiosks", do not conflict with other nodes, since they are related to standard processing procedures. Whereas "Shopping", "Emails, Phone calls and social media", "Withdraw money", "Buy a drink or meal" and "Proceed checkpoint" coexist to be selected by a passenger agent in real time. They all are influenced by time and therefore relate to the *Time Stress* node. That is, for instance, departing passengers would not undertake any of the five if boarding starts, for he/she has to walk to the gate as quickly as possible, otherwise he/she will be late.

*Time Stress* is used to determine utility values in *Utility* node. For simplicity, the five *Actions* were assigned priority values (Table 6-3). The bigger the value, the more priority the agent will take the corresponding action first. Here the basic idea is that more values can be attained if passengers perform discretionary activities other than directly go to standard checkpoints, because it simply means passengers acquire extra services or use an airport terminal better. Moreover, hunger and thirsty are considered as the worst conditions that a passenger will not least endure. So its value is the highest. "Withdraw money" seems not urgent because passenger can

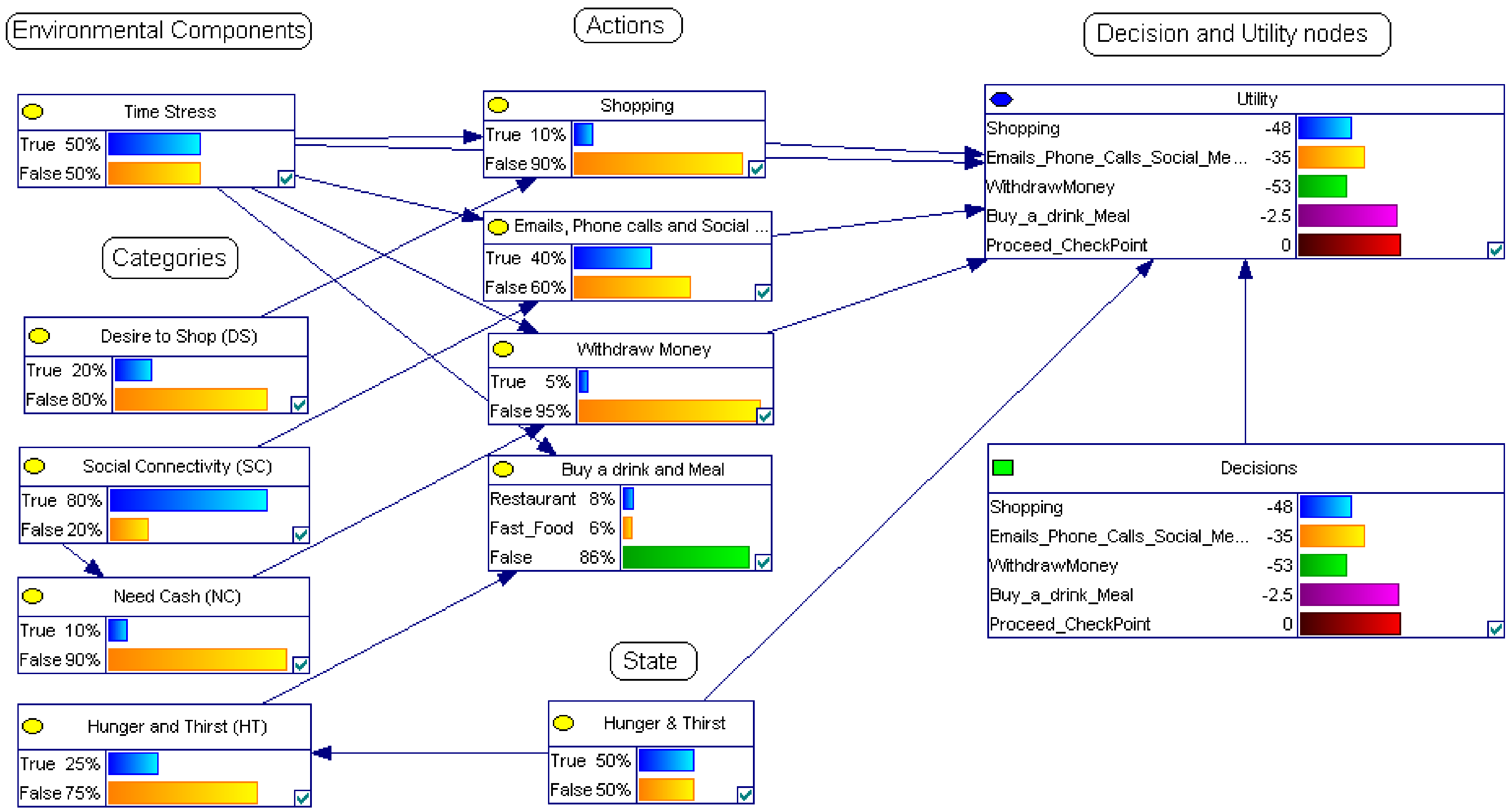



Figure 6-5: Influence diagram for selecting a decision with highest expected utility

even withdraw cash after the aircraft touching down at designation airport. So its value is the lowest. To have a feasible *Utility* definition, *Time Stress* must also be included. It is for triggering "proceed checkpoint" action once a passenger agent face "being late" hazard.

Table 6-3: Priority values for the five actions

| ***Actions*** | ***Priority values*** | ***"Time Stress" is "Yes"*** |
|---|---|---|
| Shopping | +60 | -100 |
| Emails, phone calls and social media | +40 | -100 |
| Withdraw money | +30 | -100 |
| Buy a drink or meal | +100 | range from -84 to -50 * |
| Proceed checkpoint | 0 | +100 |

(*Note: * denotes a passenger buying a fast food will feel a bit more comfortable and so gain a bit more value*)

In Figure 6-5, the *Decision* node consists of five decisions. They are "Shopping", "Emails, Phone calls and social media", "Withdraw money", "Buy a drink or meal" and "Proceed checkpoint" respectively, which are the actions a passenger would choose. *Utility* node is defined by the conditional probability algorithm involving the five *Action* nodes, *Environmental Factor* node *Time Stress* and *State* node "Hunger Level". No matter whether information from any of these nodes are missing or uncertain or fixed as evidences, *Utility* node can always calculate the highest value so as to provide *Decision* node the best valuable choice. Decision node at last executes the action with highest value, which represents a passenger agent chooses the same action.

## 6.3 CASE STUDY

Before carrying out a simulation study of passengers flow with the devised routing decision model of passengers, two examples of implementing the *Influence diagram* of agent decision-making are presented. They aim to better demonstrate the approach within the scope of route-choice decision-making of passengers in airport terminals. The two examples are for departing and arriving passengers respectively.

*Scenario 1*: A departure passenger agent arrives at Check-in hall of an airport terminal. The current time is 90 minutes prior to the scheduled departure time It is assumed that Check-in desks close exactly 40 minutes prior to the scheduled departure time. Basic traits of the passenger agent are listed in Table 6-4. The check-in desks are open. Discretionary facilities within the check-in hall include

*Information Desk*, *Self-service Check-in Desks*, *Shops*, *Internet Access facilities*, *ATM* and a *Food Court*. What is the passenger agent's target and route choices then?

Table 6-4: Basic traits for the passenger agent in Scenario 1

| ***Trait*** | ***Data Type*** | ***Value*** | ***Note*** |
|---|---|---|---|
| Age | Integer | 28 | Age information on the ticket; Discrete Normal distribution if the information is unavailable, alpha = 42 |
| Frequency of travel | Integer | 2 | Records from airlines or airport, i.e. Frequent Flyer; Uniform "0,1,…,10" if the information is unavailable |
| Baggage | Boolean | True | "Carry-on only" is False, others are True; 10% chance True, if the information is unavailable |
| Travel class | Boolean | True | "Economy" is True, others are False; 20% chance False, if the information is unavailable |
| Nationality | Boolean | False | "Native" is True, others are False; 40% chance False, if the information is unavailable |
| Gender | Boolean | True | "Male" is True, "Female" is False; 50% chance True, if the information is unavailable |
| Hunger & Thirst | Boolean | True | "Hungry" is True, others are False; 50% chance True, if the information is unavailable |

A *Pre Check-in* factor is included in the model. The passenger agent has an 80% chance to proceed to check-in first. Since the probability of *Action* "Inquire and ask for assistance" is 90%, the passenger agent would have 90% chance to go to *Information Desk* first. Then he would have 90% chance to go to a normal Check-in desk other than the Self-service Check-in desk. After all of those activities have been accomplished, the influence diagram shows the instant decision the passenger make is "Buy a drink or meal" (Figure 6-6). Once he spends a certain time in the *Food Court*, the state of "Hunger Level" is changed to "*False*" right away. The next target is *Internet Access Facility* as long as *Time Stress* node does not change value (Figure 6-7). Since the utilities of "Shopping" and "Withdraw Money" in *Utility* node is lower than "Proceed Checkpoint", the passenger agent will go to Security after accomplishing activities at *Internet Access facility*. At this moment, the flow of the passenger agent within check-in hall is finished. The target and route choices are illustrated in the layout of an example check-in hall layout (Figure 6-8).

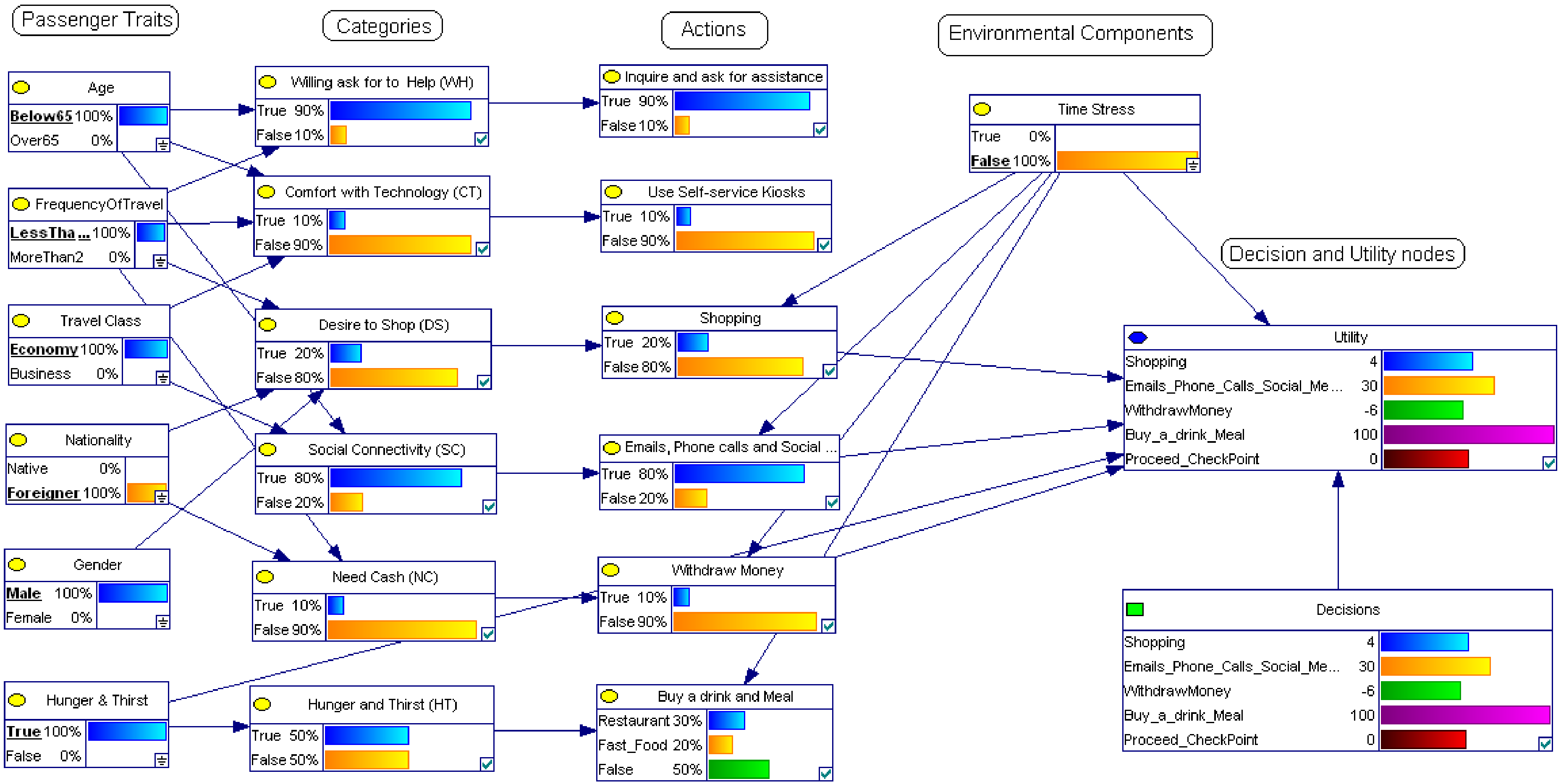



Figure 6-6: A decision is made by the influence diagram when entering check-in hall

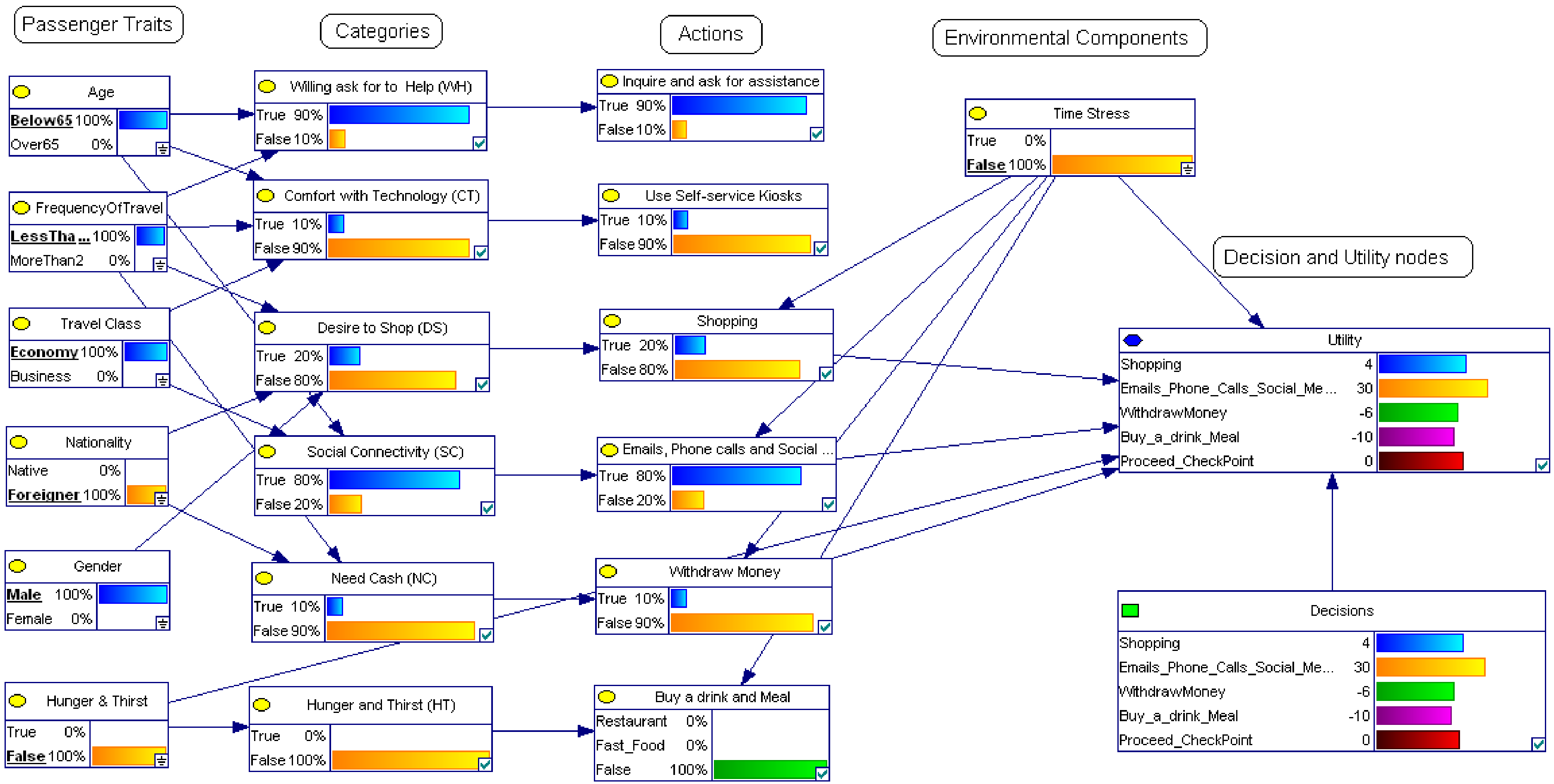



Figure 6-7 The decision made by the influence diagram after Food Court

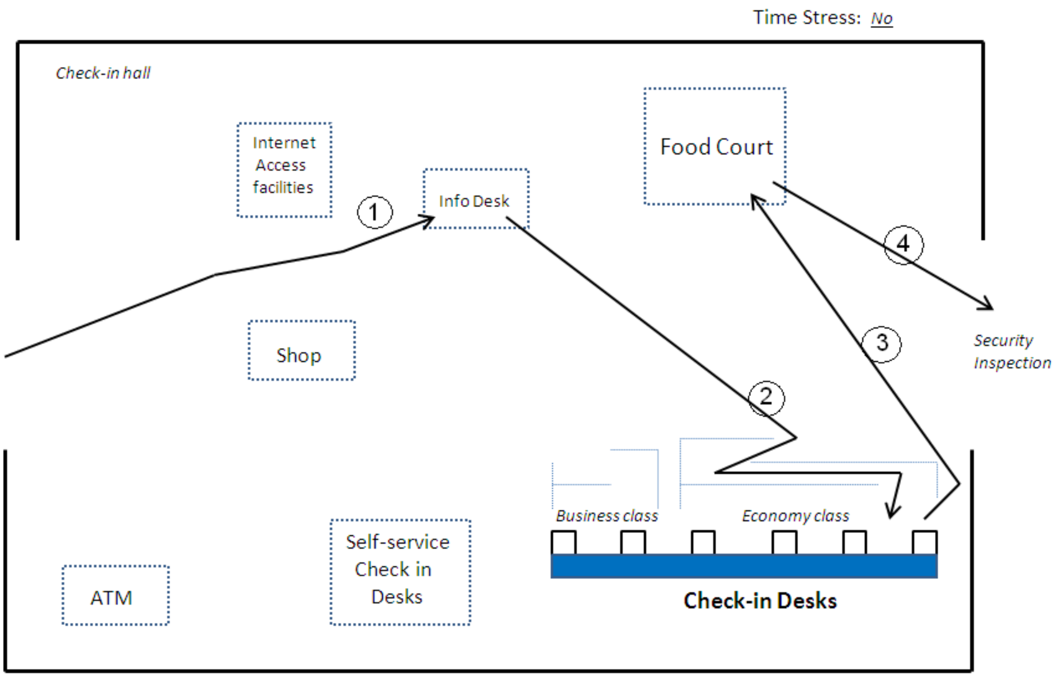



Figure 6-8: Sequential target and route choices of the passenger agent

The *Time Stress* node for Check-in hall scenario will change value when the simulation time reached 50 minutes prior to the scheduled departure time. In this case, the passenger agent simply chooses to proceed to check-in as soon as possible if he has not done it and goes to next checkpoint *Security Inspection* (Figure 6-9). The following activities at *Security Inspection*, *Immigration*, *Airside Terminal* and *Boarding Gates* are to be determined by successive (and separate) influence diagrams.

*Scenario 2*: An arriving passenger agent walks out through a pier gate and arrives at the airside portion of an airport terminal. The flight is on time. She needs to clear customs/immigration and baggage reclaim and exit the terminal within half an hour as scheduled since a family member has agreed to pick them up at this time. However, time is not tight for her anyway. Related basic traits of the passenger agent are listed in Table 6-5. The baggage reclaim carousel will start delivering carried baggage soon. Discretionary facilities within the airside portion include *duty-free shops*, *food court*, *Internet access facilities*, *ATM* and *money change agency*. What is the passenger agent's target and route choice?

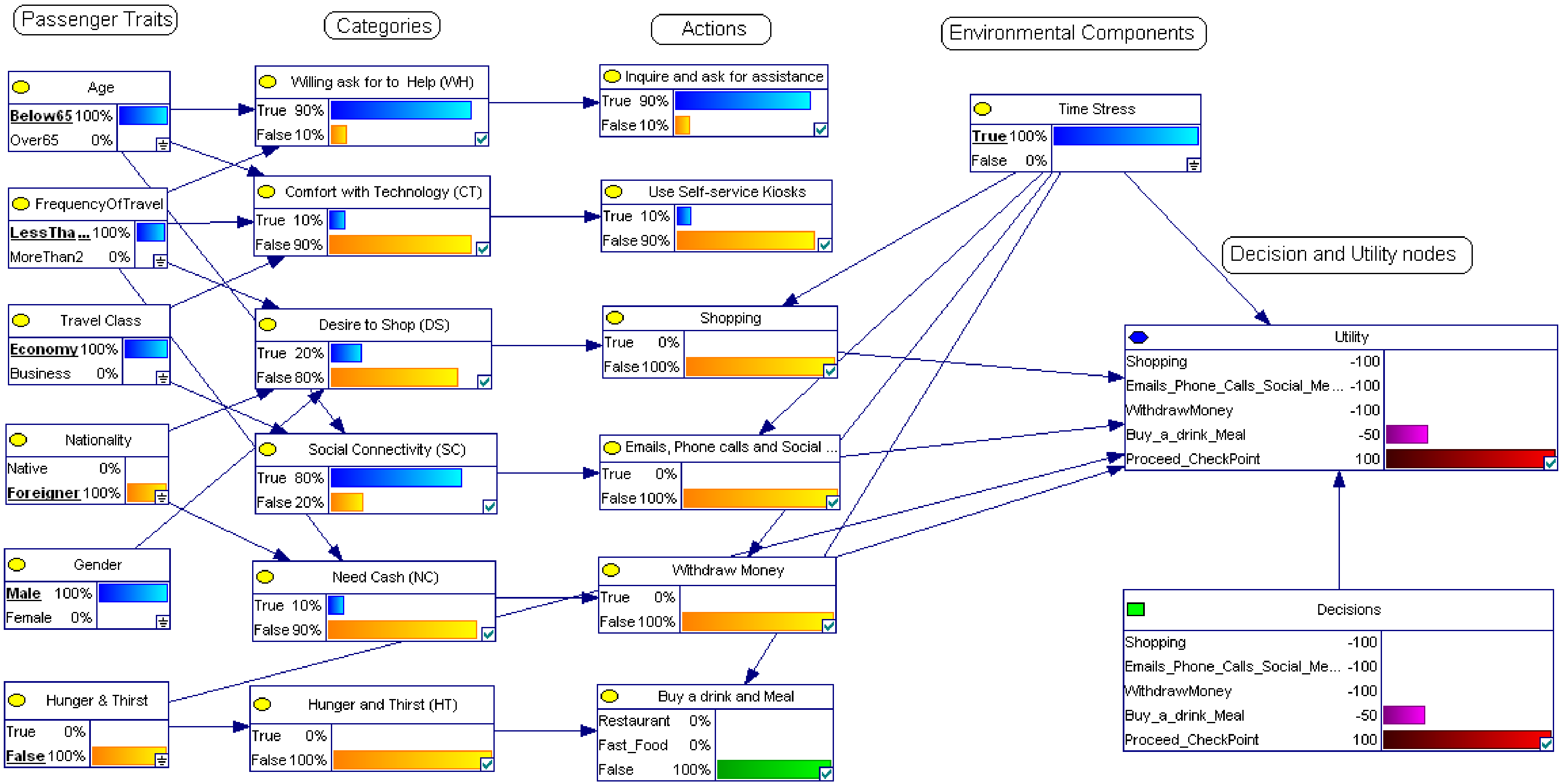



Figure 6-9: The decision made by the influence diagram once *Time Stress* changes value

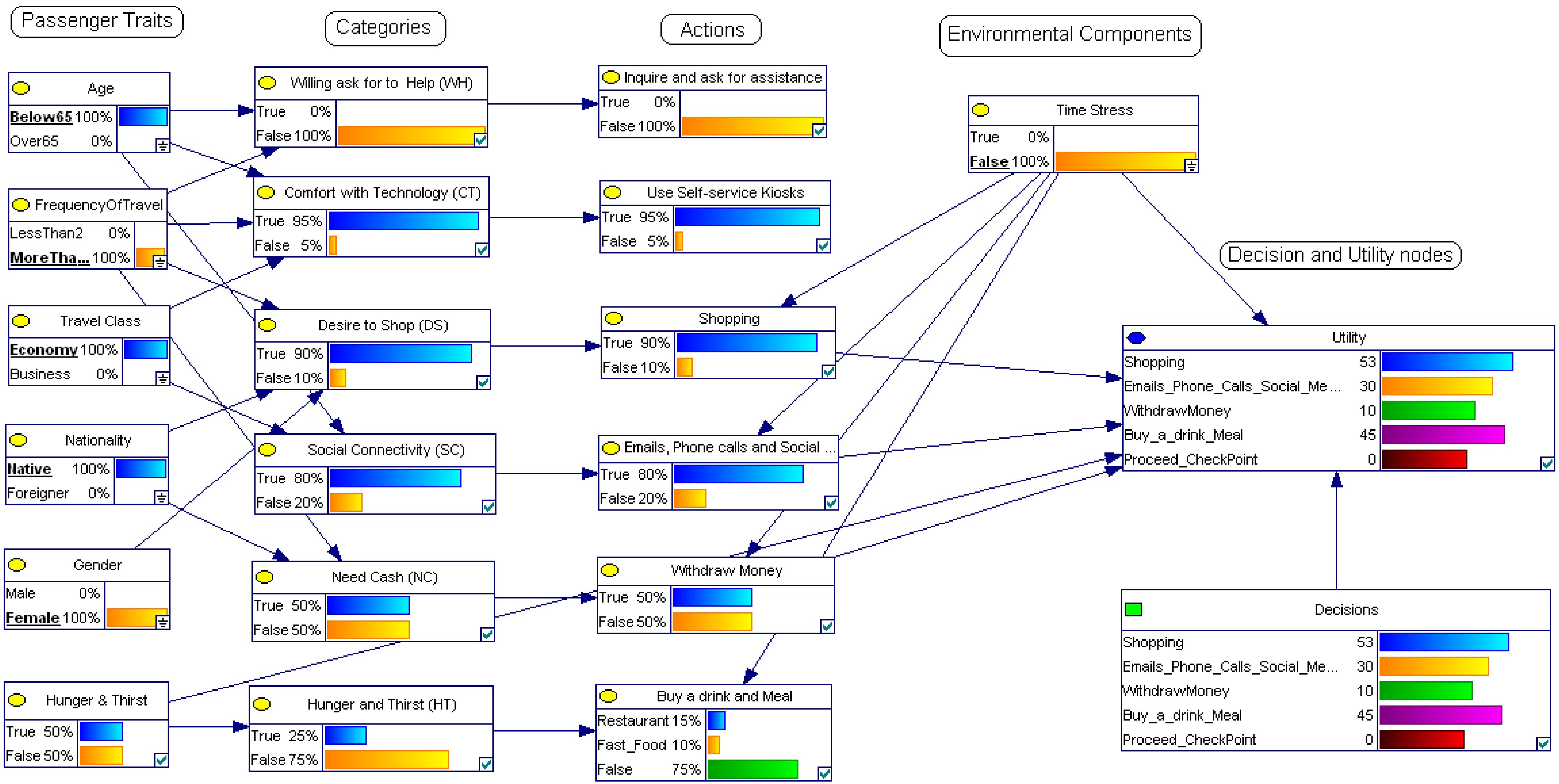



Figure 6-10: A decision is made by the influence diagram when arriving at airside portion of the terminal

Table 6-5: Basic traits for the passenger agent in Scenario 2

| ***Trait*** | ***Data Type*** | ***Value*** | ***Note*** |
|---|---|---|---|
| Age | Integer | 32 | Age information on the ticket; Discrete Normal distribution if the information is unavailable, alpha = 42 |
| Frequency of travel | Integer | 5 | Records from airlines or airport, i.e. *Frequent Flyer*; Uniform "0,1,…,10" if the information is unavailable |
| Travel class | Boolean | True | "Economy" is *True*, others are *False*; 20% chance *False*, if the information is unavailable |
| Nationality | Boolean | True | "Native" is *True*, others are *False*; 40% chance *False*, if the information is unavailable |
| Gender | Boolean | False | "Male" is *True*, "Female" is *False*; 50% chance *True*, if the information is unavailable |
| Hunger & Thirst | Boolean | N/A | "Hungry" is *True*, others are *False*; 50% chance *True*, if the information is unavailable |

Since a trait "*Hunger & Thirst*" is not specified, the value of the node has a 50% chance of being *True*. The next checkpoint is *Immigration* counters. Within the airside portion of the terminal, the passenger agent starts processing her decision by the devised decision-making model of influence diagram (Figure 6-10). She chooses to visit Duty-free shops. Since there is no specific time stress for passengers in the instance of arrivals, she might spend more time dwelling at Duty-free shops area. She would then decide to clear immigration and collect checked bags at baggage claim areas. After that, she might go to café because of thirty and at last leave the airport terminal.

## 6.4 CHAPTER SUMMARY

This chapter set out to develop a novel tactical route-choice model of passenger agents inside airport terminal environments. The devised passenger agent decision-making model was illustrated. It considered the relationships among *Basic Traits*, *Categories*, *Actions* and *Environmental Components*. In particular, in terms of the causal relationships among basic traits and key behaviours of passengers, it proposed that in airport terminals the probable activities of passengers are able to be concluded accordingly through the devised decision-making model of influence diagram. Since a passenger agent is possible to be a member of multiple *Categories*, influence diagram model can be implemented to select a best expected decision.

The research question of this thesis asked how to model passenger flows in airport terminals intuitively. In earlier chapters, it was demonstrated that several decision points were located in terminal environment for the route-choice decisions made by passenger agents. In this chapter, it was then hypothesised that the kinds of basic traits which passengers possess were significant evidences for route-choice decision-making process. They could potentially provide additional information to facilitate tactical route choices of passengers. It was further hypothesised that passengers were more likely to have a best expected decision if it had a set of *Actions* with different *Utility* values. The observation of this chapter suggest that both personal traits and environmental factors have an impact on the decision making process. This chapter concluded that passenger agents possess the capacity to store both personal and environmental information and consequently induce the information to make target and route-choice decisions during a journey.

In next chapter, simulations are conducted to show the passenger flow model in airport terminals.

# Chapter 7: Passenger Flow Simulation Outputs and Analysis

Modelling the tactical routing preferences of passengers who are walking inside airport terminals was the major focus of the work reported in Chapter 6. It studied the psychological impact on routing decisions of passengers. Basic/advanced traits of passengers and the probabilistic graph models were built in the agent decision model, aiming to finalise a route choice with the best expected utility at any devised decision point. In this chapter, three passenger flow simulation case studies are demonstrated by utilising the previously devised passenger traits and routing decision models. In terms of the capacity of representing adequate psychological characteristics of passengers, the developed fuzzy membership functions and the novel graph models are compared.

The first simulation addresses the capabilities of modelling the activities of passengers at discretionary areas and in standard processing procedures by the agent-based method. Fuzzy membership functions are used to build up the model of advanced traits of passengers aiming to have route-choice decision-making of passenger agents in terms of utilising on-airport facilities.

The second case study demonstrates a full-day simulation of passenger flows in the international terminal of an airport in Australia. To address the limitation of the first case study, the full-day simulation showed overlaps of passengers of different flights at all on-airport facilities. The capability of the potential application by the devised advanced traits of passengers in airport terminals is addressed. Besides the basic capability of studying queue length and queuing time at checkpoints, three other important issues – the utilisation of discretionary facilities, dwell time distribution throughout the whole travel experiences of passengers, and the correlations between passengers and overall arrangements of the airport terminal – can be fulfilled in the study.

The last simulation considers abnormal circumstances and assesses how it impacts on the passenger flow and the overall service at the airport. Based on the scenario of the second case study, a flight is envisaged to be delayed and the boarding gate is also changed. It becomes more crowded in the airport since passengers for the flight are detained in the section. During the length of stay, they can also perform discretionary activities at both the boarding gate and discretionary areas, such as waiting lounge and restaurants.

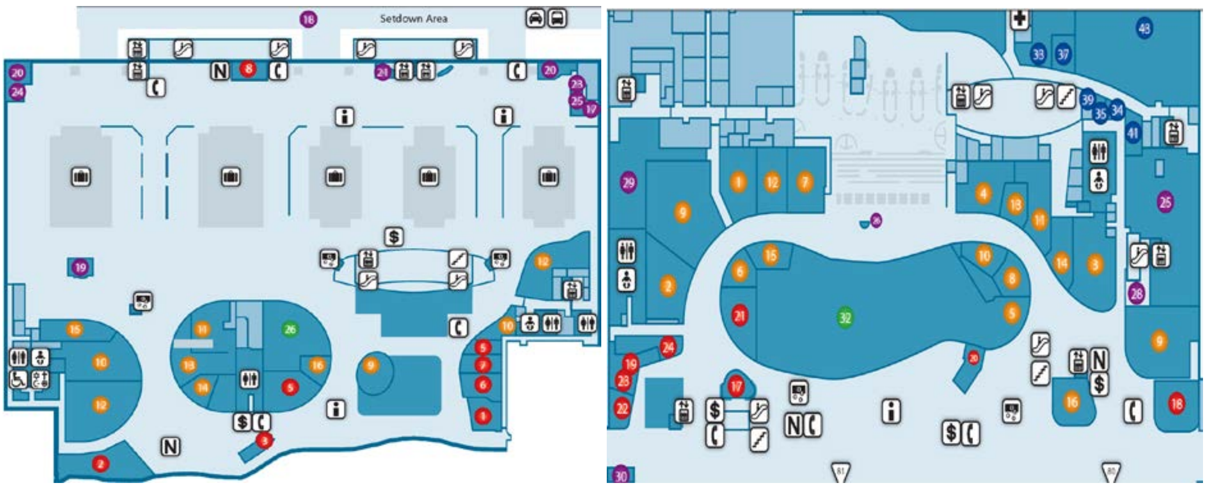
## 7.1 PASSENGER FLOWS ON CONDITION OF A SINGLE SCHEDULED FLIGHT

The probabilities of passengers utilising any on-airport facilities are determined by the values of advanced traits as advised in this thesis, that is, a passenger agent will use an on-airport facility only if one of the advanced traits of the passenger agent indicate he has an exclusive preference to choose the alternative decision. To achieve this, fuzzy membership functions are used to determine instance values of advanced traits. These values are dynamic variables stored as characteristics of the passenger agents and will change in real time to reflect route decisions and consequences of actions when executing the simulation.

### 7.1.1 Simulation overview

With the proposed advanced airport passenger characteristics in Chapter 3, the case study aims to address the concept of implementing discretionary activities of passengers into passenger flows within a real airport terminal. An airport in Australia is chosen as the context.

The airport is the third busiest in Australia, after Melbourne and Sydney Airports. For the 12 months ending June 2011, the total number of international passengers was 4,287,681, with an average growth rate of 3.6% (taken from passenger statistics on the airport's website). Level 2 of the international terminal handles arrivals, Level 3 houses the departure lounge, and Level 4 houses the departure check-in. The simulation environment was drawn based on the layout of Level 4 (Figure 7-1b) and Level 3 (Figure 7-1a). In Figure 7-1, the yellow circles represent shop facilities. The red circles represent food facilities. Purple and blue circles denote other airport and airline service facilities, such as oversized baggage, baggage weighing and wrapping, and airlines sales. The symbolic signs show where other various ancillary facilities are located. The phone booth, information kiosks, Internet facilities and ATMs are located near check-in counters.




a b

Figure 7-1: Layout of the airport's departure terminal

In order to clearly demonstrate the utility of the advanced characteristics of passengers, only one flight is scheduled in this particular case. Therefore, the physical environment of the simulation was revised in terms of processing counters open at a particular time. At check-in there are single service counters for business class and bag drop, with one queue for each of them, and three counters for economy.

For security/immigration, there are three counters for security and five counters for immigration. For immigration in particular, there are two queues: one for two counters catering for Australian/New Zealand passport holders, and one queue for the other three counters for foreigners.

In simulation (Section 7.1.2), passenger agents are tracked with an identification number (id). An agent is automatically assigned a number in its trait when it is initially generated in the simulation. The id of the agent cannot be changed during simulation since it is not a variable in the simulation system. Hence, information about the times when all passenger agents enter and exit every on-airport facility is recorded. By counting the numbers of passenger agents dwelling at a facility in a certain period, instantaneous utilisation of the facility can be obtained, namely, the numbers of passenger at the facility versus the time. Similarly, time spent in every section of the airport by passenger can also be calculated. Travel delay and queue length are recorded by tracking dwell time per passenger at a specific section and the number of passengers in the checkpoint counter areas.

This scenario incorporates common check-in configurations with dedicated business and economy class check-in desks, as well as dedicated bag drop facilities for those checking-in prior to arrival. It is very common for frequent flyers to have completed Internet check-in before arrival at the airport. The scenario also incorporates security inspection and immigration, as well as common boarding configurations with business passengers boarding prior to economy passengers. With the exception of the bag drop facility, all passengers are required to pass through all the mandatory processing facilities. For international travel, all passengers are assumed to have both carry-on bags and checked baggage.

Discretionary facilities are interspersed throughout the terminal space and between key checkpoints (as per the real-world terminal layout). For this case study in particular, ten sorts of common facilities are included to demonstrate passengers performing discretionary activities. They include fast food outlets, cafés, information booths, in-airport telephones, shops, Internet facilities, restrooms/baby-care rooms, a prayer room, ATMs and money exchange agencies.

Table 7-1: Examples of advanced passenger characteristics proposed for outbound passenger flows

| ***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 |
| Need to pray | Boolean | True |
| Need cash | Boolean | True |
| Need foreign currency | Boolean | True |
| Baby need a care/restroom | Boolean | True |
| Need to see a doctor | 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) |
| Level of eagerness to shop | Double | 0 (no eager to), 5 (very eager to) |

Some passengers will use ancillary facilities, and other passengers may not. Routing decision capability of passenger agents to determine where to go is provided. Fuzzy membership functions and probabilistic graph models are the agent decision-making framework. They are used to infer passengers' performing discretionary activities or not at an instantaneous simulation time.

Using the local social force motion model combined with medium-range route planning enables the tactical movement decisions. A long-range planning function is devised to calculate the remaining time to boarding and remaining distances to the boarding gate, which in turn affect medium-range decision-making. It is also assumed that passengers have to terminate the current discretionary activity and proceed to mandatory standard processing checkpoints if the remaining time to boarding is less than 30 minutes.

Based upon the basic information such as travel class, travel frequency and remaining time to board, passengers who are experienced with travelling through the terminal and also have sufficient time available before boarding would spend considerable time at discretionary sections.

The decision model utilises ten mental preferences of individual passenger. Four major discretionary activities are chosen to be set by member functions (Figure 7-2) assisting passengers' route-choice decisions in real-time simulations. They are "ask for help", "go to café", "go shopping" and "use self-service facility". When first entering, passengers are able to either use the ancillary facilities or proceed directly to check-in counters; assuming approximately 80% of passengers will proceed directly to check-in. The other 20% of passengers will use the café, information booth, telephone or shops prior to check-in. In particular, passengers who are “hungry” and have sufficient time to board (45 minutes) will use the take-away or café. Here, the magnitude of “h” is used to represent the corresponding level of hunger (where h1=1 and h2=3). The higher value of “h”, the more hungry a passenger feels. Passengers who are inexperienced at this particular airport (f1=2 and f2=5) and are willing to ask for assistance (w1=2.5 and w2=4) will use the information booth. The higher value of “w”, the more likely a passenger asks for help. Passengers who are experienced in travelling to the airport (c1=3 and c2=5) and have sufficient time to board will be most likely to buy a newspaper from the newsagent outlet. At post-immigration, passengers who “desire to shop” (e1=1 and e2=3) and have enough spare time to board (more than 30 minutes) will linger around the duty-free shop area.

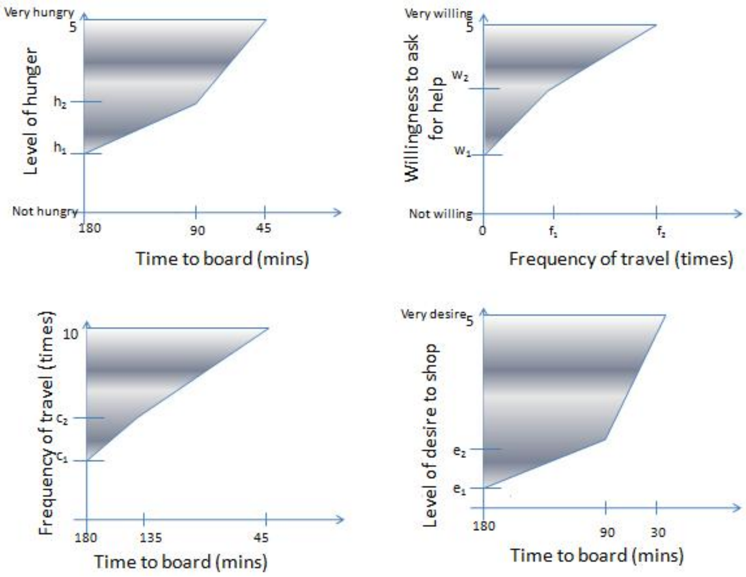



Figure 7-2: Membership functions used in simulations

While this set of logic mechanisms is not all-inclusive, it is sufficient for validating the proposed inclusion of advanced passenger traits. Six main decision points have been chosen to demonstrate the necessity for both physical and non-physical passenger characteristics (Section 7.1.2). Decision and logic mechanisms of simulating the outbound passenger flow scenario are discussed in detail as follows.

### 7.1.2 Simulation set-up

The passenger characteristics described in Table 3-3 have been implemented for this case study. Only one flight was modelled, however the time of this flight was used to continually calculate the time until passengers need to board the flight. Passengers arrive at the terminal up to 3 hours before the flight is scheduled to board, through to 30 minutes prior.

The model framework is devised as shown in Figure 7-3. According to the decision framework in Figure 7-2, at least three parameters have to be calibrated, i.e. $r_1$, $r_2$, $r_3$. Denote $r_1$ as the proportion of passengers who had used Internet check-in before they arrived at the departure hall. Some passengers who had Internet check-in may not use bag drop facility because they do not have checked bags. This proportion $r_2$ stands for Internet checked-in passengers who use the bag drop. $r_3$ represents a portion of passengers who would like to do check-in first when they initially entered check-in hall (as opposed to performing some discretionary activity). The values are $r_1$=0.12, $r_2$=0.8 and $r_3$=0.8.

Apart from the advanced traits decided by membership functions, a few other distributions of the passenger characteristics are assigned as follows:

- Prob (“Business”) = 0.1
- Prob (“Phone Call”) = 0.05
- Prob (“Use Internet”)=0.1
- Prob (“Use ATM”) = 0.1
- Prob (“Use Money Exchange”) = 0.1
- Prob (“Prayer”)=0.15
- Prob (“Use discretionary facilities after immigration”) = 0.75
- Distribution of travel frequency = Triangular (0, 10, 1.5)
- Distribution of numbers of bags = Uniform (0, 2)
- Distribution of {willingness to seek assistance, level of hunger, lever of eagerness to shop} = Uniform (0, 5)

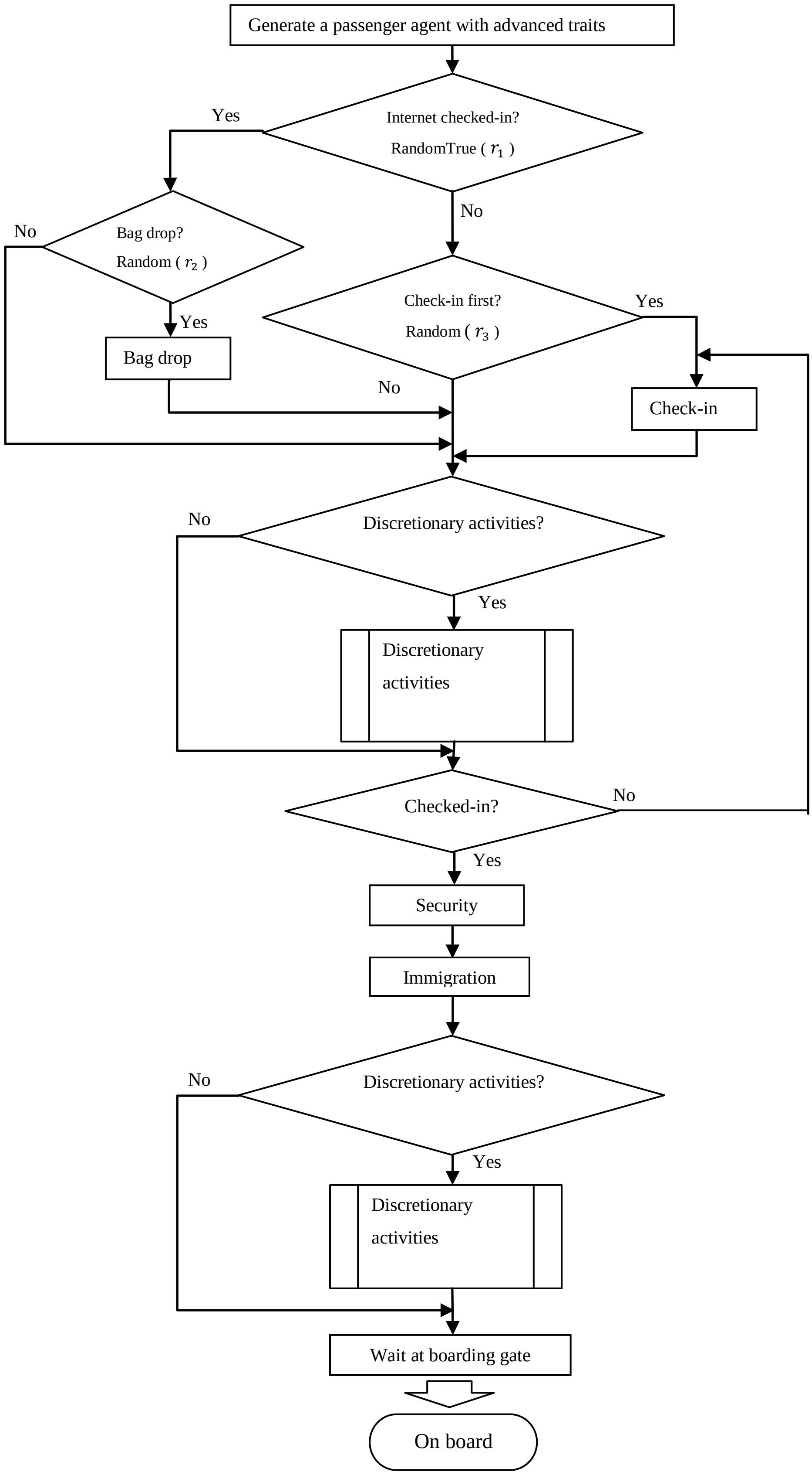



Figure 7-3 Model framework

The passenger flows to every ancillary facility can be instructed by the above parameters. The internal advanced traits of passenger agents indicate whether they move on to another ancillary facility. The states of passengers are recorded and changed during simulation. Hence, a passenger agent will not repeat the same activity if it ever did it, except shopping activities. For example, the state of "*Level of hunger*" is set to 0 if the agent used a food service facility. The agent will not again use the food service facility. However, this is not the case in duty-free shops, because passengers are assumed to visit several shops before they head to another ancillary facility or the boarding gate.

Using the above configuration, two experimental scenarios have been devised, each with 30 simulation runs over which the results are averaged for the analysis presented in Section 7.1.3. Scenario 1 simulates the case where passengers have no interaction at all with the ancillary facilities, thereby replicating most previously reported airport passenger simulations. In this circumstance, all passengers proceed to the business class, economy class or bag drop counter based on their pre-check-in status and class of travel. Passenger flows only follow the mandatory processing procedures. Passengers pass check-in counters, security counters and immigration counters and arrive at the boarding gate.

Scenario 2 introduces all of the rule sets to enable passengers to utilise any (or all) of the ancillary facilities at pre-security and post-immigration. Major significant discretionary activities of passengers in airport terminals are considered within this scenario.

Table 7-2: Planned dwell time that passengers spend at ancillary facilities

| *Ancillary facility* | *Dwell time (seconds)* | *Distribution* |
|---|---|---|
| Shop | 300s – 450s landside | Normal distribution, alpha = 371s |
| | 600s – 750s airside | Normal distribution, alpha = 685s |
| Take-away | 30s – 120s | uniform |
| Café | 1650s – 1750s landside | Normal distribution, alpha=1709s |
| | 1300s – 1400s airside | Normal distribution, alpha=1333s |
| Internet | 1600s – 1700s | uniform |
| Restroom/Baby care | 160s – 230s | uniform |
| ATM (cash withdraw) | 60s – 70s | uniform |
| Money exchange | 140s – 190s | uniform |
| Information kiosk | 5s – 60s | uniform |
| Phone booth | 60s – 300s | uniform |
| Prayer room | 780s- 900s | Uniform |

The time passengers spend at ancillary facilities are detailed in Table 7-2. The data of dwell time at the international airport terminal are obtained from surveys executed by Philip Kirk and Alison Livingstone of the Human System team in the Airports of the Future project. One of the major tasks of the Human System team is to identify and understand passengers' movements and interaction between standard processing and discretionary activities in airport environments. Based on these observations, a distribution of passengers' dwell time at each ancillary facility was determined.

According to passenger arrival distributions per airline (empirical data acquired from the airport), an average of all data is accomplished and a smooth fitting line to model the arrival rate of passengers has been done (Figure 7-4). In all 30 simulations, 150 passengers are scheduled to board an aircraft in terms of the fixed arrival rate. Only a single flight has been simulated to demonstrate the concepts without the complexity of having multiple departing flights with overlapping arrivals of passengers. During each of the simulations, statistics related to the utilisation of service facilities and time-spent within each service were collected. Moreover, the average time-spent at standard processing areas and discretionary areas are validated through the data of facility usage acquired by the Human System team (for international departures in particular, average time-spent per passenger at processing and discretionary areas of landside are both around 19 minutes, and at processing and discretionary areas of airside are around 12 minutes and 78 minutes, respectively).

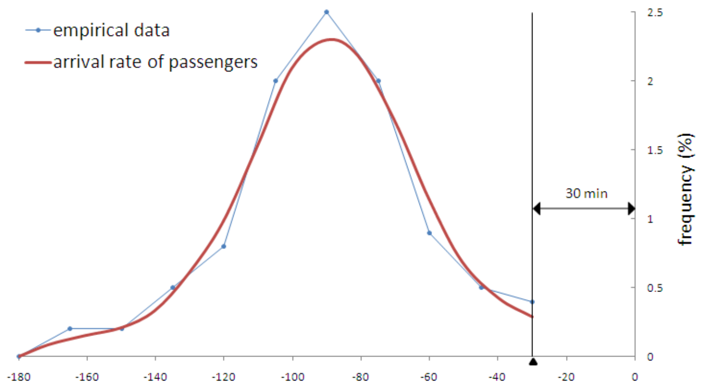



Figure 7-4: Departing passenger arrival schedule for a single flight

Travel delay and long queue lengths are usually the problems of most concern for airport stakeholders. To analyse delay and queue length in the simulation, the time spent by passengers through every facility and the number of passengers instantaneously utilising facilities are recorded. The dwell time at standard processing counters and discretionary areas for each passenger agent are assigned by virtue of the data of the Human System team (Table 7-2). With the processing time of passengers at counters and dwell time at discretionary areas, the time-spent at certain sections in landside (e.g. check-in hall) or airside (e.g. departure lounge) can be calculated.

The pedestrian library of Anylogic is used to set up the air passengers' walking in the airport terminal circumstance. *Ped Source* generates the departing passenger arrival schedule. Simulation of passenger processing procedures is devised according to the model framework (Figure 7-3). The 2D simulation environment is shown in Figure 7-5. The colourful small dots represent passenger agents. At the specific check-in counter in the middle of the figure, three green square shapes stand for economy check-in desks, a red square is the business check-in desk and a black square is the bag drop. For the departure terminal, check-in and security counters are the places where delays and long queues mostly occur. The numbers of passengers who occupy check-in and security areas at any one time reflect the queue length in those sections. The more passengers are there, the worse service delay occurs. By subtracting the time when a passenger agent enters and leaves a counter, the time-spent per passenger is recorded. With all the 30 simulation runs, the recorded data are averaged with the aim to obviate error.

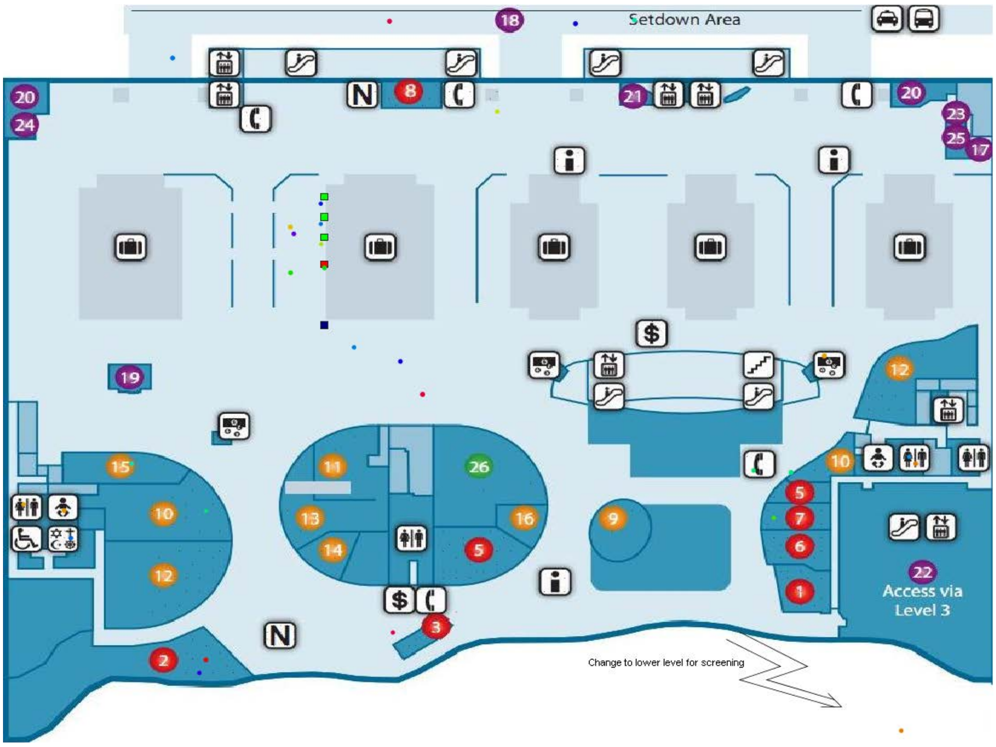



Figure 7-5: Simulation environment (check-in hall part)

### 7.1.3 Simulation analysis

Figure 7-6a shows the average instantaneous utilisation of check-in counters for both scenarios. In Scenario 1, the red curve, passengers directly proceed to check-in without any interactions with other on-airport ancillary facilities. In Scenario 2, however, the load is distributed across the check-in time as passengers have other activities that they can undertake prior to check-in. Owing to discretionary activities, passengers in the check-in hall changed queue length. The number of passengers utilising the check-in facility at the peak is 18 in Scenario 1, slightly higher than 15 in Scenario 2. Investigating the two scenarios, passengers have a longer queue length in Scenario 1.

Two classes of passengers can be distinguished in Scenario 2: passengers who used airport discretionary facilities ("scenario 2 - d" in Figure 7-6b), and passengers who did not ("scenario 2 - no d" in Figure 7-6b). As could be expected, the general dwell time for passengers who did not use ancillary facilities in Scenario 2 is very similar to that for Scenario 1, both around 7 minutes. In Figure 7-6, since discretionary activities of passengers are implemented in the check-in hall, the peak period in Scenario 1 is earlier than in Scenario 2. In Scenario 2, passengers who go to the check-in desks are allocated evenly at different time periods. It only shows a peak at about 70 minutes till boarding. In addition, discretionary activities will postpone the time that passengers come to the check-in desks.

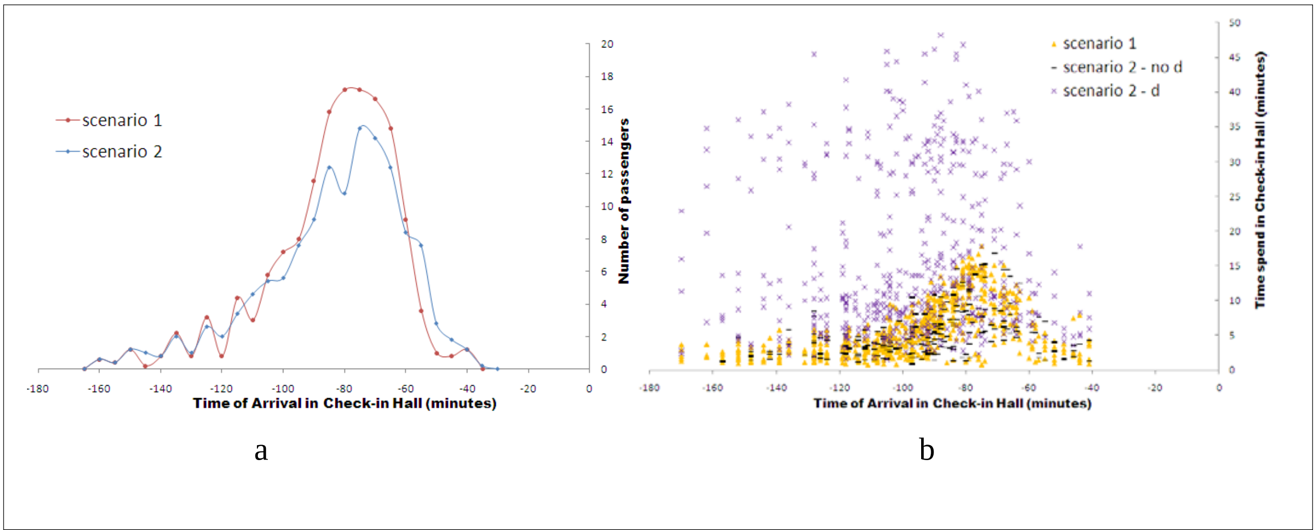



Figure 7-6: Instantaneous utilisation of check-in counters

In Figure 7-6a, the peak times of both scenarios are more or less the same (90 to 70 minutes to boarding). In Scenario 2, passengers who previously used ancillary facilities join the check-in queue a little late, together with those who do not undertake any discretionary activities. It consequently reduces the queue length in Scenario 2 in comparison to Scenario 1. Moreover, it is intuitive that passengers who arrive at the departure terminal earlier are inclined to perform discretionary activities at ancillary facilities. In Figure 7-6b, at 70 minutes before boarding time, the density of passenger agents who use discretionary facilities is much thicker. The numbers of passengers who dwell at ancillary facilities reach the maximum. As time goes on, passengers who might be afraid of boarding late would proceed to security quickly (as shown in Figure 7-6b at time 60 to 40 minutes till boarding).

The international departure has the security and passport control sections tied together (i.e. there is no possibility of undertaking discretionary activities between these two processes). In Figure 7-7a, the simulation results of both Scenario 1 and Scenario 2 have peak values at around 60 minutes to boarding. A bottleneck happens and longer queuing is expected in both scenarios. Passengers who enter security around this time experience delays. However, the maximum value of Scenario 2 is approximately 5 passengers less than that in Scenario 1, suggesting that queue lengths are reduced to some extent in Scenario 2. At the time 80 to 50 minutes to boarding in Figure 7-7b, the average time spent per passenger in Scenario 2 is much nearer approaching 12 minutes. It costs passengers much less time to pass through security and passport control in Scenario 2.

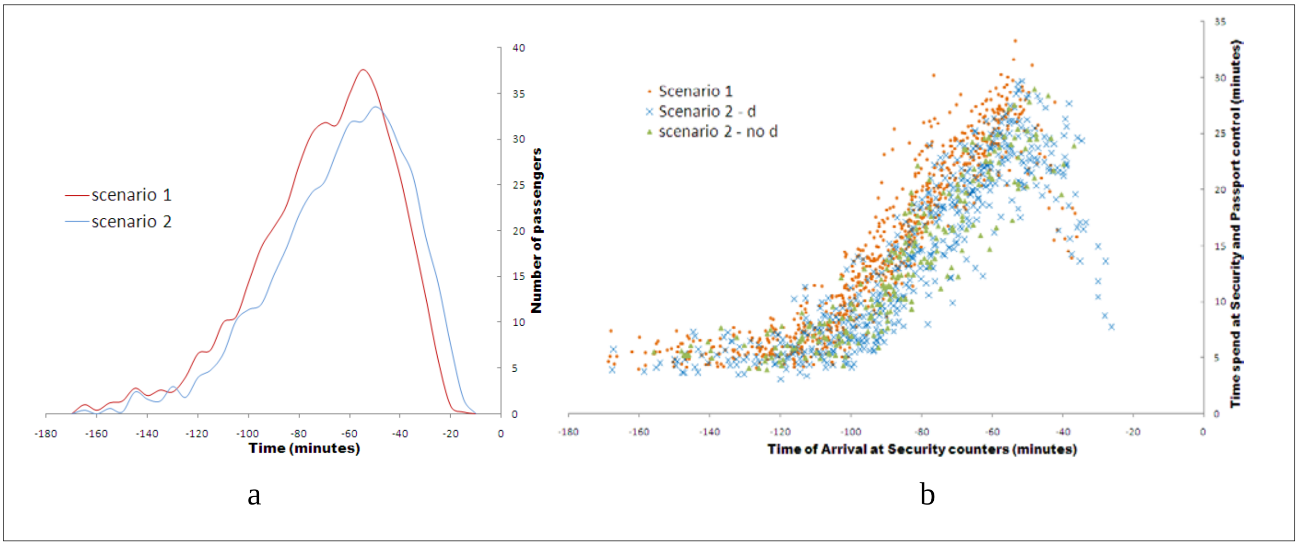
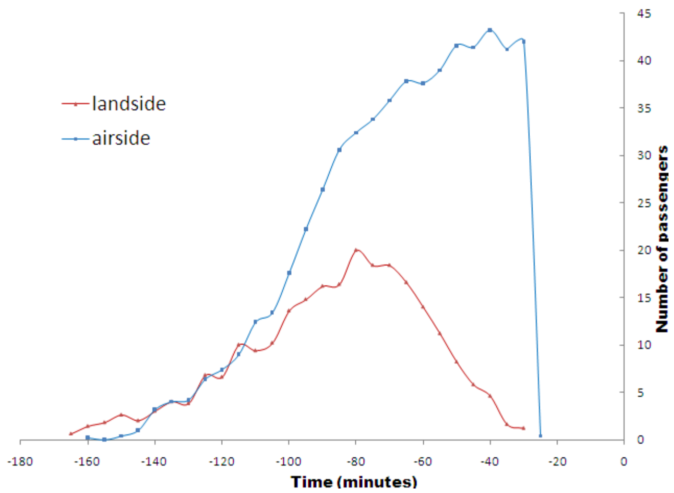



Figure 7-7: Instantaneous utilisation of security and immigration and time spent at security and immigration counters

Through investigating the instantaneous utilisation of security and immigration in Figure 7-7a, it is obvious that the overall curve of Scenario 2 is a little postponed in time axis than that of Scenario 1. However, passengers who do not undertake discretionary activities have almost the same shape as Scenario 1. Hence, it is assumed that the occurrence of the postponed curve could be caused only by discretionary activities. It would barely impact on the queuing delay at security and immigration, although major proportions of passengers go to ancillary facilities prior to security. The wide dispersion of passengers in ancillary facilities at all times reduced the queue length.



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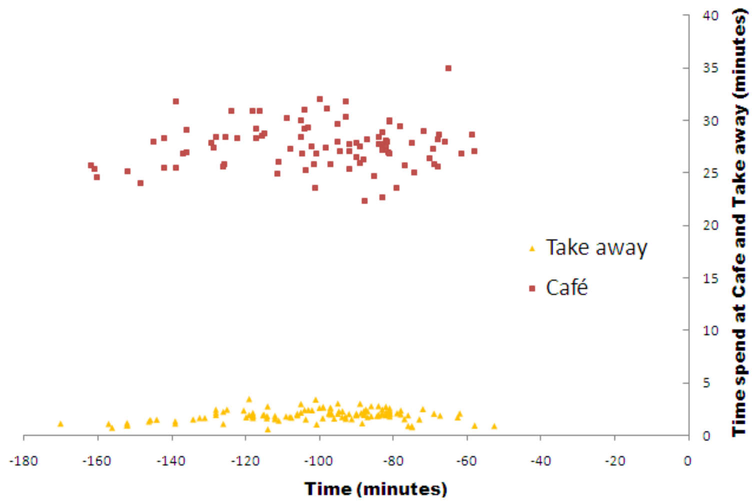

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Figure 7-8: Instantaneous usage of discretionary facilities and time spent in food facilities

Take food facilities as an example to illustrate instantaneous utilisation at discretionary areas. Time spent by passengers at take-away facilities is about two minutes on average, much lower than the time spent at a café (Figure 7-8b). The instantaneous usage of take-away facilities is a little more than that of cafés, because dwell time at take-away facilities is much lower than that in cafés and passengers may prefer to have a quick meal so as to save time for standard processing. The peak time of instantaneous utilisation of discretionary facilities is between 100 minutes and 80 minutes before boarding.

## 7.2 A FULL-DAY SIMULATION OF PASSENGER FLOWS

For a normal daily operation of an airport, aircrafts touch down and take off on scheduled timetables. Thus, passengers arrive at the check-in hall and move to the airside of the terminal in compliance with a regular pattern based on the scheduled timetable (refer to Appendix C). Unlike the previous case with only a single flight, studying full-day passenger flows in one terminal evidently involves overlaps of passengers for different flights at every section inside the terminal, which makes the flows even more complex.

Bayesian brief networks are implemented in the case study to compose the route-choice decision-making model of passenger agents. Bayesian networks can represent true personal traits of air passengers thanks to the natural graph networks. Therefore, the causal relationships are easily validated and clarified, compared to fuzzy membership functions in the previous case study. Although fuzzy membership functions are also able to deal with uncertainties, the Bayesian network has better performance in the aspect of clearly understanding a problem through graph models.

Fuzzy membership functions and the Bayesian network framework are the methods both devised in this thesis aiming to tackle the issue of routing decisions of air passengers. Fuzzy membership functions need to be pre-defined so as to map numeric data into linguistic variable terms and to make fuzzy reasoning. As long as experts or experienced users in the domain of passengers travelling in airport terminals are available, the membership functions can be accurately defined. At this stage, however, few studies are adequately covering realistic experiences of passengers travelling through airport terminals according to the literature review in Chapter 3.

At this stage, it is difficult to obtain enough materials to fully support the fuzzy membership functions. The only available data is the limited surveyed statistics of passengers dwelling at every section of the international terminal, which are acquired from the current ongoing work conducted by Human System group in the Airports of the Future project. There are many uncertain issues which relate to the routing decisions of air passengers in terminals. Bayesian networks are capable of tackling uncertainty with limited known information and can infer the probability of specific nodes. The Bayesian network framework is devised for the domain of passenger flow in airport terminals and is demonstrated in simulation in this section.

### 7.2.1 Simulation overview

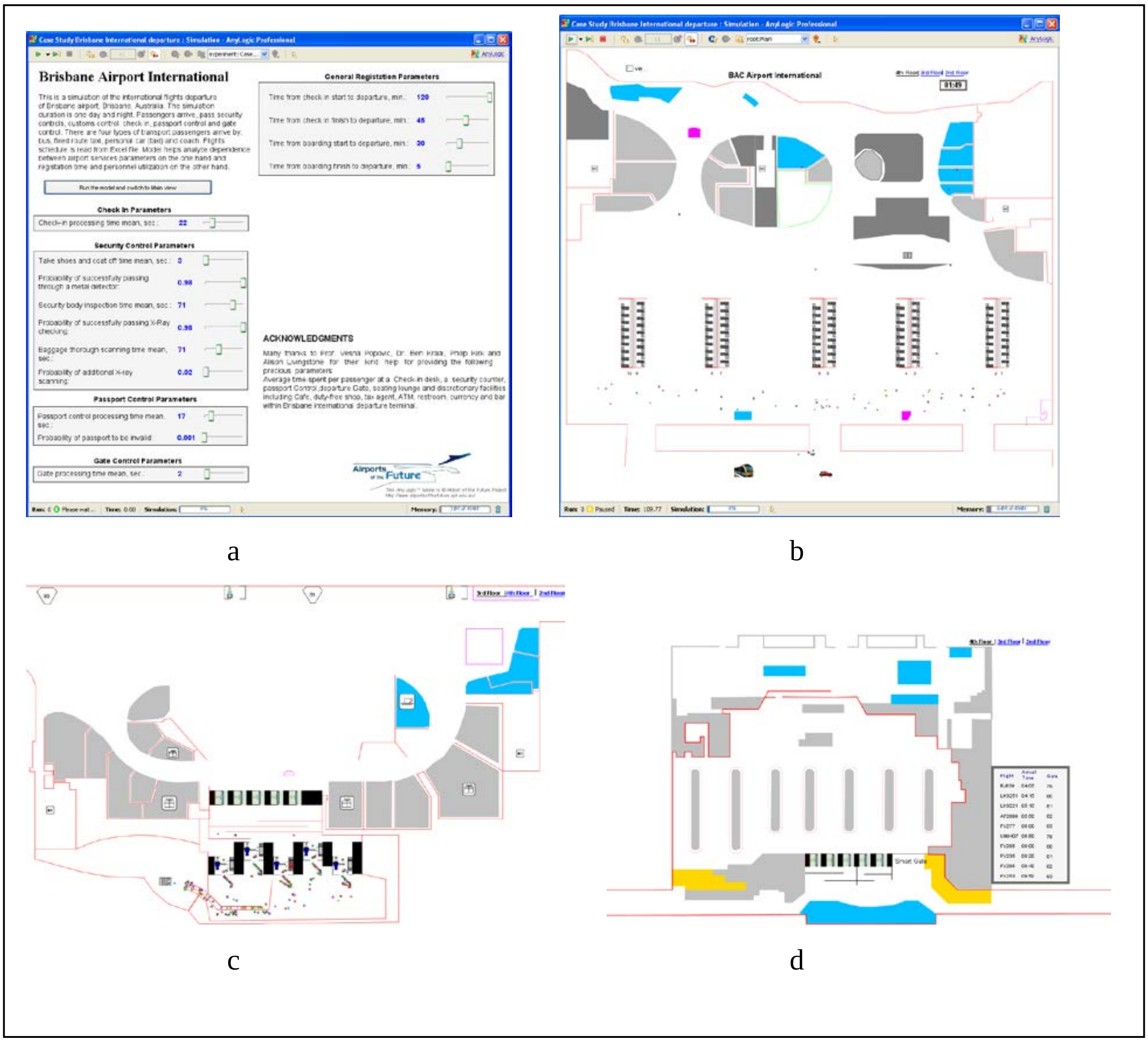


Figure 7-9: Overall layout of the simulation

In order to demonstrate the full-range prototype of passenger flows in the international terminal, true layouts of the three levels were built. Figure 7-9 shows the four view areas of the model. Figure 7-9a is the parameter set-up page, where the dwell time at each standard processing counter is initially stored based on the surveyed data in Table 5-4. For example, the processing time per passenger at a check-in desk is 22 seconds. The remaining three figures are the check-in hall (Level

4 of the international terminal, Figure 7-9b), departure hall (Level 3 of the international terminal, Figure 7-9c) and arrival hall (Level 2 of the international terminal, Figure 7-9d).

The simulation contains all the standard processing procedures for both departure and arrival operations. Departure operations are addressed in the section to illustrate the routing decision framework of Bayesian networks. The number of check-in desks and security inspection counters as well as discretionary facilities and the settled locations are exactly as true arrangements in the international terminal. Some counters might be closed at a given time of day due to off-peak periods; however, for succinctness, all counters are assumed to be open during the simulation. In other words, only full capacity of the airport terminal is considered. Ten rows of check-in counters are located in the check-in hall for different airlines. Each row has nine check-in desks, six of which are for economy check-in. Four security inspection counters and five immigration counters are located in the departure hall. The numbers of the departure gates are the same as in the real terminal. In addition, two different colours are used to distinguish food court and shopping areas: deep sky blue stands for the food court area, and shopping areas are silver. Other discretionary facilities such as phone booths are symbolised as signs given in the simulation legend.

The behaviours of passengers changing levels by using elevators or escalators are not covered in the case. It is simply shown that passengers who change levels disappear at a typical escalator shape and will be automatically generated on the other level. Traits of passenger agents are inherited from the precedent agents and remain the same.

One important aspect of a full-day simulation of passenger flow is generating the arrival rate of passengers. The arrival rate of passengers is based on the scheduled flight information (see Appendix C). In general, passengers start arriving at the terminal about 3 hours before their flights depart. The whole arrival rate is envisaged to follow a normal distribution. However, since in reality passengers could arrive at the terminal by four different transport approaches (i.e. train, taxi, coach and private car), there would be a certain number of passengers arriving at the terminal simultaneously by a particular mode of transport. For the case in particular, a coach could deliver 20 to 30 passengers at a time. A train could deliver about 15. A taxi or a private car usually delivers 1 or 2 passengers to the terminal. The numbers of passengers delivered by each of the four transport modes are devised uniformly. In addition, in terms of one flight, the arrivals of the four transport modes are calculated to deliver the major amount of passengers to the terminal at one to two hours before departure. The timing complies with the arrival schedule for a single flight in the previous case study.

Passenger traits consist of the basic traits and flight information. They are developed as the *Passenger* class. The class structure is shown in Figure 7-10. The basic traits of passengers are devised as static variables in the *Passenger* class. Age, gender, travel class, nationality and frequency of travel are initialised only once at the start of the simulation. Hunger level belongs to *Passenger* class, but its value will be changed in the simulation if passengers utilise on-airport food facilities. *Flight* is a subclass which contains four variables: check-in counter, departure time, boarding gate, and flight notation. All the variables are initialised according to the scheduled flights, but they could be changed if abnormal conditions occur, such as flight delay or boarding gate change. Abnormal conditions are included in the discussion in Section 7.3.

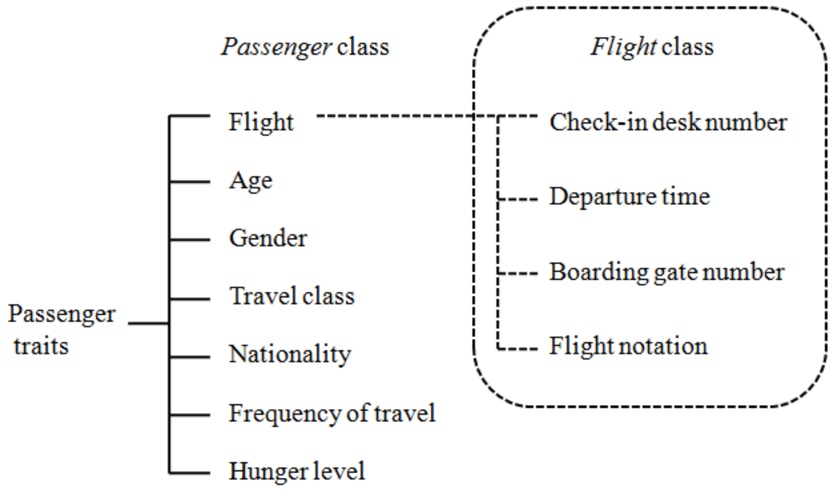


Figure 7-10: Structure of the passenger class

The interrelated hypotheses among nodes within the proposed Bayesian networks are the causal relationships of basic traits and advanced traits (Figure 7-11). The interrelated dependencies are listed in Appendix C (Table C-2). Each node in the graph represents a variable. Each variable denotes a trait which may be uncertain. It has a set of mutually exclusive and collectively exhaustive possible values. Only one of the possible values is or will be the actual value. Basically, it is uncertain which one it is. The Bayesian networks graph represents direct qualitative dependence relationships between basic traits and advanced traits. The edges represent conditional dependencies; nodes which are not connected represent variables which are conditionally independent of each other. Each node is associated with a probability function that takes as its input a particular set of values for the node's parent variables and gives the probability of the variable represented by the node. The graph represents the direct qualitative dependence relationships. The local distributions of nodes of advanced traits represent quantitative information about the strength of those dependencies. The graph and the local distributions together represent a joint distribution over the random variables denoted by the nodes of the graph.

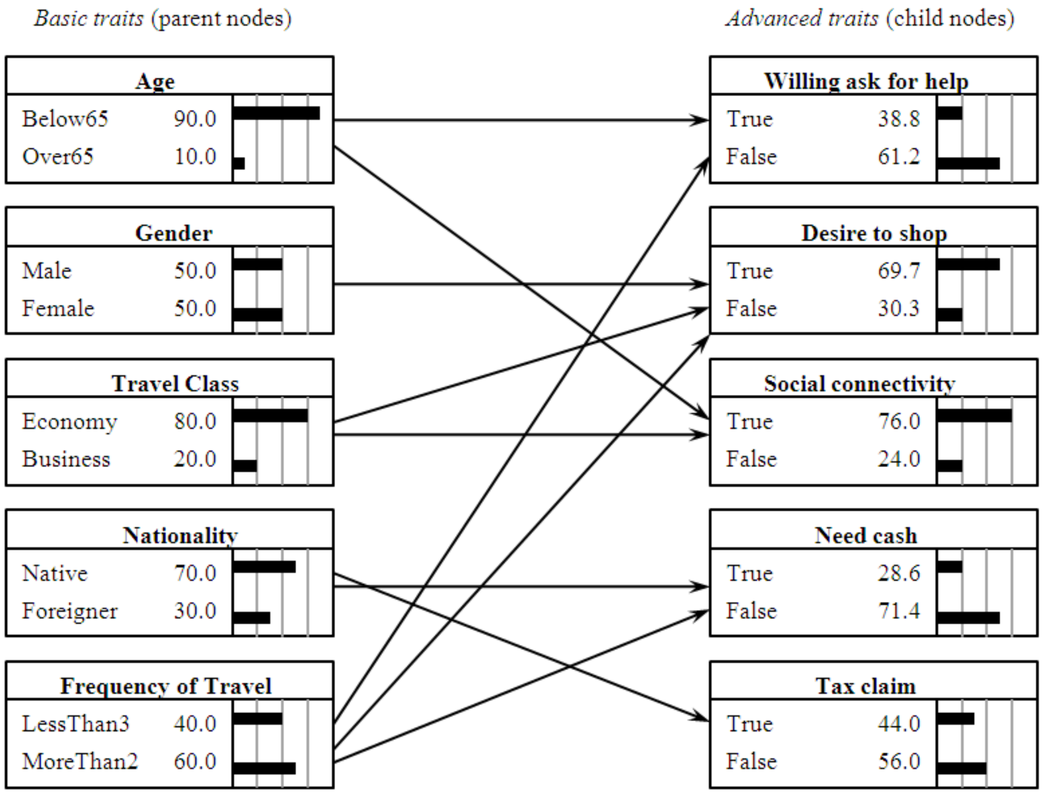


Figure 7-11: Bayesian networks graph

The nodes of advanced traits in the Bayesian networks can denote five of the multiple categories to which passengers belong. Multiple categories of passengers represent the respective actions which passengers would undertake. In Figure 7-11, it is shown that the node "Desire to shop" and "Social connectivity" have higher values compared to the other three nodes. Generally, the passenger agent will go to shops first and then Internet access PC desks. However, it might not be the case when the passenger arrives at the terminal late and it is very soon for boarding. Under the hypothesis, the passenger must go through standard processing procedures as quickly as possible just in case the boarding gate is closed. Considering this, the environmental factor *time stress* is involved in the routing decision framework. It refers to time points when the passenger should suspend discretionary activities and finish the remaining standard processing procedures. It is 45 minutes before the boarding gate closes for passengers who still dwell at the check-in hall. For passengers who are airside, it is the time when boarding starts.

In addition, actions denoted by multiple categories of passengers are assigned with utilities with regard to the rate of major activities. Based on the study conducted by the Human System group in Airports of the Future project, the order of major activities from high percentage to low are using restaurant/cafe, shops, information kiosk, Internet access PC desks, ATM, and tax refund counter. Thus, in the *Utility* node, the action of using restaurant/cafe has the highest pre-set utility value. The utility value is devised on a 0 to 100 scale. If at a time in the simulation, a passenger agent who is a member of both categories “Desire to shop” and “Hungry and Thirsty” has to make an alternative choice – either go to a shop or restaurant/café – it determines the best expected action by inferring the final values for each route-choice decision in the *Utility* node. The decision with the highest value is the action which the passenger agent undertakes.

### 7.2.2 Simulation set-up

Table 7-3: Selected advanced traits of passengers

| **Advanced Traits** | **Target Preferences** |
|---|---|
| Hungry and thirsty | Restaurant/café |
| Desire to shop | Shop areas |
| Willing to ask for help | Information desk |
| Need cash | ATMs |
| Social connectivity | Internet access PC desks |
| Tax claim | Tax refund counter |

By considering all the advanced traits of passenger in Chapter 3, a set of advanced traits were selected for the special case. Since the international terminal does not have self-service check-in counters, the preference for using “self-service check-in desks” is ignored. Table 7-3 presents the selected advanced traits of passengers which were addressed in this simulation. Decision points where passengers make routing decisions in the simulation are the same as in previous case study. The only difference is that Bayesian networks are devised as the agent decision model in the case instead of fuzzy membership functions.

The attributes of advanced traits of passengers are determined by the devised Bayesian networks (Figure 7-12). Every passenger is initially generated with random values for the basic traits, namely, age, frequency of travel, gender, travel class and nationality. Then, the conditional probabilities of advanced traits are calculated according to the Bayesian rules. The Conditional Probability Table is given in Appendix C. The conditional probabilities are only illustrative.

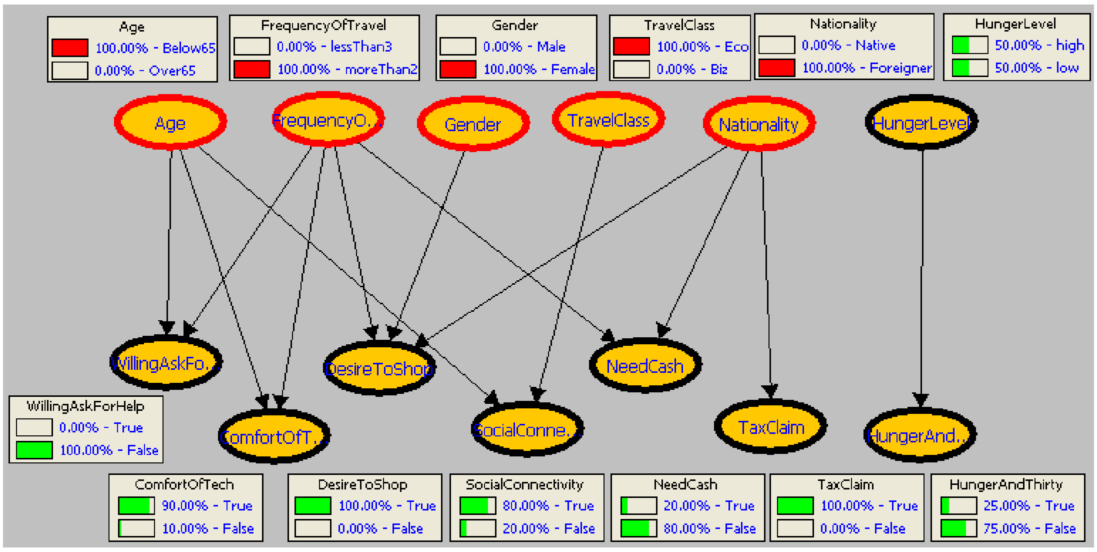


Figure 7-12: Conditional probabilities of advanced traits

Route-choice decision-making is made by utilising a devised utility table. To acquire a sequential route-choice, targets are chosen at every decision point in the simulation. Basically, the traits related to direct standard processing operations have the highest priority. Other traits are assigned with different utility values according to urgent circumstances or special needs. If a passenger has been to a discretionary facility, the value of that advance trait is changed to “false” automatically. For example, a passenger agent goes to a restaurant/cafe in the last time period and fulfils his desire to eat food; meanwhile, the value of the node “hunger level” becomes “low”. At the next decision point, it is compulsory that the utility value of using a restaurant/cafe is zero.

In addition, *Time Stress*, which is one element of *Environmental Components* addressed in Chapter 6, is used to evaluate the utilities of choosing a target. An illustration of evaluating the utility of choosing a target is shown in Figure 7-13. It shows an instant decision-making procedure by the probabilistic graphical model. Four portions of nodes are constructed together. They are *The Advanced Traits*, *Time Stress*, *Decision* and *Utility*. The seven colourful shapes simply represent seven sorts of on-airport facilities in numerical order. They are standard processing facility, restaurant/cafe, shops, information desk, ATM, Internet access PC desks, and tax refund counter. Since the expected utility value of the sixth action, namely, social connectivity, is the highest, the passenger agent chooses the corresponding target instantly, namely the Internet access PCs. The values of the advanced traits will change to "false" because of accomplished activities. For instance, if a passenger has been to the Internet access PC desks, he/she is assumed not to use the facility again. Then, the passenger agent will repeat the same decision-making procedure and decide next target-choice.

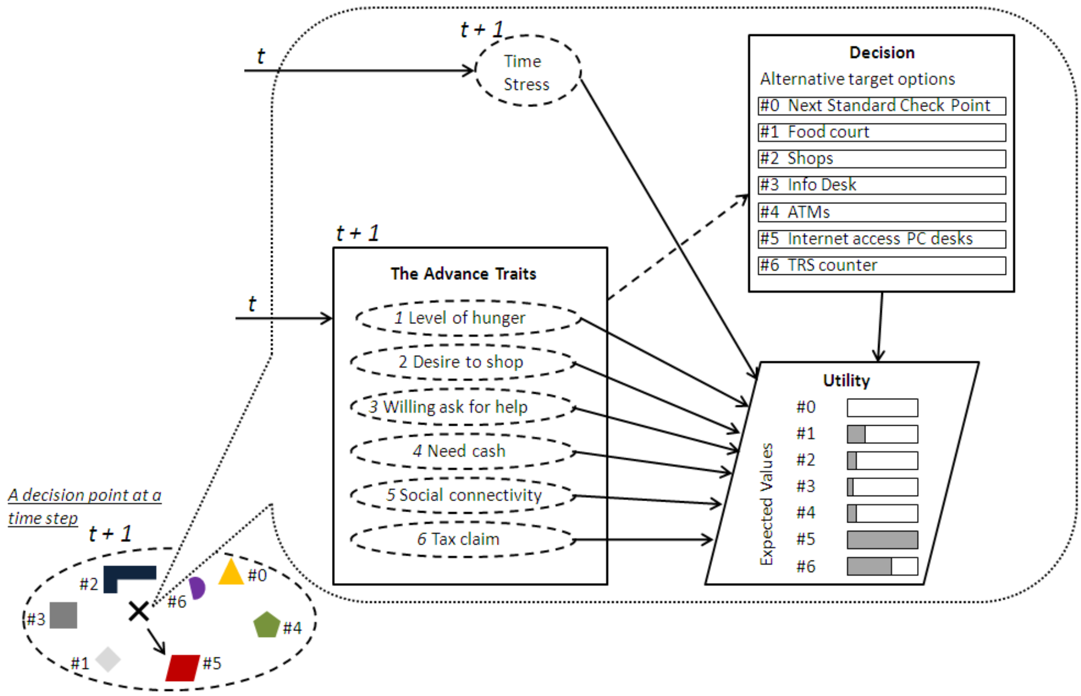


Figure 7-13: Illustration of route choice at a decision point

However, once the simulation time reaches the condition of time constraint, the value of the node *Time Stress* is true, and thus the utility of directly proceeding to checkpoints is the highest due to the results of expected values. Time constraint in the simulation is set as 30 minutes, which is the scheduled boarding time for a flight. When boarding starts, passengers may feel anxious if they have yet not passed through standard processing checkpoints. So *Time Stress* will become effective at this time point and make all alternative utilities become zero except the utility of processing standard checkpoints. In this approach, the decision of “#0 Next Standard Checkpoint” possesses the highest utility value among others. Passengers will proceed through the remaining standard processing procedures.

### 7.2.3 Simulation analysis

With the above settings, three major portions of simulation outcomes are generated. They are average dwell time, service utilisation and queue length. Every passenger is assigned an exclusive id number and is tracked during simulation. Dwell times at standard processing counters and discretionary facilities are recorded. The dwell times of each passenger are counted so as to calculate time statistics on each on-airport facility.

Since instantaneous utilisation of an airport terminal involves all scheduled flights, it is normal that passengers for the different flights may coexist in different sections of the airport terminal. It seems insufficient to study passenger flow based on a single flight. Congestion and capacity bottleneck can only be truly observed by considering all flights. Thus, overall utilisation of both standard processing counters and discretionary facilities are studied through a full-day simulation.

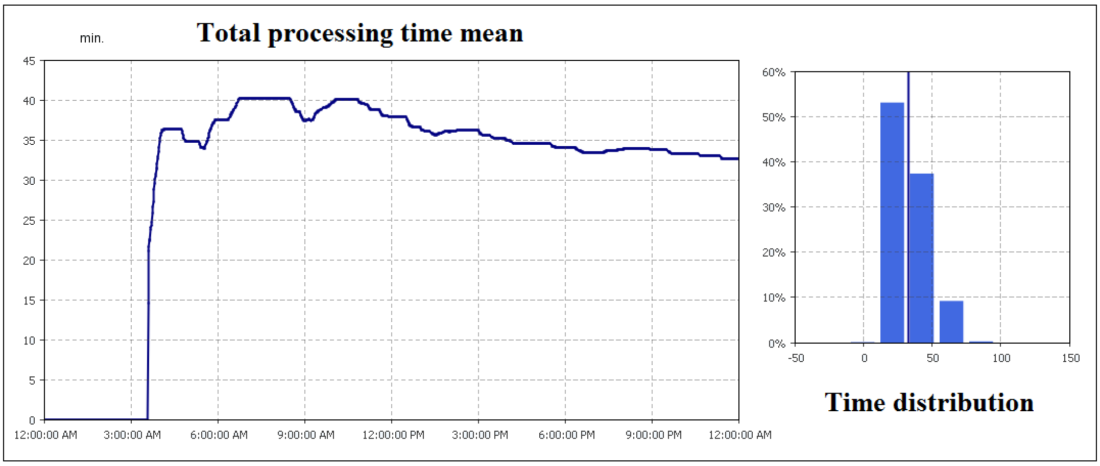


Figure 7-14: Dwell time statistics of standard processing procedures

Figure 7-14 shows the statistical results of the overall dwell time at all standard processing procedures. It displays the mean of processing times as well as their distribution. According to the flight information in Section 7.2.1, a morning peak can be observed in the airport terminal more or less from 7:00am to 10:00am. The peak value is about 40 minutes for a passenger going through all the standard processing counters. Moreover, the major cause of the morning peak can also be observed in Figure 7-15. The average time spent per passenger in check-in and immigration seems steady. In contrast, the average time spent per passenger in security and at the boarding gate varies to a larger extent. The peak variation in security contributes a lot to the peak variation of the total processing time mean in Figure 7-14. Congestion and capacity bottleneck for the case mainly happens in the security section of the airport terminal.

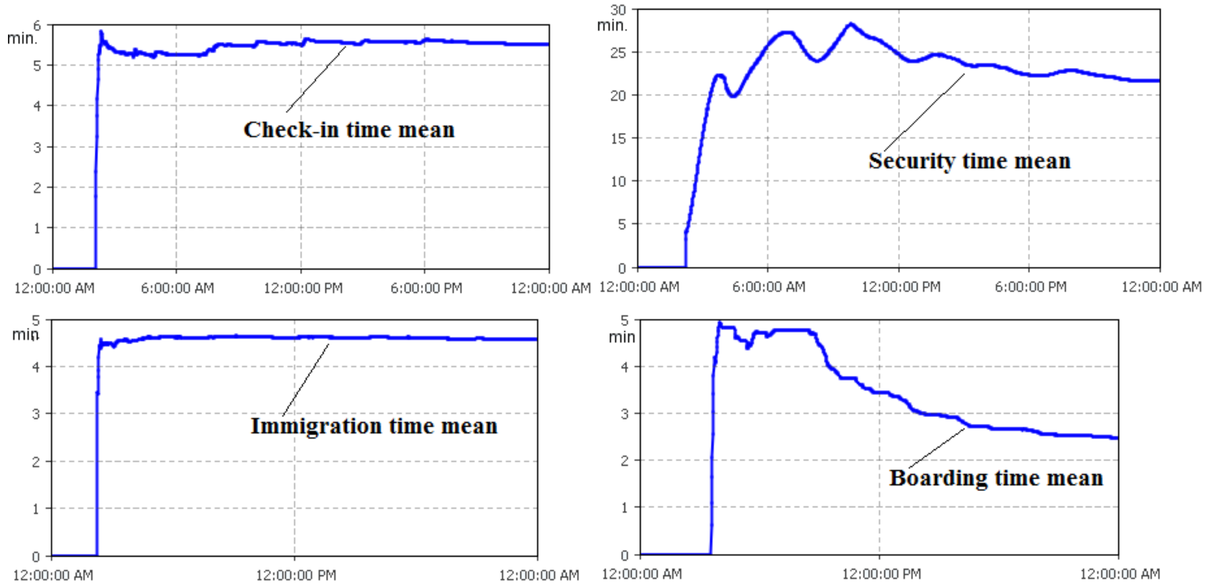


Figure 7-15: Time statistics of standard processing procedures

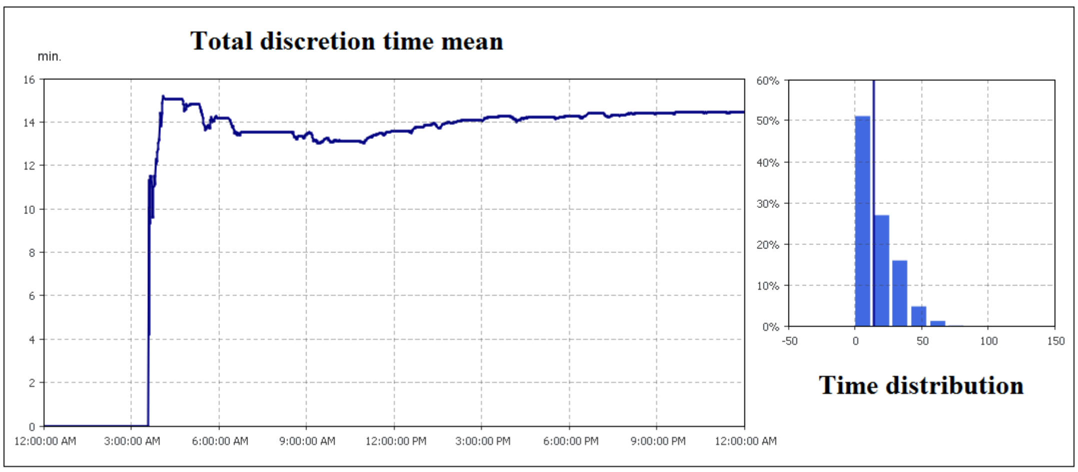


Figure 7-16: Dwell time statistics of discretionary activities

The total discretion time mean is as shown in Figure 7-16. It also displays their distribution. The mean value is around 14 minutes. It should be noted that there is an obvious decrease in around 7:00am to 10:00am. Passengers spent less time in discretionary areas because they had to stay in the queue in security for more time due to the limited capacity in such a simulation setting (Section 7.2.1). If there is only one flight considered in the simulation, average time spent per passenger in discretionary areas would be longer than that involving full-day scheduled flights. At security and immigration counters, the number of passengers would increase in the scenario of full-day scheduled flights. So, passengers would spend more time in the queues and consequently spend less time in discretionary areas. For the first flight in the schedule, in Figure 7-16, passengers spent about 15 minutes in discretionary areas which is a little higher than average.

In addition to the dwell time of passengers at on-airport facilities, two other sorts of data can be acquired in the simulation. The first is the statistics of service utilisation, as shown in Figure 7-17. It consists of utilisation statistics of every standard processing counter; for example, the utilisation rate of the five passport control counters. The higher the utilisation, the more frequently the specific counter is in operation. In the simulation, service utilisation for security and passport procedures is around 50%, which is high and implies that it would serve more efficiently if more counters were imported into the two procedures.

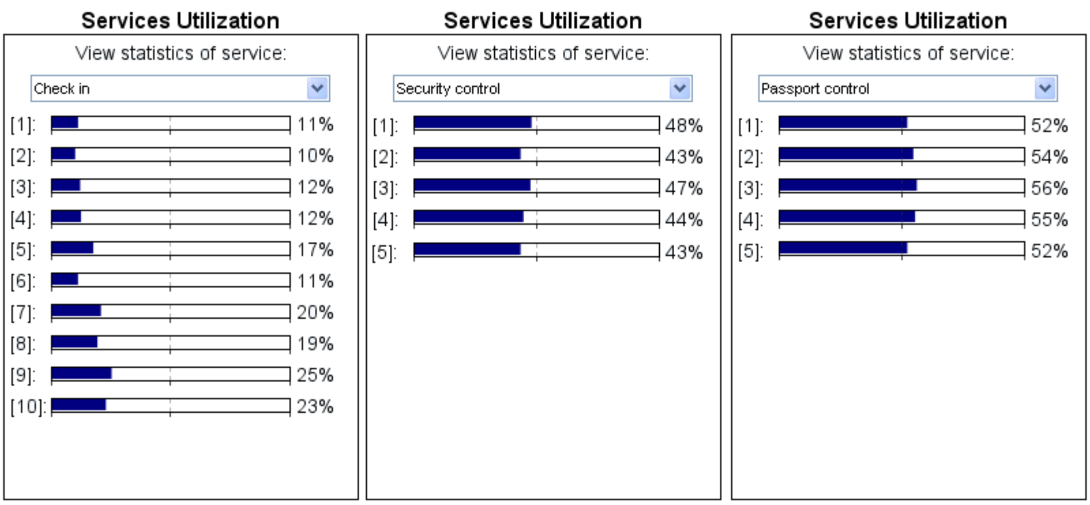


Figure 7-17: Illustration of service utilisation

The second sort of data obtained in the simulation is the real-time counting of passengers (Figure 7-18). Queue length is calculated by counting the numbers of passengers before the standard processing counters. Changing the processing time per passenger in respect of counters would have an impact on queue length before the particular counters. In the case, however, processing time per passenger in check-in, security, immigration and boarding gate remained constant to maintain simulation consistency.

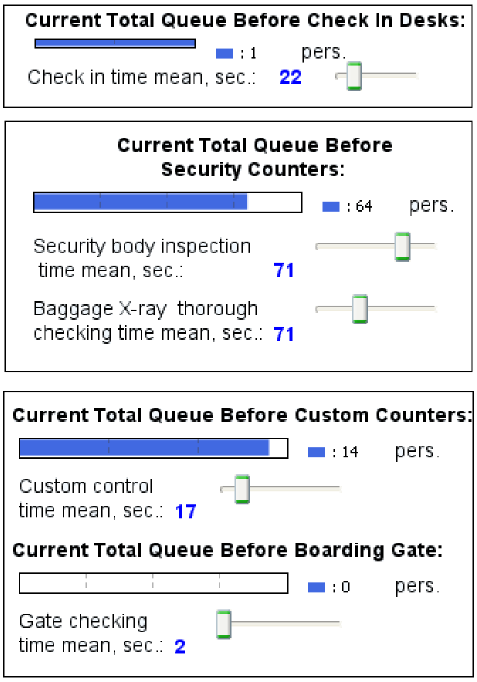


Figure 7-18: Illustration of queue length

The other simulation output is demonstration of service rate (i.e. LOS). Service rate before standard processing counters can be observed by counting the number of passengers in the typical areas. The spatial criteria in Chapter 5 are used to estimate the service rate. Simply comparing the numbers of passengers in typical areas in the simulation with the spatial criteria can provide the service rate of the airport. For instance, the maximum number of passengers at one security counter is 35 (Figure 7-19). Service rate is calculated by 30 ($m^2$) dividing 35 and obtaining 0.86. It is between level C and level D according to Table 5-1. To achieve level C, either more security counters should be imported or more space should be dispatched for each security counter.

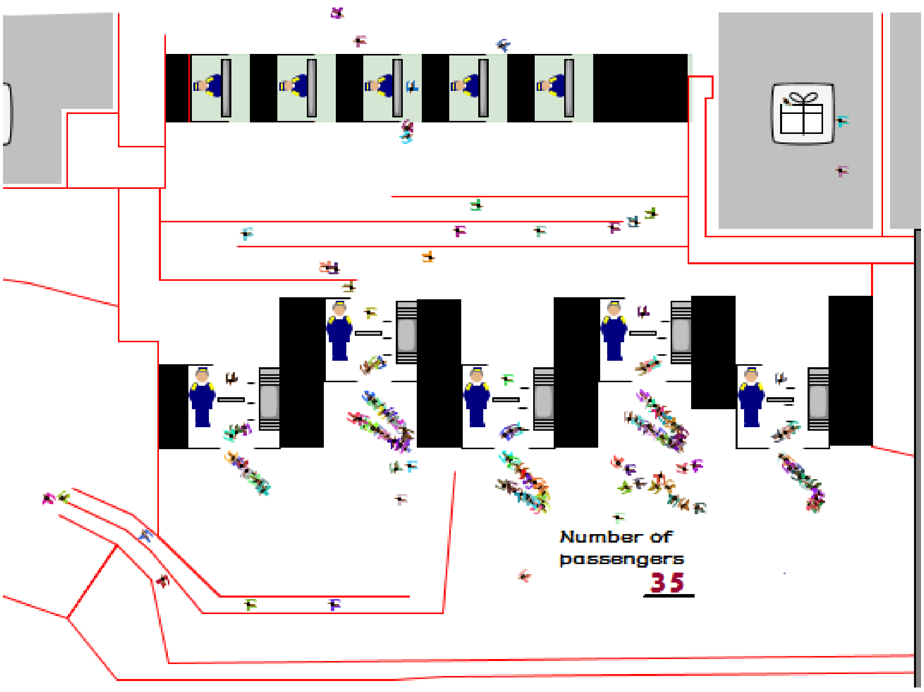


Figure 7-19: Illustration of security

Chapter 5 provides surveyed data to verify the simulation outcomes. Philip Kirk and Alison Livingstone in the Human System group of the Airports of the Future project conducted such data collection (Table 5-4). Instantaneous occupancy by passengers at specific terminal areas can be validated to some degree. Instantaneous occupancy should denote the number of passengers who dwell at on-airport facilities in particular time periods and the average time spent by passengers at every on-airport facility. It is observed that time spent by passengers in all standard checkpoints was between 28 to 60 minutes. In ancillary facilities, the time spent ranged from a minimum of 5 minutes to a maximum of 60 minutes. In comparison with the simulation, simulation outcomes in Section 7.2.3 (Figure 7-14 and Figure 7-16) show that the time distributions for standard processing procedures and discretionary activities range from about 20 to 60 minutes and 0 to 60 minutes, respectively.

## 7.3 SIMULATION OF PASSENGER FLOWS IN ABNORMAL CONDITIONS

Reflecting on the literature reviewed in Chapter 3, it would not normally be feasible for conventional airport landside models regarding passengers to adapt to changes. Such changes involve not only new passenger processing procedures caused by regulatory policies and technologies, but also by abnormal conditions such as cancelled flights, boarding gate changes and evacuation. Basically, it is easy to calculate how new passenger processing procedures will affect passenger flow before regulatory policies and technologies are actually implemented in an airport terminal. In contrast, abnormal conditions are usually unpredictable to some degree. There are more stochastic dynamics of passengers under abnormal conditions.

Abnormal conditions have a significant impact on the daily operations of passenger flow in airport terminals. Flight delay is a common situation in most large airports. Due to some special cases for airlines, boarding gates could also be changed. The scenario envisaged in this section is that a flight is delayed and the boarding gate for the scheduled flight is also changed. Passengers for the flight would have to linger for more time at the airside of the terminal and board the flight at another gate. The simulation analyses the service rate and instantaneous utilisation of the airside terminal in abnormal conditions in comparison with the normal conditions addressed in Section 7.2.

### 7.3.1 Simulation set-up

In the simulation, the scheduled flights in the previous case study are to be changed due to one flight being delayed unexpectedly. Flight “EK433” is set to be delayed for one hour in simulation. The boarding gate of the flight was previously 79 and is to be changed to 80. In this regard, passengers for the flight have no choice but to linger inside the airside of the airport terminal. They will board the plane at gate 80.

The other features of the simulation are the same as those in the previous case study. The agent routing decision model and the layouts of the international terminal remain unchanged through the entire simulation. So, passengers for the delayed flight would again undertake discretionary activities in the airside terminal after they are informed the flight is delayed and the boarding gate is also changed. In addition, the new boarding time and gate information are updated accordingly.

### 7.3.2 Simulation analysis

The condition of a delayed flight and changed boarding gate bring forth the variations of instantaneous utilisation of discretionary facilities in the airside terminal. A 2D animation of the simulation is illustrated in Figure 7-20. Firstly, passengers are informed the flight is to be delayed for one hour and the new boarding gate is 80 instead of the one at which they currently stand. Then, the passenger agents are devised to make their personal routing choices again by the developed agent routing decision model. Passengers would again use the restaurants/cafes, duty-free shops and other on-airport facilities or simply walk to gate 80 and wait there. When it is the new boarding time, passengers all assemble at gate 80. Following the boarding order in terms of business and economy, passengers finally all get on board.

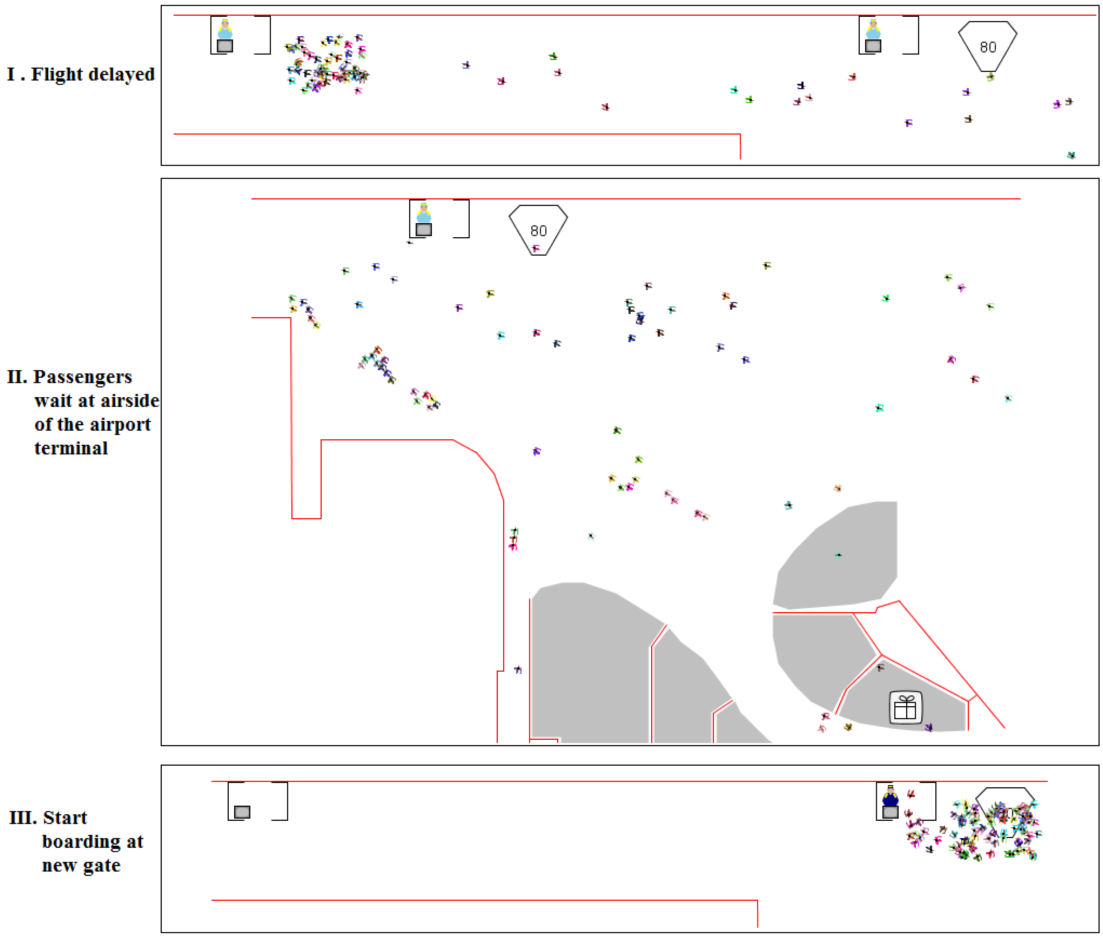


Figure 7-20: Animation of passenger flow in the abnormal conditions

The statistics of total processing time remain more or less the same as that in the previous case study, since the abnormal conditions only happen before the last departure procedure and do not affect check-in, security, immigration and boarding. It is evident that the statistics for the total discretionary time are influenced by the case. Passengers for the delayed flight have to linger inside the airside terminal for a longer time.

Figure 7-21 shows the variation of total discretion time compared to that in Figure 7-16. Due to the delay of Flight EK433, certain portions of passengers spent more time at discretionary areas in the airside terminal. The mean value of discretionary time before 6:00am is 20.5 minutes. It is around 6 minutes more than the normal case reported in Section 7.2.

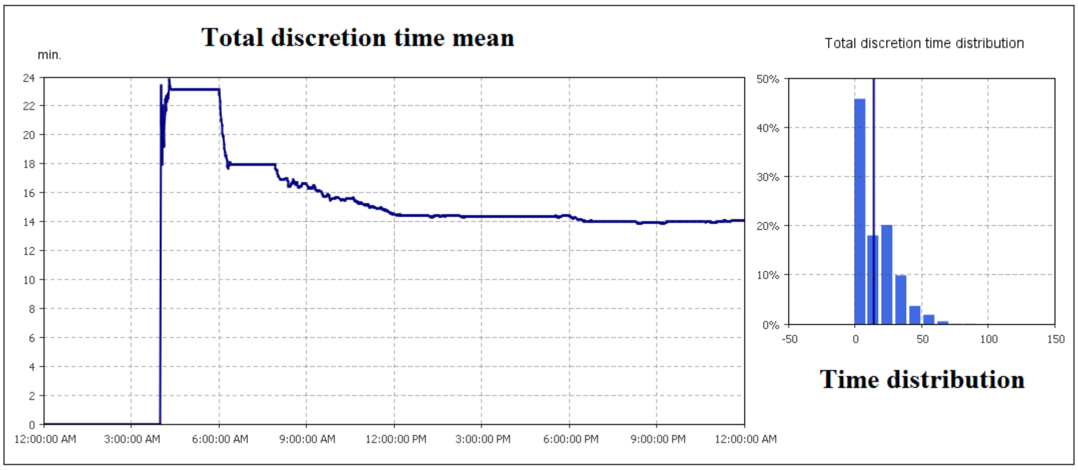


Figure 7-21: Discretionary dwell time due to abnormal conditions

The case study considers only flight delay and boarding gate change at the airside terminal. It may be able to cover more complex problems such as evacuation. At this stage, it is adequate to demonstrate the issues of instantaneous utilisation on which the agent routing decision model has impact. Passengers are considered to prefer to undertake discretionary activities. It would not, however, study the detailed reasons why passengers undertake discretionary activities.

## 7.4 CHAPTER SUMMARY

This chapter demonstrated two case studies of passenger flow simulation for the departure process in the context of an international airport terminal. The first study used only one flight in the simulation. It could clearly show how passengers disperse throughout halls during travel, without the disturbance of passengers for other flights. The inclusion of the advanced passenger traits in the tested scenarios has the effect of distributing passengers within the space, resulting in greater dwell times in the departure hall, and shorter queues and less queuing times at check-in, security and immigration counters. It is believed that by enabling these types of interactions, passenger simulation in airports could be more realistic and reliable for use in planning exercises.

The second case study represented a scenario of a whole-day passenger flow simulation in the terminal. Three typical outputs were devised to be generated, namely, average dwell time at all on-airport facilities, space utilisation and queue length. Route trajectories were discovered as the result of the route-choice decision-making of passenger agents. Dwell time denoted the average dwell time for both standard processing procedures and discretionary activities. Individual dwell time at each of sequential stops along standard processing checkpoint and discretionary facilities were collected. Then, they all were averaged to output the diagram results. Queue lengths at check-in, security and customs were dynamically shown in the simulation.

The last case study studied the influence of abnormal conditions on instantaneous utilisation of the airside terminal by passengers. A delayed flight gave rise to longer dwelling time of the passengers in the terminal. The utilisation of discretionary facilities was a little higher, although standard processing time more or less remained unchanged. The phenomenon of passenger flow among multiple boarding gates due to changing gates was also observed.

# Chapter 8: Discussion and Conclusion

This chapter takes the conclusions of all chapters and combines the individual conclusions whilst discussing their implications in a wider academic and application-based context. It concludes with a statement of future research directions that could arise from the work forming this thesis.

## 8.1 SUMMARY AND DISCUSSION

In this research, the significance of modelling passenger flow in the field of airport terminal simulation was addressed, as set out in Chapter 1. As the growth of air transportation continues, airports are encountering the phenomena of large crowds and operation bottlenecks in the terminals due to the increasing numbers of passengers. In addition, airport terminals involve the interests of many stakeholders. There are challengers regarding unceasing changes to operational policies, security issues and new technologies. Usually, it is a complex problem to tackle these issues in order to maintain adequate terminal capacity for passengers' processing and travelling. Passenger experience is also a key issue, because passengers themselves are the important subjects who use the airport.

In Chapter 2, the research on pedestrian dynamics in the real and simulated world was reviewed. A feasible approach for the present research purpose was selected from the literature. The micro-simulation approach was considered more capable for the research in terms of modelling the individual person. Agent-based modelling was considered most able to deal with the study of passenger flow via a bottom-up approach. To have a microscopic simulation of passenger flow in this way, which addresses the influence of self-consciousness for individual passenger's routing decisions, can result in a more intuitive and realistic model of passenger flow. It is meaningful that passengers are dispersing throughout both standard processing areas and on-airport discretionary areas.

In the particular case of airport terminals, Chapter 3 developed the advanced traits of passengers aiming to represent the causal relationships between routing decisions and self-consciousness of passengers. Unlike the basic traits which are all the information that could be obtained directly from either airports or airlines, the advanced traits were devised to be able to summarise major mental preferences of passengers in terms of routing decisions in airport terminals. The advanced traits of passengers were first introduced in the thesis. They have a very promising application in the airport terminal context, although they are only limited categories of traits.

Then, the envisaged model was illustrated by a concept case study in Chapter 4. The advanced traits of passengers were implemented in a simulation of the check-in process. The simulation provided an intuitive description of passenger flow through both standard processing counters and discretionary facilities. Utilisations of check-in counters and discretionary facilities were compared. Passenger dwell times in on-airport facilities were analysed in contrast with the conventional simulation approach.

In order to make the proposed model meaningful, terminal characteristics related to passenger experiences were outlined in detail in Chapter 5. In addition, the mechanism of route-choice decision-making of passengers was introduced. Bayesian networks framework was identified as the methodology to be applied in the following chapters.

Chapter 6 devised the tactical route-choice decision-making model of passengers in the context of airport terminals. The Bayesian networks framework linked the basic traits and advanced traits of passengers and was able to infer the probabilities of actions in the light of the possibility values of advanced trait categories. Final routing decisions could be achieved according to one action which has the highest expected utility.

Chapter 7 showed the case studies based on the real scenarios in an international airport terminal in Australia. They were simulations of passenger flow in a one-flight context, full-day context and abnormal conditions. Dwell time in sections of the airport terminal and instantaneous utilisations of on-airport facilities were analysed.

### 8.1.1 Research summary

The primary finding of this thesis is that it is possible to utilise advanced traits of passenger agents into agent-based passenger flow models to simulate passengers' likely behaviours in a real airport terminal environment. In essence, these traits can be regarded as psychological preferences which are inherent to the knowledge and experiences of passengers. The route-choice decision-making model for passenger agents who travel through airport terminal environments can utilise these traits to continuously update the probabilities of alternative decisions.

The simulated airport terminal environment is complex and sophisticated. The airport terminal is regarded as a complex system and includes several dynamic factors regarding the environmental components, such as the spatio-temporal factors addressed in Chapter 4. In terms of passengers inside the terminal, the modelled agent attributes consist of basic traits and the proposed advanced traits. Locations of decision points where passenger agents make their decisions were also devised in simulation, and the causal relationships through which advanced traits of passenger agents can be attained according to the immediate basic traits were accomplished. Furthermore, the utilities were included in the proposed influence diagram model to realise an optimal alternative decision and to steer the passengers towards their next targets.

With the proposed advanced traits of passengers, realistic passenger flows within the airport terminal environment are able to be modelled, since such traits are envisaged as significant conscious elements which are rationally possessed by passengers due to their cognitive capability and hence can be treated as intelligent parameters which have an impact on the final route-choice decisions. Although they are not concrete psychological mechanisms, the traits can (at this stage) be used to study the behaviours of passengers with most airport terminal environments. For a very few special airports, however, the devised advanced traits might not be very suitable (for example, small airports or temporary airports). In practice, the advanced traits can be generated through the probabilistic graph models, namely, the Bayesian network and influence diagram by using the existing information (basic traits of passengers). Then, the agent decision model was devised. Basically, the agent decision model works by constantly updating the probabilities of each node in the graph models (i.e. nodes of basic traits and advanced traits in the Bayesian network, and the *Decision* node in the influence diagram), and thus the results of route choices of passenger agents can be determined when simulations were executed in real time.

Not only are the route-choice decisions of passenger agents diverse at the decision points in simulation (i.e. various instantaneous expected targets that a passenger would choose to reach), but the simulated environment of an airport terminal is also dynamic (i.e. available counters at processing checkpoints, *Time Stress* and *Distance Stress*). The criteria which are devised to consider such dynamics of the simulated environment were provided. They are the spatial and temporal criteria addressed in Chapter 5. A meaningful passenger flow simulation can be attained by considering the criteria. Due to the configuration of simulation, the outputs can provide dynamic results of both passenger and simulated terminal environments. The route trajectories of passengers, instantaneous utilisation of on-airport facilities (i.e. exact number of passengers presently dwelling at a facility), and dwell time at all facilities are the results in the aspect of passengers. Queue length and queuing time are the only two results addressed in this thesis in terms of the simulated environment, because they are the important issues about which most macroscopic airport terminal simulations are concerned. The results and related analysis were also provided in the discussion of the case studies.

### 8.1.2 Passenger flow validation discussion

With the devised agent-based passenger flow model, every passenger agent possesses sets of the basic traits and the advanced traits, and is able to execute sequential route-choice decision-making along the decision points in the simulation. Simulation outputs may also be generated for the interests of different stakeholders. Retailers can refer to the dwell time at the duty-free shopping area in the statistics of the simulation in terms of the current airport terminal. Airport managers should have an interest in queue length and average queuing time before standard processing counters. Validation is to testify the research and its potential application in airport terminal. Further validation of the simulation is needed to qualify it and improve the model.

The passenger flow modelling process has undergone many changes in the past few years in order to evaluate more complex policy actions resulting from changes of airport terminals. Since airport models have become more complex, they need to be validated. Due to the limited real-world statistical data available for the particular airport terminal, the present study can only validate a few simulation outcomes with available passenger data. The validation objectives and methods are provided.

The validation of passenger flow in airports consists of three major aspects: speed of passenger flow through the terminal, instantaneous occupancy by passengers at specific areas in the terminal, and the routing phenomena by passengers who use on-airport facilities. The speed of passenger flow involves validating the physical walking speed of passengers with real-world collected data. In simulation, the time statistics of the walking by passenger agents through facilities are to be collected. The walking speed mean would then be generated. They should be compared with real-world data to verify the walking function of the passenger agents in simulation. The walking speeds of passengers in airport terminals have been studied and reported in the literature (Young, 1999). They are around 1.4m/sec and 1.3m/sec for males and females, respectively. The average walking speed of passenger agents in simulation is 1.34m/sec, which is consistent with the specific data in the literature.

Instantaneous occupancy by passengers at specific terminal areas should denote the number of passengers who dwell at on-airport facilities in particular time periods and the average time spent by passengers at every on-airport facility. It can at least be validated through the surveyed data addressed in Chapter 5. Chapter 7 did a comparison of the simulation outcomes with the real data and showed that the surveyed data is feasible to validate the simulation for the airport terminal case study to some degree. In order to have more precise validation, however, more relevant data on the instantaneous occupancy by passengers need to be collected in future work.

For example, surveillance cameras can be equipped in several locations of the airport terminal. This would enable the collection of passenger data from video pictures, as well as collecting passenger data manually. It could be more efficient and accurate in terms of acquiring samples and volumes of samples, because video cameras can usually record a full day or even a week/month data. Analysing these large amounts of passenger data can provide approaches for various objectives.

Validation of routing phenomena would need the statistics of the proportions of passengers who go to any on-airport facilities. Take outbound processes, for example: three virtual thresholds can be devised at locations after entry, finishing check-in, and finishing security/immigration. Video data of passengers would be analysed to identify the proportions of passengers at respective thresholds who then walk to standard processing counters or discretionary areas. Following that, a routing decision model would be able to be verified by the statistical data.

## 8.2 RESEARCH CONTRIBUTIONS

The main contributions of this thesis to the body of knowledge on airport passenger flow simulation are as follows:

- The concept of modelling discretionary activities has been revealed. Conventional studies of passenger flows in airport terminals have mostly addressed only the standard processing procedures in terms of airport operation efficiency. However, the thesis indicates that the activities of passengers at on-airport discretionary facilities play an important role in airport operations as well. Discretionary activities not only affect overall dwell time but also relate to the interests of all the stakeholders inside airport terminals, including retailers, banks, airlines, government agencies and the airports themselves. The types of interest include revenues, security issues and reputation of airports.

- Advanced traits of air passengers are envisaged. Advanced traits are derived in contrast to basic traits of air passengers. Basic traits are simple traits which can be easily specified based on existing information such as age, gender and travel class. Advanced traits try to outline the psychological preferences of air passengers when they are travelling through and using an airport terminal. Although the advanced traits are not clearly known and determined, they can be inferred through existing information, including basic traits. By defining ten general categories of advanced traits, psychological preferences of on-airport facility utilisation can be evaluated.

- A route-choice decision-making model of passenger agents is devised in the agent-based passenger flow model. Localised motion dynamics have been addressed in detail by previous research efforts. Medium distance dynamics of passenger walking involves way-finding and tactical target choosing. Although walking behaviour is normally uncertain and it is also hard to know which way a passenger should choose and which facility to use, Bayesian networks have the advantage of being able to address such uncertain events. On the other hand, in airport terminals, the standard processing procedures are quite certain, besides the discretionary activities which are commonly regarded as random. As passengers are basically goal-directed for the purpose of using airports and a proportion of the stochastic activities of passengers is to some extent under control, an airport terminal is consequently a good application to observe the randomness of activities of passengers. By extending Bayesian networks with utility of decisions, the best expected decision is determined. It is the finalised instantaneous decision of a route choice by a passenger agent.

The thesis also suggests a possible application of the work that focuses on pedestrian experience in terms of built environment design. Previous design works have usually taken pedestrian experience into account simply by arbitrarily thinking of which layout people may like and which layout might be more efficient to facilitate pedestrian flows, or in other words, to pursue architectural aesthetics that do not consider the true experience of pedestrians at all. Testing pedestrian flows in the designed building by this kind of simulation approach and demonstrating the benefits related to pedestrians' experience, the proposed design could be more convincing and prove to be much more practical.

## 8.3 RECOMMENDATIONS

The body of knowledge on agent-based passenger flows in airport terminals can have more applications than may have been previously thought. This research initiated a concept of the agent-based passenger flow model integrating both discretionary and standard processing activities. Then, it primarily focused on developing the agent decision model for route-choice decision-making of passenger agents in the model. In the course of this research, the simulation model had two major limitations.

- The first limitation is in relation to how an airport operates. Different airports would manage passenger flow differently. Also, in one airport, the international terminal is distinct from the domestic terminal in terms of passenger processing procedures. Domestic terminals usually do not have immigration and customs counters. These are related to actual facility settlements in airport terminals. In the thesis, the novel idea of modelling passenger flow is discussed largely in relation to scenarios which occur in the international terminal. It is evident that it can be applied to domestic terminals if facility settlements in the simulation are adjusted accordingly. In addition, a few other routing conditions may not be entirely covered in the model due to the research limitations. For instance, there may be other behaviours of passengers after purchasing food. Passengers would look for somewhere to sit to eat the food after they made a purchase at a fast-food restaurant. The simulations carried out in this thesis only set up sections where passengers undertake respective activities without wandering away from them.

- The second limitation is in regard to pedestrian flow studies. One thing that is difficult in pedestrian flow studies is capturing the element of randomness. Although behaviours of passengers in airport terminals can be random, major activities could to some extent be determined since passengers have to proceed to standard checkpoints and would also typically use discretionary facilities (such as shops). The thesis enables the implementation of a more sophisticated agent routing decision approach to model the stochastic behaviours of passengers who are travelling through facilities (shops etc.). The model results in being almost deterministic given a set of initial attributes for a passenger. Even within these behaviours, however, there is still an element of randomness involved. The probabilities of the passenger traits and other conditional probabilities of the developed Bayesian networks may not be totally determined in the light of real circumstances.

Further research efforts into four particular areas may greatly advance the current state of knowledge in this field. The first area is to integrate group behaviours of passengers into the passenger flow model. A method to describe group behaviours should be devised. In the present study, group behaviours and related motion preference were not considered in detail. Traits of passenger agents should include classes regarding groups of passengers, for it is more intuitive that passengers sometimes travel as a couple or with family members and friends. In this regard, group categories can be thought of from three perspectives: groups of a couple or of more than three people in terms of the number of people in the group; adults with children and adults in terms of age; and tourist groups and business groups in terms of purpose. With this integration, the traits of passengers would be more comprehensive, but more importantly, the passenger flow models would be more reflective of real-world airport terminal environments.

The second area of further research is to validate the simulation outcomes with true scenarios inside airport terminals. Accuracy of simulation always increments after extensive validation compared with real scenarios. Regarding real scenarios of passenger flows in airport terminals, consulting airport operators and extracting video footage from terminal surveillance cameras are the most appropriate approaches. Consulting airport operators means communicating with airport staff and making them understand the project. To some extent, however, the data they can provide may not be the exact data as expected. Thus, it is important to identify what can be determined from the research. Terminal video recordings are always from the surveillance cameras. The video recordings usually last long and are quite massive. Techniques that can analyse video contents and extract passenger flow information from the video recordings would be needed. It would be feasible to get assistance from other disciplines. Data mining techniques, for example, could be used to analyse computer images and extract information about passenger flows.

The third area of further research is to identify standardised evaluation systems for pedestrian experience within built environments. This scope of research would mainly investigate pedestrian walking, dwelling and sitting behaviours in a present or designed built environment. If the proposed pedestrian flow model can be applied to the virtual design of a built environment in order to critique how the design involves pedestrians, it could contribute to an approach that sets up the criteria for deciding the trade-off and benefits of a design idea before it is finalised.

The fourth area of further research is to devise other types of agent which represent any other different stakeholders in built environments except pedestrians. In terminal buildings, other potential elements which affect air passengers flow can be taken into consideration. These elements include the employees of airports, services, visitors and other stakeholders in airports. Agents devised in the thesis are currently representing passengers arriving, departing and transferring. For the agent based research theory however, other stakeholders in airport terminals can also be devised as agents with respective traits and interact functions. By devising agents to represent various stakeholders in airports, the whole interaction phenomena of all agents are enriched. For example, if each duty free shop is devised as an agent with at least a revenue trait, every time passengers walk in the shop and purchase certain products, the revenue of the shop agent increase a certain amount consequently. Revenues of all duty-free shop agents can be compared in terms of location in the terminal building and time period in a day. These also implicate the application of devised agent-based model can also be useful for simulating building environments other than airports. In a built environment, pedestrians and other services within it can be devised as respective agents with specific advanced traits, which represent intelligent preferences of pedestrians using the building facilities. First, pedestrian agents are generated in terms of arriving rate at certain building entrances. Next, in setting up simulation by using the agent-based theory in the thesis, pedestrian agents walk and interact with the building layout and other service agents according to devised agents' interaction mechanism which symbolise intelligent preference of pedestrian in reality. At last, statistics results, such as instantaneous utilisation of every facility, space utilisation and walking phenomena in terms of density and crowd, can be collected during simulation rounds.

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# Appendices

## Appendix A: Bayesian Networks

The so-called Bayes theorem is shown in the eighteenth century by the Reverend Thomas Bayes. This theorem allows us to use a model that tells us the conditional probability of event at a given event *a* given event *b* (say, a symptom given a disease) in order to compute the contrapositive: the conditional probability of event *b* given event *a* (the disease given the symptom). This type of reasoning is central to the use of graphical models, and it explains the choice of the name *Bayesian network.*

In Bayesian networks, all of the definitions refer only to probabilistic properties such as conditional independence. The Bayesian network structure may be directed, but the directions of the arrows do not have to be meaningful. On the other hand, it is common wisdom that a "good" BN structure should correspond to causality, in that an edge X -> Y often suggests that X "causes" Y, either directly or indirectly. Bayesian networks with a causal structure tend to be sparser and more natural. However, as long as the network structure is capable of representing the underlying joint distribution correctly, the answers that we obtain to probabilistic queries are the same, regardless of whether the network structure corresponds to some notion of causal influence.

***Representation, Inference, Learning***

The graphical language exploits structure that appears present in many distributions that we want to encode in practice: the property that variables tend to interact *directly* only with very few others. Distributions that exhibit this type of structure can generally be encoded naturally and compactly using a graphical model.

This framework has many advantages. First, if often allows the distribution to be written down tractably, even in cases where the explicit representation of the joint distribution is astronomically large. Importantly, the type of representation provided by this framework is transparent, in that a human expert can understand and evaluate its semantics and properties. This property is important for constructing models that provide an accurate reflection of our understanding of a domain. Models that are opaque can easily give rise to unexplained, and even undesirable, answers.

Second, the same structure often also allows the distribution to be used effectively for inference - answering queries using the distribution. In particular, we provide algorithms for computing the posterior probability of the some variables given evidence on others. For example, we might observe that it is spring and the patient has muscle pain, and we wish to know how likely he is to have the flu, a query that can formally be written as P(Flu = *true* | Season = *spring*, Muscle Pain = *true*). These inference algorithms work directly on the graph structure and are generally orders of magnitude faster that manipulating the joint distribution explicitly.

Third, this framework facilitates the effective construction of these models, whether by a human expert or automatically, by *learning* from data a model that provides a good approximation to our past experience. Probabilistic graphical models support a *data-driven* approach to model construction that is very effective in practice. In this approach, a human expert provides some rough guidelines on how to model a given domain. For example, the human usually specifies the attributes that the model should contain, often some of the main dependencies that it should encode, and perhaps other aspects. The models produced by this process are usually much better reflections of the domain than models that are purely hand-constructed. Moreover, they can sometimes reveal surprising connections between variables and provide novel insights about a domain.

## Appendix B: Influence Diagram

The influence diagram, sometimes also called a *decision network*, is a natural extension of the Bayesian network framework. It is a directed acyclic graph representing a sequential decision problem under uncertainty (Howard and Matheson, 1981). Value of information is very naturally encoded within the influence diagram framework. It models the subjective beliefs, preferences, and available actions from the perspective of a single decision maker. Solving and simplifying influence diagrams need algorithmic techniques.

Influence diagram encodes the decision scenario via a set of variables, each of which takes on values in some space. Some of the variables are random variables and their values are selected by nature using some probabilistic model. Others are under the control of the agent, and their value reflects a choice made by him. Finally, numerically valued variables can be encoded into the agent's utility.

Nodes in an influence diagram are of three types, corresponding to *chance variables*, *decision variables*, and *utility variables*. These different node types are represented as ovals, rectangles, and diamonds, respectively. Circle shaped *chance* nodes represent random variables which the decision maker cannot control, square shaped *decision* nodes represent decisions, *i.e.* sets of mutually exclusive actions which the decision maker can take (Figure B-1). The diamond shaped *value* node represents the decision maker's preferences. Arcs represent *dependencies*.

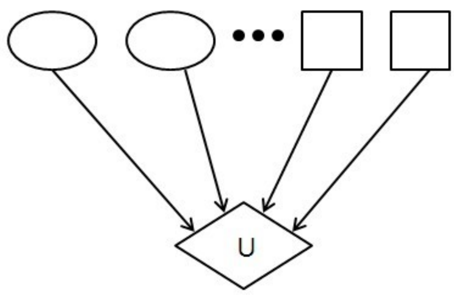


Figure B-1 Illustration of Influence Diagram

A chance node is conditionally independent of its non-descendants given its direct predecessors. A decision maker will observe a value for each of a decision node's direct predecessors before an action must be taken. The decision maker's preferences are expressed as a function of the value node's direct predecessors. In an influence diagram, there is a conditional probability table associated with every change node (unconditional, if it has no predecessors), and a value function associated with the value node.

***Constructing influence diagrams***

Constructing influence diagrams and models is not a science. This means the diagrams different people create to represent a system could each be different. The influence diagram makes clear the span of the problem being tackled and the criteria being considered.

Influence Diagram is for finding optimal policy. Regarding Shachter and Peot's Transformation (1992), it converts a value node v to a binary random node

$$P(v = 1|\pi_v) = \frac{f_v(\pi_v)}{M_v} \quad \text{(B-1)}$$

$$M_v = max_{\pi_v} f_v(\pi_v) \quad \text{(B-2)}$$

Given a policy, denote the reformulated Bayesian network (BN) as $N_\Delta$ ,

$$E_\Delta[v] = \sum_{\pi_v} P_\Delta(\pi_v) f_v(\pi_v) \quad \text{(B-3)}$$

$$\begin{aligned} E_{N_\Delta}[v] &= \sum_{v\in\{0,1\}} vP_{N_\Delta}(v) \\ &= 0 \cdot P_{N_\Delta}(v = 0) + 1 \cdot P_{N_\Delta}(v = 1) \\ &= P_{N_\Delta}(v = 1) \\ &= \sum_{\pi_v} P(v = 1|\pi_v) P_\Delta(\pi_v) \\ &= \frac{1}{M_v} \sum_{\pi_v} f_v(\pi_v) P_\Delta(\pi_v) \\ &= \frac{1}{M_v} E_\Delta(v) \end{aligned} \quad \text{(B-4)}$$

$$E_\Delta[v] = P_{N_\Delta}(v = 1) M_v \quad \text{(B-5)}$$

Evaluating the expected value for a given policy:

$$E_\Delta[N] = \sum_{v\in U} E_\Delta[v] = \sum_{v\in U} P_{\mathrm{N}_\Delta}(v = 1) M_v \quad \text{(B-6)}$$

Evaluating the expected value for an optimal policy:

$$E[N] = max_\Delta E_\Delta[v] = max_\Delta \sum_{v\in U} P_{\mathrm{N}_\Delta}(v = 1) M_v \quad \text{(B-7)}$$

Horch and Poole (1996) gave an example (Figure B-2) to shows an augmented version of the well known *Weather* Influence diagram (Shachter and Peot, 1992). The influence diagram represents the information relevant to a hypothetical decision maker, whose problem is to decide whether to take an umbrella to work. The goal is to maximize the decision maker's expected *Satisfaction*, which depends on the *Weather* and decision maker's decision to *Take Umbrella*? The decision maker can choose to *Bring Umbrella*, or *Leave Umbrella*, which are not explicit in the figure. The decision maker has two sources of information: a *Radio Weather Report*, and the *View From Window*. These random variables are explicitly assumed to be independent given the weather, and both have three possible outcomes: *Sunny*, *Cloudy*, and *Rainy* (not explicit in the figure). The Weather is also a random variable, not directly observable at the time an action must be taken; it has two states: *Sun* and *Rain*, (not explicit in the figure).

For brevity, probability and utility information for this example has not been shown. However, conditional probability tables of the form P(*Weather*), P(*Radio Weather Report* | *Weather*), and P(*View From Window* | *Weather*) are necessary to complete the specification. The value function, *Satisfaction* (*Weather*, *Take Umbrella*) is also necessary (Horch and Poole, 1996).

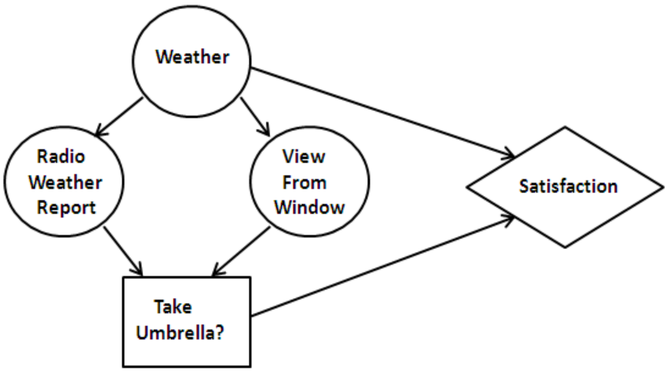


Figure B-2 Weather Influence diagram

A policy prescribe an action (or sequence of actions, if there are several decision nodes) for each possible combination of outcomes of the observable variables. In one of the possible policies for the above example, the decision maker always takes an umbrella, regardless of the information available. An optimal policy is the policy which maximizes the decision maker's expected *Satisfaction*, without regard to the cost of finding such a policy.

The goal of maximizing the decision maker's expected *Satisfaction* can be achieved by finding an optimal policy, if computational costs are assumed to be negligible. If computational costs are not negligible, the decision maker's expected utility might be maximized by a policy which is not optimal in the above sense. Horch and Poole (1996) use Bayesian networks (BNs) as the underlying computational engine for our technique to compute posterior probabilities and expected values (Shachter and Peot, 1992).

***Decision tree***

A decision tree has two types of internal nodes (denoted t-nodes to distinguish them from nodes in a graphical model) – one set encoding decision points of the agent, and the other set encoding decisions of nature. The outgoing edges at an agent's t-node correspond to different decisions that the agent might make. The outgoing edges at one of nature's t-nodes correspond to random choices that are made by nature. The agent's overall behaviour in a decision problem encoded as a decision tree can be encoded as a *strategy*. *Strategy* is a mapping from agent t-nodes to possible choices at that t-node. A decision-tree strategy specifies, for each $v$ belongs to $V_a$, one of the choices labelling its outgoing edges.

Conventional approaches use a single tree to represent a policy (Heckerman et al., 1989; Lehner and Sadigh, 1993). Horch and Poole (1996) extended the previous work by building a decision function, in the form of a tree, for each decision node, taking advantage of efficient probabilistic inference techniques

## Appendix C: Parameters for Simulation

The departure flight schedule of an international airport in Australia at Friday, 13 July 2012:

Table C-1 Flight Timetable

| Flight | Time | Quantity | Gate |
|---|---|---|---|
| EK433 | 3:30 | 116 | 81 |
| QF008 | 6:30 | 112 | 84 |
| DJ184 | 6:45 | 54 | 81 |
| EK434 | 8:25 | 75 | 79 |
| DJ066 | 8:50 | 54 | 82 |
| DJ110 | 9:00 | 52 | 83 |
| QF123 | 9:10 | 50 | 85 |
| DJ175 | 9:30 | 54 | 78 |
| DJ074 | 9:45 | 56 | 76 |
| DJ4191 | 10:00 | 54 | 77 |
| DJ4197 | 10:15 | 54 | 80 |
| QF015 | 10:35 | 100 | 81 |
| QF349 | 11:05 | 76 | 79 |
| VA007 | 11:15 | 74 | 82 |
| QF397 | 11:30 | 100 | 84 |
| CX102 | 11:45 | 54 | 85 |
| CI053 | 12:05 | 96 | 86 |
| AS040 | 12:25 | 52 | 78 |
| QF051 | 13:40 | 100 | 76 |
| TG474 | 14:00 | 55 | 77 |
| SQ236 | 14:40 | 56 | 80 |
| DJ082 | 17:50 | 74 | 81 |
| DJ188 | 18:00 | 70 | 79 |
| NZ804 | 18:30 | 70 | 82 |
| QF125 | 18:35 | 100 | 83 |
| NZ734 | 18:50 | 70 | 84 |
| DJ068 | 19:00 | 56 | 85 |
| QF377 | 19:00 | 74 | 86 |
| DJ086 | 19:15 | 74 | 78 |
| EK435 | 20:45 | 100 | 75 |
| DJ097 | 21:30 | 126 | 76 |
| CI054 | 23:05 | 74 | 77 |
| MH134 | 23:20 | 100 | 80 |
| SQ246 | 23:45 | 50 | 81 |
| QF347 | 23:55 | 54 | 79 |

Table C-2 Conditional Probability Tables

| **Willingness to ask for assistance** | | | | |
|---|---|---|---|---|
| Age | Less65 | | Over65 | |
| FrequencyOfTravel | LessThan3 | MoreThan2 | LessThan3 | MoreThan2 |
| TRUE | 0.9 | 0.0 | 1.0 | 0.4 |
| FALSE | 0.1 | 1.0 | 0.0 | 0.6 |

| **Comfort of Technology** | | | | |
|---|---|---|---|---|
| FrequencyOfTravel | LessThan3 | | MoreThan2 | |
| Age | Less65 | Over65 | Less65 | Over65 |
| TRUE | 0.2 | 0.0 | 0.9 | 0.1 |
| FALSE | 0.8 | 1.0 | 0.1 | 0.9 |

| **Desire to Shopping** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Gender | Male | | | | Female | | | |
| Nationality | Native | | Foreigner | | Native | | Foreigner | |
| FrequencyOfTravel | LessThan3 | MoreThan2 | LessThan3 | MoreThan2 | LessThan3 | MoreThan2 | LessThan3 | MoreThan2 |
| TRUE | 0.4 | 0.5 | 0.2 | 0.5 | 1.0 | 0.9 | 1.0 | 1.0 |
| FALSE | 0.6 | 0.5 | 0.8 | 0.5 | 0.0 | 0.1 | 0.0 | 0.0 |

| **Social Connectivity** | | | | |
|---|---|---|---|---|
| Age | Less65 | | Over65 | |
| TravelClass | Economy | Business | Economy | Business |
| TRUE | 0.8 | 1.0 | 0.0 | 0.2 |
| FALSE | 0.2 | 0.0 | 1.0 | 0.8 |

| **Need cash** | | | | |
|---|---|---|---|---|
| Nationality | Native | | Foreigner | |
| FrequencyOfTravel | LessThan3 | MoreThan2 | LessThan3 | MoreThan2 |
| TRUE | 0.1 | 0.5 | 0.1 | 0.2 |
| FALSE | 0.9 | 0.5 | 0.9 | 0.8 |

| **Tax Claim** | | |
|---|---|---|
| Nationality | Native | Foreigner |
| TRUE | 0.2 | 0.95 |
| FALSE | 0.8 | 0.05 |

| **Hunger and desire to food** | | |
|---|---|---|
| Hunger level | high | low |
| TRUE | 0.5 | 0 |
| FALSE | 0.5 | 1 |

# Appendix D: Complementary Figures for Outbound Passenger flows Simulation

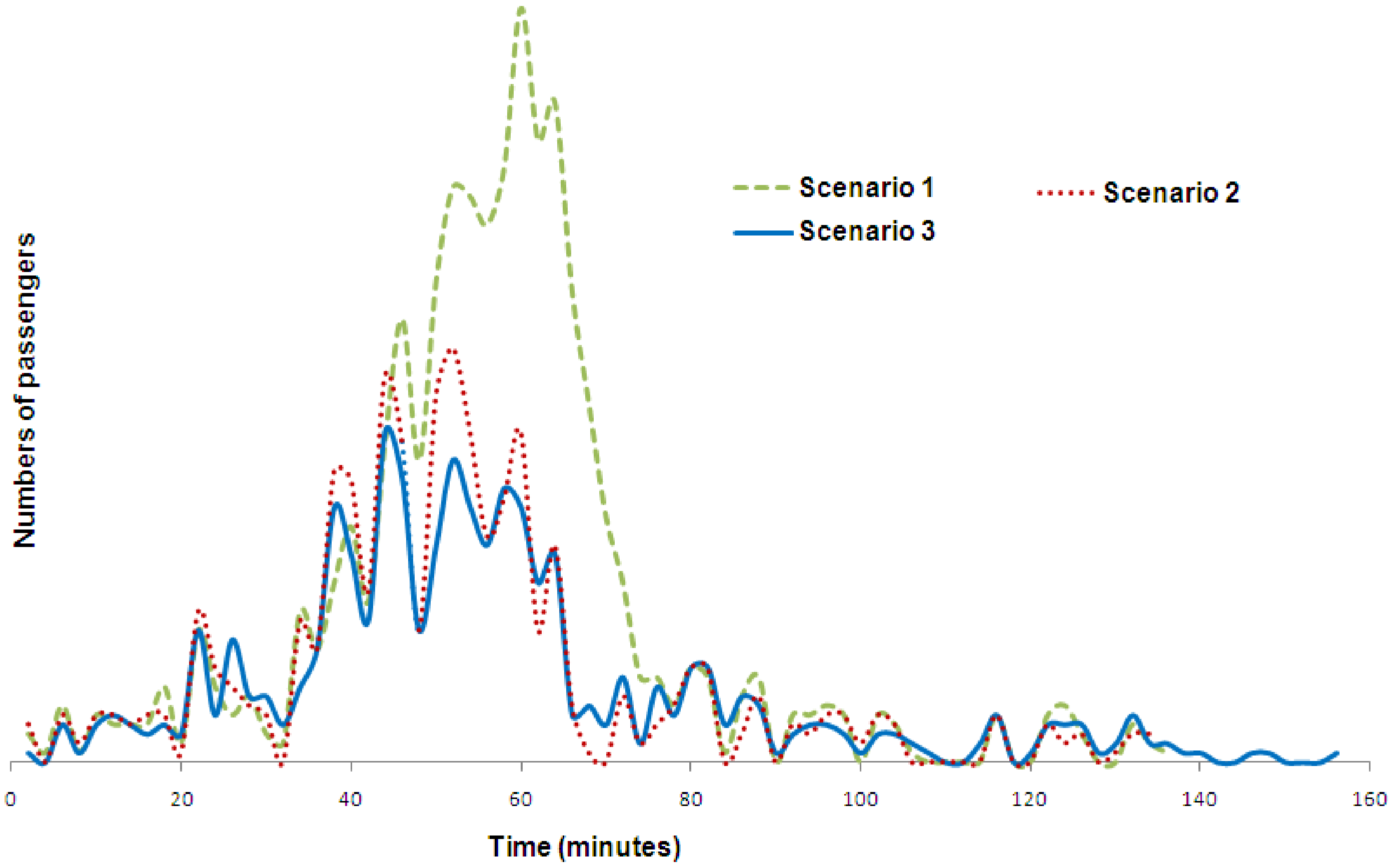


Figure D-1 Instantaneous utlisation of normal check-in counters

(Scenario 1 – Simulated passengers do not undertake any discretionary activities; Scenario 2 – Simulated passengers can use self-service check-in kiosks; Scenariso 3 – Simulated passengers not only can use self-servcie check-in kiosks but also undertake sorts of discretionary activities, shopping etc.)

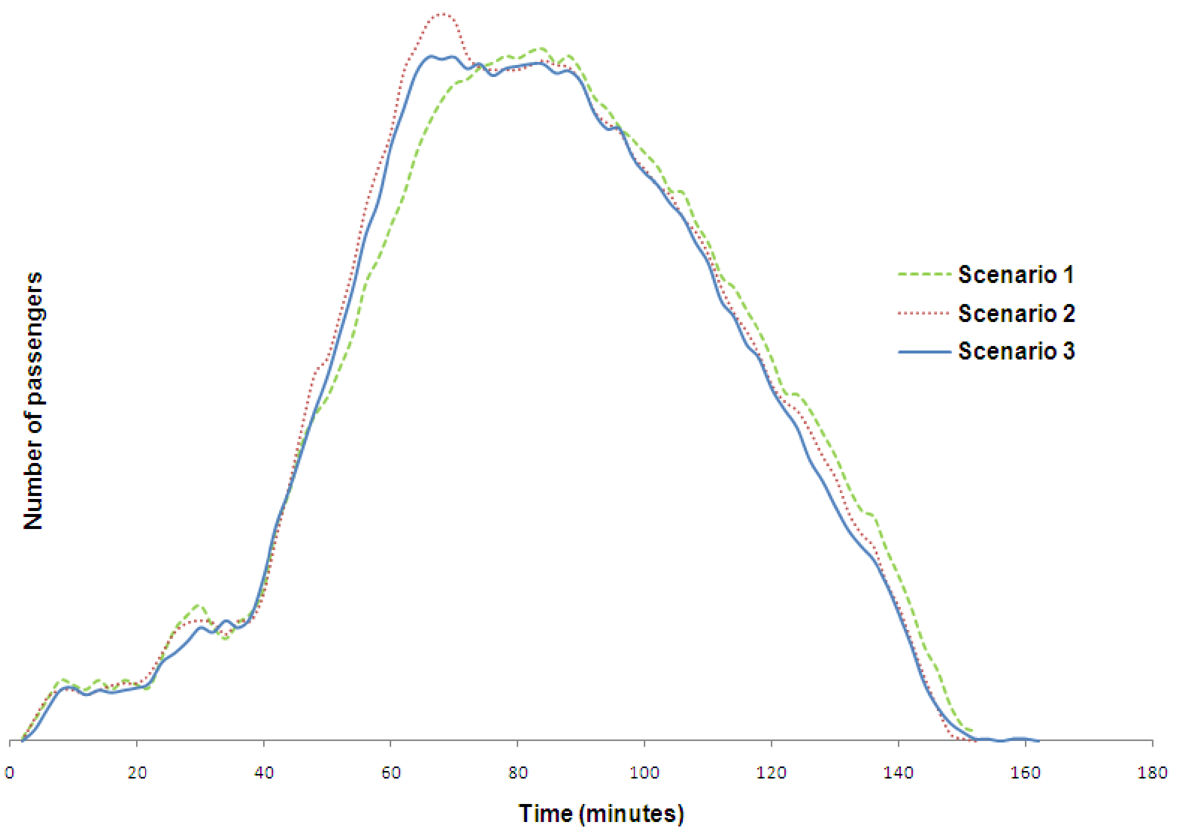


Figure D-2 Instantaneous utilisation of security and immigration counters

(Scenario 1 – Simulated passengers do not undertake any discretionary activities; Scenario 2 – Simulated passengers can use self-service check-in kiosks; Scenariso 3 – Simulated passengers not only can use self-servcie check-in kiosks but also undertake sorts of discretionary activities, shopping etc.)

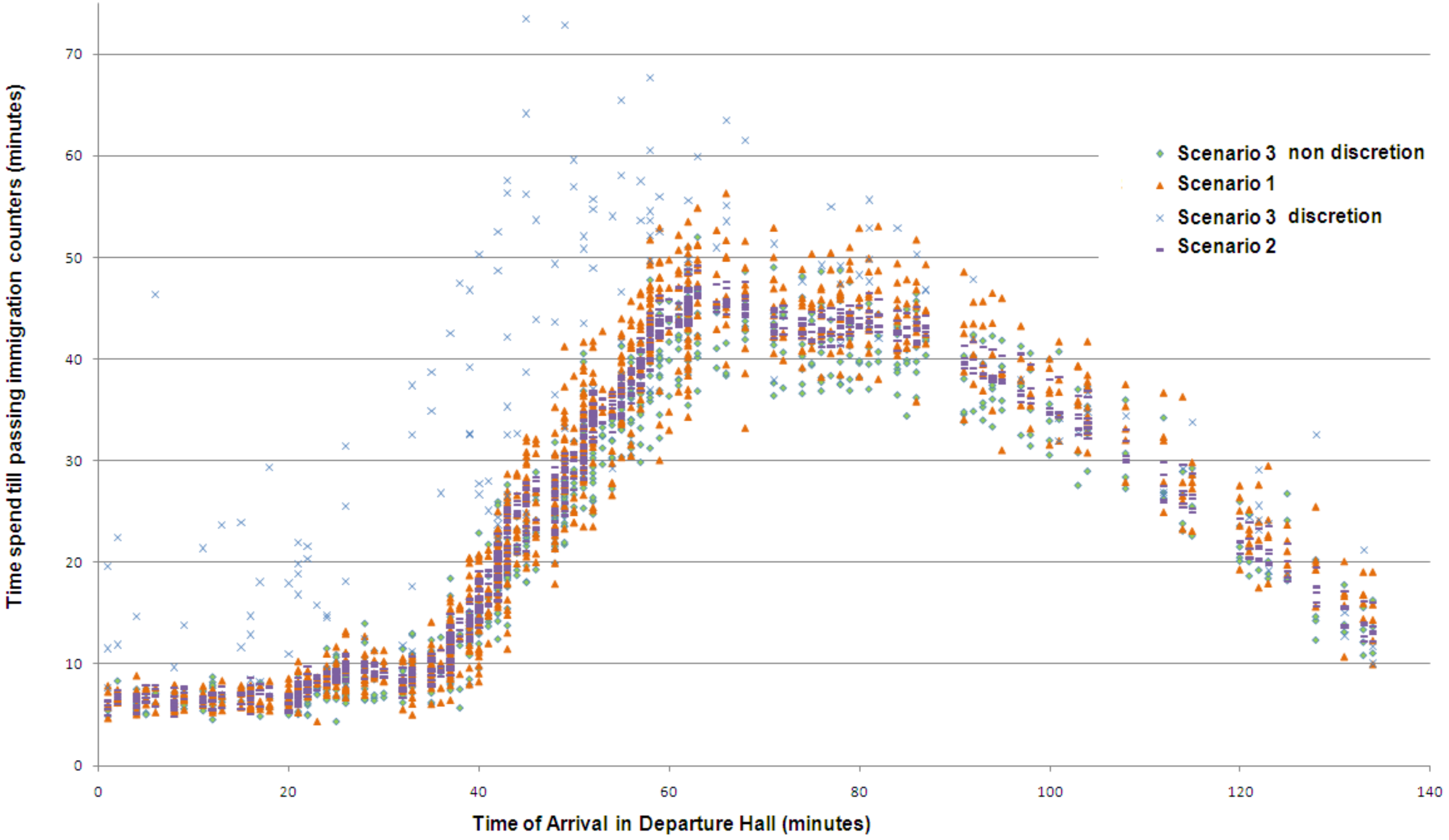


Figure D-3 Instantaneous utilisation of the airport terminal till passing immigration counters

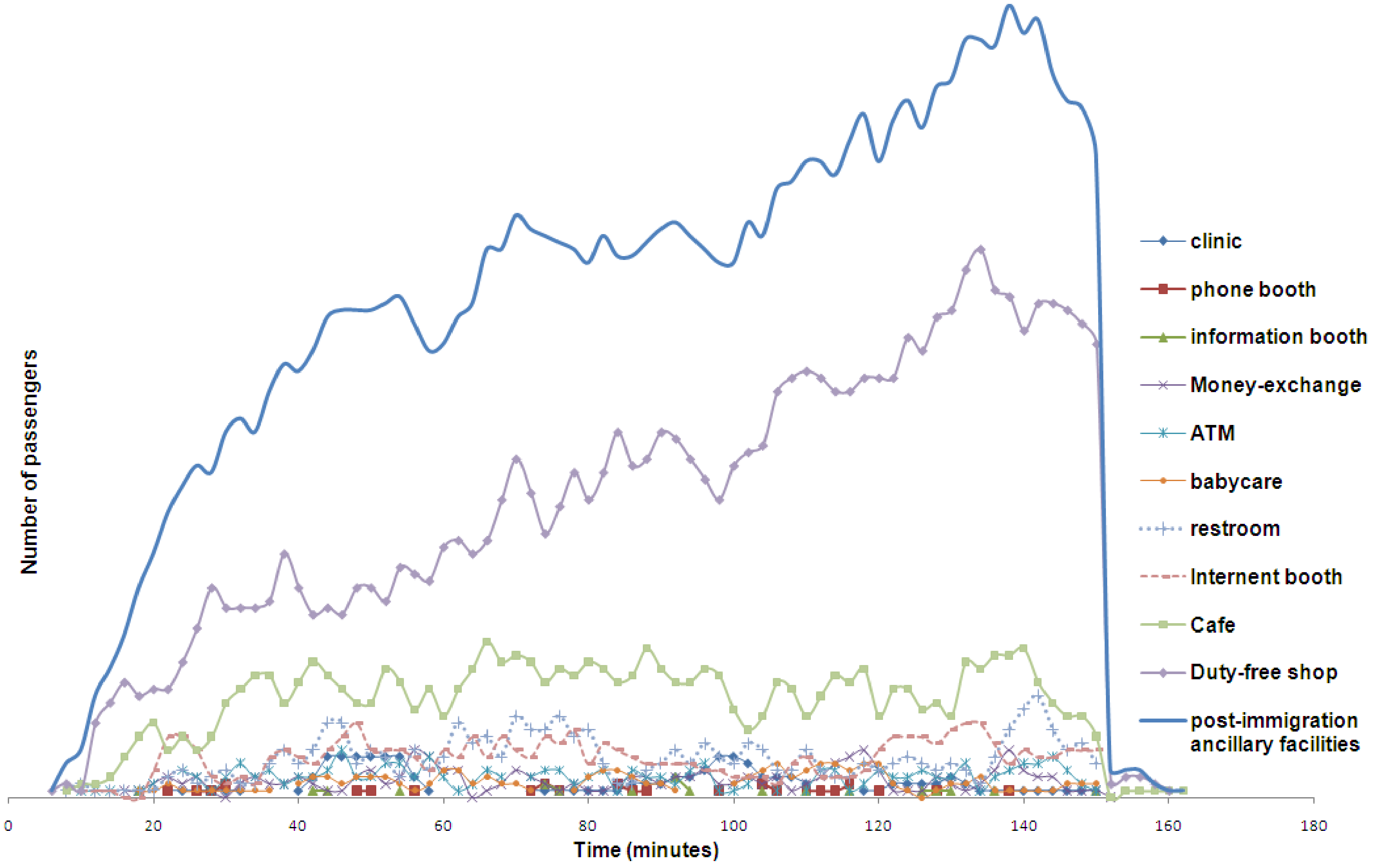


Figure D-4 Instantaneous utilisation of sorts of discretionry facilitiessecurity after immigration counters