Trade-off Analysis between Security and Efficiency of Airport Operations

A methodological underpinned modelling approach to identify, analyse and evaluate trade-offs based on empirical choice observations

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Delft University of Technology

Master Thesis

TU Delft

ATO

Air Transport and Operations

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Trade-off Analysis between Security and Efficiency of Airport Operations

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Master Thesis

by

Marson Simeon Jesus

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Preface

This Master Thesis report is written in partial fulfilment of the requirements for the degree of Master of Science in Transport, Infrastructure and Logistics (TIL) at Delft University of Technology, Faculty of Civil Engineering and Geosciences (CEG). The thesis is my final product, which I proudly have been working on for the past seven months. The project has been conducted for the Air Transport and Operations (ATO) section of the Faculty of Aerospace Engineering (AE) in collaboration with different other faculties at the university, namely the Faculty of Technology, Policy and Management (TPM) and the Faculty of Mechanical, Maritime and Material Engineering (3mE). Altogether, this shows the multi- and interdisciplinary character and foundation of the TIL programme, which I started with in September 2015. I want to thank all the key persons behind this programme for providing me a comprehensive view of the field of Transport, Infrastructure and Logistics in the past 2 and a half years. It has been a tough but nevertheless great experience.

Getting back to my thesis, I really want to thank Dr.ir. S. (Sander) van Cranenburgh, which was my daily supervisor. I want to thank you for the supervision and new ideas you brought on table that really had a major contribution to this final product. Your open office, which I could walk in at any moment when I got stuck was really helpful in the progress of this big project.

A special thank you also goes to Dr. O.A. (Alexei) Sharpanskykh as my ATO supervisor for showing confidence in me at our first meeting, which basically was the first concrete moment for me realizing that my thesis life was about to begin. Your meetings with me were very helpful in providing me new insights and new ideas that I could use to improve this major project. Furthermore, I would like to thank the whole ATO team, especially PhD. Candidate S.A.M. (Stef) Janssen for all the insights you provided me during the last months. Thanks for the key role you played in my data collection phase as a contact person between me and the corresponding local airport.

Also Dr. W.W.A. (Wouter) Beelaerts van Blokland as my secondary supervisor had a key role in my project. I want to thank you for being available at all moments that I wanted to share my ideas and progress with you. Thanks for being critical at all moments. This really kept me sharp in the decisions I made along this journey.

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I also would like to thank dhr. A. (Alexander) Dilweg, Airport Security Advisor; Dr.ir. E.J.L. (Emile) Chappin, Assistant Professor at TPM; Dr.ir. Y. (Yashar) Araghi, Junior Researcher at Significance and the different security screeners and team leaders at a local airport for having their own peace of contribution in my Master of Science Thesis Project. It really helped me in achieving this major result.

Last but not least, I would like to thank my family, friends, TIL fellow students, ex-colleagues of the Engineering Student Association ABC Compas for your patience at any moment I was zoned out in the last period. Of course your (mental) support in this period also meant a lot to me.

THANKS TO ALL OF YOU!!! YOU GUYS ROCK!!!

Marson S. Jesus
Delft, January 2018

Summary

Since 9/11 security has become an important component in the air transport industry. Due to a stricter security control, the cost of the air transportation industry has increased, resulting in a cost component of more than one-quarter of airports operating costs. Besides affecting the operational costs of airports, the stricter controls also have been having an impact on the efficiency of airport operations. The degree of security control for instance affects the privacy, waiting times, convenience and delay experienced by passengers. Not only passengers are affected by the stricter security control, but also airlines, service providers, Air Traffic Controllers and the airport itself, which on their turn increase the pressure on the security operation to be more efficient. However, it is known that efficiency and security are not always in line with each other, as measures taken to increase the security at airports can have negative effects on the efficiency of airports and vice versa. This pressure and conflicting relation between security and efficiency put airport security screeners in a challenging process when taking security operational decisions like 'ultimate decisions on extra checks or higher level of security based on real-time passengers and baggage information', 'decisions on the degree of negotiations with negotiating passengers during security checks', 'when to open or close a security lane', 'the operational speed and time taken to conduct a particular check' etc. This challenging process can lead to ad-hoc security decisions, which can affect both the security and efficiency of the operations at airports.

Although that one believes and assumes that such security decisions are determined by rules and protocols, there are hard (anecdotal) evidences found in literature that this thought/assumption is problematic. Evidences that show that workers allow passengers to pass with liquids exceeding maximum allowed requirements or suspicious items in their bags as a consequence of social contextual pressure and (unique) situations such as long waiting times at checkpoints. Or security personnel that disclosed that breaking protocols sometimes is necessary to get their job done. This all results in operational choices and decisions that are based on security and efficiency trade-offs that airport security screeners are forced to take, when considering both the security and efficiency of the operation of airports. These trade-offs can be issues between security speed vs. accuracy, number of false alarms vs. missed threats, security degree vs. the level of service experienced by passengers etc.

But although one knows that these operational trade-offs between security and efficiency are made and recognizes the importance to better understand these trade-offs, there miss (a) methodological underpinned modelling tool(s) to explicitly determine and evaluate security and efficiency operational trade-offs made by airport security decision-makers. Therefore, two research goals have been established, which are based on methodological underpinned modelling tools, of which 1) is to identify and analyse airport security screeners' trade-offs between security and efficiency in an airport operational environment and 2)provide implications that can be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports. The first goal was addresses by answering the following (main) research question:

'*How do airport security screeners trade-off security and efficiency when taking airport terminal operational trade-off decisions?*',

which forms the core of this research. In order to achieve the second research objective the above formulated main research question was extended with the following question: 'How can the gathered trade-off insights be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports?'

To answer the main research question a trade-off analysis between security and efficiency variables has been conducted based on Discrete Choice Modelling (DCM). During this process; choice data have been collected among 67 security screeners at a local airport by using an Orthogonal in the Difference Fractional Factorial Choice Experiment. In addition to this, based on the insights of this analysis, implications have been provided that can be used to evaluate, by the means of Agent Based Modelling (ABM), the trade-off effects of airport security screeners on the operations of airports.

For the trade-off analysis between security and efficiency variables, four (relevant) determinants were found, which are considered by security screeners when taking airport operational trade-off decisions. These determinants can be categorized under two terms, namely Security Detection Performance and Security Efficiency Experienced by Passengers. The determinants under Security Detection Performance that impose trade-offs during the operations of airports have found to be Hit Rate and False Alarm Rate[1]. The determinants that are categorized under Efficiency Experienced by Passengers, considered by security screeners during the operations of airports, have found to be Average Passengers Waiting Time and Passengers Missed Flights.

[2]The results of the trade-off analysis, which are based on these four security/efficiency indicators show that Hit Rate is the number one most valued/important attribute among the average security employee, followed by consecutively Missed Flights, Average Passengers Waiting Time and False Alarm Rate. The average security screener has an importance weight of more than 40% for Hit Rate relative to the other indicators. Missed Flight has, among the average security screener, a relative importance weight of more than 30%, while this measure for Passengers Waiting Time is around 17% for the average security screener. The least valued indicator (i.e. False Alarm Rate) scores around 10% among the average security screener for this measurement of relative importance weight. Expressed in percentage points Hit Rate, derivations have been made that each missed flight, passenger minute waiting time and percentage point false alarm (among the average security screener) values respectively 7.73, 0.38 and 0.15 percentage points Hit Rate. These results also show that Missed Flight has the highest value and False Alarm Rate the least value among the average security screener. Furthermore, their found to be significant heterogeneity among the security screeners, which indicates taste variation among security screeners for these attributes. Some security screeners, namely value these attributes higher and some lower that the average values presented above. There are also different classes in which security employees can be clustered. There found to be a group of security screeners that can be labelled as highly efficient employees and a group that find the level of service for passengers very important. However, the vast majority of the security employees (almost 60%) still belongs to the group that values the security aspect (i.e. Hit Rate) as most important compared to the efficiency of the security operation. For this group their found to be a significant positive class membership-specific constant that contributes to the higher membership probability of almost 60% of security screeners to this class, which attach the highest value to Hit Rate. This significant positive class-membership specific constant can be explained by the general context that security screeners' job is to secure the passengers and their belongings, which in general is of high value among security screeners.

[1] Hit Rate: the probability of a detection registration given that a target was present (i.e. the probability of a correct detection)
False Alarm Rate: the probability of a detection registration given that no target is present (i.e. the probability of incorrect detection)

[2] Note that the values in this section are rounded. The exact and more detailed values are covered in the chapter: Empirical Results

All these (different) trade-offs of security screeners between security and efficiency can have a (wide) effect on the operations of airports. Therefore, the framework of combining DCM and ABM methodologies, found out to be a suitable framework to evaluate the effects of these empirical security and efficiency trade-offs on the operations of airports. This can be done by specifying agents in Agent Based Simulation Models (which describes security agents working in airport environments) with the empirical trade-off parameters gathered from this study. One of such Agent Based Simulation Models that already is able to model and simulate airport operational environments with (among others) security agents, is the Agent-based Airport Terminal Operations (AATOM) Model of the ATO section at the Faculty of Aerospace Engineering (TU Delft). However, this model does not take operational trade-offs of security screeners into account yet. Therefore, the gathered trade-off parameters in this study should be used in addition to the already existing security operators' input parameters which are the 'Activity Assignment Parameter' indicating which activities the security agents must perform and the 'Threat Level Threshold Parameter' which determines if a luggage under investigation needs to be checked or not. Yet, this threshold parameter only is used to determine if the luggage under investigation needs to be checked (or not) but does not contain insights, based on empirical trade-off parameters, to indicate if a security operator actually checks these luggage and in what degree. Including these trade-off parameters will improve the realism and validity of AATOM with empirical security behaviour to derive to a more realistic AATOM simulation environment. The empirical parameters can furthermore also be used to create diversity between security agents. This can be done by specifying different security agents, by taking draws from empirical found parameter distributions or by modelling the three different types of security agents that were mentioned earlier. In addition to this, the composition of security agents during operations should also be taken into account by modelling the probability of a security screener of being/of belonging to one of the security types/groups. These implications, based on the combination of DCM and ABM methodologies, forms a promising approach to evaluate the security and efficiency trade-offs of airport security screeners in an airport operational simulated environment such as the AATOM model. This enables one to evaluate the trade-off effects on the operations of airports but also to fortify the realism and validity of the simulation models themselves.

Furthermore, airport operators should also consider different measures based on the found trade-off insights. Since their found to be significant heterogeneity between security screeners of which some groups value some attributes more than others, it is important to mix and shift security teams as much as possible to decrease the chance that a group that is highly sensitive for for example passenger level of service is grouped (for a long time period) in one shift during operations. Another measure that can be taken is to invest in more resources to avoid long waiting times or passengers missing their flights, which can trigger security employees to trade-off security and efficiency during operations. Also the introduction of a passenger track system, which keeps track of passengers and how much time they have left to catch their flights in order to provide them priority service, can be considered. Such measures can lead to a more efficient system experienced by passengers, which can avoid security screeners to be triggered to trade-off security and efficiency, which can lead to inaccurate and (potentially) dangerous trade-off decisions. However, one knows that investing in more resources can be an expensive measure. Therefore, it is important to also increase the awareness and importance of security among the employees. This measure is relatively cheap and can lead to more security screeners that are more secure in terms of airport security.

Although the goal of this research has been met; this research has some limitations that should be taken into account in future research. Firstly, this research has estimated relatively complex models with a relative small sample size of 67 respondents. Therefore, this research was limited in the amount of security classes that have been estimated. Increasing the amount of respondents makes the use of complex models more effective, as more parameters (attributes) can be estimated, while the standard errors of these parameters are (still) able to be low. Furthermore, this research did not collect socio-demographic data. For future research it is recommended to gather socio-demographic data, since such data can provide new explanatory knowledge and variables that can be used to (better) explain the trade-offs of security employees. In addition to this, new research can be set up to derive the influence of context/scenarios (e.g. busy or non-busy working days, flight type: risk or no-risk flights etc.) on the trade-offs of security screeners. It is also recommended to do further research on how security agents can explicitly be specified/modelled with the gathered security trade-offs, so (Agent-based) simulation models can be used to explicitly determine the security and efficiency trade-off effects of security screeners on the operations of airports.

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1. Introduction

1.1 Background

Security is an important component in high-risk organizations and industries such as the air transportation industry. This important character in air transportation has become more dominant after 9/11 when the security of aviation has been challenged. Due to a stricter security control, the cost of the air transportation industry has increased resulting in a cost component of more than one-quarter of airports operating costs (Kirschenbaum, 2013). Besides affecting the operational costs of airports, the stricter controls also have been having an impact on the efficiency of the operations. The degree of security control for instance affects the privacy, waiting times, convenience and delay experienced by passengers (Burge, Kim, Potoglou, Robinson, & Warnes, 2010; Bjørnskau, Flügel, & Veisten, 2011). Decisions made on the level of airport security immediately impacts one or more of these factors, which makes decision-making on the degree and form of airport security a challenging process for airport decision-makers. Airports in Europe for instance, have faced increased passengers delay in 2017 in some cases up to 300% compared to 2016 due to new security measures introduced by the EU as a response to the Paris, Brussels and Nice terrorist attacks. Airlines for Europe (A4E) declared that travellers needed to wait for up to 4 hours, while others have missed their flights. (BBC, 2017; Euronews, 2017)

This challenging process in decision-making is more present when considering that security, in essence, has a different primary aim than efficiency. While the one is focussed on the quality or state of being secure, the other tries to increase certain outputs, while decreasing the efforts being put in the corresponding process. Gkritza, Niemeier, & Mannering (2006) also show that these two factors are not always in line with each other, as measures taken to increase the security at airports can have negative effects on the efficiency of airports and with this at the end the experience of passengers. Not only passengers can be affected by such measures, but since airports are organizations composed of complex and interdependent groups of decision-makers, they are influencing other stakeholders as well and (as a consequence) are continuously under threat and pressure of these stakeholders. Security and efficiency measures for example[3] affect airlines, service providers, Air Traffic Management (ATM) and the airport itself, which on its hand results in these stakeholders to pressure the security processes leading to decisions that are not always in line with established rules and protocols. (Kirschenbaum, et al., 2012)

Although that one believe and assume that security decisions are determined by rules and protocols; Kirschenbaum et al. (2012) states that this thought and assumption is problematic based on hard (anecdotal) evidence. Examples were provided by Kirschenbaum of the behavioural patterns found of airport security workers. Examples such as workers allowing passengers to pass with liquids exceeding maximum allowed requirements or suspicious items in their bags as a consequence of social contextual pressure and (unique) situations such as long waiting times at checkpoints. These evidences provide ground to question that security decisions are carried according to rules and protocols. Also the Behavioural Model of Security in Airports (BEMOSA) results show that things that should be done are not always the things that are actually done. BEMOSA (2011) preliminary results showed that 10% of questioned security personnel in a survey disclosed that they exceed or bend the rules when situation calls for it and that 12% of the security personnel disclosed that breaking protocols sometimes is necessary to get the job done.

[3] For example, airport authorities want to maintain security but this may conflict with airlines wanting to keep to their schedules, passengers demanding little or no delays, control tower personnel seeking minimum disruption over air space and service providers wanting easy access for employees. An example used by (Kirschenbaum, et al., 2012)

This phenomenon of affecting multiple stakeholders and the pressure experienced by these stakeholders demands ad-hoc operational choices and decisions that airport security decision-makers and the security personnel i.e. Security Screeners, Security Team-leaders, Security Operational Planners and Security Operational Managers are pressured to take.

These can be decisions that can influence the efficiency of the security process such as[4]

- the opening of extra security lanes (Fayez, Kaylani, Cope, Rychlik, & Mollaghasemi, 2008)
- the closing of security lanes
- the degree of negotiations between negotiating passengers and employees (Kirschenbaum, 2013)
- distribution of passengers over the available screening checkpoints
- the quantity of screening personnel (de Lange, van der Rhee, & Samoilovich, 2013)
- the operational time to perform a task considering speed/accuracy trade-offs. (Abeynayake, Aidman, & Jain, 2011)

But also decisions that can influence the aviation security such as[2]

- the team configuration of security screeners, based on their performance, years of experience and quality
- amount of work pressure on the screening process, depending on the varying work pressure experienced of the airport/airlines to process passengers (Kirschenbaum, et al., 2012)
- varying operational decision's threshold (above minimum level) such as the number of random checks considering the number of incorrect alarms vs. missed threats (Abeynayake et al., 2011)
- ultimate decisions on extra checks or higher level of security based on real-time situations and information, which together results in a judgemental call of security screeners. (Kirschenbaum, et al., 2012)

The situation becomes more complex if one considers the numerous trade-offs security decision-makers and security personnel are facing in making these decisional-choices. Trade-offs on issues such as:

- Speed vs. Accuracy (Abeynayake et al., 2011)
- Incorrect alarms vs. Missed threats (Abeynayake et al., 2011)
- Security vs. the Level of Service provided (Gkritza et al., 2006)
- Privacy vs. Security
- Uniform Screening vs. Selective Screening (Bjørnskau et al., 2011)
- Vulnerability and threat vs. Deployment of resources (Bjørnskau et al., 2011)
- Resilience vs. Deployment of resources

[4] Note that these decisions very often do not only affect the efficiency or only security performances but often both of them. The operational time to perform a task for example also can influence the aviation security, while the team configuration based on the employees performances and the amount of pressure on the screening process also can impact the efficiency of the process.

Although that these security and efficiency factors on a frequent basis are being compared and considered in combination, there have been a lack of tools to provide airport decision-makers an integrated and total view on the operational effects of their decisional-choices (Zografos, Madas, van Eenige, & Valdes, 2005; Zografos, Madas, & Salouras, 2013). Through the years the Supporting Platform for Airport Decision-making and Efficiency Analysis (SPADE) project has introduced a system that provides support in airport development, planning and operations that includes trade-off analysis between a variety of airport performance indicators (van Eenige & Muehlhausen, 2007). However, beside the introduction of this project Zografos et al., (2013) state that there are only a few integrated modelling tools and capabilities that assess multiple airport performance measures such as airport security and airport efficiency simultaneously. Besides this finding, Kirschenbaum (2015) even states that airport architects and security professionals have been ignoring the reality of the influence of security decision-making by security employees on the operational effects of airports and have only focussed on the influence of technology on airport (operational) systems.

Considering the need of integrated modelling capabilities and tools to assess airport performance measures such as airport security and efficiency simultaneously by trade-off analysis and the increasing awareness of taking (beside the technical influence of airport systems) also the social influence of airport (security) decision-makers decisional-choices into account; there found to be room for further research on modelling tools that takes airport decision-makers' trade-offs into account. To address this issue for security and efficiency performance indicators the following knowledge gap has been derived:

"*There miss a methodological underpinned modelling tool to explicitly determine and evaluate security and efficiency operational trade-offs made by airport security decision-makers.*"

Addressing this knowledge gap will lead to a better understanding of the security operational decisional-choices. The evaluation of the effects of the encountered trade-offs made by the airport security decision-makers can furthermore lead to more insights on their operational impact such as the impact on the passenger flow, waiting times, delay experienced by passengers, degree of missed flights, security risks, security costs etc.
Since this project will focus on the operations of airports, the airport security decision-makers referred in the knowledge gap must be interpreted as security screeners, who frequently take operational decisions based on security and efficiency trade-offs. Further information on the scope of this project is covered in paragraph 1.4.

1.2 Research Objectives and Questions

Research objectives

Besides the awareness of trade-off analysis to evaluate the effects of decisional-choices on the operations of airports by considering different outcomes of interest such as airport efficiency and security together, their still misses a methodological underpinned modelling tool to explicitly determine and evaluate security and efficiency operational trade-offs made by airport security decision-makers (i.e. in this study airport security screeners).

This knowledge gap will be addressed by focussing on the following two research objectives, which are based on methodological underpinned modelling tools that will be presented in paragraph 1.3:

1. Identify and analyse airport security screeners' trade-offs between security and efficiency in an airport operational environment.

Agent Based Models **Intermezzo**

The knowledge gathered during this process will be used in combination with other airport security-related (Master of Science thesis) projects for the development of a socio-technical Agent-Based Simulation Model (ABM) that describes typical airport terminal processes. This ABM is expected to be implemented in an airport simulation environment developed by the Air Transport and Operations (ATO) section of the Aerospace Engineering faculty at Delft University of Technology.

This project will use ABMs as a collaboration model, as these models are widely used at the ATO section and will be used to develop future airport operational models. One of the application themes at the ATO section is Air Transport and Safety. This includes, among others, the modelling of human coordination impact on air transport systems performances. This latter part is done by using ABMs, which can be used to simulate and evaluate (operational) decisions in socio-technical systems that are made by decision-makers (van Dam, Lukszo, & Nikolic, 2013).

2. Provide implications that can be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports.

Research Questions

In order to bridge the encountered knowledge gap to achieve the research objectives; research questions are formulated. Furthermore, sub-questions are stated, which (together with the research question) are related to the aim of the research to bridge the encountered knowledge gap. Below the research question and corresponding sub-questions are stated.

How do airport security screeners trade-off security and efficiency when taking airport terminal operational trade-off decisions?

- What are the security and efficiency determinants that airport security screeners consider when taking airport terminal operational trade-off decisions?
- What are the relations between security and efficiency trade-off variables in the context of airport terminal operations?
- What are the airport security screeners' valuation of security and efficiency when taking airport terminal operational trade-off decisions?

In order to achieve the second research objective the above formulated research questions are extended with the following question.

- How can the gathered trade-off insights be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports?

To answer the research questions a trade-off analysis between security and efficiency variables is conducted based on Discrete Choice Modelling (DCM). In Addition to this, based on the insights of this analysis, implications are proposed that can be used to evaluate, by the means of ABMs, the trade-off effects of airport security screeners on the operations of airports. A further elaboration on these methods is stated in paragraph 1.3.

1.3 Research Method

1.3.1 Discrete Choice Modelling

In order to analyse the trade-offs between security and efficiency in airport security decision-making, a Discrete Choice Model can be made. A Discrete Choice Model is a model that provides insights in how people make discrete choices, which are choices that one takes by selecting one alternative above others (Ben-Akiva & Lerman, 1985). The modelling of these discrete choices (Discrete Choice Modelling) is a statistical method to observe people's choices. From these choices, the preferences and trade-offs of people can be inferred.

Since people are poor analysts of their own behaviour and therefore do not explicitly give reliable answers on pure trade-off questions, it is neither efficient nor effective to simply ask people's trade-offs. On the other side, people are continuously making choices, which make these choices a much more reliable measurement unit. Nisbett and Wilson (1977) also highlighted this phenomenon about the inability of people to observe directly the working of their own mind in evaluations, judgements and their behaviour. Nisbett and Wilson (1977) show (through different quotes) that the result and product of thinking are the ones that are conscious and not the process of this thinking itself. Due to these matters it is much more reliable to analyse people's trade-offs by modelling their choices (which are the results/products of a thinking process), rather than asking pure questions about their behavioural trade-offs, which can be seen as the process of thinking.

1.3.2 Agent-Based Simulation Models enhanced by empirical insights of Discrete Choice Models

Simulation models, as one of the most powerful tools for decision-makers, play an important role in the evaluation of operational decisions made by one or another decision-maker (Shannon, 1998). According to Shannon (1998) simulation models have numerous advantages over analytical and mathematical models. The basic concept of simulation is easy to comprehend and easier to justify to managers and decision-makers compared to some analytical models. Among others, simulation allows to explore new policies, operating procedures and new decision rules. However, gathering highly reliable input data is very important for simulation models. Besides this, creating a realistic simulation model which resembles the reality is also very important for the reliability and justification of such models.

Therefore, the output of Discrete Choice Models can have a promising role in enhancing such simulation models, especially when considering that these models are based on empirical data. Discrete Choice Experiments can therefore play an important role in the success of simulation models such as Agent Based Models (ABMs). By simulating the operations of systems and by running multiple simulations with ABMs these models allows to explore and with this evaluate a set of relevant "decision spaces" (van Dam et al., 2013). This key characteristic of ABMs make it possible to evaluate the decision-behaviour such as the trade-offs made by decision-makers.

According to van Dam et al., (2013) it is possible to influence agents and with this the system by changing the environment in which the agents act. Since these environments are influenced among others by the decisional choices made by one or another decision-maker based on for example their trade-offs; these trade-offs can be evaluated by looking at their effects on the system formalised by the ABMs. The outputs of Discrete Choice Models must therefore be seen as inputs of ABMs (Araghi, Bollinger, & Lee, 2014). With this collaboration between DCMs and ABMs a joint model can be created in which the trade-offs made by decision-makers can be evaluated, while at the same time the ABMs are empowered by empirical insights of DCMs. In figure 1 a conceptual model is depicted, which indicates the relations within and between DCMs/ABMs which will be followed in this project.

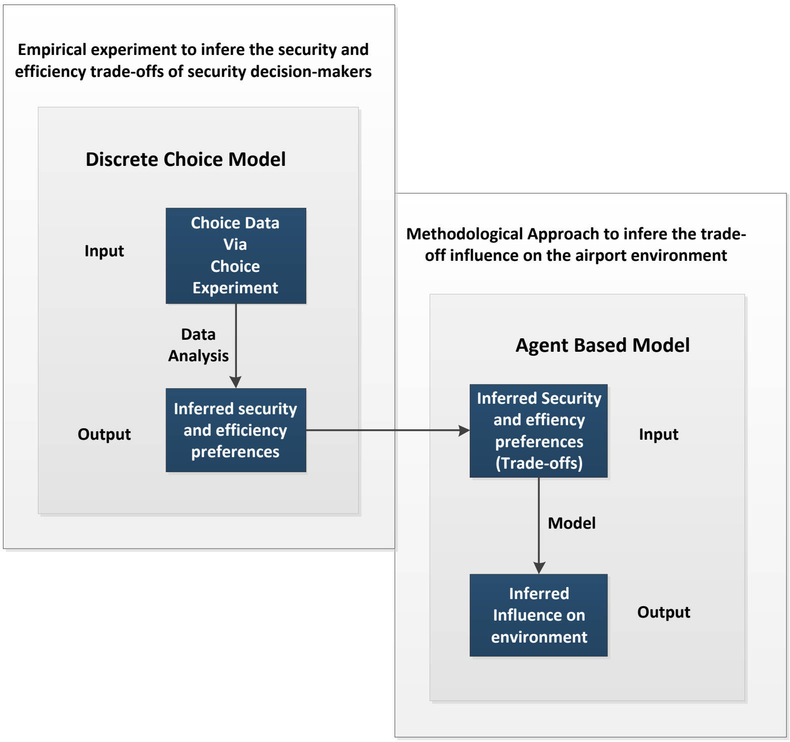


Figure 1: Conceptual model of the research indicating relations within and between DCMs and ABMs.

The results of the trade-off analysis gathered from the Discrete Choice Modelling section can provide insights on the valuation of the security and efficiency variables of airport security screeners. Based on this analysis; scenarios can be created and simulated to analyse and evaluate, by the means of ABMs, the effects of security and efficiency trade-offs made by airport security screeners on the operations of airports.

1.4 Research Scope

Although that trade-offs also play a role in strategic and tactical decisions, this research will only focus on operational trade-offs that can influence the behaviour of and choices made by security personnel. This research will therefore focus on security screeners and security team leaders/ supervisors who frequently make operational decisional choices. This project will not consider tactical and strategic decisions, which non-frequently/occasionally are taken by actors such as Security Tactical Planners, Security Managers, Directors, Executive Officers etc. In doing so, insights can be gathered in the (ad-hoc) operational trade-offs and choices that airport security screeners make. Trade-offs that influence mid and long term decisions such as security costs, security terminal investment, material investment and high level security regimes will be left out of the scope of this research.
The trade-offs that are studied in this project are further mainly focussed on social (subjective) trade-offs rather than more technical (objective) trade-offs. This means that this project will study trade-offs made by human operators (i.e. security screeners) and their decisional choices. More technical (objective) trade-offs based on technical settings such as the settings and security thresholds of machines and sensors will be left out of the scope of this project. Therefore, the trade-offs that will follow out of this project will also be based on human observation, interpretation, perception and intuition and will not primarily be driven by machines and sensors. However, although this project is scoped on the more social side of the security trade-offs made by human operators based on their observations; it should always be kept in mind that these operators are operating in a social-technical security system. Therefore, an introduction to this socio-technical security system is briefly covered in chapter 2.

The research will furthermore focus on the screening process of passengers/hand-luggage, which is carried out by airport security screeners to prevent the introduction of a weapon or hazardous device or material on board an aircraft or in security restricted airport areas. Other security processes such as securing aircraft with air marshals, will be left out of the scope of this project.

Besides the above, this research will mainly focus on the security process and trade-offs at regional airports. In this project these are airports processing not more than 10 million passengers per year such as Eindhoven Airport, Rotterdam the Hague Airport, but also smaller airports such as Groningen Airport Eelde. The idea is to start this project for small/regional airports, before jumping into more complex and larger airports. Furthermore, it is important to distinguish between regional and large airports, since such airport types have quite different characteristics.

This research will also explore and provide implications to evaluate, by the means of ABMs, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports. This means that the objective is not to implement an Agent Based Model to evaluate these trade-off effects on the airport operations, but instead of this to propose implications that can be used to achieve this.

To finalize (although that ABMs can be used to simulate interactions between agents directly) this research will not focus on the direct interactions between agents, but rather on the interaction between the (to be evaluated) decisional trade-offs of decision-makers and its implication on the operation of the airport environmental system in which the agents act.

1.5 Thesis Outline

The report will follow (in chapter 2) with an in-depth analysis of security and efficiency within airport security, which is based on literature study and an airport security systems analysis. In chapter 3 the methodology is outlined, which is used to approach and answer the research questions. The next chapter (chapter 4) will elaborate on the data and data collection that is essential to come up with results for this project. The results themselves are presented in chapter 5, while these are evaluated in chapter 6. The report will end with conclusions, contributions and recommendations followed by a chapter covering discussions and limitations, which respectively will be disclosed in chapter 7 and 8.

2. In-depth Analysis of Security and Efficiency within Airport Security Systems

This chapter will provide (in paragraph 2.2) an in-depth analysis of security and efficiency of airport security systems in order to better understand airport security systems and their complexity. This in-depth analysis (based on an airport security systems analysis, which can be found in appendix A) will provide insights into the relations between security and efficiency variables of airport systems and provide in paragraph 2.3 results of the security and efficiency determinants that airport security personnel considers when making operational trade-off decisional-choices. Before elaborating on the complex security system and its relations with efficiency; the chapter will start in paragraph 2.1 with a brief history of airport security and efficiency to provide a clear understanding where these security and efficiency issues come from and what these terms actually mean.

2.1 Security and efficiency in the air transport industry

Airport security has become an important character in the air transport industry. This was confirmed again after the most recent major attacks on aviation security on 9/11, where the security of the air transport industry has been challenged. Although these attacks (back in 2001) had a big impact on the security of aviation, criminal attacks on aviation is almost as old as commercial aviation. The first criminal attack dates back at May 1930, where Peruvian revolutionaries hijacked a Pan American mail plane (Thomas, 2008). In 1933 the first recorded bombing of commercial aircraft took place, which is thought to be the first proven act of air sabotage in commercial aviation. Although the first attacks date back to 1930s, the birth of aviation security was caused by the mass of aircraft hijackings in the 1960s. Due to these hijackings, the International Civil Aviation Organization (ICAO) council's legal committee was instructed to develop international conventions to deal with security of aviation, which lead (at the Tokyo Convention) to the start of aviation security. (Thomas, 2008)

For a better understanding of the term security, ICAO has defined this term in the ICAO Annex 17. Although several organizations and airport books have defined these terms using their own descriptions, this research will use the general definition formed in the ICAO Annex 17, which states that **security** *is safeguarding Civil Aviation against acts of unlawful interference, which are acts or attempted acts as to jeopardize the safety of civil aviation and air transport* (ICAO, 2006). ICAO further provides different examples to explain the term "*acts of unlawful interference*". Acts of unlawful interference can vary from "*unlawful seizure of aircraft in flight*", "*communication of false information such as to jeopardize the safety of an aircraft in flight of on the ground"* to "*the introduction on board an aircraft or at an airport of a weapon or hazardous device or material intended for criminal purposes*". This research will focus (as stated in paragraph 1.4) on the latter example to refer to an act of unlawful interference. With this said, the research is scoped down into the screening process of passengers/hand-luggage, which is carried out by airport security screeners.

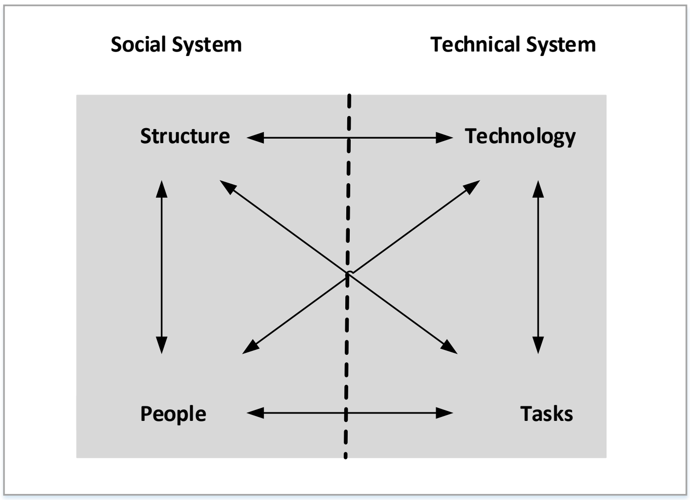
With the birth of aviation security and its increasing influencing factor on the operation of airports, efficiency also has started to play a role in choices and decisions, which are made by security personnel. The stricter security controls at airports have been having an impact on the privacy, waiting times, convenience and delay experienced by passengers (Burge et al., 2010; Bjørnskau et al., 2011). Efficiency must be seen as a measure to compare inputs vs. outputs of corresponding processes. **Efficiency** can therefore be defined as *the ratio of (useful) output to the total input of processes*. This definition has been applied by Ülkü (2014) to determine the efficiency of airports with Data

Envelopment Analysis (DEA). DEA is a non-parametric linear programming approach, which determines the relative efficiency of decision-making units (DMUs) on the basis of a weighted sum of multiple outputs divided by a weighted sum of multiple inputs (Ülkü, 2014). Output variables can be variables such as passenger numbers, the flow of passengers, the Level of Service (LoS) at airports, passengers' satisfaction, while airport costs, the number of deployed employees, the amount of used lanes etc. can be denoted as input variables. Putting these output and input variables near each other, will lead to airport efficiency indicators, which can be used to indicate how efficient an airport or airport process is.

2.2 The complex socio-technical airport security system coping with efficiency

2.2.1 Airport security as a complex socio-technical system

Airport security consists of a number of elements and entities, which are closely related to each other to achieve a more secure air transport by reducing the risk of attacks on aviation. This characteristic of elements and relations between elements together form a system, which is defined as a collection of components that are in relation with each other to achieve a certain objective (Sommerville, 2011). Airport security systems consist of security technologies, security activities, security personnel and the rules and regulations that govern such systems. Beside the interaction between these components, the security system has interaction with the airport infrastructure and passengers that pass through this system. These elements and interaction between these elements together form a complex socio-technical system, which according to Sommerville (2011) are systems that include technical components but also operational processes and people who use and interact with the system. Socio-technical systems furthermore are governed by organizational policies and rules and are systems that may be affected by external effects. As the term complexity is based on the number and variety of elements and their interrelation needed to achieve a certain objective, the airport security systems and its characteristics of the varied elements and relations presented above fulfils the criteria to be categorized as a complex socio-technical system. In figure 2 a perspective of complex socio-technical systems is presented, which is derived from Bostrom and Heinen (1977). Bostrom and Heinen describe such systems as two jointly interactive systems, namely the social and technical system. Where the social system encompass the attitude of people, the relations among them and the authority structure, the technical system consists of processes, tasks and the technology that is needed to (together with the social system) achieve a certain goal.



(Bostrom & Heinen, 1977)

Figure 2: The perspective of (complex) socio-technical systems

The technical system of airport security

The technical system of airport security consists of different tasks and processes supported by different machines that are in relations with the social system to achieve a more secure air transport. This system consists of image-based security technologies such as face recognition, baggage screening and passengers screening applications. These applications are technological applications, which further consists of different machines such as image recognition hardware and software, computer monitors, scanners, cameras, X-ray machines, Walk Through Metal Detectors (WTMD), Hand-held Metal Detectors (HHMD), Radioactive Material Detectors and Explosive Trace Detectors (ETD) (Skorupski & Uchroński, 2016). These materials, machines and applications are used and monitored by security screening personnel to intercept unlawful materials, which are broad into the system by passengers or airport personnel.

The security screening process consists of several steps in which the above mentioned machines are used to prevent acts of unlawful interference. Passengers at airports first must (with the help of a security employee) place personal items, wallets or purses in their carry-on baggage and place metallic items (keys, coins etc.) and electronics items (laptops, mobile phones etc.) in a tray on the security belt together with bulky outwear, jewellery etc. This process is known as Baggage Dropping at the security screening. After this process, the X-ray Handling process starts to detect illegal items in the belongings of passengers. If necessary the Baggage Check is broad into execution, where the responsible employee for baggage checking performs manual checks in the baggage of passengers. For the Passengers' Check, passengers will be screened via millimetre wave advanced imaging technology and walk-through metal detectors. However, passengers can decline the use of these technologies due to for example medical reasons. These passengers then must go through a Physical Check. For the Physical Check, the Hand-held Metal Detector (HHMD) or pat-down screening procedure of the passengers is performed to check if they carry illegal items. Passengers can further be asked to go through the security screening process again until he or she is cleared if an issue is identified or may be randomly selected for a body scan or an explosive trace detection test.[5]

The social system of airport security

Besides the technical system, the socio-technical airport security system also consists of elements with a more social character. Airport security personnel are one of the key players in this social system. The social system of airport security consists of different people that are interacting with the system. Security personnel (as one of these actors) are seen as key players, since they (with the support of the different technological tools) are the human operators taking ultimate decisions whether a passengers or a baggage is classified as a threat or not. The security personnel are working with the different technological means to filter out security threats by identifying possible threats based on images of items & baggage or attitudes of passengers. Abeynayake et al. (2011) state that without capable human operators, the security technology cannot achieve the required level of security performance. The human operators, besides operating and monitoring the technology, also has to undertake other tasks that are not related to the operation of the technology, such as the opening of new lanes, guiding passengers through the different processes of the system and interacting with other airport personnel, passengers and their baggage. (Abeynayake et al., 2011)

[5] The security process treated above is based on the security process of a local airport based on a working document of an airport case study (2017) by Stef Janssen, the Australian Government: Department of Infrastructure and Regional Development (2017) and Wilson (2017). However, note that this aviation security process is not fixed and therefore can differ from airport to airport.

Passengers must also be seen as important elements of the social system. These passengers can be seen as special elements of the system, since they are not (fully) in control of airport security personnel. The amount of passengers for instance, cannot be influenced by the security personnel. However, this aspect (although out of control of the security personnel) has a major influence on the operations of the system. The amount of passengers can lead to an increase of the pressure on the security system coming from ATC, airlines and the airport itself with all the consequences this can have on the outcomes of the system. One must think of outcomes such as the screening accuracy, security risk and the level of services experienced by passengers (i.e. waiting times and the probability of missed connections). Due to these influence of the social system on outcomes of the security system, this system (together with the technical system forming the complex socio-technical system) must be fully considered when further analysing the complex socio-technical airport security system.

2.2.2 Analysis of the Airport Security System and its influence on security and efficiency variables and outcomes of interest

To better understand the airport security system, a system analysis is performed, which can be found in appendix A. A system analysis is a method to map out a system by showing the elements and the relations between these elements that are relevant for analysing and understanding a certain system. The analysis applies scientific methods to analyse large and complex systems by defining the boundaries and the structure of the system. The results of the system analysis provide the level of analysis of the system and also the elements that are linked with the corresponding level of analysis. (Enserink, et al., 2010)

The analysis shows that one of the high level objectives of airports is to improve the competitive position of airports, an issue that according to Fodness & Murray (2007) airports have been focussing on to survive the increasingly competitive marketplace. One of the means in achieving this is to increase the efficiency experienced by passengers, which results in a more attractive airport terminal for passengers. This will lead to an improved passengers experience, which is favourable for the competitiveness of (a certain) airport(s). However, to increase the efficiency of airports; some lower level (operational) means must be used such as the improvement of waiting, process and walking times of passengers. This is where the dilemma with processes such as the security process comes into picture.

The reduction of the waiting and process times for instance can lead to measures that can have negative effects on the security process. Measures such as a faster operation or the deployment of more resources can diminish the security processes at airports or increase the operational costs of these processes (Abeynayake et al., 2011; Kirschenbaum, 2013). Increasing the speed of security operation means that the reaction time for security officers will be lower, which can lead to an increase in error rates. The increase of error rates or false alarms leads to a less efficient system as these errors will result in sending passengers and or bags unnecessarily to higher level (secondary) search, with unnecessary increase of waiting times as a result (Hättenschwiler, Michel, Kuhn, Ritzmann, & Schwaninger, 2005). Not only the false alarm rates might be affected, but also the number of hits (i.e. hit rates). Therefore, the consequences of making an inaccurate (and potentially dangerous decision) must be weighed against the process of rapidly handling travellers and their baggage to meet efficiency criteria in beneficial of the travellers' experience to achieve the more strategic airports objective of improving their competitive position. On the other hand; focusing on the security only (e.g. focusing on the hit rate), can influence the efficiency of the security system as a higher hit rate (can) require(s) more screening procedures such as the opening of more bags, which can result in higher false alarm rates and waiting times.

Besides focusing on the passengers' efficiency, the deployment of more resources is a commonly used measure to improve passengers experience at airports. Recently during summer 2017 airports, among them, Amsterdam Airport Schiphol have been struggling with passenger flows, which resulted in measures of deploying more resources to handle the increasing amount of passengers at the airport (Security Management, 2017). The opening of extra security lanes by deploying more security personnel and machines leads to higher security costs for airports, which puts security personnel in front of an extra decisional trade-off pressure of opening extra security lanes or not.

These relations between airport security and efficiency factors treated above are summarized in a relation-quadrant in table 1.

Table 1: Relation quadrant between airport security and efficiency factors

Y / X	Hit Rate	False Alarm Rate	Waiting Time	Missed Connection		Screening Accuracy/ performance	Screening Efficiency Experienced by pax.		Security Costs
Hit Rate						See false alarm cell			
False Alarm Rate						See hit rate cell			
Waiting Time by faster operations							See false alarm cell		
Missed Connection by faster operations							See false alarm cell		
Screening Accuracy/ Performance							See dynamics through hit rate		
Screening Efficiency Experienced by pax.						See dynamics in hit and false alarm rate			
More Resources			More Resources	More Resources			Lower waiting time vs. higher cost		More Resources

-
Improving Attribute X (can) negatively influence(s) attribute Y
Improving Attribute X (can) positively influence(s) attribute Y
Improving Attribute X (can) negatively or positively influence(s) attribute Y depending on the dynamics in the system: A quantitative analysis might give more insights
Improving Attribute y (can) positively influence(s) attribute x

These (conflicting) relations introduce dilemmas between security and efficiency objectives leading to double standard criteria such as short waiting times, short process times, low amount of missed connections on one side and low increasing effect on security cost, high hit rates, low false alarm rates and risk reduction on the other side. This double standard composition of criteria introduces a phenomenon for security personnel that demands choices and decisions based on different trade-offs such as:

- Speed vs. Accuracy (Abeynayake et al., 2011)
- Incorrect alarms vs. Missed threats (Abeynayake et al., 2011)
- Security Costs vs. the Level of Service provided (de Lange et al., 2013)
- Risks vs. Security Cost
- Vulnerability and threat vs. Investment/Deployment of resources (Bjørnskau et al., 2011)
- Resilience vs. Investment/Deployment of resources

However, not all of these factors have an operational trade-off character. An elaboration on the trade-offs that security personnel are confronted during the operations and the considered attributes are presented in the following paragraph.

2.3 Attributes introducing Operational Trade-offs between Security and Efficiency of Airport Operations

In paragraph 2.2.2 different factors have been mentioned that can influence the decisional choice-making process of airport security decision-makers. In this paragraph the different variables/attributes that introduces operational trade-offs for airport security screeners in their decisional choice-process are summed. Recall from paragraph 1.4 (Research Scope) that this report will only focus on these (operational) decisional choices of security screeners and their supervisors/team leaders rather than tactical and strategic decisions of other airport security decision-makers such as security managers, directors etc.

Attributes of interest and their implication on the operational trade-offs made by security screeners and their team leaders.

Important Reflection

Interpretation of rules and regulations

For the EU rules (protocols), regulations and common basic standards on aviation security; one is referred to EUR-Lex (2015).

Recall from Chapter 1 that, although one believes and assumes that security decisions are determined by rules and protocols; there is hard (anecdotal) evidence provided by Kirschenbaum et al. (2012) that this thought and assumption are problematic. Examples are provided by Kirschenbaum of the behavioural patterns found of airport security workers. Examples such as workers allowing passengers to pass with liquids exceeding maximum allowed requirements or suspicious items in their bags as a consequence of social contextual pressure and (unique) situations such as long waiting times at checkpoints. These evidences provide insights that security decisions (in this project coupled to security screeners) are not always carried according to rules and protocols. The Behavioural Model of Security in Airports (BEMOSA) preliminary results showed that 10% of questioned security personnel in a survey disclosed that they exceed or bend the rules when situation calls for it and that 12% of the security personnel disclosed that breaking protocols sometimes is necessary to get the job done. This all provide ground to reason that security decision-makers (in this project security screeners) make trade-offs between factors that on what first hand are thought to be strictly regulated factors determined by rules and standards. This all due to different social contextual pressure such as pressure from the Airlines, Air Traffic Control, the airport itself and (whether or not) negotiating passengers.

Security Detection Performance

Hit Rate

Detection Performance is a performance measure, which can be calculated from Hit Rate and False Alarm Rate (Schwaninger, 2005). Hit Rate is defined as the probability of a correct detection by a certain operation (Elias, 2009). Since practise proves that perfect operating systems hardly exist, it is important to take this attribute into consideration as a measure to indicate (together with the False Alarm Rate) the performance of an operation. Security screeners and their team leaders, continuously take this factor into account, since one of their objectives is to detect as much unlawful materials as possible. The Hit Rate is further a considered attribute for security personnel, since security personnel are (explicitly or not) judged and evaluated among others by their Hit Rate. Schwaninger (2003) showed that scientific methods from visual cognition and signal detection can be used to create reliable and valid tests in order to select, evaluate and certify airport screeners. Knowing this, security screeners and their supervisors (explicitly or not) are continuously considering this attribute in their daily work to reach a higher security performance.

False Alarm Rate

Besides Hit Rate, False Alarm Rate is also an important attribute to consider when determining the detection performance of security. Schwaninger (2003) and Elias (2009) both indicate the importance of False Alarm Rates in determining the detection performance of security operations. Achieving a 100% Hit Rate, intuitively make one conclude that this is a perfect performance. However, in security operations the Hit Rate is not the only factor that matters. One could achieve a 100% Hit Rate by judging all hand luggage and passengers as carriers of unlawful materials and therefore opening all luggage and sending all passengers to secondary checks, which result in the detection of all forbidden items. However, this leads to an extremely high False Alarm Rate if for instance only one out of a high number of hand luggage/passengers contains a forbidden material. Unnecessarily judging a luggage or passenger as 'not ok' will lead to unnecessarily processes, which on its hand again leads to higher waiting times and even a higher chance of people missing their flights. As these false alarms can have a major influence on the efficiency of the security operation experienced by passengers, security screeners and their supervisors are inquired to keep this efficiency indicator as low as possible.

Note that although the False Alarm Rate is a security measure to determine Security Detection Performance, it is also denominated as an efficiency indicator, which influences the waiting time and with this the probability of missed flights among passengers (Elias, 2009: Hättenschwiler et al., 2005).

Security efficiency experienced by passengers

Average Pax. Waiting Time

The (maximum) waiting time for passengers is one of the two indicators (besides the minimum space per passenger) that determines the Level of Service (LoS) of airports. LoS is used for the planning of new terminal facilities and for the monitoring of the operational service that airports deliver to passengers. (Renner, 2015)

Since waiting times at security checkpoints directly influence the LoS and with this the satisfaction of passengers, it is a meaningful attribute to consider. Security screeners and their team leaders can influence these waiting times by opening or closing extra security lanes or by increasing the operational speed of the process when the waiting times for passengers falls beyond acceptable levels. According to Renner (2015) a "short to acceptable" waiting time at security checkpoints varies between 0 to 3 minutes, while 3 to 7 minutes maximum waiting time is considered as "acceptable to long" for passengers. Beyond this point the waiting time is considered not acceptable anymore, with other actors such as the ATC, airlines and the airport itself putting more pressure on among others the operational speed of the security process. Increasing the security operational speed results in lower screening accuracy, with all the consequences this can have on the Hit and False Alarm Rates. Therefore, security screeners are continuously under pressure of weighing these security factors against the consequences for the waiting times and missed connections that passengers experience due to choices of rapidly processing passengers through the security system or choices not to do so. (Abeynayake et al., 2011)

Passenger Missed Flights

Consideration of passenger missed flights as additional attribute **Intermezzo**

Although 'Passenger Missed Flights' on the first sight seems to be correlated with passenger waiting times, it is expected that the factor of 'passenger missed flights due to the security process' introduces an extra disutility for security screeners, which leads to a higher disutility if passengers waiting times are combined with missed flights due to the security process. By only considering average passengers waiting time, no statements can be made on the security screeners' trade-off between possible 'Passenger Missed Flight' and other attributes such as 'Hit Rates', nor how big the disutility is when passenger waiting times are, whether or not, combined with the circumstances of passenger missing their flights due to the security process.

‘Passenger Missed Flights’ is used as the number of passengers that misses their flights due to the security process. This factor has become important, since airports have been struggling to handle all passengers within a certain timeframe to avoid passengers of missing their flights. The number of missed flights due to waiting times at security for example, has become a concern for airports due to the increase of passenger numbers[6]. Fitzpatrick (2016) reported that more than 70.000 passengers of American Airlines missed their flights in only the first 5 months of 2016 due to security lines. Also Amsterdam Airport Schiphol had been facing missed flights due to waiting times, among others, at security checkpoints. In April 2017, almost 100 passengers missed their flights on only one day due to massive waiting times at the airport (NOS, 2017).

The increase of passenger numbers is challenging security screeners and their team leaders to screen all passengers and their hand luggage in reasonable time limits. This is even more the case when ATC, airlines and the airport itself increase the pressure on the security process and with this implicitly obligate security screeners to trade-off the consequences of their handling times (e.g. more waiting for passengers) against their screening accuracy.

Figure 3 shows a summary of the operational trade-offs between the security and efficiency attributes that were introduced in this paragraph. The figure shows (with the double headed arrows) the operational trade-offs that the security and efficiency attributes introduces for airport security screeners and their supervisors, such as the trade-off between Hit Rate (i.e. element of Screening Accuracy/Detection performance) and average passengers waiting time, which indicates the security efficiency experienced by passengers. These trade-offs between security screening elements on one side and security efficiency attributes on the other side are indicated with curved arrows. Besides these trade-offs, figure 3 also summarizes the trade-offs between security screening elements themselves (e.g. trade-off between Hit Rate and False Alarm Rate). Although trade-off dilemmas where not explicitly mentioned between efficiency factors themselves, one can imagine that it is possible that (some) security personnel find the number of passenger missed flights more important than their waiting time or the other way around. This is also a trade-off that should be considered in future analysis. The trade-offs between security attributes and efficiency attributes themselves are depicted with straight arrows.

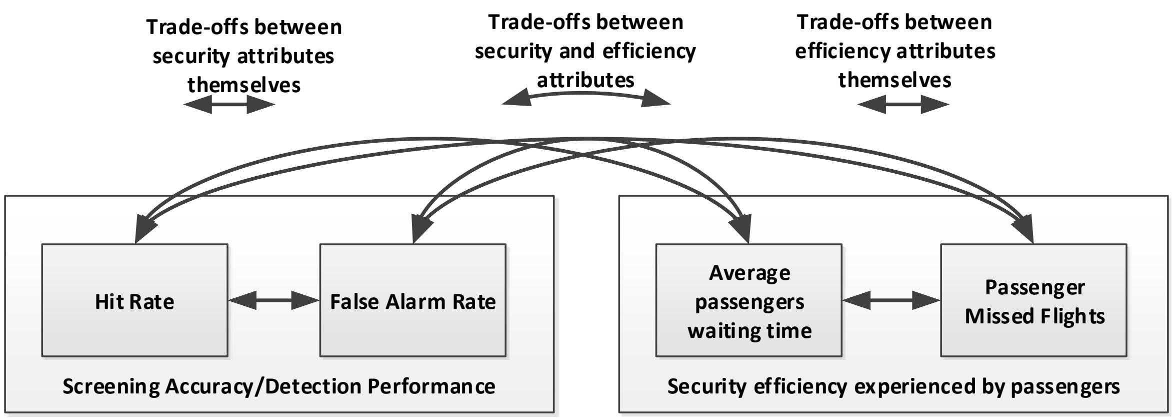


Figure 3: Operational trade-offs between the security and efficiency attributes - including trade-offs among themselves

[6] 5.1% yearly increase in number of passengers from 2012 onwards (IMM International, 2016)

2.4 Conclusion of Security and Efficiency within the Airport Security System

The airport security system is a complex socio-technical system, which not only consists of technical components of processes, tasks and technology, but also includes social aspects such as the attitude of people, the relations among them and their (decisional) behaviour which influence the operations of airport security. Due to this influencing factor of this complex (socio-technical) security system on the operations of airport security; efficiency have also started to play a role in the decisional choices of airport security personnel. However, the decisions and choices made by airport security personnel are not always self-evident, since security and efficiency of airport operations are not always in line with each other. This can be derivated from the different conflicting relations between these two components, which demands airport security personnel to trade-off these components before or while making security choices.

The conflicting relations can be found between the screening accuracy and detection performance on one hand and the security efficiency experienced by passengers on the other hand. To reduce passengers waiting time at security checkpoints and the probability of missed connections due to the security process, security screeners have the option to or open new lanes or increase the speed of the security process at the checkpoints. Besides increasing the security operational costs as a consequence of more deployed resources, the screening accuracy/detection performance of the security screeners can negatively be influenced due to the lower times that security screeners and their supervisors have to process all passengers and their hand luggage. Due to these conflicting relations, security screeners and their team leaders are continuously under pressure to make trade-offs during their behavioural choices that can influence factors such as the Hit Rate, False Alarm Rate, Average Passengers Waiting Time and the Number of Passenger Missed Flights, which are seen as outcomes of interests of complex socio-technical airport security systems.

Besides trade-offs between these security and efficiency trade-offs, their also found to be trade-offs between security elements and efficiency elements themselves. The attributes Hit and False Alarm Rates (both indicator of security screening performance) also introduce operational trade-offs for security screeners and their supervisors. The same can be said for efficiency indicators (i.e. passengers waiting time and the number of passenger missed flights), where security personnel can find one of them more important than the other.

3. Methodology

This chapter will provide an overview of Discrete Choice Modelling and Agent Based Modelling methodologies. Paragraph 3.1 will introduce DCM and the framework of this methodology to better understand the choice modelling paradigm. In paragraph 3.2 and 3.3, respectively, different choice models and data collection methods are introduced together with their limitations and (dis-) advantages. After describing ABM, a methodology to combine DCM and ABM is provided in paragraph 3.4. Based on the different limitation and (dis-) advantages of the different methodological applications, a methodological selection is made in paragraph 3.5 providing an overview of the methodological applications that will be used to infer and evaluate decision-makers trade-offs.

3.1 Discrete Choice Modelling

As stated in paragraph 1.3.1 Discrete Choice Modelling is a statistical method that can be used to infer people's preferences and trade-offs by observing their choices. With discrete choice models insights can be gathered in how people make discrete choices, which are choices one take by selecting one alternative choice above others. (Ben-Akiva & Lerman, 1985)
The origin and roots of discrete choice models can be found back in the years 1860 in the early studies of psychophysics (i.e. the study of relations between physical stimuli and sensory response) and was applied later in biology as models with discrete responses. Although these first signs of discrete choice models can be found back in the eighties, Thurstone (1927) is often seen as one of the first to actual do research on choice behaviour and be able to describe preferences with the law of comparative judgment. This law of comparative judgment can be described as a model to determine preferences from pairwise comparison. The law states that alternative i with level V_i is perceived together with a random error term into $V_i + \varepsilon_i$. Thurstone have shown that the probability that such alternative i is chosen above another alternative j (the choice probability from a paired comparison) follows a specific model that today is known as the Binomial Probit Model. (McFadden, 2000)
Mcfadden (2000) further states that Thurstone law of comparative judgement was (in the years 1950s) generalized by Marschak to 'stochastic utility maximization in multinomial choice sets'. Marschak continued its analysis on choice probabilities and random utility functions, and generalized Thurstone law to what today is known as the Random Utility Maximization (RUM) model (paragraph 3.1.2 will elaborate more on this type of choice modelling paradigm). Through the years different specifications of choice models have been introduced in the name of Probit and logit Models of which certain had more applicable success compared to others due to computational constraints that existed for quite some years. (McFadden, 2000; Wittink, 2011) Before treating these types of choice models, a Discrete Choice Modelling framework is set out in the following paragraph in light of a better understanding of the choice modelling paradigm and the different types of choice models.

3.1.1 Discrete Choice Modelling Framework

Following Ben-Akiva and Bierlaire (1999) the framework for discrete choice models is formed by assumptions about decision-makers, alternatives, attributes and the decision rule. In the following these four terms are explained more in depth.

- A ***decision-maker*** is an entity that makes choices or takes decisions and is often assumed to be an individual person, group of persons or an organizational entity that represents the decision-maker (Ben-Akiva & Bierlaire, 1999). Example of decision-makers can be travellers in a transportation market choosing for example between different modes or routes, clients choosing between a number of companies or patients seeking for a hospital to get threaten. These are just few examples of decision-makers out of the wide range of possible decision-makers that can be part of a discrete choice modelling framework.

- ***Alternatives*** are the choice options that are presented or that are available to a decision-maker. For this framework element assumptions must be made about the options that the decision-makers consider when taking decisions or when making choices. The set of alternatives considered by or available to decision-makers is commonly referred as a choice set. A Choice set can consist of for example the different transport modes that travellers can choose from to get from an origin point to a destination. Also a set of considered grocery stores can together form a choice set. A universal choice set contains all potential alternatives in the choice context, while a limited considered or available set of choices from this universal choice set to a decision-maker is referred as a reduced choice set or a sub set of the universal choice set. (Ben-Akiva & Bierlaire, 1999; Labbe, Laporte, Tanczos, & Toint, 1998)

- The ***attributes*** are the variables that decision-makers take into account when choosing between alternatives. With other words, those are the variables, which the decision-makers base their decisions on. Each alternative is characterised by a number of attributes that together form the character of the particular alternative. Examples of attributes are travel time and travel cost of a particular travel route, the available number of teachers and courses of schools etc. The values that these attributes can take are named the attribute values. Some attributes are characteristics of all the different alternatives in the choice set; the so called generic attributes, while others only describe the character of a specific alternative in a choice set. (Ben-Akiva & Bierlaire, 1999; Labbe et al., 1998)

- Assumptions and decisions about the ***decision rule*** of a discrete choice model is also very important. The decision rule is the process of decision-makers to determine a choice by evaluating the attributes of an alternative. According to Chorus (2012a) the decision rule translates the decision-makers' preferences and tastes together with the attributes into choices and choice patterns. The majority of Discrete Choice Models are based on the well-known Utility Maximization decision rule. This decision rule assumes that decisions-makers attach a certain value (called utility) to alternatives in the choice set and then choose the alternative with the highest utility. Discrete choice models that are based on this decision rule are called Random Utility Maximization-models (RUM-models). (Chorus, 2012a)
The underlying assumption of this decision rule is often violated as the complexity of human behaviour, which leads to all kind of uncertainties, impose that the decision rule is lacking a probabilistic character (Ben-Akiva & Bierlaire, 1999). Random Utility Models which are used in econometrics and travel behaviour are namely based on deterministic decision rules. As this underlying assumption often is violated, other decision rules have been introduced through the years, such as models with a probabilistic decision rule and models that follow a Regret Minimization decision rule. The Regret Minimization decision rule is an alternative decision rule for Utility Maximization in Discrete Choice Models and has the assumption that decision-makers choose alternatives with minimal regret instead of maximum utility (Chorus, 2012a). Choice models that are based on this latter decision rule are known as the Random Regret Minimization-Models (RRM-models).

Since RUM-models are (by far) the most used Discrete Choice Models and RRM-models recently have become an interesting but also usable alternative to this traditional utility models, the following paragraphs will elaborate more on these two different types of Discrete Choice Models.

3.1.2 Random Utility Maximization Models

As stated before, RUM-models are based on the Utility Maximization decision rule, which states that decisions-makers attach a certain value (called utility) to alternatives in the choice set and then choose the alternative with the highest utility. The utility function of the alternatives is known as the linear-additive random utility-function which has the following formula:

$$U_i = V_i + \varepsilon_i = \sum_m \beta_m \cdot x_{im} + \varepsilon_i \qquad (3.1),$$

where

U_i denotes the random (or: total) utility associated with a considered alternative i
V_i denotes the 'observed' utility associated with i
ε_i denotes the 'unobserved' utility associated with i
β_m denotes the estimable parameter associated with attribute x_m
x_{im} denotes the value associated with attribute x_m for the considered alternative i

For each alternative the utility of that alternative is computed by multiplying the decision-weights (i.e. the estimable parameters β_m) with their corresponding attribute levels that is considered for the corresponding alternative (i.e. x_{im}). Chorus (2012a) reframe this utility determination as the combination of the decision-makers tastes (i.e. the decision-weights) with the attribute-values to determine the utility of a certain alternative. By comparing the computed utilities of the different alternatives with each other, the choice can be derived by selecting the alternative with the highest utility. In figure 4 this choice process is summarized with an airport choice example.

Random Utility models furthermore assume that the decision-makers are perfect rationalizers, when making choices. However, the analyst do not have all information such as incomplete observed attributes (i.e. the unobserved attributes), non-observed characteristics of respondents, measurement errors etc. This lack of information brings in a certain level of uncertainty, which makes it necessary to model the utility with a random term. In equation 2.1 this random term (also known as the error term) is denoted with ε_i which captures the uncertainty/unobserved part of the utility associated with alternative i. The observed or deterministic part is captured with V_i. (Ben-Akiva & Bierlaire, 1999)

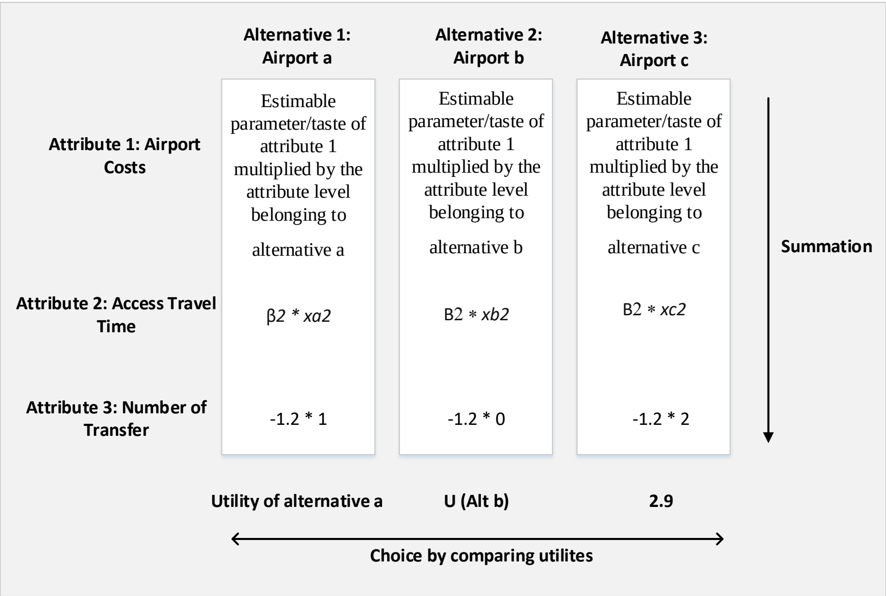


Figure 4: Choice process of the RUM-Models derived and edited from Chorus (2012a)

The benefit of RUM is that it enjoys a wide range of popularity and privilege and is used widely in research and practise. The easiness to use these maximization models and the solid foundation that have been built on through the years, contribute to this popularity. RUM-models are by far the most used Discrete Choice Models compared to other Choice Models. However, for a long time researchers have been seeking for alternatives for RUM-models and with success. (Chorus, 2012a)

Random Regret Minimization Models for instance have recently been introduced and promoted by Chorus and his colleagues as a relative easy and usable alternative (Hensher, Greene, & Chorus, 2011; TU Delft, n.d.). Rather than maximizing utility, RRM-models assume that decision-makers are aimed to minimize regret by choosing the alternative with minimum regret. Although RRM have (successfully) been introduced as an alternative for RUM, the RUM paradigm (due to its wide application and solid foundation gained through the years) will be used in the remaining project. More details about RRM-models can still be found in appendix B.

3.2 Choice Models

3.2.1 Multinomial Logit Model[7]

The Multinomial Logit (MNL) Model is a well-known choice model and is one of the most widely-used and applicable choice models. This MNL model owns its popularity to its easiness of use and its closed form formula that can be used to calculate the choice probabilities of decision-makers. (Train, Discrete Choice Methods with Simulation, 2009) This closed formula of the (RUM-) MNL has the following form:

$$P_{ij} = \frac{e^{V_{ij}}}{\sum_{m \in Si} e^{V_{im}}} \qquad (3.2),$$

where

- P_{ij} = the probability that individual/decision-maker i chooses for alternative j
- V_{ij} = the structural utility that individual/decision-maker i links to alternative j
- S_i = choice-set of individual/decision-maker i, where
    - m is the element of set S_i
- e = the base of the natural logarithm (±2,72)

[7] Recall from paragraph 3.1.2 that this project will use the RUM paradigm in the remaining project. Therefore the MNL features and limitations that will be described in this paragraph are followed from the RUM context instead of the RRM context.

Problematic i.i.d. type I Extreme Value (EV) distribution of the RUM-MNL Model[8]

Although MNL model is a simple model, it is based on assumptions that are not always fully realistic. One of the assumptions is that the parts of the utility that are not observed (i.e. attributes that are not considered explicitly in the choice-experiments but still can govern choices made by decision-makers; also known as the random errors), are independent of each other. In other words the not observed utilities/random errors of the different provided alternatives are considered not to be correlated with each other. However, when two or more alternatives 'intuitively' have things in common that are not considered/captured in the structural utility and therefore by definition ends up in the not observed utility or random errors; one cannot speak anymore of independent (non-correlated) random errors. In this case, assuming independent not observed utilities or random errors will result in biasness and flawed choice probabilities. Ignoring this will lead to strange results such as misplaced, counterintuitive and/or inappropriate choice probabilities. (Train, 2009; Vojáček & Pecáková, 2010; Wittink, 2011) Examples of such misplaced, counterintuitive and/or inappropriate choice probabilities are provided after stating the remaining two assumptions on which the MNL model is based on.

The MNL model is namely based on two more assumptions. One, which states that the not observed utilities of the different alternatives are identically distributed, which means that the mean, variance and shape of the random errors of the different alternatives are the same. The third assumption is that the not observed utilities of the different alternatives have a type 1 Extreme Value distribution (with a location parameter 0 and a scale parameter 1), which results in the MNL choice model. These three assumptions together are also known as the i.i.d. (independent, identical) type I Extreme Value distribution of the random errors and results in the specific MNL model.

A limitation of the MNL model as a result from this i.i.d assumption is the Independence of Irrelevant Alternatives (IIA). This IIA results into a property that the probability of choosing a certain alternative i over alternative j (i.e. the ratio of choice probabilities between i and j) does not depend on the presence of another alternative j' in the choice set. With this limitation, the MNL would decrease the choice probabilities of alternative i and j with the same proportion, even if alternative j' (if it obtains stronger related characteristics with alternative j than i) *-intuitively right*-* competes stronger with alternative j than with alternative i. (Train, 2009; Vojáček & Pecáková, 2010)

Intuitively right-* A bus with the same characteristics with another competing bus would compete much stronger with this competition than with a completely different transport mode having different characteristics, such as a car. However this is intuitively right, the MNL model is not able to forecast these choice probabilities right, with misplaced, counterintuitive and inappropriate choice probabilities as a result. This example is derived from the famous red-bus–blue-bus problem exposed in Train (2009).

Furthermore, the MNL Model does not allow for correlation between preferences across different choice observations over time. Decision-makers that choose a certain alternative with a certain characteristic at time t=1 are more likely to choose that alternative again at time t=2, due to its same characteristic as in the previous choice. However, the MNL model sees each choice situation by the same and each decision-maker as separate (non-correlated) observations. This type of correlation between choices that are made over time by the same individual (also known as panel effects) are not captured by the MNL model, leading to this model not being able to accommodate for these types of effects. (Train, 2009) Ignoring these types of correlation in panel data, can lead to overestimation of t-values, as the model considers every observed choice as independent and therefore links an equal

[8] Recall from paragraph 3.1.2 that this project will use the RUM paradigm in the remaining project. Therefore the MNL features and limitations that will be described in this paragraph are followed from the RUM context instead of the RRM context.

amount of information to every observed choice in the process of parameter estimation. However, due to the correlation in preferences; the observed choice t=2 contains less information than the observed choice t=1. The provision of an equal amount of information to every choice observation, incorrectly, leads to the assignment of too much certainty to the parameters. This results in the overestimation of t-values and with this the overestimation of the significance of these parameters.

Beside the above mentioned limitations, the MNL model cannot represent random taste variation and with this cannot differentiate in tastes that are linked to unobserved characteristics. For these unobserved characteristics, the MNL model implies the same tastes for everyone, although one decision-maker's taste can differentiate from another decision-maker. So, however the importance of attributes (can) vary per decision-maker, the MNL is not able to capture this taste variation for unobserved variables. (Train, 2009)

The different limitations of the MNL model have been considered for quite some time already and have resulted into new models that can cope with these limitations. In paragraph 3.2.2 and 3.2.3 two alternative models that can cope with one or more of these MNL-limitations will be introduced.

3.2.2 Nested Logit Model

As in the case of the MNL model, Nested Logit (NL) model also is an attractive and relatively easy to use model due to its closed form formulation that makes it computationally straightforward to use and often is seen as the preferred extension of the MNL Model (Hensher & Greene, 2002; Heiss, 2002; Wittink, 2011).
The Nested logit Model has the following closed form formula to calculate choice probabilities:

$$P_i = \frac{e^{\frac{V_i}{\lambda_k}} . \left(\sum_{j \in B_k} e^{\frac{V_j}{\lambda_k}}\right)^{\lambda_k - 1}}{\sum_{l=1}^{L}\left(\sum_{j \in B_l} e^{\frac{V_j}{\lambda_l}}\right)^{\lambda_l}} \qquad (3.3),$$

where

- P_i is the probability of alternative i
- V_i is the observed utility of i
- λ_k nest parameter belonging to nest k (to be estimated)*
- λ_l nest parameter belonging to nets l (to be estimated)*
- B_l set of alternatives in nest l*
- $j \in B_l$ all alternatives in set B_l*

∗ The nest structure will be explained in the following section

The NL model is a gain for researchers, analysts and users of choice models, as it generalizes the MNL model by accommodating for correlation between the non-observed utilities of different alternatives and solves part of the limitations of the MNL model. The NL model, by relaxing some strong assumptions of the MNL Model, provides users with an alternative model to cope with the limitations of the MNL model. One of the limitations of the MNL model (as explained in paragraph 3.2.1) is its IIA property, which states that "the probability of choosing a certain alternative i over alternative j does not depend on the presence of another alternative j' in the choice set". This resulted into the MNL model decreasing the choice probabilities of alternative i and j with the same proportion, even if alternative j' competes stronger with alternative j. The NL model relaxes this property by structuring the different alternatives in nests. Alternatives with the same characteristics are placed into the same nest. For these alternatives, the ratio of choice probabilities is still independent of the presence of other alternatives in the same nest, meaning that the IIA property still holds within each of the different nest. The IIA property however, does not hold for any two alternatives between different nests. The ratio of the choice probabilities of two alternatives with less related characteristics and therefore ending in different nests; can depend of an alternative corresponding to the other nest(s). (Train, 2009)

This relaxation of the IIA assumption makes it possible for one alternative to compete stronger with other alternatives with related characteristics (i.e. alternatives placed in the same nest) than with other alternatives in other nests which are less related to the corresponding (competing) alternative. An example of this NL nest structure, which reflects the relaxation of the MNL IIA property is depicted in figure 5.

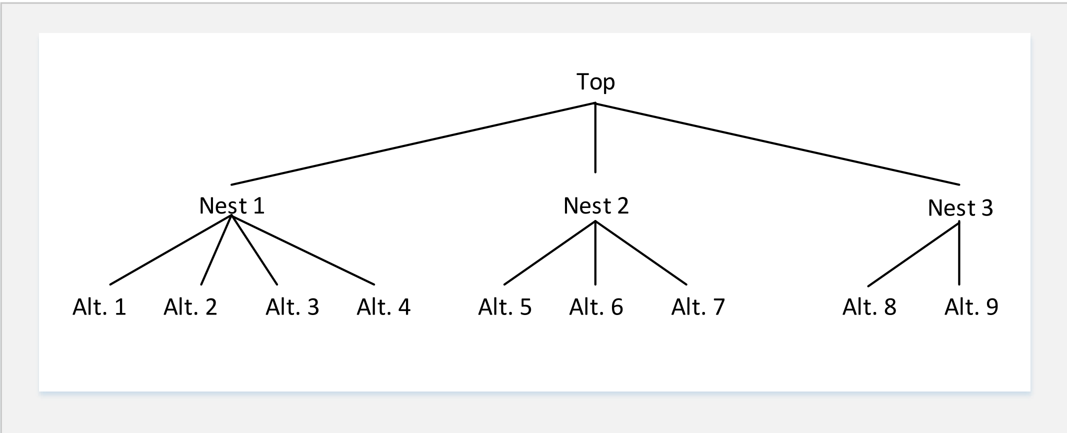


Figure 5: Nest structure of the Nested Logit Model

3.2.3 Mixed Logit Model

This model (as the NL model does, but in contrast to the MNL model) takes into account correlation between attributes of different alternatives that are not explicitly considered in the choice-experiments, but which can govern choices made by decision-makers. Besides allowing for this correlation between not observed utilities of provided alternatives, the Mixed Logit (ML) model also captures correlation between unobserved factors that are made over time by the same individual. With this feature the ML model can accommodate for panel effects, which is the accommodation of numerous choices made by a decision-maker. Beside allowing for 'unrestricted substitution patterns' and 'correlation in unobserved factors over time' the ML model also allow for 'random taste variation', which is the accommodation of taste differences that are linked to non-observed attributes (Train, 2009). With these features, the ML Model resolves the three limitations of the MNL model which are explained in paragraph 3.2.1 and form a promising alternative model for the MNL.

The ML Model can be derived from utility maximizing behaviour in different ways. According Train (2009) the most used and straightforward derivation is based on random coefficients. The Utility is specified as

$$U_{nj} = \beta'_n . x_{nj} + \varepsilon_{nj} \qquad (3.4),$$

where

- U_{nj} is the Utility of person n from alternative j
- x_{nj} are the observed variables that relate to alternative j and decision-maker n
- ε_{nj} is referred to a random term that is iid extreme value
- β_n is a vector of coefficients of these variables for person n representing that person's tastes

The coefficients β_n varies over decision-makers with density $f(\beta)$, which is a function of parameters that indicates the mean and covariance of the coefficients (i.e. $\beta's$). Note that this specification is the same as the specification of the standard logit model, except that the coefficients vary over decision-makers instead of being fixed. The Mixed Logit model is determined by an extra parameter sigma (σ) that is (also) estimated from the choice-data. This extra parameter σ reflects the correlation between utilities and the level of variation in unobserved utilities. If the estimated σ is zero then the ML model falls back into the MNL model, as a σ of zero implies that there are no correlation between utilities and no variation in unobserved utilities. (Train, 2009)

The choice probabilities of the ML model are integrals of the standard logit probabilities evaluated over a density of parameters and take the following form:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d(\beta) \qquad (3.5),$$

where

- P_{ni} is the choice probability of decision-maker n for alternative i
- $L_{ni}(\beta)$ is the logit probability for parameter β
  - $L_{ni}(\beta) = \frac{e^{V_{ni}(\beta)}}{\sum_{j=1}^{J} e^{V_{ni}(\beta)}}$
  - $V_{ni}(\beta)$ is the observed utility, evaluated at parameter β
- $f(\beta)$ is the density function

In case of a linear utilities then the ML model takes the following form

$$P_{ni} = \int \frac{e^{\beta' \, . \, x_{ni}}}{\sum_j e^{\beta' \, . \, x_{nj}}} f(\beta) d(\beta) \qquad (3.6),$$

Panel Data

When taking panel effect into account, the ML model accommodates for numerous choices made by a decision-maker over time. The utility of alternative j in choice situation t by person n is equal to $U_{njt} = \beta_n x_{njt} + \varepsilon_{njt}$ with ε_{njt} being iid extreme value distributed over time, people and alternatives. In case of more than one choice/observation per individual, conditional on β, the probability that the person makes this sequence of choices is the product of logit formulas (Train, 2009):

$$L_{ni}(\beta) = \prod_{t=1}^{T} [\frac{e^{\beta'_n x_{ni_t t}}}{\sum_j e^{\beta'_n x_{njt}}}] \qquad (3.7),$$

With i = $\{i_1, \ldots, i_T\}$ indicating the sequence of alternatives over different time periods.
Note that the unconditional probability is the integral of this product over all values of β i.e.
$P_{ni} = \int L_{ni}(\beta) f(\beta) d(\beta)$.

Furthermore, one can observe that the difference between the mixed logit with repeated choices and one with only one choice per decision-maker is that the integrand involves a product of logit formulas, namely one for each time period.

3.2.4 Latent Class Logit Model

Considering again that the standard Multinomial Logit (MNL) model assumes same preferences and tastes for individuals, different models (among others the Nested Logit and the Mixed Logit Model) have been developed through the years. An alternative model, next to the ML model to capture heterogeneity across individuals, is the Latent Class Model (LCM). The LCM accommodates for this heterogeneity across individuals by using separate groups (classes) with different values for the taste parameter β's. The difference with the ML model is that the individuals are grouped in classes which share joint taste parameters. In a model with for example S classes, there will be S parameter specifications namely β_1 to β_S for each attribute corresponding to the different classes. (Hess & Daly, 2014)
The theory behind LCM's shows that individual behaviour depends on observable attributes and latent heterogeneity, which varies with unobserved factors. With LCM's this heterogeneity can be analysed by modelling the discrete parameter variations as mentioned above.
The Latent Class Model uses a probabilistic class allocation model, where the probability that a certain individual n belongs to a certain class s $(i.e. \pi_{ns})$ can be modelled.

The Latent Class Choice Model is specified by the following formula:

$$P_n(i|\beta) = \sum_{s=1}^{S} \pi_{ns} P_n(i|\beta_s) \qquad (3.8),$$

where

- $P_n(i|\beta) =$ Probability that decision-maker n chooses alternative i, conditional on the model parameter β
- π_{ns} = The probability that decision-maker n belongs to class s (Class Membership Probability)
- $P_n(i|\beta_s) =$ Probability that decision-maker n chooses alternative i, given that he/she belongs to class s

Latent Class Models are usually specified by a MNL model, by using same specifications of this Model. However, LCM's can also be specified by other models such as Nested Models (Hess & Daly, 2014). In the simplest version of the Latent Class Model, the class allocation probabilities are constant across individuals, such that $\pi_{ns} = \pi_s$ holds for all n (Hess & Daly, 2014).

The class membership model can then be specified as follows:

$$\pi_{ns} = \frac{e^{\delta_s}}{\sum_{l=1..S} e^{\delta_l}} \qquad (3.9),$$

where

- $0 \le \pi_{ns} \le 1$, for all n, s
- $\sum_{s=1}^{S} \pi_{ns} = 1$ for all n
- δ_s = to be estimated class specific constants

3.3 Data collection methods

In order to estimate model parameters, choice data must be collected. To collect choice data one can use Stated Preference (SP) and/or Revealed Preference (RP) method. These two methods are based on two different choice collection paradigms. When applying the SP method, one would ask what people would choose if a set of hypothetical alternatives were provided. This in contrast to the RP method, where people are asked to make choices among existing real-market alternatives. One of the advantages of the RP method is that it observes what people actually have chosen, which creates a high potential to result in high valid models if market conditions and policy measures do not change much. However, the RP method is problematic if choice data is collected for new market alternatives with new attributes that are not included in existing markets (Kroes & Sheldon, 1988). Kroes and Sheldon (1988) further state that there is often strong correlation (multi-collinearity) between the exploratory variables/attributes, which leads to difficulties in estimating model parameters. Due to this multi-collinearity phenomenon, coefficients might get wrong signs and can result even in parameters not becoming significant. This phenomenon leads to the RP method requiring much more choice data than the SP method. With the SP method hypothetical choice-alternatives can be made, which enables one to construct choice-set variations based on (hypothetical) combinatorial mixes of attributes one is interested in (Hensher, 1994; Wittink, 2011). This can be seen as a more efficient way to collect choice-data, which (can) result(s) in the need of less choice data than the RP method.

Beside the flexibility of being able to design choice-experiments based on combinatorial mixes of attributes one is interested in, the SP method is also cheaper to apply and easier to control (Kroes & Sheldon, 1988). Although these SP advantages exist, this SP method of data collection also has a disadvantage. The disadvantage of the SP method, which asks what people would choose given a set of hypothetical alternatives, is that people may not necessarily do what they say they would. These advantages and disadvantages of both methods requires one to consider both of these methods and make a decision of using one of the methods or consider to combine these two for the collection of choice data.

3.4 Combined Methodology of Discrete Choice Modelling and Agent-Based Modelling

This paragraph will elaborate more on the possibilities and gains of extending Discrete Choice Models with Agent-Based Models. Agent-Based Modelling (ABM) is a computational study to model systems that are composed of autonomous and interacting agents (Janssen, 2004; Macal & North, 2010). In paragraph 3.5.1 this ABM method will be introduced more in depth. Paragraph 3.5.2 will focus more on the combination of this agent-based methodology with Discrete Choice Modelling and shows the possibilities and gains that can be achieved by combining these to methodologies with each other.

3.4.1 Agent-Based Modelling

As said in the previous section, according to Janssen (2004) and Macal and North (2010), ABM is a computational study to model systems that consist of autonomous and interacting agents. The idea behind ABM is that (in essence) every system can be modelled with a description of agents, the environment in which the agents act, a description of interaction between the agents themselves (agent-agent relationship) and an interaction description between the agents and their environment (agent-environment relationship) (Wilensky & Rand, 2015). Agent-Based Models therefore can be based on three basic elements, namely:

1) agents (or a set of agents)
2) a set of agent relationships

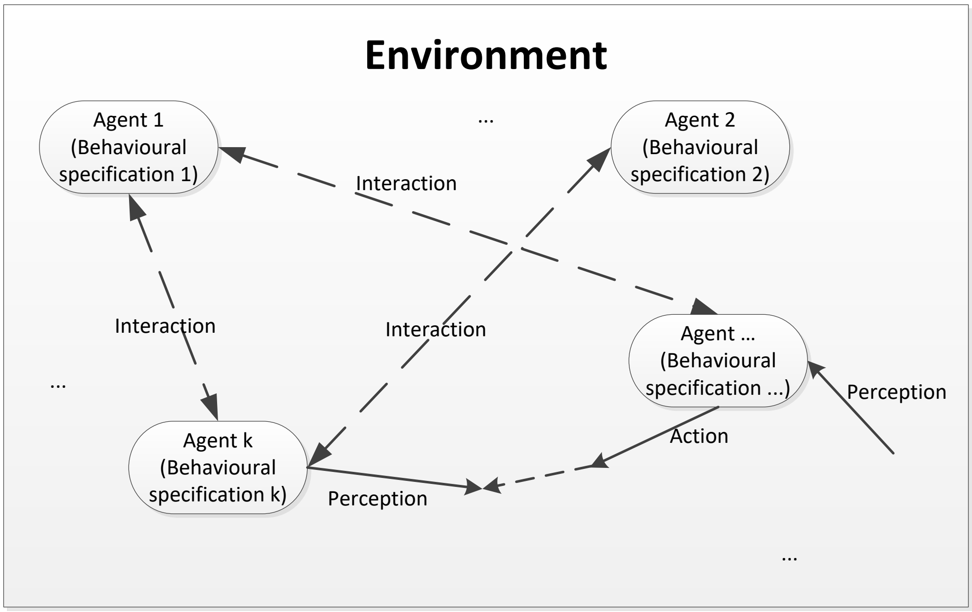
3) the agents’ environment (Macal & North, 2010).

Agents – Agents are autonomous individuals or objects each having their own properties, actions and often a goal to reach. Besides representing a person, an agent can also correspond to an organization or firm. The term autonomous relates to the ability of the agent to self-control its internal state and behaviour. Agents (often) contain sensors to absorb information of the environment and the ability to act upon this through effectors (van Dam et al., 2013). Beside the ability to act upon the environment, agents also have the ability to communicate with other agents. The architecture of agents can be derived and have been influenced by Multi-agents systems in Artificial Intelligent (AI) that studies the behaviour of adaptive autonomous agents (Janssen M. A., 2004). AI can be seen as a deeper analysis into agents to replicate many elements of intelligence such as the process of learning, object detection & recognition and the process of decision-making of agents (van Dam et al., 2013).

Relations – The relations in ABM also referred as interactions are the topology of connectedness that defines how and with whom the agent acts. A typical topology is the spatial grid or network where the relations are expressed as links that connects the agents, which are denoted as nodes (Macal & North, 2010). Agents can have a direct interaction, where agents communicate directly with each other or indirectly through other media or via the environment. This latter form of interaction focusses on the agents’ environment as a surrounding wherein agent interactions occur. Macal and North (2010) state that the two main things of interacting and agent relationship are the specification of “who is, or could be, connected to who” and “the dynamic mechanisms” of the interactions. With the description and modelling of these interactions, ABMs are enabled to observe among other the behaviour of human interaction and the systems in which these behaviours take place.

Environment – Besides the interaction between agents themselves, agents also interacts with their environment. The environment is simply the surrounding and conditions in which the agents ‘live’ and act. This environment (can) contain information that agents can use to act. Besides providing and receiving information to and from agents, the environment can also be used to constrain agents in their action and possibilities (Macal & North, 2010). An environment can for example restrict the access area of an agent, but also can limit the number of agents in a certain area with capacity constraints of the environment. This all shows that the environment, through relations, can affect and be affected by agents.

In figure 6 a conceptual model derived from Bandini, Manzoni and Vizzar (2009) is shown that shows an abstract of agents, their relations and the environment in which they act.



(Bandini et al., 2009)
Figure 6: Conceptual Agent Based Model including its elements

The benefits of ABMs, exposed by Bonabeau (2002) compared to other modelling techniques, lie into [1)]its ability to capture emergent phenomena, [2)]its flexibility to deal with complex systems[9] including its agents and [3)]the ability of the model to 'naturally' model, describe and simulate (complex) systems and with this making the model looks closer to reality.

- ***Emergent phenomena*** can be described as a phenomena where the interaction of and between individual entities play a key role. Example of such a phenomenon is the behaviour of a flock, where the flocking behaviour results from the aim of individual birds to fly close to each other, while still has the internal rule to avoid collision with other birds (Burbeck, Complexity and the Evolution of Computing: Biological Principles for Managing Evolving Systems, 2007). ABMs have the ability to model and simulate and with this also analyse and evaluate such systems, since these models have the ability to model such individual entities and their behaviour within one environmental system.

- ABMs also have the characteristic that they are ***easy to adapt to systems as they become more complex***. Bonabeau (2002) claims this flexibility as users/modellers easily can add more agents if the system requires this and since ABM provides the possibility to change the complexity of agents by adapting their 'behaviour, degree of rationality, ability to learn & evolve and their rules of interactions'.

- The ability to ***'naturally' model, describe and simulate (complex) systems*** is the third benefit of ABMs. ABMs are, according to van Dam et al., (2013), the most suitable tool to model such complex systems. Although ABMs model complex systems, they can still be used as a tool to describe and simulate such systems in a 'natural' manner that is easy to understand for users of the model. ABMs namely, model each agent as a real person, firm or organisation that interacts in the same way real entities/actors do. This natural modelling characteristic makes the system looks closer to reality and therefore easy to grasp by the users. (van Dam et al., 2013)

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[9] Recall from paragraph 2.2.1 that a system is defined as a collection of components that are in relation which each other to achieve a certain objective (Sommerville, 2011)

Furthermore, ABMs can be used to explore and evaluate, by running multiple simulations, a set of relevant decision spaces. This makes it possible for ABMs to function as a decision support tool for decision-makers to model, simulate and evaluate their policy, decisions and choices. (van Dam et al., 2013) However, gathering highly reliable input data is very important for such simulation models to resemble reality and with this increase the reality and justification power of such simulation models. Since DCM is based on empirical data, they form a promising role in enhancing such Agent-Based Simulation Models. The following paragraph will elaborate more on the combination of Discrete Choice Modelling and Agent-Based Modelling methodology for the simulation and evaluation of decisional choices by decision-makers.

3.4.2 Combining the Methodology of Discrete Choice Modelling and Agent-Based Modelling to evaluate Choice Behaviour

As mentioned in paragraph 3.1 Discrete Choice Modelling is a statistical method to observe people's choices. These models are widely used in different markets and industries to infer people's preferences among products and with this predict market shares and demand for corresponding products. Although the origin of these models can be found back in the late 80's and were further developed more concretely in the 90's and have widely been used through the years (recall paragraph 3.1), this method has a limitation that it is a static method of inferring people's preferences and trade-offs (Araghi et al., 2014). However, it is known that the choices people make (as a result of their trade-offs) change over time depending on local conditions (Vag, 2007; Araghi et al., 2014). Such local conditions may vary from changes in other people's behaviour and their interactions with each other to changes in the local environment that the decision-maker observes. These dynamic changes are barely taken into account by Discrete Choice Models when inferring preferences, making it problematic for the model to tackle real-time 'what-if type' of questions and scenario's (Vag, 2007). As Discrete Choice Models lack the ability to handle these type of dynamic situations, Agent-Based Simulation Models are known for their strong ability to deal with dynamic changing environments and emergent phenomena (recall paragraph 3.5.1). However, gathering highly reliable input data is a starting point for basically all simulation models, including Agent-Based Models. Gathering empiric and reliable input data increases the reality, validity and with this the justification and convincing power of such simulation models. ABMs can therefore benefit from empirical measures that can be provided by Discrete Choice Models. Discrete Choice Models are namely based on empiric data which can be used as input data for ABMs. On the other hand ABMs can be used as a dynamic extension for DCMs.
Combining these two methodologies together, ABMs can be enhanced by empiric behavioural data provided by DCMs, while ABMs can introduce dynamics in preferences of people and with this simulate and evaluate people's choice behaviour by introducing scenarios of changed environments in which the people act (Araghi et al., 2014; Bruch & Atwell, 2015; Holm, Lemm, Thees, & Hilty, 2016).

As said before, trade-offs and with this the choice-behaviour of people may change when the environment in which they act changes. Examples of environmental changes are changes in a certain target product, changes in other people's behaviour and other more (in-) direct changes through the environment of other media, all which are observed by the corresponding people.

These three environmental changes that are observed by people and their influence on their preferences and choice-behaviour will be explained with some examples during the following.

Changes in Target Products

Example of changing market conditions derived from Araghi et al. (2014)

When buying (choosing) a certain product (alternative), the buyer (decision-maker | agent) obtain a certain value (utility) from each product based on the characteristics (attributes) of the product. In this process the buyer will choose the product with the highest utility that meets him or her utility threshold. When this threshold is not met, the buyer lands in a status quo position, waiting until the market conditions (e.g. prices, product quality etc.) changes before evaluating the products again. By changing the market conditions, the preferences and choice behaviour of the choice-maker can be influenced leading to the buyer changing its behaviour and buying the product or not.

Changes in other people's behaviour

Flocking example derived from Burbeck (2009)

When flying in groups (set of agents) certain birds (agents) form flocks, where the aim of a bird is to fly closely to its neighbours, but not colliding with them. The behaviour of one bird of flying to the right may influence another bird to adapt its fly-direction (choice-behaviour) to also fly to right. These changes in other agents' behaviour influence the choices of others. This type of direct influence also counts for other types of agents such as people. A decision (action) of one person (agent) can directly influence the decisions and choices of other persons based on their preferences or even leading (due to the changed situation) to other preferences of the corresponding person.

Changes in people's environment

Security screening example at airports (recall chapter 2)

When screening passengers at airports (the environment), security screeners inspect passengers based on hard rules and regulations, but also according to their instinct and trade-offs. The security choices of for example opening a luggage or sending a person to a higher level of security may be influenced by for example the number of passengers in the queues, the chance of missing a forbidden item and/or the chance of committing a false alarm. The increase in queue lengths (environmental change) can be seen as an environmental impulse, which may influence security screeners' choices based on their trade-offs.

All these examples have the characteristic that people's preferences play a key role in their behaviour and that they act/behave in a quite dynamic environment. The dynamic/real time changes can influence the choice-behaviour of decision-makers based on their trade-offs and preferences (Vag, 2007; Araghi et al., 2014). These choices and trade-offs can be evaluated with Agent-Based Simulation Models by first gathering empirical choice data of the consumers choice-behaviour to infer their trade-offs, followed by the simulation of different (in-)direct environmental scenarios as illustrated above (Bruch & Atwell, 2015; Holm et al., 2016). These examples again show the importance and gain that can be achieved by combining Discrete Choice Modelling and Agent-Based Modelling with each other. In figure 7 a conceptual framework is shown, which illustrates a framework of the combined methodology of DCM and ABM.

In figure 7 one can see that agents (in ABM) can be modelled with a behavioural specification (recall the conceptual ABM framework of Bandini et al. (2009) in figure 6). This behavioural specification can be gathered from the theory behind DCM and specifies among others the agents' trade-offs, preferences and decision-rule which they follow and determines how the agents act and take decisions by modelling among others their utility. This principle of specifying agents' behavioural specification has also been used by Holm et al. (2016) to model agents' behaviour in the negotiations of contracts. The out coming agents' actions result in an agent behaviour that is observed by other agents, which may influence them or their behavioural specification directly or indirectly via changes in the environment. All these changes are observed by the agents, which on its hand again act according to their, whether or not, changed behavioural specification such as their trade-offs. This will result again into new behaviour (i.e. new decisions and choices) of the agents. This choice-behaviour and as such the trade-offs and preferences of the agents can be evaluated by assessing these in Agent Based Simulation Models and see what effects the (changed) choice-behaviour has on the outcome of the system in which the agents act. This is possible since the actions of agents, based on their choices derived from their trade-offs, can cause modifications to their environment (Bandini et al., 2009).

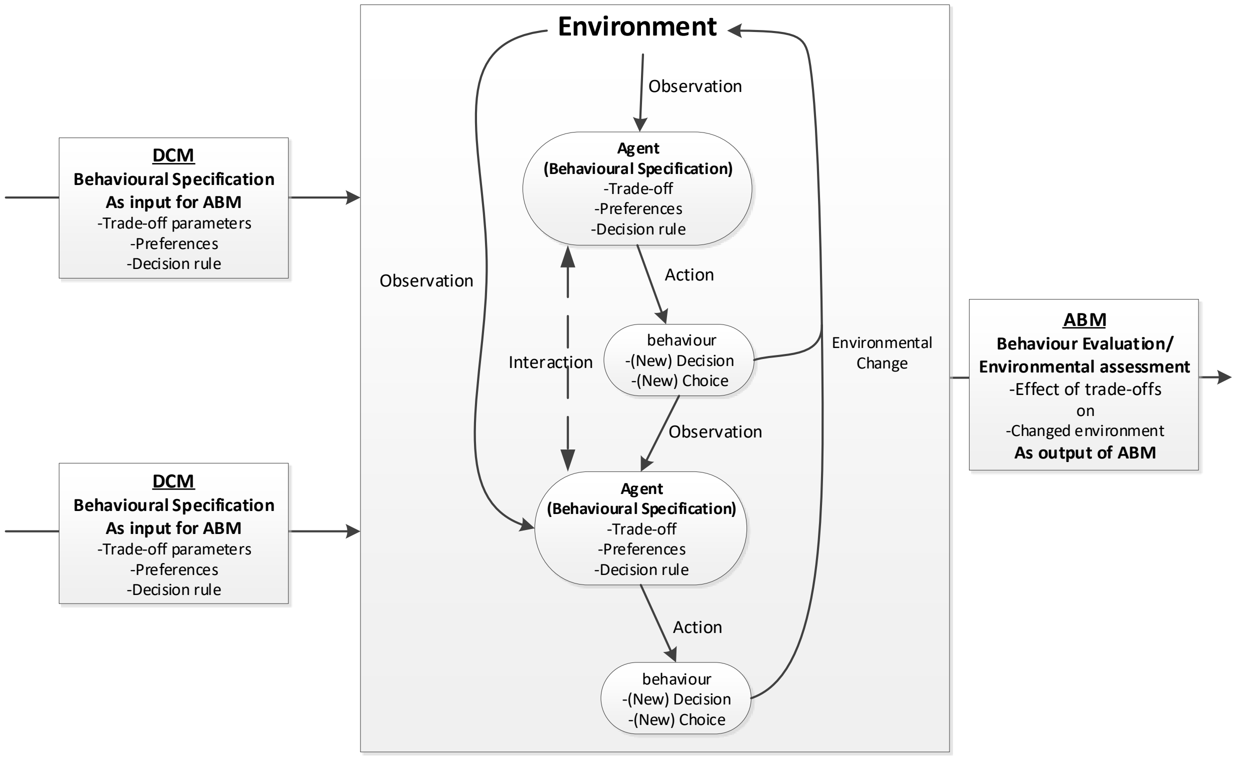


Figure 7: Dynamic framework of combined DCM and ABM methodology

3.5 Methodological Selection

Now that the different methodologies have been explained together with their limitations/ disadvantages and advantages compared to other methodological applications, a selection can be made among the different methodological applications. This paragraph will elaborate on the choice between the different choice models (i.e. Multinomial, Nested and Mixed Logit Model) and the two data collection methods (i.e. Revealed vs Stated Preference method). Furthermore, this paragraph will also state the kind of environmental changes (introduced in paragraph 3.4.2) this report will further focus on to combine DCMs and ABMs.

Selection of Mixed Logit Model, Latent Class Model and Stated Preference method

In paragraph 3.2 the limitations, advantages and disadvantages of the different choice models have been presented. This paragraph showed that, although the MNL model has a closed form formula and is easy to use, the model have different limitations due to the i.i.d. type I Extreme Value (EV) distribution of this model. These were limitations leading to problems with capturing taste variation, dealing with panel data and problems regarding substitution patterns. The Nested Logit model (also

having a closed form formula and relatively easy to use) brought solutions for the last mentioned limitation of substitution pattern by nesting alternatives into nests. However, this model only provides solutions to part of the limitations of the MNL model. The Mixed Logit model in its case provides solutions to all three the MNL limitations.
Besides covering the limitation of the other models, more importantly, the Mixed Logit Model has benefits which are beneficial for the purposes of this project. Since this project will use ABMs to introduce some dynamics to the (more static) DCM; it is necessary to use a Discrete Choice Model that provides outputs, which can be used by ABM to simulate dynamics. According to Brown (2013) Mixed Logit Models are models that can introduce variety in trade-off results by not only estimating mean parameters but also a distribution of parameters. This distribution can be used in Agent Based Models to create/simulate for example a variety in agents, which can for example reflect different security screeners or variety in the behaviour of security screeners depending on the environmental influences. Due to these several benefits of the Mixed Logit Model and its well connection benefits with Agent Based Models; this model will further be used to explicitly determine the trade-offs and preferences of security decision-makers.
Beside the selection of the Mixed Logit Model, Latent Class Models will also be considered as an alternative model that can be used to contrast the Mixed Logit Model. The Latent Class Models, which can derive (discrete) heterogeneity among respondents, can be seen as an alternative model to create variation among security screeners. Furthermore, this model can be used to group the respondents into different classes based on their preferences and tastes. This can be beneficial in the determination and interpretation of the type of security screeners.

The collection of choice data can also be based on different methods (i.e. Revealed and Stated Preference methods). Respecting the flexibility that the Stated Preference method provides to data collectors to make hypothetical choice-alternatives based on different combinatorial mixes of attributes; the choice is made to use this method to collect choice-data. This method, due to its flexibility, is seen as a more efficient way to collect choice data, which can lead to less respondents needed for the choice experiment compared to the Revealed Preference method. Considering the limit potential respondents that fall under the target audience of this project, this SP-method and its efficiency can help to deal with this limited amount of respondent available that will take part of the choice experiment.

Selection of environmental changes to simulate and with this evaluate decision-makers' trade-offs
In paragraph 3.4.2 three methodological applications were introduced that can influence the choice-behaviour and preferences of decision-makers depending on the context that is observed by decision-makers. To summarize; these were changes in [1)]target products, [2)]others people’s (agents) behaviour and [3)]changes in the environment, all which can be observed by the decision/choice-makers. Since this project focusses on the evaluation of the effects of trade-offs made by security decision-makers on the operations of airports and since the operations of airports form the environment in which the decision-makers act and take decisional choices; the choice for the third methodological application (i.e. environmental changes) is self-evident. This option enables one to focus on the interaction between the (to be evaluated) decisional trade-offs of decision-makers and its implication on the operation of the airport environmental system in which decision-makers act. Since this project does not focus on the direct interactions between agents, the second option (i.e. changes in other people’s/agents behaviour) is not further considered for the combination of DCMs and ABMs. Furthermore, the change of target products, will not be considered as well, as this project does not take into account any evaluation and/or simulation of market conditions.

4. Data Collection

4.1 Discrete Choice Experiments for Data Collection

To get to know the airport security screeners' valuation of and trade-off between security and efficiency when taking airport terminal operational decisions, data about their choices must be collected. Discrete Choice Experiments (DCE) can be used to collect choice data of these respondents. DCE is an attribute-based survey method that is used to infer people's trade-offs and preferences. The survey presents respondents with (hypothetical) choice sets, which include two or more alternatives of which the respondents have to choose from based on the characteristics (i.e. the attributes and attribute levels) of the different alternatives (Ryan, Gerard, & Amaya-Amaya, 2008). To construct a choice experiment, four key steps must be followed. These key steps, derived from Ryan et al. (2008), are:

1. Problem definition: characterising the choice decision
2. Identification of relevant attributes, attributes levels and customisation
3. Selection of experimental design and construction of choice sets
4. Experimental context and questionnaire development

Problem Definition - Before collecting choice data and constructing choice models, sufficient time must be taken to analyse the problem. In this step attention must be allocated to the scoping, understanding and definition of the problem, identification of the decision-makers who make trade-offs and the evaluation of the decision-making process of the decision-makers. Note that this step has already been carried out in chapter 2 and appendix A and will therefore not be treated again in this chapter. One is referred to the corresponding chapter and appendix for the detailed problem and system analysis of the airport security system.

Step 2; the identification of the relevant attributes and attribute levels is carried out in paragraph 4.2, while step 3 and 4 (which focus on the actual construction of the choice experiment) will be treated in paragraph 4.3.

4.2 Relevant Attributes and Attribute Levels

Attributes

The attributes that are used in the choice experiment are based on the in-depth airport security systems analysis carried out in chapter 2 and appendix A. These attributes are 'Hit Rate', 'False Alarm Rate', 'Average Pax. Waiting Time' and 'Passenger Missed Flights'. Recall from paragraph 2.3. that these are attributes that introduce operational trade-offs between security and efficiency for security screeners and their supervisors.

Attribute Levels

Hit Rate 70 - 80 - 90 [%]

The attribute 'Hit Rate' that is used in the choice experiment is varied among three levels, namely 70, 80 and 90 and has percentage as operational unit. A Hit Rate of 70% means that out of each 100 bags/passengers that contains a prohibited item; the security screener judges 70 of them as 'not ok'. The other 30% is declared as missed threats. A Hit Rate of 90% means that almost all bags/passengers characterised as ‘not ok’ are detected by the security screener, which means that the security screener has a missed threat of 10%. The Hit Rate variation has been chosen between empirical Hit Rate margins, which are gathered from two different experimental studies.

McCarley, Kramer, Wickens, Vidoni and Boot (2004) conducted an experimental study, where 16 participants across several days had to search for a knife as workers at an airport-security station. During this experiment each observer completed five experimental sessions in which 60 trials contained a target and 240 did not contain forbidden items. The results of this experiment showed Hit Rates varying between 54 and 89 percent. Besides this experimental study of McCarley et al. (2004), Wales, Halbherr and Schwaninger (2009) also conducted an experimental study. During this experiment 67 professional screeners had to judge a 2048-image battery that varied in different conditions such as different view difficulty, different bag complexity and different superposition. The images that were judged, contained different prohibited items varied from knifes, guns, Improvised Explosive Devices (IEDs) etc. The results from this major study showed Hit Rate variations between 45 and 97%. However, out of several interviews and pre-experiments that have been conducted with security screeners at a local airport (see appendix F), came out that security screeners are not willing to trade Hit Rate when the Hit Rate performance is too low. Therefore, the minimum Hit Rate level in this choice experiment has been adjusted to 70%, which (during the interviews and pre-experiments) were mentioned by some security screeners as the lowest Hit Rate level that they would be willing to trade.

False Alarm Rate 10 - 20 - 30 [%]
The attribute 'False Alarm Rate' used in this choice experiment is also varied among three levels. The three levels are 10, 20 and 30 each having percentage as operational unit. A False Alarm Rate of 30% means that out of each 100 bags/passengers that does not contain any prohibited item; the security screener judges 30 of them unnecessarily as not being ok and therefore unnecessarily sending or scrutinizing the bags or passengers to/through a higher level of security. The variation between 10 and 30% is based on four different experimental studies of which all show considerably lower rates than the Hit Rates. McCarley et al., (2004); Hättenschwiler et al., (2005); Hofer and Schwaninger (2005) and Godwin (2008) all performed screening experimental studies based on different conditions among participants (all) resulting in False Alarm Rates which varies between 0 and 20 percent. However, these ranges were slightly adapted in the choice experiment to 10-30% to avoid optimal values in the choice experiment like a False Alarm Rate of 0%.

Average Pax. Waiting Time 2 - 13 - 24 [Minutes]
The operationalization of the average passenger waiting time is on one hand based on the International Air Transport Association (IATA) LoS which states that a “short to acceptable” waiting time at security checkpoints varies between 0 to 3 minutes, while 3 to 7 minutes maximum waiting time is considered as “acceptable to long” for passengers. Beyond this point the waiting time is considered not acceptable anymore. (Renner, 2015)
However, these are standards that in real life are not always met. Therefore, to increase the validity of these attribute levels, the ranges are stretched to include realistic scenarios. The range between 2 and 24 minutes is based on empiric arrival and processing rates of a local airport[10]. It should be said that this range can slightly vary depending on which scenarios (defined by among others the number of opened security lanes) are simulated.

Passenger Missed Flights 0 - 1 - 2 [passengers]
Considering the number of/or the possibility of passengers missing their flights due to the security process, it is important to take this attribute along the choice experiment. The number of passenger

[10] The arrival rates used to calculate/simulate the average passenger waiting times were on average 5 passengers per minute in the morning hours and on average 10 passengers per minute in a peak hour. The used process rates to calculate/simulate the average passenger waiting times were on average 2.04 and 2.26 passengers per minute belonging to one server. These arrival and process rates were gathered from empiric data on 22nd March and 18th April at a local airport.

missed flights due to the security process is varied between 0, 1 and 2 and is based on an average work day of a security worker. The choice for 0, 1 and 2 has been made since the number of passengers that misses their flights due to the security process at regional/small airports is quite small/(close to) zero. However, it is important to still consider this attribute in order to make statements about how security screeners trade-off this factor with other attributes such as Hit Rate and to see how much this attribute contributes to the (dis-)utility of security screeners.

In table 2 the attributes and attribute levels are summarized.

Table 2: Varied Attributes and Attribute Levels in the Stated Choice Experiment

Considering an average working day	-legal bags/passengers do not carry/contain prohibited items - Illegal bags/passengers carry/contain prohibited items
Attributes	Attribute Levels
Hit Rate [%] The percentage of <u>illegal</u> bags/passengers that <u>is intercepted</u> by the security screener	70% 80% 90%
False Alarm Rate [%] The percentage of <u>legal</u> bags/passengers that is judged as <u>'not ok'</u> by the security screener; unnecessarily leading to extra security processes and waiting times	10% 20% 30%
Average Passengers Waiting Time [Minutes] The average waiting time in minutes, which passengers are standing in the queue before passing through security	2 minutes 13 minutes 24 minutes
Passenger Missed Flights [passengers] The number of passengers that at the end of a normal workday (i.e. shift of the security screener) unnecessarily have missed their flights as a consequence of the working behaviour (i.e. the work process, -actions and/or -decisions) of the security screener.	0 passengers 1 passenger 2 passengers

4.3 Construction of the Stated Choice Experiment

In this paragraph the Stated Choice (SC) experiment is defined, which is used to collect choice data among the respondents. The SC experiment is constructed following the three general steps provided by ChoiceMetrics (2014), which are:

1. Model specification
2. Generation of experimental design
3. Construction of questionnaire

Model specification

Note that step 1 (the model specification) has been treated in paragraph 3.2, while the selection of the model type (i.e. the Mixed Logit Model and Latent Class Model) has been covered in paragraph 3.5. One is referred to these two paragraphs for more details about this step.

Generation of experimental design

In order to find a good experimental design, it is necessary according to ChoiceMetrics (2014) to consider a couple of questions, namely:

-Should the design be labelled or unlabelled?
-Should the design be attribute level balanced?
-How many attribute levels are used?
-What are the attribute level ranges?
-What type of design to be used?
-How many choice situations to use?

For this experiment the model specification has no alternatives with alternative-specific parameters. Therefore, the option is made to use unlabelled alternatives, which are defined as 'sets of airport security operational performance indicators'. Each set will be described by four attributes, namely Hit Rate, False Alarm Rate, Average Passengers Waiting Time and Number of Passenger Missed Flights (recall paragraph 4.2). The experiment will further aim for attribute level balance, which will lead to each attribute level to appear an equal amount of times for each attribute (ChoiceMetrics, 2014).

The number of attribute levels for each attribute that is used in this experiment is three. This (fixed) number for all the four attributes is beneficial in order to limit the number of choice situations. The higher the number of attribute levels and using different numbers of attribute levels for the attributes (may) lead to a higher number of choice situations. Especially if one wants to hold firmly to the attribute level balanced property. (ChoiceMetrics, 2014)

Note that the attribute level ranges that are used in the SC experiment are stated and treated in paragraph 4.2

Type of design – In order to determine the design type of the SC experiment; the properties and (dis-) advantages of several designs have been considered. ChoiceMetrics (2014) provides a list of designs, which all have their own properties, advantages and disadvantages. These design types, their properties and main (dis-) advantages are listed in table 3.

Table 3: List of experimental designs and their properties and main (dis-) advantages

	Property	**Main Advantage (s)**	**Main Disadvantage (s)**
Orthogonal Designs	Zero correlation between attributes	No priors are needed	(Possibly needing) higher number of respondents
Full Factorial Designs	All possible combinations between attribute levels are used	No correlation between attributes No priors are needed	Often results in to many choice sets
Orthogonal Fractional Factorial Design	Orthogonal selection from Full Factorial Design	Reduces considerably the number of choice sets No correlation between attributes No priors are needed	Does not allow for the estimation of interaction effects
Orthogonal in the Difference Fractional Factorial Design	High attribute variation across experiment	Respondents forced to trade a wide range of attribute combination No correlation between attributes No priors are needed	Presence of dominancy Dominant attributes may govern experiment
Efficient Designs	Designs that generates parameter estimates with small standard errors	Minimizes standard errors of parameters	Requires an extra step: determining best estimates of parameters

A Full Factorial Design generates all possible choice situations, which can lead to the estimation of all possible (main and interaction) effects. This design has the advantage that the correlation between attributes is zero. However, this design often results in high number of choice situations, which makes this design almost not practical to use for the collection of choice data among respondents. An Orthogonal Fractional Factorial design is a selection out of the Full Factorial Design. For the Fractional Factorial Design, one assumes that the interaction effects are zero. Therefore, not all choice set combinations are needed. The advantage of the Fractional Factorial Design is that the number of choice sets is reduced considerably, while maintaining the correlation between the attributes zero. Besides these advantages, there is one design that also considers the variation of the attributes across the experiment, namely the Orthogonal in the Difference Fractional Factorial Design. This design holds the advantages of the Fractional Factorial Design, while increasing the combination/variation of the attributes across the experiment. This advantage of the Orthogonal in the Difference Fractional Factorial Design forces respondents to trade a wide varied attribute combination during the experiment. A disadvantage of this design is the possibility of dominant profiles in the experiment and the possibility that dominant attributes govern the experiment. (ChoiceMetrics, 2014)

Another design family is the efficient design. Such designs generate parameter estimates with small standard errors. However, a downside of these designs is that they require priors (best estimates of parameters), which can be derived from literature or by doing a pilot study. Considering the lack of prior information that is available in literature for this study and the minimum amount of respondents that is forecasted for this experiment that possibly want to participate in both the pilot and final study; it has been decided not to use these types of designs that require priors.

The benefits of the Orthogonal in the Difference Fractional Factorial Design that respondents are obliged to trade a wide range of attributes with each other and the no need of priors, have resulted in this experiment to be chosen for the SC experiment. Furthermore, the disadvantages of dominant profiles of this design have been reduced considerably by a technique of recoding/relabelling/recolumning and reordering provided by Bliemer and Julian (2014).

Appendix C elaborates more on how the Orthogonal in the Difference Fractional Factorial Designs is generated for the SC experiment. The questionnaire (the last step of the SC experimental construction) can also be found in Appendix C

4.4 Collection of the Choice Data

The target audience of the experiment was security screeners of regional airports. Therefore, it was decided to collect data from local airports. However, no agreement could be made with some of the local airports to collect data at the airport on a relatively short time span. Therefore, the choice experiment was held among security screeners at (only) one local airport. The choice experiment, among security screeners, was held during 4 days in the period of 23th October 2017 up to and including 26th October 2017. The choice experiment was conducted in a normal period for the corresponding local airport after the autumn break. In this period 68 security screeners participated in the choice experiment of which one did not fill in the complete survey. Therefore, it was decided to discard this participant from the choice experiment, which then resulted in 67 valid respondents. The participants were directly approached during their brake-session, where they could fill in the choice experiment. The experiment was done with pen and paper and was conducted in a separate room (i.e. the break room of the security screeners) apart from the daily security operation of the airport.

5. Empirical Results

In this chapter the empirical results of the Multinomial Logit (MNL), the Mixed Logit (ML) and the Latent Class (LC) models are presented and contrasted with each other. This chapter will first present the estimate results of the different models (see paragraph 5.1) followed by the interpretation of these results in paragraph 5.2.

5.1 Estimate Results

In table 4 the estimated results of the MNL, ML and the LC models are presented. The number of parameters listed in table 4 that is estimated for the MNL model is four based on 670 observations that were gathered from the choice experiment that is covered in paragraph 4.3. The Null log-likelihood for the MNL model is -736.070 and the Final log-likelihood is -545.293, which result in a McFadden's Rho^2 (ρ^2) of 0.259 indicating that the model is able to explain the data reasonably[11]. The ρ^2 (i.e. $1 - \frac{LL(\hat{\beta})}{LL(0)}$) indicates how good the model with the estimated parameters fits the data better than a model without (estimated) parameters (i.e. a model with parameters equal to zero). The parameters of the different attributes can be seen in table 4, where Hit Rate[12] (as expected) has a positive sign and False Alarm Rate, Average Passengers Waiting Time and the number of Missed Flights (also as expected) have a negative sign. For the ML model the number of estimated parameters is eight. The McFadden's Rho^2 (ρ^2) of 0.397 indicates that the ML model is able to explain the data reasonably good. Also for this model the signs are (as expected) positive for Hit Rate and negative for the remaining attributes. Furthermore, compared to the MNL model four extra parameters are estimated, which are Sigma Hit Rate, Sigma False Alarm Rate, Sigma Waiting Time and Sigma Missed Flights. The interpretation of these parameters is provided in paragraph 5.2. To contrast the ML model, a LC model has additionally been estimated. A three latent class model was selected as the best fit out of several class models of which the model performances are presented in table 5. The model performances of these LC models are based on the Bayesian Information Criterion (BIC), which takes parsimony into account, which is a better model performance measurement for LC models. Although a four latent class model has been estimated; the model with three classes has been chosen, since the four class model could not be interpreted well, while the majority of the parameters also became insignificant.

The BIC model performance measurement is calculated with

$$-2 * \mathrm{LL} + \mathrm{k} * \mathrm{LN(N)} \qquad (5.1),$$

where

- LL = Final Log-likelihood
- k = Number of parameters to be estimated
- N = number of observations

Note that the model details (e.g. utility functions) of the different models can be found back in appendix D.

[11] Indication/Interpretation of model fit
$\rho^2 < 0.1$ indicates that the model fits the data quite limited
$0.1 < \rho^2 < 0.3$ indicates that the model fits the data reasonable
$0.2 < \rho^2 < 0.5$ indicates that the model fits the data reasonably good
$\rho^2 > 0.5$ indicates an (extremely) good model Fit

[12] In this chapter Hit Rate is referred to the attribute Hit Rate and not to the term that is used as model performance for unseen data explanation

Table 4: Estimated discrete choice models (t-test in parentheses)

Note that the estimated parameters are significant for (abs(t-value) > 1.96), which corresponds to the well-known 5% significance level.

Attributes	MNL	LCM			Panel ML
		Class 1	Class 2	Class 3	
Hit Rate	0.0851 (13.87)	0.0197 (1.27)	0.148 (6.76)	0.0174 (0.52)	0.136 (7.29)
False Alarm Rate	-0.0131 (-2.27)	0.000397 (0.03)	-0.0361 (-3.03)	-0.947 (-12.94)	-0.0367 (-3.09)
Waiting Time	-0.0324 (-6.16)	-0.0913 (-4.85)	-0.0149 (-2.11)	-0.86 (-13.57)	-0.0493 (-4.66)
Missed Flights	-0.657 (-11.25)	-0.818 (-3.48)	-0.445 (-3.19)	-12.2 (-34.03)	-1.00 (-7.28)
		Class Memb. 0 Fixed (0) fixed	Class Memb. 0.758 (2.29)	Class Memb. -0.744 (-1.72)	
		Class1 Prob. 0.28	Class2 Prob. 0.59	Class3 Prob. 0.13	
Sigma Hit Rate	-	-	-	-	0.147 (6.19)
Sigma False Alarm Rate	-	-	-	-	0.0528 (4.36)
Sigma Waiting Time	-	-	-	-	0.0566 (5.58)
Sigma Missed Flights	-	-	-	-	0.981 (6.19)
Number of estimated parameters	4	14			8
Number of observations	670	670			670
Null log-likelihood	-736.070	-736.070			-736.070
Final log-likelihood	-545.293	-454.702			-443.546
Rho-square (ρ^2)	0.259	0.382			0.397
BIC	1117	1000			939

Table 5: Model fit for the 2 to 4 latent class models.

Number of Classes	Number of Parameters	Final Log-likelihood	BIC
2	9	-478.1	1015
3	14	-454.7	1000
4	19	-425.7	975

From the results in table 4, based on the Log-likelihood values of the different models (as well as the BIC measurements), one can safely reject the MNL model in favour of either the ML or LC model. One can see that the ML model fits the data better than the MNL model (note the large drop in Goodness-of-Fit of the MNL model compared to the ML model). In addition; since the estimated sigma's are significant, the ML model does not convert back into the MNL model (recall paragraph 3.2.3) and indicates (individual specific) taste variation for the attributes among security screeners. Therefore, besides paying attention on the good signs of the different parameters of the MNL model and the relative importance of the attributes, this model will not be covered in much detail.

5.2 Interpretation of parameter values

Parameter Interpretation of the Multinomial Logit Model

Referring back to table 4 one can note the parameters that have been estimated are in line with expectations. The Hit Rate parameter has a positive sign; meaning that the respondents (i.e. the security screeners) value this attribute positively. The parameters of False Alarm Rate, Waiting Time and Missed Flights have a negative sign; meaning that these attributes are negatively valued among the respondents (i.e. security screeners).

In table 6 the Relative Importance (RI) of the attributes derived from their part-worth utility (based on the used attribute levels in the choice experiment) are shown for the MNL model. The relative importance of the attributes is calculated using the following equation

$RI_i = 100 * \frac{UR_i}{\sum_{j=1}^{n} UR_j}$ (5.2) - (Halbrendt, Wang, Fraiz, & O'Dierno, 1995; Wang & Sun, 2003),

where

- $RI_i =$ Relative Importance of attribute i
- $UR_i =$ Utility Range of attribute i

The results of the MNL model indicate that Hit Rate, is the number one ranked most important/valued attribute followed by Missed Flights, Waiting Time and False Alarm Rate.
Since one can safely reject the MNL model in favour of either the ML or LC model, no more attention will be given to this model. In the following sections the ML and LC parameters are interpreted in more detail.

Table 6: Relative importance of attributes based on their part-worth utility (MNL outcome)

Attributes	Parameter	Attribute Levels	Part Utility	Utility Range	Relative Importance [Percentage Weight]
Hit Rate	0.0851	70% 80% 90%	5.96 6.81 7.66	1.70	**42.7%**
False Alarm Rate	-0.0131	10% 20% 30%	-0.131 -0.262 -0.393	0.262	**6.6%**
Waiting Time	-0.0324	2 minutes 13 minutes 24 minutes	-0.06 -0.42 -0.78	0.71	**17.8%**
Missed Flights	-0.657	0 pax. 1 pax. 2 pax.	0.00 -0.66 -1.31	1.31	**33.0%**
Sum of Utility Ranges				3.98	

Parameter Interpretation of the Mixed Logit Model

The results of the mean parameters of the Mixed Logit model can be interpreted as follows:

- The mean parameter value of 0.136 for Hit Rate (provided in table 4) indicates that the utility contribution of Hit Rate is 0.136 for each percentage point increase in Hit Rate.
- The mean parameter value of -0.0367 for False Alarm Rate (provided in table 4) indicates that the utility contribution of this attribute is -0.0367 for each percentage point increase in False Alarm Rate.
- The mean value of -0.0493 (provided in table 4) indicates a utility contribution of -0.0493 for each minute increase in average passengers waiting time.
- The mean parameter value of -1.00 indicates a utility contribution of -1.00 for each increase in the number of passenger missed flights.

The relative importance of the different attributes based on the mean parameter values of the ML results presented in table 4 are, based on equation 5.2, determined and shown in table 7.

Table 7: Relative importance of attributes based on their part-worth utility (ML outcome based on the mean parameter values)

Attributes	Parameter	Attribute Levels	Part Utility	Utility Range	Relative Importance [Percentage Weight]
Hit Rate	0.136	70% 80% 90%	9.52 10.88 12.24	2.72	**41.7%**
False Alarm Rate	-0.0367	10% 20% 30%	-0.37 -0.73 -1.10	0.73	**11.2%**
Waiting Time	-0.0493	2 minutes 13 minutes 24 minutes	-0.10 -0.64 -1.18	1.08	**16.5%**
Missed Flights	-1.00	0 pax. 1 pax. 2 pax.	0.00 -1.00 -2.00	2.00	**30.6%**
Sum of Utility Ranges				6.53	

The results suggest that on average Hit Rate, which is characterised as a security aspect, is the number one attribute in importance among security screeners. This outcome is likely plausible since security in general plays an important role in the work of security screeners at airports. The least valued/important attribute (on average) among security screeners is False Alarm Rate. This outcome is also likely plausible with the thought that the amount of False Alarms is not the primary goal of security screeners that is or should be optimized. Furthermore, in efficiency terms, the Average Passengers Waiting Time is valued on average more important compared to the False Alarm Rate, but on average less important compared to the Number of Passengers Missed Flights.

Mixed Logit Parameters indicating taste heterogeneity between respondents
In table 4 the ML results cover four extra parameters, namely Sigma Hit Rate, Sigma False Alarm Rate, Sigma Waiting Time and Sigma Missed Flights. The parameter results of 0.147, 0.0528, 0.0566 and 0.981 that respectively belong to Hit Rate, False Alarm Rate, Waiting Time and Missed Flights indicate a degree of unobserved taste variation among the respondents for these four attributes. Since these four parameters are significant (i.e. abs(t-value) > 1.96); the taste variation among respondents is significant different form zero. Since the estimated σ's are significant different from zero the ML model does not fall back into the MNL model.

Recall from paragraph 3.2.3 that the coefficients β_n vary over decision-makers with density $f(\beta)$, which is a function of parameters that indicates the mean and covariance of the coefficients ($\beta's$). According to Train (2016) the vast majority of studies have used normal and lognormal for the distributions and a few have been using Johnson's Sb, gamma, and triangular distributions. The lognormal distribution is useful when coefficients are considered to have the same sign for every decision-maker, such as price parameters known to be negative for everyone (Train, 2009). In appendix D examples are given of Lognormal, Normal and Triangular distributions that indicate what form the distributions of the different parameters can take, which are dependant of the assumed distribution and parameter specifications.

Parameter Interpretation of the Latent Class Model
The estimated parameters of the three classes, which are presented in table 4, are (except of one non-significant parameter) in the expected direction. The Hit Rate parameters have positive signs, meaning that utility increases with increasing Hit Rate. The other attributes have negative signs, meaning that these attributes are valued negatively among respondents. However, the False Alarm Rate of class 1 has a positive sign, indicating that the respondents of this class attach value to False Alarms. This can be plausible if one consider that the False Alarm Rate can provide a feeling of security certainty among the respondents. Recall from chapter 2 that False Alarm Rate is also a measurement that can influence the security at airports. Some security employees might rather take more False Alarms during the security operation, since lowering the number of False Alarms can negatively influence the Hit Rate (recall the relation between False Alarm Rate and Hit Rate in table 1). Although this parameter for class 1 offers new insights on how some respondents value False Alarms, the parameter itself is not significant and therefore, this new insight cannot be generalized to the population of such security employees (i.e. a particular group type of security screeners in the population).

Also for the different classes of the Latent Class model the relative importance of the different attributes is, with equation 5.2, determined. These outcomes (see table 8) based on the results of table 4 provide the following insights for the different classes.

Table 8: Relative importance of attributes based on their part-worth utility (LC outcome)

Attributes	Parameter	Attribute Levels	Part Utility			Utility Range	Relative Importance [Percentage Weight]
Hit Rate (Class 1-28%)	0.0197	[70% - 80% - 90%]	1.379	1.576	1.773	0.394	**9.7%**
Hit Rate (Class 2-59%)	0.148	[70% - 80% - 90%]	10.36	11.84	13.32	2.96	**60.4%**
Hit Rate (Class 3-13%)	0.0174	[70% - 80% - 90%]	1.218	1.392	1.566	0.348	**0.6%**
FAR (Class 1-28%)	0.000397	[10% - 20% 30%]	0.00397	0.00794	0.01191	0.00794	**0.2%**
FAR (Class 2-59%)	-0.0361	[10% - 20% 30%]	-0.361	-0.722	-1.083	0.722	**14.7%**
FAR (Class 3-13%)	-0.947	[10% - 20% 30%]	-9.47	-18.94	-28.41	18.94	**30.3%**
WT (Class 1-28%)	-0.0913	[2 – 13 – 24 min.]	-0.1826	-1.1869	-2.1912	2.0086	**50.0%**
WT (Class 2-59%)	-0.0149	[2 – 13 – 24 min.]	-0.0298	-0.1937	-0.3576	0.3278	**6.7%**
WT (Class 3-13%)	-0.86	[2 – 13 – 24 min.]	-1.72	-11.18	-20.64	18.92	**30.2%**
MF (Class 1-28%)	-0.818	[0 – 1 – 2 pax.]	0	-0.818	-1.636	1.636	**40.4%**
MF (Class 2-59%)	-0.445	[0 – 1 – 2 pax.]	0	-0.445	-0.89	0.89	**18.2%**
MF (Class 3-13%)	-12.2	[0 – 1 – 2 pax.]	0	-12.2	-24.4	24.4	**39.0%**

Class 1: Passengers Level of Service Sensitive Employees.
28% of the security screeners attach much value to the waiting time of passengers. This efficiency indicator has a relative importance weight of 50.0% compared to the other attributes. Also Missed Flight (with a relative importance weight of 40.4%) is relatively important for security screeners of this class. Hit Rate is the third most/second least important attribute for this class, while this group is relatively not sensitive for False Alarms. Since Hit Rate and False Alarm Rate (i.e. measurements for security detection performance) are the two least important attributes for this class, one can conclude that the detection performance for this class is relatively less important compared to the efficiency experienced by passengers. Since waiting time (i.e. a measurement for Airport Level of Service) is the most important attribute for this class together with passengers missed flights, one can label this class as security screeners that attach much value to the Level of Service of the security checkpoint for passengers.

Class 2: Highly Secured Employees
Class 2, by far the biggest class (almost 60% of class probability) attach a lot of value to Hit Rate (60.4% relative importance weight to be exact). Missed Flight for the majority of the security screeners is the second most important attribute, while Waiting Time and False Alarm Rate are relatively less important for the security screeners of this class, with waiting time being the least important one. Since this class attach high value to the security attribute and less value to the efficiency attributes; this class can be characterised as the class of ‘Highly Secured Employees’.

Class 3: Highly Efficient Employees
About one-tenth (13% to be exact) of the security screeners belong to this class, which attach very strong value to Missed Flights. Missed Flight, namely has a Relative Importance weight of almost 40% (see table 8). In this class Hit Rate has the smallest Relative Importance weight, indicating that security values less in importance compared to the other efficiency indicators. Since the efficiency attributes are the number one, two and three most important/valued attributes in this class; this class can be labelled as the class with ‘Highly Efficient Employees’, which can be considered as employees that attach a lot of value to efficiency and less value to security.

Class Membership Parameter

Out of the class membership model (see table 4), their found to be a positive significant class-specific constant (of 0.758) for class 2. This positive parameter contributes to the higher membership probability of security screeners to this class, which is a class that attach a lot of value to Hit Rate. This finding can be explained by the general context that security screeners' job is to secure the passengers and their belongings, which in general is of high value among security screeners. Therefore, this finding of a significant positive class specific constant for the membership of class 2 is highly plausible.

5.3 The Value of Security and Efficiency

Since the utility is a linear function of the different attributes; the Value of Security (VoS) and the Value of Efficiency (VoE) can be calculated by looking at the ratio of partial derivatives of the different attribute parameters.

In this section Hit Rate (HR) is used as base unit to express the Value of Efficiency.

The Value of Efficiency, which can be derived from the Value of the three efficiency attributes (i.e. Value of False Alarm Rate (FAR), Value of Waiting Time (WT) and Value of Missed Flights (MF) can be calculated as follows:

$$VoFAR = \frac{\frac{\partial V}{\partial FAR}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{FAR}}{\beta_{HR}} \qquad VoWT = \frac{\frac{\partial V}{\partial WT}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{WT}}{\beta_{HR}} \qquad VoMF = \frac{\frac{\partial V}{\partial MF}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{MF}}{\beta_{HR}}$$

The Value of Security on its turn, which can be derived from the Value of Hit Rate (HR) can be expressed in Missed Flights, Waiting Time and False Alarm Rate and can be calculated respectively as follows:

$$VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial MF}} = \frac{\beta_{HR}}{\beta_{MF}} \qquad VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial WT}} = \frac{\beta_{HR}}{\beta_{WT}} \qquad VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial FAR}} = \frac{\beta_{HR}}{\beta_{FAR}}$$

Note that this approach only holds for non-continuous models like the MNL and the Latent Class models. Therefore, this section provides the VoS and VoE based on the parameters derived from the MNL and Latent Class models.

In the tables 9 and 10 the VoS and VoE are expressed derived from respectively the MNL model and LC model with class 2 as an example[13].

[13] Since this class has the highest class probability, the VoS and VoE of this class is chosen to be shown as an example. The VoS and VoE of the remaining classes can be found back in appendix E.

Table 9: Value of Security and Efficiency derived from the MNL model

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	6.50 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	2.63 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.13 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	7.73 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	0.38 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	0.15 Percentage Points Hit Rate

Table 10: Value of Security and Efficiency derived from class 2 of the LC model

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	4.10 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	9.93 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.33 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	3.01 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	0.10 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	0.24 Percentage Points Hit Rate

Interpretation of the VoS and VoE

Value of Security

Value of Security ~Value of Hit Rate (VoHR) is:

- the willingness of False Alarm Rate acceptance for increase in Hit Rate or
- the willingness of average waiting time acceptance for increase in Hit Rate or
- the willingness of Missed Flights acceptance for increase in Hit Rate.

A VoS (~VoHR) of for example 2.63 average passengers waiting time states that 1 percentage point Hit Rate is equal to 2.63 minutes average passengers waiting time.

-Or with other words-

Security screeners are (implicitly) willing to accept on average 2.63 minutes extra waiting time for (each) 1 percentage point increase in Hit Rate.

Value of Efficiency

- Value of Efficiency ~Value of Passengers Missed Flights (VoPMF) = willingness of Hit Rate reduction for less passengers missed flights.
- Value of Efficiency ~Value of Average Passengers Waiting Time (VoWT) = willingness of Hit Rate reduction for waiting times savings.
- Value of Efficiency ~Value of False Alarm Rate (VoFAR) = willingness of Hit Rate reduction for less False Alarms

A VoE (~VoWT) of for example 0.38 percentage points Hit Rate states that 1 minute Average Passenger Waiting Time is equal to 0.38 percentage point Hit Rate.

-Or with other words-

Security screeners are (implicitly) willing to accept 0.38 percentage points reduction in Hit Rate for (each) 1 minute average passenger waiting time savings.

Note that in chapter 6 the trade-off results presented in this chapter and their effects on the operations of airports are evaluated in more detail together with implications to fortify this evaluation process.

6. Evaluation of the Security and Efficiency Trade-offs and their implications

This chapter focusses on the evaluation of the security and efficiency trade-offs based on the trade-off results presented in chapter 5 that security screeners make during operations of airports and how this evaluation process can be fortified with additional (simulation) models.

Paragraph 6.1 evaluates the trade-offs gathered from chapter 5. Based on these insights and evaluations, implications are provided in paragraph 6.2 for airport operators, which can be used to improve the security system. As discussed in paragraph 3.4.2 simulation based models can be used in addition to model security screeners with trade-off specifications to simulate and with this evaluate these trade-off effects on the operations of airports. Therefore, in paragraph 6.3 implications are provided for (among others) the ATO section which can be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners in an airport operational/simulated environment.

Note that this chapter mainly is -if otherwise said- based on the Mixed Logit and Latent Class trade-off results from chapter 5.

6.1 Evaluation of security and efficiency trade-offs of airport security screeners

Evaluation of the security and efficiency trade-offs based on the average security employee

To evaluate the security and efficiency trade-offs for the operations of airports, one should have a close look at figure 8. Figure 8 provides a good overview of the relative importance of the different attributes based on the average security screener. The results show that Hit Rate, which is characterised as a security aspect, is the number one attribute in importance among the average security screener, followed by Missed Flights, Waiting time and False Alarm Rate (recall table 7).

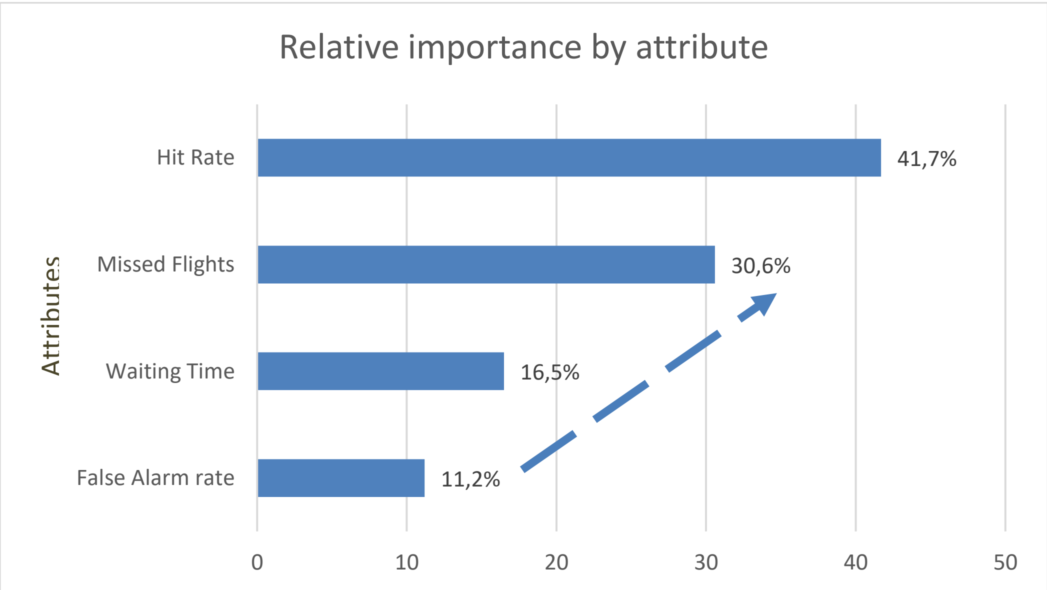


Figure 8: Relative importance of attributes

Waiting time with a score of 16.5% and as the second least important attribute among the average security screener is, compared to for example Hit Rate, not a really high valued attribute among the average security employee. The VoS also provides clear indications that on average security screeners are (implicitly) willing to accept on average 2.63 minutes[14] extra waiting time for (only) 1 percentage point increase in Hit Rate when trade-offs are made. This finding indicates that security screeners are willing to hand in relatively much waiting time in favour of Hit Rate when trade-offs between these two attributes are or needs to be made. Trade-off actions in favour of security to increase the Hit Rate with for example 5% mean that the average employee (implicitly) is willing to let the average passengers waiting time deteriorates with already 13 minutes. This mean that a relatively small focus on improving security can already have a big impact on the efficiency experienced by passengers, when trade-offs between these two attributes are or needs to be made.

On the other side, if the security employees trade off security in favour of the efficiency experienced by passengers, this can (according to the VoE) deteriorate the security being covered by the security checkpoint. However, the VoE implies that the average security screener is (implicitly) willing to only trade 0.38 percentage points[14] in Hit Rate for (each) 1 minute average passenger waiting time savings. This means that security screeners are willing to accept only a relatively small reduction in security Hit Rate to improve the waiting time experienced by passengers.

However, taking a closer look at the VoE in terms of missed flights, one can conclude that the average security screener is willing to hand in more Hit Rates to avoid passengers missing their flights. The VoE of 7.73 percentage points Hit Rate[14] implies that the average security screener is (implicitly) willing to hand in almost 8 percentage points Hit Rate to avoid one passenger of missing his/her flight. The average security screener is willing to deteriorate security more when passengers are (in circumstances of) missing their flights compared to when passengers are standing in the queue and are not (in circumstances of) missing their flights.

In figure 8 one can also observe this increasing attribute importance among the different efficiency attributes under the security screeners (see increasing arrow in figure 8). This difference/increase in importance can be coupled to an order of consequence effect of the efficiency attributes. False Alarm Rate for example can be considered as a consequence of the work behaviour of the security screeners, while the attributes that have a more direct effect on passengers and other stakeholders such as airlines, ATC and the airport itself are the Average Passengers Waiting Time and the Number of Passengers Missed Flights, with the latter having a bigger effect (i.e. higher order consequence) on passengers and the remaining stakeholders. This shows that the efficiency attributes that impose a bigger effect on other stakeholders at the airport can be considered as the attributes that are higher valued among the average security employee.

Evaluation of the security and efficiency trade-offs taking heterogeneity of security employees into account

As covered in chapter 5 the parameters that indicate taste heterogeneity among the security employees are significant and therefore should be taken into account. For the efficiency parameters the results suggest that on average security employees value the efficiency attributes (i.e. False Alarm Rate, Waiting Time and Missed Flights) negatively. However, there are also security screeners that deviate from these mean values. Some security screeners value these attributes higher and some lower than average. This with the result that the trade-offs being made (and therefore also the trade-off effects on

[14] Based on the MNL results – Note that the used method in chapter 5 to derive to the VoS and VoE only holds for non-continuous models such as the MNL model.

the operations of the airport terminal) differ from person to person among the security employees. Taking these heterogeneity effects into account can lead to other operational effects and insights compared to when these effects are ignored.
Looking at the possible distributions these efficiency parameters can take (recall appendix D), one can note that a part of the security screeners (can) value these attributes positively. This means that the utility of these security screeners increase when for example the number of false alarms increases. This might be plausible if one consider that the False Alarm Rate and the other efficiency attributes can provide a feeling of security certainty among the security employees. Recall from chapter 2 that False Alarm Rate is also a measurement that can influence the security at airports. Some security employees might rather take more False Alarms during operations, since lowering the number of False Alarms can negatively influence the Hit Rate (recall the relation between False Alarm Rate and Hit Rate in table 1). Also the waiting time (among some security employees) can be valued positively. Also this can be plausible with the thought that a higher waiting time (due to a less fast operation) can give the security employees more freedom in performing their job and with this improve the security (recall the relation between Waiting Time and Hit Rate in table 1).
This finding (of positively valued efficiency attributes among certain security employees) can have an impact on the efficiency of the security checkpoint. Since this group of security screeners value a longer waiting time or higher False Alarm Rate; it can result that the waiting times and or False Alarms increases under the work behaviour of these security screeners in order for them or the system to reach a higher security performance.

Furthermore, the different classes of security employees, namely the classes of 'Highly Efficient Employees', 'Highly Secured Employees' and 'Passengers Level of Service Sensitive Employees' can (from one another) have a different impact on the operations of airports. Having a security checkpoint with only highly efficient employees can be beneficial for the efficiency experienced by passengers, but less beneficial for the security. On the other side; having a security checkpoint with only highly secured security employees will lead to a lot of focus on the security, while losing the efficiency experienced by passengers out of sight. This on its turn can be beneficial for the security, but less beneficial for the efficiency experienced by passengers.

6.2 Implications for Airport Operators

In this paragraph four implications are presented directly to airport operators based on the found security and efficiency trade-off insights and evaluations. The four implications vary from short term actions, which can be taken in beneficial of the detection performance of the security to more mid-longer term actions.

Changing teams, groups and shifts in favour of the security detection performance

From the results and their evaluation, one can notice that some security screeners or a group of security screeners put a lot of value to missed flights and waiting times, which can be less beneficial for the security. However, for the airport and security operators it is still unknown, which security screeners/employees exactly belong to this group that is labelled as 'Passenger Level of Service Sensitive Employees'. Therefore, it is important to mix and shift security teams as much as possible to decrease the chance that a group that is highly sensitive for the passenger level of service is grouped (for a long time period) in one shift during operations. By changing teams, groups and shifts as much as possible, one would bring diversity in the operating groups that include also highly secured employees. This will decrease the chance of a diminished detection performance due to for example a team, which mainly/only consists of employees that are sensitive for the passengers Level of Service.

Reduce the possibility of missing flights and waiting times by investing in for example more resources

Since (from previous studies) it is known that security screeners make trade-offs between security and efficiency of which these values have been made explicit in this study, measures can or should be taken by airport operators to reduce the chance that such trade-offs (which can negatively influence the security or efficiency experienced by passengers) are made. One of such measures is to invest in more resources to reduce the possibility of high waiting times and missed flights. Such measures can avoid security screeners to be triggered to trade-off security and efficiency, which can lead to inaccurate and (potentially) dangerous trade-off decisions. With such measures both the efficiency experienced by passengers and the security of airports can be improved or at least not be diminished due to triggered trade-off decisions as a consequence of high waiting times, possible missed flights etc.

Increase awareness of security among the highly efficient employees and passengers Level of Service sensitive employees

However, it is known that investing in more resources is not cheap and not a decision that is taken or could be in place on short term. Therefore, it is important to increase awareness of security among employees in order to reach also the security employees that are highly efficient or sensitive for the passengers level of service. This measure is relatively cheap and can lead to an increase of highly secured security screeners, which attach (much) value to the security of the operation. However, as evaluated in paragraph 6.1, a security checkpoint with only highly secured security employees will lead to a lot of focus on the security, while losing the efficiency experienced by passengers out of sight. Therefore, it is still important to consider the measure of investing in more resources if waiting times and other efficiency measures diminish as a consequence of this implication that can lead to less focus to the efficiency of the security operation.

Reduce the possibility of missing flights by a track system

From the Value of Efficiency (VoE) one can notice that the average security screener values missed flights with 7.73 percentage points Hit Rate as the most important efficiency indicator. Since 7.73 percentage points is relatively high to trade on Hit Rate, it is important to reduce the possibility of a missed flight or the feeling among security screeners that their might be passengers in the queue, which are in circumstances of missing their flights. This can be done by introducing a track system for passengers, which keeps track of passengers and how much time they have left to catch their flights. Passengers in the security queue that are in the circumstances of missing their flights can be taken out of the queue and be processed in a fast lane. This implication can reduce the social pressure on security screeners that can lead to potentially dangerous trade-off decisions of trading Hit Rates with Missed Flights. However, it should be noted that this implication on the long run can lead to passengers being sloppy in their on-time arrival at the airport if they now this implication is in place. Therefore, one should be careful in communicating this policy to passengers and only use this policy in seldom occasions.

6.3 Implications for ATO

As said in paragraph 1.2 this project will collaborate with other ATO airport security-related projects, which models Agent-Based Airport Simulations that describes typical airport terminal processes. Therefore, this paragraph will provide implications that can be used (among others) by the ATO section to evaluate the trade-off effects on airport operations using such Agent-based Simulation Models based on the gathered empirical results, which are discussed in chapter 5.

AATOM including security agents **Intermezzo**

The AATOM simulation environment (see figure 9) developed by PhD. Candidate S.A.M. Janssen of the ATO section, is an Agent-based Simulation Model that is used to estimate security and efficiency indicators such as security risks, waiting times, passengers missed flights etc. The model consists of three types of agents that formalize the operations of an airport, namely orchestration agents, passengers and operators (Janssen, Blok, & Knol, 2017) (see figure 10). Such agents can be for example business passengers, but also check-in and security operators. The security operators in AATOM are defined with assignment(s) that defines which activity the security operator is assigned to (Janssen, Blok, & Knol, 2017). These security agents can perform different activities such as Travel Document Check, Assisting Passengers in the drop of their Luggage (i.e. Luggage Drop Activity), Operating of the X-Ray machines, Luggage Check, Passenger Physical Check and Explosive Trace Detector (ETD) Check. AATOM furthermore, describes environments in which such agents act and make observations. These environments are among others defined by operational areas and facilities. In figure 9 these areas and facilities are marked with letters, where A, B and C are facility areas and D and E are respectively check-in and queuing areas. G represents the gate area to the aircraft, while F is the checkpoint/security area.

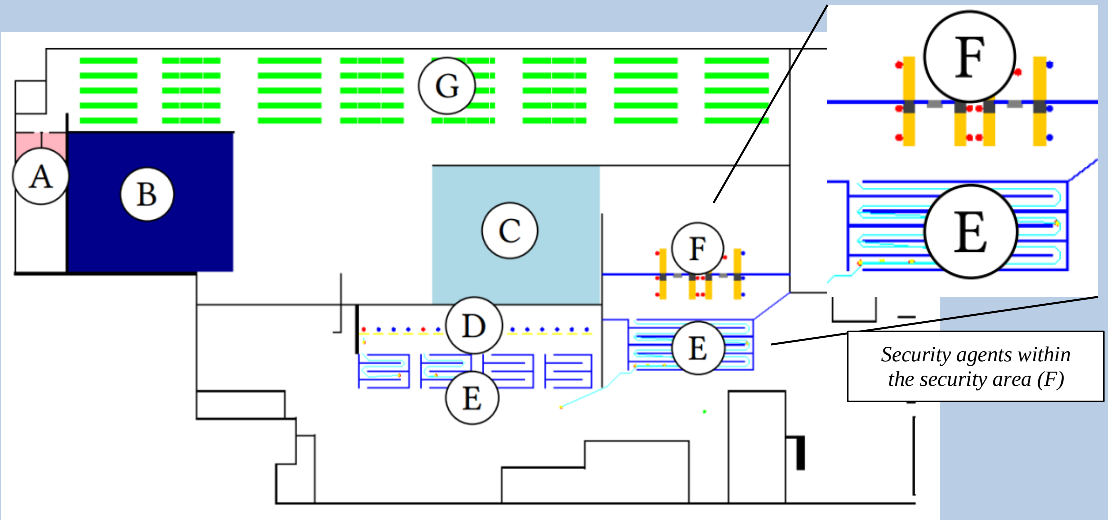


Figure 9: Airport layout visualized in the AATOM simulator developed by PhD. candidate S.A.M. Janssen (ATO section AE, TU Delft)

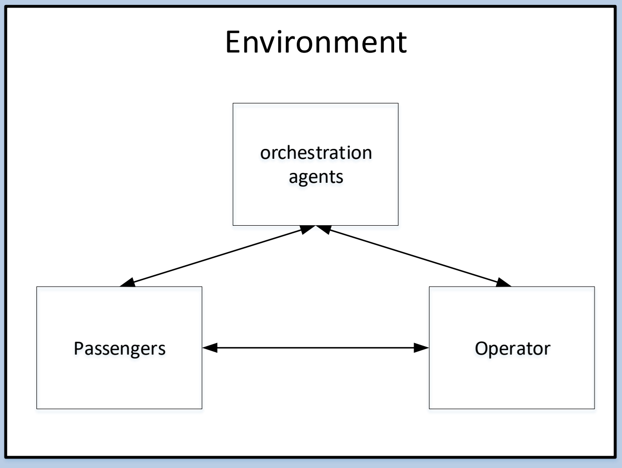


Figure 10: The different agent types that operate in the AATOM simulation environment

As mentioned in the description of the AATOM simulation environment, the model is able to simulate and with this describe airport terminal operational processes by modelling airport processes and airport operators as agents and there activities. This simulation is based on different input parameters as listed below, which can be categorized in parameters belonging to the environment and parameters of agents (Janssen, Blok, & Knol, 2017).

Current (input) parameters within AATOM

Environment Parameters

Map Layout
- Area locations
- Physical object locations

Airport Parameters
- Flight set
  - Type
  - Time
  - Set of checked-in passengers
  - Gate area
  - Set of check-in desks

Sensor Parameters
- WTMD sensor
  - Recovery time
  - Processing time
- X-ray sensor
  - Recovery Time
  - Processing Time
- ETD sensor
  - Recovery Time
  - Processing Time

Agent Parameters

Passenger Parameters
- Arrival time
- Flight
- Luggage set
  - Type
  - Complexity
  - Threat level
- Checked-in
- Facility visitor
- Observation radius
- Observation angle

Operator Parameters
- Check-in Operator
  - Flight Set
- Security Operator
  - Activity Assignment
  - Threat level threshold

From this list one can note that the AATOM model (yet) does not take (empirical) operational trade-off parameters of airport operators into account. However, one knows that trade-offs between security and efficiency play a role in the work-behaviour of security operators. Therefore, the security operators/agents of the AATOM should additionally be specified with the empirical trade-off results gathered from chapter 5, which will fortify the realistic behaviour of AATOM. These trade-off parameters, namely, can have an effect on the different activities of the security operators, which are discussed in the description of the AATOM simulation environment (see description of AATOM including security agents on page 51). The trade-off parameters can be used in addition to the threat level threshold parameter of security operators, which currently is used to determine if the luggage under investigation needs to be checked (Janssen, Blok, & Knol, 2017). Yet, this threshold parameter only is used to determine if the luggage under investigation needs to be checked (or not) but does not contain insights, based on trade-off parameters provided in chapter 5, to indicate if a security operator actually checks these luggage. Including these trade-off parameters will improve the realism and validity of AATOM with empirical security behaviour to derive to a more realistic model.

Since the AATOM simulation environment is able to model (security) agents, their work behaviour and are able to measure security and efficiency effects, they are also suitable to evaluate the effects of these empirical trade-offs results. This can be done by applying the framework of combined DCM and ABM methodology, which will be covered in the following section.

Apply the combined DCM and ABM methodology to evaluate security and efficiency trade-off effects on airport operations using Agent-based Airport Models

From figure 7 one can recall the framework of combining DCM and ABM that can be used to specify and simulate (among others) agents' trade-offs and preferences. This specification can be used to simulate agents' actions and decisions by deriving these actions and decisions from their utilities. The utilities, which can be used to determine this choice-behaviour of the agents; can be based on the agents' trade-offs, preferences and attribute levels derived from environmental characteristics such as queue length, waiting times, baggage & passengers information, security performance indicators etc. The resulting choice-behaviour of security agents can on its turn affect the performance indicators of the security system such as the waiting times, security level of service and security indicators such as security risk, Hit Rate, False Alarm Rate etc. This choice-behaviour based on the trade-offs of security screeners, can therefore be used to assess and evaluate the trade-off effects of the security screeners on the operation of airports.

This methodological approach of combining DCM and ABM introduced in paragraph 3.4.2 therefore, forms a suitable framework to evaluate the effects of the empirical security and efficiency trade-off results that were presented in chapter 5.

Figure 11 (which applies the combined modelling approach) shows how security agents in ABM can be modelled with behavioural specifications. These specifications can be defined with the empirical trade-off parameters that were gathered and covered in chapter 5 to evaluate their effects on the operations of airports.

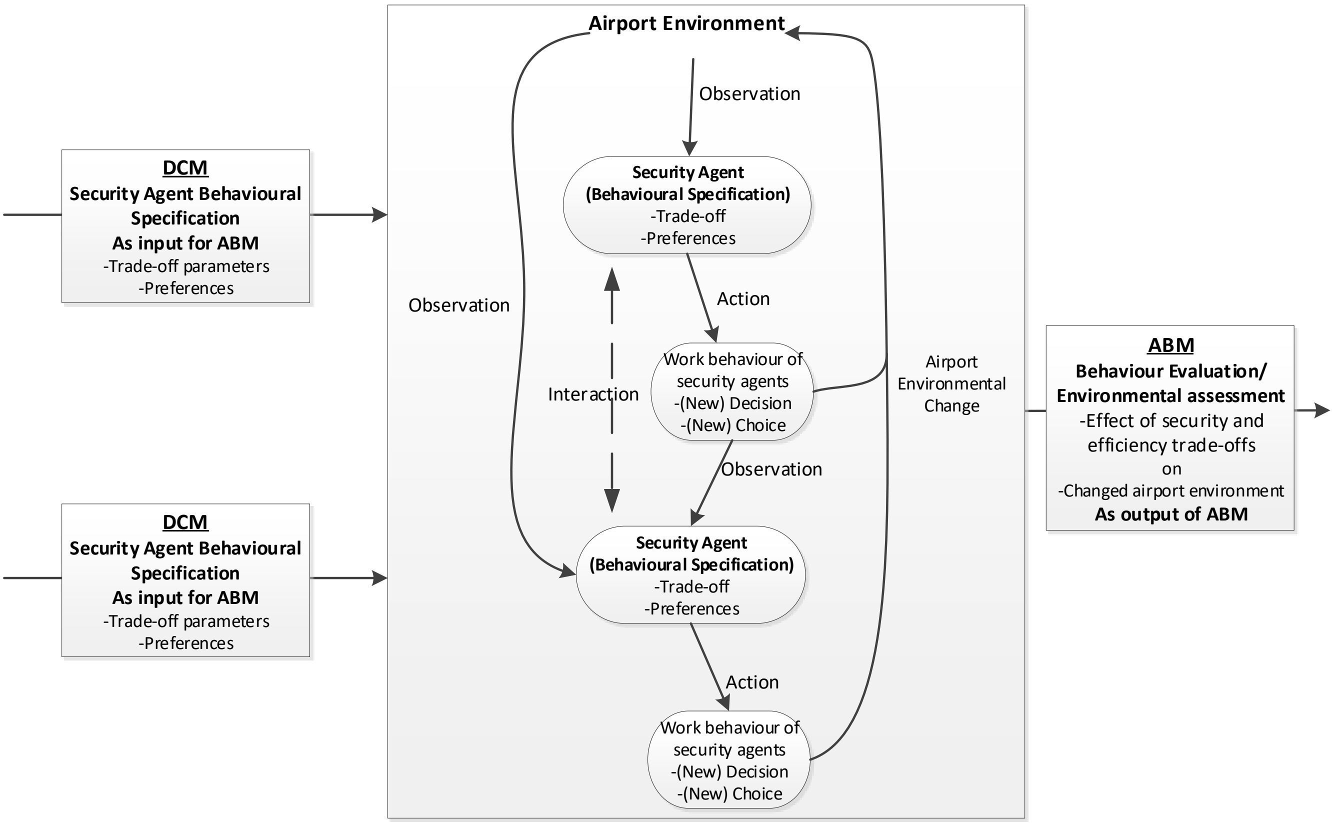


Figure 11: Applied framework of combined DCM and ABM methodology

Create diversity between security agents in ABM when assessing the effects of the security and efficiency trade-offs on airport operations

Recall that the results from chapter 5 suggest that not every security agent trade efficiency and security in the same magnitude. Therefore, it is important to take this heterogeneity between security screeners into account and model these to assess the diverse trade-off effects of the (diverse) security employees. To model the difference between security agents, one can take draws from the parameter distributions (recall chapter 5). These parameter distributions can be used to model different security agents based on their varied trade-offs (see figure 12). This enables one, not only to evaluate the effects of security and efficiency trade-offs based on the average security screener, but also to assess the trade-off effects of different types of security screeners on the operations of airports based on a range of trade-off specifications.

Furthermore, diversity between security agents can also be created by modelling the three different types of security agents that were derived from the results in chapter 5, namely Passengers Level of Service Sensitive Employees, Highly Secured Employees and Highly Efficient Employees (see figure 12). This can be done by specifying the agents with the trade-off parameters encountered from the three different classes of the LC model (see chapter 5). In addition to this, the composition of the security agents should also be taken into account by taking the percentage (probability of a security screener of belonging to a certain class) into account. These percentages, namely 28% of Passenger Level of Service Sensitive Employees, 59% of Highly Secured Employees and 13% of Highly Efficient Employees can also be adjusted to assess the effects of different compositions of security employees' teams in an airport simulated environment.

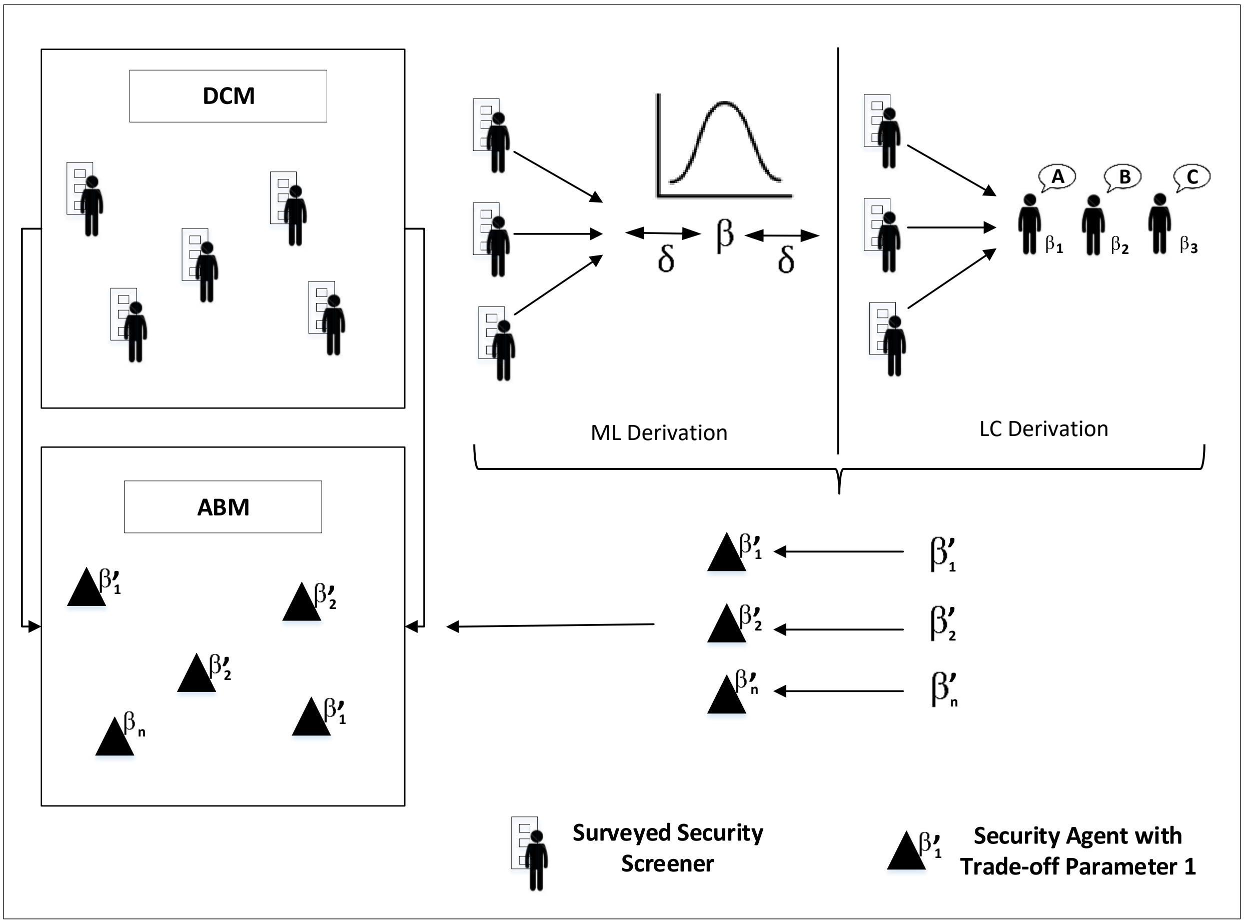


Figure 12: Modelling diversity between security agents

Ignoring or not considering this heterogeneity/diversity between security agents can lead to a loss of insights on the trade-off effects on airport operations that results from the different (types of) security operators at airports. Loss of insights in the operational effects if for example the operation is (mainly) based on a security team that is highly sensitive for the level of service for passengers or (mainly) based on a security team that highly values security. Taking this heterogeneity between security agents into account can provide answers to these types of what-if-situations. Furthermore, it is important to take heterogeneity into account (based on the trade-off parameters gathered from chapter 5) to create realistic security operations, which (recall from chapter 5) consist not only of one type or an average security screener, but a diverse of security employees.

7. Conclusion, Contribution & Recommendations

7.1 Conclusions

The goal of this thesis is to gather insights on how security screeners at small/regional airports trade-off security and efficiency during the operations of airports. Therefore, a couple of research questions have been set up to reach this goal. The conclusions that are derived from the previous chapters are made explicit in this paragraph by, concretely, answering the different research questions. The answers to the different sub questions provide a general conclusion on '**how airport security screeners trade-off security and efficiency when taking airport terminal operational trade-off decisions'**, which is the main focus of this research. These can be decisions on for example 'when to open or close a security lane', 'ultimate decisions of extra checks or higher level of security based on real-time situations and information', 'the amount of negotiations between negotiating passengers and employees during security operations' etc.

The goal of the first research question is to find the security and efficiency determinants that security screeners consider when making trade-offs during the operations of airports. Therefore, the following question was formulated:
'What are the security and efficiency determinants that airport security screeners consider when taking airport terminal operational trade-off decisions?'

The determinants that security screeners consider when taking airport trade-off decisions during the operations of airports can be categorized under two terms, namely Security Detection Performance and Security Efficiency Experienced by Passengers. The determinants under Security Detection Performance that impose trade-offs during the operations of airports have found to be Hit Rate and False Alarm Rate, which both are measurements that can influence the security of the operations at airports. Under the Efficiency Experienced by Passengers are two efficiency indicators that security screeners consider during the operations of airports, namely Average Passengers Waiting Time and Passengers Missed Flights. These four determinants together form the security and efficiency determinants that airport security screeners consider when taking one or more operational trade-off decisions.

The second research question:
'What are the relations between security and efficiency trade-off variables in the context of airport terminal operations?'
has been stated to find the relations between the security and efficiency operational trade-off variables.

The (conflicting) relations can be found between the screening accuracy/detection performance on one hand and the security efficiency experienced by passengers on the other hand. Reducing the waiting time experienced by passengers can for instance demand a faster operation of the security checkpoint, which can diminish the security detection performance at the checkpoint as security screeners will have less time to make operational decisions. This can result in an increase of Error Rates/False Alarm Rates. This increase of Error Rates or false alarms leads to a less efficient system as these false alarms will result in sending passengers and or bags unnecessarily to higher (secondary) level of security search. This can (unnecessarily) lead to an increase of waiting times and even missed flights among passengers. Not only might the False Alarm Rates be affected, but also the number of hits (i.e. Hit Rate). Therefore, the consequences of making an inaccurate (and potentially dangerous decision) must be weighed against the process of rapidly handling travellers and their baggage to meet efficiency

criteria experienced by passengers. However, focusing on the security only (e.g. focusing on the Hit Rate) can also influence the efficiency of the security system since improving the Hit Rate (can) require(s) more screening procedures such as the opening of more bags, which on its turn also can result in higher false alarm rates and waiting times.
These (conflicting) relations between security and efficiency play a key role when trade-offs are or need to be made during the operations of the security system.

The aim of the third research question is to identify the valuation/importance of the airport security and efficiency determinants by airport security screeners. Therefore, the following research question has been formulated:
'What are the airport security screeners' valuation of security and efficiency when taking airport terminal operational trade-off decisions?'

[15]From the results of this project, one can conclude that security screeners value Hit Rate (i.e. security indicator) as most important. The average security screener has an importance weight for Hit Rate of more than 40% relative to the other indicators. Missed Flight is, with a relative importance weight of more than 30%, the second most valued/important indicator among the average security screener. Waiting time with around 17% of importance weight is, compared to the other security/efficiency indicators, the third most valued/important indicator under the average security screener. The least valued indicator is False Alarm Rate with only a relative importance weight of around 10%.
Expressed in percentage points Hit Rate, one can conclude that each missed flight, passenger minute waiting time and percentage point false alarm (among the average security screener) value respectively 7.73, 0.38 and 0.15 percentage points Hit Rate. This result also shows that Missed Flight has the highest value and False Alarm the least value among the average security screener. Besides these values their also found to be significant heterogeneity among the security screeners, which indicates that some security screeners value security and efficiency higher or lower than the average security screeners' values presented above. Furthermore, it can be said that some (groups of) security screeners value efficiency more than security; the so called highly efficient employees or employees that find the level of service for passengers very important. However, the vast majority of the security employees (almost 60%) still belongs to the group that values the security aspect (i.e. Hit Rate) as most important compared to the efficiency of the security system. For this group there found to be a significant positive class-membership specific constant that contributes to the higher membership probability of almost 60% of security screeners to the class, which attach high value to Hit Rate. This significant positive class-membership specific constant can be explained by the general context that security screeners' job is to secure the passengers and their belongings, which in general is of high value among security screeners.

The fourth research question:
'How can the gathered trade-off insights be used to evaluate, by the means of Agent Based Models, the effects of security and efficiency trade-offs of airport security screeners on the operations of airports?'
has been formulated with the aim to provide implications which can be taken to evaluate, by the means of Agent Based Simulation Models, the effects of the gathered security screeners' trade-offs on the operations of airports.

[15] Note that the figures presented in this section are rounded. The exact numbers can be found back in chapter 5.

The framework of combining DCM and ABM methodologies, found to be a suitable framework to evaluate empirical trade-off parameters and their effects on a changing environment. This framework can therefore be applied as a methodological modelling approach to provide additional insights on the effects of the gathered security and efficiency trade-offs of this project on the operations of airports. The gathered empirical trade-offs can be used to specify security agents' trade-off behaviour. This can be done by using the trade-off parameters as input of agents in Agent Based Simulation Models, which describes security agents working in airport environments. One of such Agent Based Simulation Models that already models and simulates security agents during airport operations is the Agent-based Airport Terminal Operations (AATOM) Model of the ATO section at the Faculty of Aerospace Engineering (TU Delft). However, this model does not take the operational trade-offs of security screeners into account yet. The gathered trade-off parameters should therefore be used in addition to the currently existing input parameters that provide threat levels of passengers' baggage. Currently these parameters are (only) used by security agents to determine if the luggage under investigation needs to be checked (or not) but does not contain insights, based on trade-off parameters that determines if a security operator actually checks these luggage after making trade-offs between security and efficiency. Including these trade-off parameters will improve the realism and validity of AATOM with empirical security behaviour to derive to a more realistic model.
The gathered trade-off parameters can furthermore also be used to create diversity between security agents. This can be done by specifying different security agents, by taking draws from the parameter distributions discussed in chapter 5 or by modelling the three different types of security agents that were derived from the results in chapter 5, namely 'Passengers Level of Service Sensitive Employees', 'Highly Secured Employees' and 'Highly Efficient Employees'. In addition to this, the empirical composition of the security agents should also be taken into account by modelling the probability of a security screener of being/belonging to one of the security types/classes. Note that these probabilities can also be found back in chapter 5.

Main Research Question
As mentioned in the introduction of this paragraph, the goal of this thesis is to gather insights on how security screeners trade-off security and efficiency during the operations of airports. The main research question stated below was formulated to achieve this goal.
'How do airport security screeners trade-off security and efficiency when taking airport terminal operational trade-off decisions?'
The answer to this question, being covered during the following, provides a general conclusion based on the several conclusions that are made in this report.

Answer to the Main Research Question
Airport security screeners found to trade-off security and efficiency during airport operations by mainly considering security performance indicators such as the number of hits (i.e. Hit Rate) and the amount of false alarms (i.e. False Alarm Rate). Besides these security performance indicators, efficiency indicators experienced by passengers are also considered during trade-offs of airport operations. The average passengers waiting time and the possibility of a passenger of missing his or her flight are efficiency indicators that security screeners consider when taking operational trade-off decisions. However, focusing on the efficiency can deteriorate the security at the security checkpoints as increasing the speed of the security checks for a faster operation can lead to an increase in error rates (i.e. False Alarms) or a decrease in the number of hits (i.e. Hit Rate). On the other hand; focusing on the security only (e.g. focusing on the hit rate), can influence the efficiency of the security system since a higher hit rate (can) require(s) more screening procedures such as the opening of more bags, which can result in higher false alarm rates and waiting times and even missed flights. Therefore, the

consequences of making an inaccurate (and potentially dangerous decision) are weighed against the process of rapidly handling travellers and their baggage to meet efficiency criteria. This leads to security and efficiency trade-offs during the operations of airports, where the importance of these security and efficiency indicators have found to have a value among the security screeners. The average security screener values Hit Rate, which is an indicator to measure the security at airports as the most important indicator, followed by consecutively the amount of missed flights, waiting time and false alarms, which can be denoted as efficiency indicators. However, not all security screeners value security and efficiency in the same magnitude. There found to be significant heterogeneity (variation) between security screeners and even groups of security screeners, of which some groups (the highly secured group of employees) value the security aspect Hit Rate more and other groups (the highly efficient employees) valuing more the efficiency aspects of the security checkpoint. Furthermore, their found to be a positive significant class-membership constant parameter for the class that attach high value to security, which can be explained by the context observation that security screeners' job in general is to secure the daily operation. This positive significant class-membership constant contributes to the high class-membership probability of security screeners to this class, which attach a high value to security.

All these (different) trade-offs of security screeners between security and efficiency can have a (wide) effect on the operations of airports. Therefore, Agent-based Simulation Models such as AATOM found to be suitable to evaluate these trade-off effects on the operations of airports, by using the empirical trade-off parameters as input specification of security agents in such simulation models that take the operational environment of airports into account. In addition, these models can also be fortified by modelling different (types of) security screeners based on a varied input of empirical trade-off specifications.

7.2 Practical and Scientific Research Contribution

7.2.1 Practical Research Contribution

By explicitly determining the trade-offs of security screeners, new insights have been gathered on how airport security screeners trade-off security and efficiency during the operations of airports. These insights can be used by airport (security) managers for the evaluation of the work-behaviour of the security personnel (specified by their trade-offs) and their behavioural effects on the operations of airports. Other stakeholders such as the airport itself can use these insights as well to evaluate what effects their demands (e.g. demanding faster operations or focussing on only security) really can have on desired operational outcomes of the security checkpoint. Airports, airlines, Air Traffic Controllers etc. can for instance (by knowing how sensitive the security screeners/ or a group of security screener is for efficiency and security indicators) forecast how effective their demands and measures can be on the security checkpoint. Focussing on for example a faster security operation, with a group of security screeners that do not value the efficiency of security checkpoints will for instance (maybe) not result in the required outputs that one thought of beforehand. New policies, measurements and requirements can therefore better be mapped out if one knows the security employees, the trade-offs they make and their values for security and efficiency. Therefore, based on the empirical trade-offs and security/efficiency valuation of security screeners found in this study; some implications (as disclosed in paragraph 6.2 and summed in the following) can be provided, which can be used as practical measures for airport operators and/or security managers.

It is important, since their found to be significant heterogeneity between security screeners of which some groups value some attributes more than others, to mix and shift security teams as much as possible to decrease the chance that a group that is highly sensitive for for example the passenger level of service is grouped (for a long time period) in one shift during operations. Another measure that can/should be taken is to invest in more resources to avoid long waiting times or passengers missing their flights, which can trigger trade-offs being made among security screeners. Also the introduction of a passenger track system, which keeps track of passengers and how much time they have left to catch their flights in order to provide them priority service can be considered. Such measures can lead to a more efficient system experienced by passengers, which can avoid security screeners to be triggered to trade-off security and efficiency, which can lead to inaccurate and (potentially) dangerous trade-off decisions. However, one knows that investing in more resources can be an expensive measure. Therefore, it is important to also increase the awareness and importance of security among the employees. This measure is relatively cheap and can lead to more security screeners that are more secure in terms of airport security.

7.2.2 Scientific Research Contribution

This research provides three concrete scientific contributions that (future) scientist can build further research on. These research contributions are elaborated on in the following three sections.

Parameters that indicate the utility contribution of airport security screeners

This research provides trade-off parameters, which indicate the utility contribution/decision-weights of security and efficiency attributes. As far as knowledge goes, these are the first security and efficiency trade-off parameters that are made explicit, which can be used to derive the tastes and preferences of airport security screeners. These security and efficiency parameters can be used to calculate the utility of security screeners based on attribute levels that corresponds to these attributes.

The Relative Importance and Value of Security and Efficiency among security screeners

With the trade-off parameters, the relative importance of security and efficiency indicators of security screeners has been determined. This finding can be used to indicate how important the different attributes are relative to one another. Furthermore, the Value of Security (VoS) and Value of Efficiency (VoE) of security screeners have concretely been determined. With these values one can map out trade-offs and forecast how much security screeners are willing to trade one attribute with another if trade-offs are or need to be made. Also in this case, as far as knowledge goes, this is the first time that these values have been derived.

Modelling approach that is able to model and evaluate security screeners' social behavioural trade-off effects on the operation of airports.

This research provides furthermore, new trade-off knowledge that can be used to model and evaluate social behavioural trade-off effects of security screeners on the operation of airports. Up until now (as far as knowledge goes) the majority of airport operation models are mainly based technical processes to determine the outcome of operational key performance indicators such as queue length, security risk, real time passenger level of service etc. With the gathered empirical/social behavioural trade-offs, this research provides a contribution to the study of airport operations, which will be able to (besides the technical processes) also model social behavioural trade-offs of human operators. This can be seen as an added value in the study of (socio-technical) airport operational systems.

7.3 Recommendations for Future Research

As covered in paragraph 7.2.2 (Scientific Research Contribution), as far as knowledge goes, this is the first time that security and efficiency trade-offs of security employees have been made explicit. Based on this novelty, some recommendations are given that can be used for future research to further improve research on this topic.

Extended research with security screeners from other (Dutch) airports

This research has been used to estimate relatively complex models, with a quite relative small sample size of 67 security screeners of one specific airport. For future research it is recommended to amplify the sample of security screeners with more security employees, but also with security employees of other (Dutch) airports. This enables one to better represent the (Dutch) population of security screeners, of which new and more complex conclusions can faster be generalized to this population.

Extended research with socio-demographic characteristics

Furthermore, this research did not collect socio-demographic data of the security screeners of the local airport, since it was agreed with them that the outmost will be done to guarantee the anonymity of the employees. However, socio-demographic data can be used to couple trade-off results to the characteristics of employees, which can provide new explanatory knowledge and variables that can be used to explain the trade-offs of security employees.

Extended research to explore the type of utility function of security screeners along the whole range of practical Hit Rate levels

This research has only considered trade-offs between Hit Rates at the high end of Hit Rate levels, (namely above 70% Hit Rate). However, it is known that in practise Hit Rate levels can also fall below this level. Therefore, it is recommended to also conduct choice experiments, which include lower level of Hit Rates to explore if the trade-offs that are made between security and efficiency are linear across the whole range of practical Hit Rate levels. This with the hypothesis that security screeners make other (less) trade-offs with varying (decreasing) Hit Rate levels.

Research that derive the influence of context/scenarios on the trade-offs of security screeners

This research has used a single/fixed scenario to derive the trade-offs of airport security screeners. However, it is known that people make (/might make) different choices if the situation in which they make choices varies. Therefore, it is recommended to amplify this research with context dependant choice experiments to explore the influence of different airport scenarios (e.g. busy or non-busy working days, handling risk or no-risk flights etc.) on the trade-offs security screeners make during the operations of airports.

Further research to explicitly specify security agents with for example mathematical specifications to explicitly determine their utilities

This research has further focussed on a modelling approach to identify, analyse and evaluate security and efficiency trade-offs in the context of airport operations. But due to time constraint no specification of explicitly determining utilities of the security screeners/agents is made. Therefore, for further research, it is recommended to take a closer look on how these agents should explicitly be specified with for example mathematical utility specifications, which can lead to their utilities.

Conduct research to explicitly determine the security and efficiency trade-off effects of security screeners on airport operations

This research provides, based on a methodological underpinned modelling approach, implications to evaluate the security and efficiency trade-off effects on the operations of airports. However, this study (on its own) did not simulate these trade-offs in an airport operational simulated environment. Therefore, it is recommended to create or use existing (simulation) models that include specifications of security employees in an airport operational environment to explicitly determine these trade-off effects on the operations of airports.

8. Discussion & Limitations

Trade-offs between security and efficiency of security employees
Since the air transport industry is a highly regulated industry; one might on the first sight think that trade-off decisions between security and efficiency among security screeners is not self-evident, as such decisions are believed and assumed to be determined by rules and protocols. However, different studies among which the preliminary results of BEMOSA and the observations of Kirschenbaum et al., which are covered in the introduction, have shown that this thought and assumption is problematic based on hard (anecdotal) evidence. The hard (anecdotal) evidences show that security screeners certainly make trade-offs between security and efficiency during the operations of airports. This study has make an extra contribution to these observations by explicitly determining these trade-offs. In addition to these, there also found to be (among security screeners) values for security and efficiency based on significant security and efficiency trade-off parameters. The results of BEMOSA also provide some first indications on the reasons why these trade-offs are made. However, this research focussed on how trade-offs are made and did not (explicitly) study the reasons behind the trade-offs encountered in this study. Therefore, in contrast to the BEMOSA study this study is not able to make hard conclusions about the reasons why the encountered trade-offs are made.

Interviews with security employees and their socio-demographic characteristics
During this research different interviews have been conducted with security screeners, security team leaders and security advisors of a local airport. These interviews provided several insights on the security and efficiency indicators that are considered during the operations of airports when making operational decisions such as 'the opening or closing of new security lanes', ' decisions on the amount of negotiations between security employees and passengers' and 'decisions on ultimate or extra security checks based on real time passengers/baggage information'. These insights, together with a security systems analysis covered in appendix A and literature study have resulted in the security and efficiency indicators that were used in this report to base the choice experiment on. However, from the interviews and the choice experiment no socio-demographic data were gathered, since it was agreed with the involved parties that the outmost would be done to guarantee the anonymity of the security employees. Therefore, this research did not conduct any analysis, which requires socio-demographic characteristics. As consequence, this research is not able to couple the (trade-off) results to socio-demographic characteristics such as age, gender, the amount of working years/experience etc. as explanatory variables for the explanation of the results.

Attributes and attribute levels and their influence on the utility function
The attributes and their levels used in this research are based on interviews of security employees-, security team leaders-, security advisors at a local airport, literature study and a security systems analysis which can be found back in appendix A. The interviews, literature study and the systems analysis resulted in insights of different security and efficiency indicators that are considered during the operations of airports. However, due to a limit amount of respondents that was forecasted, this research has been limited to a set of four (most relevant) security/efficiency indicators; namely Hit Rate, False Alarm Rate, Average Passengers Waiting Time and Passengers Missed Flights. For some attributes such as Hit Rate, their found to be a wide range of attribute levels in literature. However, for Hit Rate, the choice was made to use only the high-end of the attribute levels (i.e. higher than 70%). This has been chosen so since the interviews, which were conducted from security screeners, provided indications that no trade-offs are made when the security performance is low (or lower than this point of 70%). However, it might be interesting to test if this is really the case and, if not, to see how trade-

offs are made for low-end Hit Rate levels as well. With this; the type of utility function of security screeners can be studied for the whole (including lower) range of Hit Rate levels. This with the hypothesis that security screeners make other (less) trade-offs with varying (decreasing) Hit Rate levels, which (might) indicate(s) non-linear utility function based on the corresponding parameter. By using only the high-end Hit Rate levels, this study is limited in deriving the influence of these low-end Hit Rate levels on the linearity of the utility function.

Data Collection

The data was collected at a local airport during one week, when the circumstances were told to be pretty normal. In total 67 security screeners (that were declared valid) were available to participate in the choice experiment, which is relatively a limited amount of respondents. This relatively limited amount of respondents has been used to estimate relatively complex choice models. Still, the majority of the parameters became significant. However, the Latent Class Model, due to the limited amount of respondents, was limited to the estimation of three classes. The amount of non-significant parameters became very high when models were estimated with four classes or more. Therefore, for future research, it is recommended (as covered in the recommendations) to collect more choice data by surveying more respondents. This enables one to increase the chance of significant parameters when the complexity (in this case estimating more parameters) of the models such as the Latent Class Model is increased.

Relation between Hit Rate and False Alarm Rate Based on the Receiver Operating Characteristic Curve (ROC-Curve)

From the Receiver Operating Characteristics (ROC) theory, one knows that high Hit Rates come with a price, namely higher False Alarm Rates or positively framed; higher False Alarm Rates come with a benefit of higher Hit Rates. From the ROC-curve, which plots Hit Rates vs. False Alarms Rates to express the possible detection performance of security operations, one can note the positive relation between these two detection performance indicators. Considering this feature, one can explain the positive parameter value of the False Alarm Rate of certain classes of the Latent Class model, with the assumption that the security employees of this class take this relation into account when taking trade-off decisions. Some security employees might rather take more False Alarms during operations, since lowering the number of False Alarms can negatively influence the Hit Rate. Also the higher False Alarm Rates can provide a feeling of more certainty, when more bags are inspected or opened with the thought ‘to better be safe than sorry’. However, still the majority of the security screeners, as expected, value Hit Rate as a positive feature and False Alarm Rate as a negative feature, which can provide indications that this group might not take this positive relational effect between these two attributes into account, when taking trade-off decisions.

Applicability of results and outcomes

This research has been conducted with the main focus to map out trade-offs that are made at small/regional airports. The choice experiment was also held among security screeners at a small/regional airport. Since the processes and performance criteria of small airports (e.g. waiting times and missed flights) differ from the ones of bigger airports, the results of this research must mainly be used and applied for regional airports. Furthermore, since trade-offs are (among others) dependant on the attribute levels (in this case the performance levels of security checkpoints at airports) it is expected that the trade-offs being made at bigger airport are different from the trade-offs that are made at small/regional airports. Therefore, the insights gathered from this research should be limited to regional airports like Eindhoven Airport, Maastricht Aachen Airport, Rotterdam the Hague Airport etc. and carefully be considered when one wants to use these results for applications at bigger airports like Amsterdam Airport Schiphol.

The usage of Random Utility Maximization as a modelling paradigm

This research has used the Random Utility Maximization (RUM) as a base modelling paradigm. However, as covered in paragraph 3.1.2 there is a different modelling paradigm that can be considered, namely the Random Regret Minimization (RRM) modelling paradigm. This modelling paradigm of minimizing regret when making choices instead of maximizing utility can also be used and applied for mapping out the trade-offs between security and efficiency. By assuming the RUM modelling paradigm, this study ignores the feature that the attractiveness of an alternative can depend on the availability and performance of other alternatives in the choice set (a feature also known as choice set-dependency). In the RRM modelling paradigm, this choice set-dependency is taken into account. Taking this extra feature of the RRM into account can result in better model performances. However, this research (by assuming and therefore limiting itself to the RUM paradigm) has not been able to/did not assess the difference in the modelling performance of the two modelling paradigms. Therefore, this research is limited when making any conclusions about security screeners if they make choices that better follow the RRM paradigm of minimizing regret or the RUM paradigm of maximizing utility.

Bibliography

Abeynayake, C., Aidman, E. V., & Jain, L. C. (2011). *Innovation in Defence Support Systems - 2.* Berlin Heidelberg: Springer-Verlag.

Araghi, Y., Bollinger, A. L., & Lee, E. P. (2014). Informing agent based models with discrete choice analysis: diffusion of solar PV in the Netherlands. *proceedings of Social Simulation Conference*.

Australian Government: Department of Infrastructure and Regional Development. (2017). *Security screening process*. Retrieved from Australian Government: Department of Infrastructure and Regional Development: http://travelsecure.infrastructure.gov.au/passenger-screening/security-screening-process.aspx

Bandini, S., Manzoni, S., & Vizzar, G. (2009). Agent Based Modeling and Simulation: An Informatics Perspective. *Journal of Artificial Societies and Social Simulation, 12*(4), 4.

Bates, J. (2015). *OSLO AIRPORT"S SECURITY WAIT TIMES AMONG THE SHORTEST IN EUROPE*. Retrieved from Airport World: http://www.airport-world.com/news/general-news/5170-oslo-airport-s-security-wait-among-the-shortest-in-europe.htmlhttps://www.swiftpassportservices.com/blog/worst-airport-security-wait-times/

BBC. (2017). *EU airport security checks: Holidaymakers 'face long delays'*. Retrieved from BCC: http://www.bbc.com/news/uk-40791058

BEMOSA. (2011). A Behavioral Model of Security in Airports: Preliminary Results. Madrid. Retrieved from http://www.cdti.es/recursos/doc/eventosCDTI/Aerodays2011/1A3.pdf

Ben-Akiva, M., & Bierlaire, M. (1999). *Handbook of Transportation Science: Chapter 2 DISCRETE CHOICE METHODS AND THEIR APPLICATIONS TO SHORT TERM TRAVEL DECISIONS.* New York: Springer Science+Business Media.

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand.* Mit Press Ltd.

Bierlaire, M. (2017). *Biogeme*. Retrieved from Biogeme: http://biogeme.epfl.ch/home.html

Bjørnskau, T., Flügel, S., & Veisten, K. (2011). Public's Trade-off between a New Risk-based Airport Screening and Asserted Terror Risk Impact: A Stated Choice Survey from Norway. *Journal of Transportation Technologies, 1*, 11-20.

Bliemer, M. C., & Collins, A. T. (2016). On determining priors for the generation of efficient stated choice experimental designs. *Journal of Choice Modelling, 21*, 10-14.

Bliemer, M., & Julian. (2014). *Dominant Alternatives*. Retrieved from Choice Metrics: http://www.choice-metrics.com/forum/viewtopic.php?f=2&t=90

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences of the United States of America*, *99*, pp. 7280–7287.

Bostrom, R. P., & Heinen, S. J. (1977). MIS Problems and Failures: A Socio-Technical Perspective. *MIS Quarterly, 1*, 17-32.

Brown, M. (2013). Catching the PHEVer: Simulating Electric Vehicle Diffusion with an Agent-Based Mixed Logit Model of Vehicle Choice. *Journal of Artificial Societies and Social Simulation, 16*(2), 5.

Bruch, E., & Atwell, J. (2015). Agent-Based Models In Empirical Social Research. *Sociol Methods Res., 44*(2), 186-221.

Burbeck, S. (2007). *Complexity and the Evolution of Computing: Biological Principles for Managing Evolving Systems.* Multicellular Computing. Retrieved from http://www.evolutionofcomputing.org/Complexity%20and%20Evolution%20of%20Computing%20v2.pdf

Burbeck, S. (2009). *Example Emergent Phenomena*. Retrieved from Evolution of Computing: http://www.evolutionofcomputing.org/Multicellular/Emergence.html

Burge, P., Kim, C. W., Potoglou, D., Robinson, N., & Warnes, R. (2010). Quantifying individuals' trade-offs between privacy, liberty and security: The case of rail travel in UK. *Transportation Research Part A: Policy and Practice, 44*(3), 169-181.

CCICADA. (2016). *Missed a Flight Due to Long Security Lines? TSA Official Unveils 'Intelligent' Solution at CCICADA Research Retreat*. Retrieved from CCICADA: http://ccicada.org/2016/07/07/missed-a-flight-due-to-long-security-lines-tsa-official-unveils-intelligent-solution-at-ccicada-research-retreat/

ChoiceMetrics. (2014). *Ngene 1.1.2 USER MANUAL & REFERENCE GUIDE: The Cutting Edge in Experimental Design.* Retrieved from https://dl.dropboxusercontent.com/u/9406880/NgeneManual112.pdf

Chorus, C. (2012b). Random Regret Minimization: An Overview of Model Properties and Empirical Evidence. *Transport Reviews, 32*(1), 75-92.

Chorus, C. G. (2012a). *Random Regret-based Discrete Choice Modeling: A Tutorial.* Heidelberg New York Dordrecht London: Springer.

de Lange, R., van der Rhee, B., & Samoilovich, I. (2013). Virtual queuing at airport security lanes. *European Journal of Operational Research, 225*(1), 153-165.

Elias, B. (2009). *Airport and Aviation Security: U.S. Policy and Strategy in the Age of Global Terrorism.* Boca Raton: Auerbach Publications.

Enserink, B., Hermans, L., Kwakkel, J., Thissen, W., Koppenjan, J., & Bots, P. (2010). *Policy Analysis of Multi-Actor Systems.* The Hague: Lemma.

EUR-Lex. (2015). COMMISSION IMPLEMENTING REGULATION (EU) 2015/1998: laying down detailed measures for the implementation of the common basic standards on aviation security - PASSENGERS AND CABIN BAGGAGE - HOLD BAGGAGE . *Official Journal of the European Union*, 14-24.

Euronews. (2017). *EU: stricter Shengen checks brought in to fight terror*. Retrieved from Euronews: http://www.euronews.com/2017/04/06/eu-stricter-schengen-checks-brought-in-to-fight-terror

Fayez, M. S., Kaylani, A., Cope, D., Rychlik, N., & Mollaghasemi, M. (2008). Managing airport operations using simulation. *Journal of Simulation, 2*, 41-52.

Fitzpatrick, A. (2016). *Airline: 70,000 Passengers Missed Flights Due to Security Lines*. Retrieved from TIME: http://time.com/4349766/airline-70000-passengers-missed-flights-due-to-security-lines/

Fodness, D., & Murray, B. (2007). Passengers' expectations of airport service quality. *Journal of Services Marketing, 21*(7), 492-506.

Gillen, D., & Morrison, W. G. (2015). Aviation security: Costing, pricing, finance and performance. *Journal of Air Transport Management, 48*, 1-12.

Gkritza, K., Niemeier, D., & Mannering, F. (2006). Airport security screening and changing passenger satisfaction: An exploratory assessment. *Journal of Air Transport Management, 12*(5), 213-219.

Godwin, H. J. (2008). *The Influence of Real-Word Factors on Threat Detection Performance in Airport X-Ray Screening.* University of Southampton, School of Psychology, PhD Thesis. Retrieved from https://eprints.soton.ac.uk/66381/1/Godwin_Thesis_2009.pdf

Halbrendt, C., Wang, Q., Fraiz, C., & O'Dierno, L. (1995). Marketing Problems and Opportunities in Mid-Atlantic Seafood Retailing. *American Journal of Agricultural Economics, 77*(5), 1313-1318.

Hättenschwiler, N., Michel, S., Kuhn, M., Ritzmann, S., & Schwaninger, A. (2005). A First Exploratory Study on the Relevance of Everyday Object Knowledge and Training for Increasing Efficiency in Airport Security X-ray Screening. *IEEE Conference Publications*, 25-30.

Heiss, F. (2002). Specification(s) of Nested Logit Models. *University of Mannheim, MEA*. Retrieved from http://mea-dev.mpisoc.mpg.de/uploads/user_mea_discussionpapers/dp16.pdf

Hensher, D. A. (1994). Stated preference analysis of travel choices: the state of practice. *Transportation, 21*(2), 107-133.

Hensher, D. A., & Greene, W. H. (2002). Specification and estimation of the nested logit model: alternative normalisations. *Transportation Research Part B: Methodological, 36*(1), 1-17.

Hensher, D., Greene, W. H., & Chorus, C. G. (2011). Random regret minimization or random utility maximization: An exploratory analysis in the context of automobile fuel choice. *Institute of Transport and Logistics Studies, ITLS-WP-11-23*.

Hess, S., & Daly, A. (2014). *Handbook of Choice Modelling.* Cheltenham & Northampton: Edward Elgar Publishing.

Hofer, F., & Schwaninger, A. (2005). Using threat image projection data for assessing individual screener performance. *WIT Transactions on The Built Environment, 82*, 417-426.

Holm, S., Lemm, R., Thees, O., & Hilty, L. M. (2016). Enhancing Agent-Based Models with Discrete Choice Experiments. *Journal of Artificial Societies and Social Simulation, 19*(3), 3.

ICAO. (2006). *Security: Safeguarding International Civil Aviation against Acts of Unlawful Interference.* International Civil Aviation Organization.

IMM International. (2016). *Global Air Traffic & Top Airlines 2016 (IATA)*. Retrieved from IMM International: http://www.imm-international.com/global-air-traffic-top-airlines-2016-iata/

Janssen, M. A. (2004). Agent-Based Modelling. In J. Proops, & P. Safonov, *Modelling in Ecological Economics* (pp. 155-172). Cheltenham: Edward Elgar Publishing.

Janssen, S., Blok, A.-N., & Knol, A. (2017). AATOM - An Agent-based Airport Terminal Operations Model.

Kirschenbaum, A. A. (2013). The cost of airport security: The passenger dilemma. *Journal of Air Transport Management, 30*, 39-45.

Kirschenbaum, A. A. (2015). The social foundations of airport security. *Journal of Air Transport Management, 48*, 34-41.

Kirschenbaum, A. A., Andriessen, H., Van Gulijk, C., Lubasz, S., Mariani, M., & Rapaport, C. (2012). Airport security: An ethnographic study. *Journal of Air Transport Management, 18*(1), 68-73.

Kroes, E. P., & Sheldon, R. J. (1988). Stated Preference Methods: An Introduction. *Journal of Transport Economics and Policy, 22*(1), 11-25.

Labbe, M., Laporte, G., Tanczos, K., & Toint, P. (1998). *Operations Research and Decision Aid Methodologies in Traffic and Transportation Management.* Berlin Heidelberg: Springer-Verslag.

Macal, C. M., & North, M. J. (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation, 4*(3), 151–162.

McCarley, J. S., Kramer, A. F., Wickens, C. D., Vidoni, E. D., & Boot, W. R. (2004). Visual Skills in Airport-Security Screening. *Psychological Science, 15*(5), 302-306.

McFadden, D. (2000). Disaggregate Behavioral Travel Demand's RUM Side: A 30-Year Retrospective. *Travek Behaviour Research*, 17-63.

Meuller, J., & Stewart, M. G. (2017). Risk and economic assessment of expedited passenger screening and TSA PreCheck. *Journal of Transportation Security, 10*(1), 1-22.

Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports of mental processes. *Psychological Review, 84*(3), 231-259.

NOS. (2017). *Enorme drukte op Schiphol, tientallen mensen missen hun vlucht*. Retrieved from NOS: http://nos.nl/artikel/2169578-enorme-drukte-op-schiphol-tientallen-mensen-missen-hun-vlucht.html

Orhun, A. Y. (2005). OPTIMAL PRODUCT LINE DESIGN WHEN CONSUMERS EXHIBIT CHOICE SET DEPENDENT PREFERENCES. *Haas School of Business, University of California at Berkeley*, 868 - 886.

Renner, J. (2015). Improving and optimising the LoS of an airport. *Airport Construction & Design Supplement, 19*(5), pp. 47-50.

Ryan, M., Gerard, K., & Amaya-Amaya, M. (2008). *Using Discrete Choice Experiments to Value Health and Health Care.* Dordrecht: Springer Netherlands.

Schwaninger, A. (2003). Screener evaluation and selection. *AIRPORT, 02*, pp. 14-15.

Schwaninger, A. (2003). Screener evaluation and selection. *AIRPORT, 02*, pp. 14-15.

Schwaninger, A. (2005). Increasing efficiency in airport security screening. *WIT Transactions on The Built Environment, 82*, 407-416.

Schwaninger, A. (2005). Increasing efficiency in airport security screening. *WIT Transactions on The Built Environment, 82*, pp. 407-416.

Security Management. (2017). *Nieuws: Schiphol zet extra mensen in bij controles*. Retrieved from Security Management: https://www.securitymanagement.nl/schiphol-zet-extra-mensen-controles/

Shannon, R. E. (1998). INTRODUCTION TO THE ART AND SCIENCE OF SIMULATION. *Proceedings of the 1998 Winter Simulation Conference*, 7-14.

Simonson, I. (1989). Choice Based on Reasons: The Case of Attraction and Compromise Effects. *Journal of Consumer Research, 16*(2), 158-174.

Skorupski, J., & Uchroński, P. (2016). A fuzzy system to support the configuration of baggage screening devices at an airport. *Expert Systems with Applications, 44*, 114-125.

Sommerville, I. (2011). *Software Engineering.* Boston: Pearson, Addison-Wesley.

Street, D. J., Burgess, L., & Louviere, J. J. (2005). Quick and easy choice sets: Constructing optimal and nearly optimal stated choice experiments. *International Journal of Research in Marketing, 22*(4), 459-470.

Thomas, A. R. (2008). *Aviation Security Management: The Context of Aviation Security Management.* London: Praeger Security International.

Thurstone, L. (1927). A Law of Comparative Judgment. *Psychological Review, 34*, 273-286.

Train, K. (2009). *Discrete Choice Methods with Simulation.* New York: Cambridge University Press.

Train, K. (2016). Mixed logit with a flexible mixing distribution. *The Journal of Choice Modelling, 19*, 40-53.

TU Delft. (n.d.). *Random Regret Minimization Model*. Retrieved from TU Delft: https://www.tudelft.nl/en/tpm/research/projects/random-regret-minimization-model/

Ülkü, T. (2014). *Empirical analyses of airport efficiency and costs: Small regional airports and airport groups in Europe.* Berlin: Humboldt University of Berlin.

Vag, A. (2007). Simulating changing consumer preferences: A dynamic conjoint model. *Journal of Business Research, 60*(8), 904-911.

van Dam, K. H., Lukszo, Z., & Nikolic, I. (2013). *Agent-Based Modelling of Socio-Technical Systems.* Dordrecht Heidelberg New York London: Springer.

van Eenige , M. J., & Muehlhausen , T. (2007). *SPADE: Supporting Platform for Airport Decision-making and Efficiency Analysis.* NLR National Aerospace Laboratory. Retrieved from http://reports.nlr.nl/xmlui/bitstream/handle/10921/398/TP-2007-040.pdf?sequence=1

Vojáček, O., & Pecáková, I. (2010). Comparison of Discrete Choice Models for Economic Environmental Research. *Prague Economic Papers, 1*, pp. 35-53.

Wales, A., Halbherr, T., & Schwaninger , A. (2009). Using Speed Measures to Predict Performance in X-Ray Luggage Screening Tasks. *Security Technology, 2009. 43rd Annual 2009 International Carnahan Conference on*, (pp. 212-215).

Wang, Q., & Sun, J. (2003). Consumer preference and demand for organic food: Evidence from a Vermont survey. *The American Agricultural Economics Association Annual Meeting* (pp. 1-23). Department of Community Development and Applied Economics, University of Vermont; Department of Agricultural Economics, Iowa State University, Ames.

Wilensky, U., & Rand, W. (2015). *An Introduction to Agent-Based Modeling: Modeling Natural, Social, and Engineered Complex Systems with NetLogo.* Cambridge, MA: MIT press.

Wilson, B. (2017). *TSA Explains the Complete Passenger Screening Process at Airports*. Retrieved from tripsavvy: https://www.tripsavvy.com/complete-passenger-screening-process-at-airports-54232

Wittink, L. (2011). *Choice modelling: An overview of theory and development in individual choice behaviour modelling.* Vrije Universiteit.

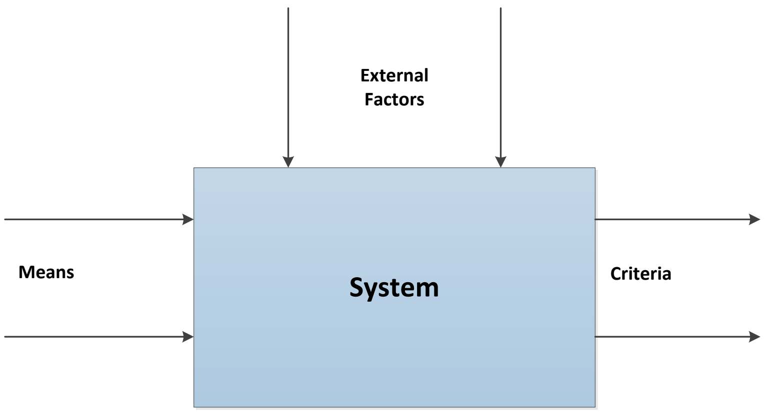
Zografos, K. G., Madas, M. A., & Salouras, Y. (2013). A decision support system for total airport operations management and planning. *Journal of Advanced Transportation, 47*(2), 170-189.

Zografos, K. G., Madas, M. A., van Eenige, M. J., & Valdes, R. A. (2005). Integrated Airport Performance Analysis through the Use of the OPAL Platform. *Air Traffic Control Quarterly, 13*(4), 357-386.

Appendix

Appendix A: Airport Security System Analysis

System analysis is a method to map out a system by showing the elements and the relations between these elements that are relevant for analysing and understanding a certain system. The analysis applies scientific methods to analyse large and complex systems. A system model is made to clarify the system by defining the boundaries and the structure of the system. The result of a system analysis is a system diagram, which illustrates the relations within the system itself and the relations between the system and the means, external factors and criteria that are linked to the system. The means are instrumental decisional measures that decision-/ choice- or policy-makers can use to influence the criteria, which are described as the interest outcomes of the system. The external factors are factors that are not in control of these decision-makers, but can influence the system and with this the criteria. (Enserink, et al., 2010)
In figure A1, an illustration of a system diagram is depicted, which forms the conceptual framework for the system analysis.



(Enserink, et al., 2010)
Figure A1: System Diagram as a conceptual framework for system analysis

In order to better understand the Security System of Airport Terminal Operations and its efficiency, a Security Operational system Analysis is made to map out the main elements of security operational systems and the relations within such systems. The outcome of the security system analysis is a system diagram, which contributes to a better understanding of the security operation.

There are different ways to develop a system diagram. To develop a Security System Diagram, which follows from a suitable system boundary and which considers the main elements and their relations; the four-step approach is used, which is provided by Enserink et al. (2010). The four steps are defined as follows:

1. Creating the initial problem demarcation and level of analysis.
2. Specifying objectives and criteria (outcomes of interest).
3. Identification of potential means and mapping of the main causal relations and their influence on the outcomes of interest.
4. Creating a system diagram to provide an overview of the problem area.

1. The initial problem demarcation and level of analysis

To illustrate the level of analysis and the problem demarcation, a Means-Ends Diagram is created. A Means-Ends Diagram can help to determine the appropriate level of analysis by selecting a particular objective of a system. By continuously asking “why” this objective needs to be met; the higher (more strategic) levels of the analysis are formed. By asking “how” these objectives can be met; the lower (more operational) level of the analysis is broad into picture. In figure A2 this technique has been applied to differentiate between the potential levels of analysis. In figure A2 one can note that airport processes such as the security process are linked with the efficiency experienced by passengers. The efficiency experienced by passengers can be seen as a mean to make the airport terminal more attractive for passengers and with this to improve the passengers’ experience. Improving the passengers experience can be seen as one of the means to improve the competitive position of airports, which according to Fodness & Murray (2007) is an important issue that airports have been focussing on to survive the increasingly competitive marketplace.

To increase the efficiency experienced by passengers, one can use means to reduce the waiting, process and walking times for passengers. These are outcome factors that can be reached by deploying more resources and improving the operational speed at servers. Although these means positively influence the passengers’ experience, they also have side effects on investment/operational costs and the processes such as the security operational process. Since this dilemma is derived from this level of the Means-Ends Diagram, the level of analysis will focus on this lower (operational) level. This level of analysis also determines the problem demarcation and the aspects/factors that will be taken into account in the further system analysis, namely the security and efficiency factors derived from the Means-Ends Diagram.

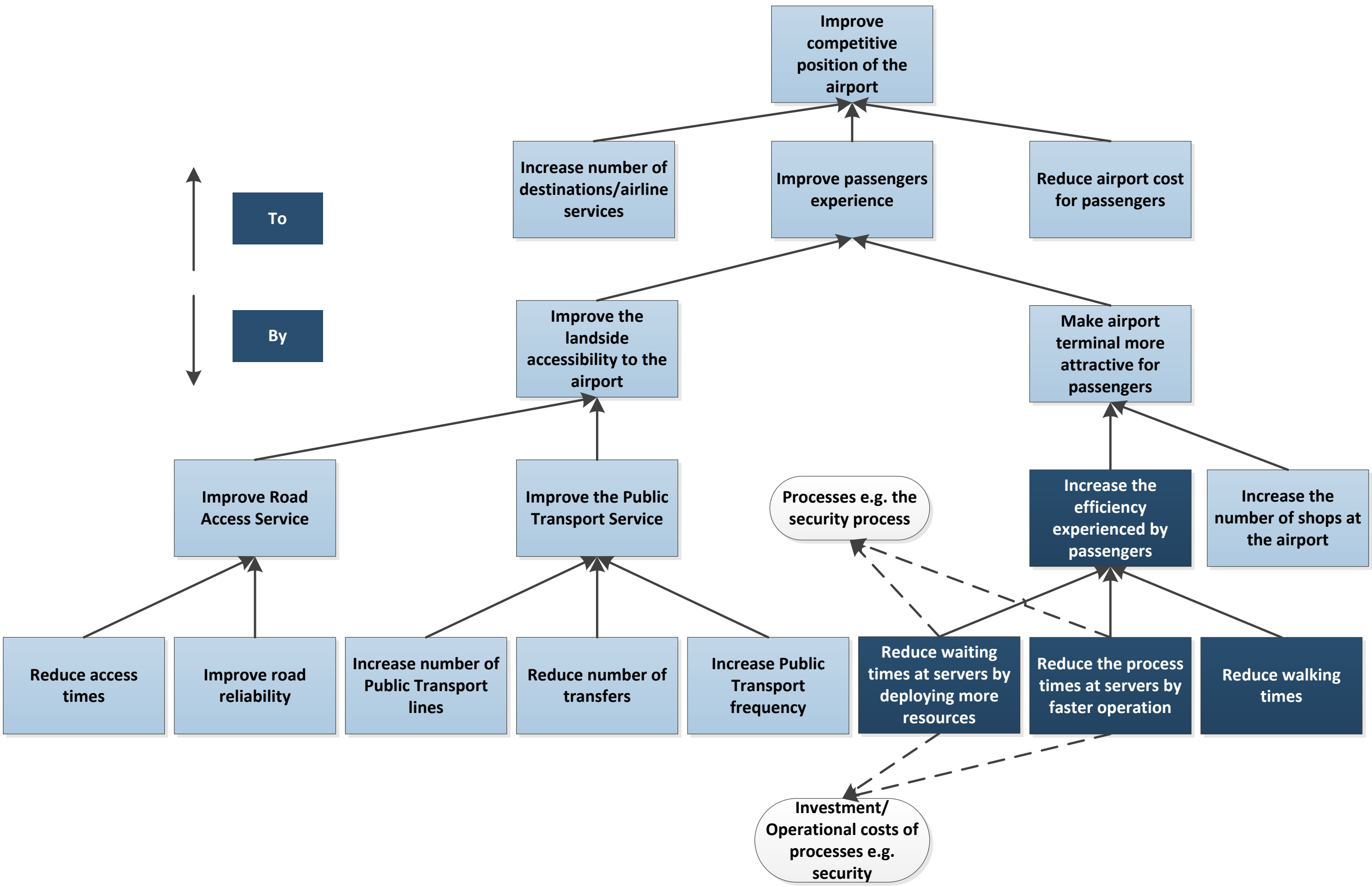


Figure A2: Means-Ends Diagram determining the problem demarcation & level of system analysis

The dilemma introduced in figure A2 is made explicit by defining the following problem formulation:

How can the efficiency of Airport Terminal Operations experienced by passengers be increased without diminishing the security process and without (too much) increasing effect on the security costs?

This problem formulation, which reflects the dilemma encountered in the Means-Ends Diagram will be used as a base formulation in the process of defining the objectives/criteria i.e. the outcomes of interest of the Security Operational System. Although this problem formulation covers some parts of the broader research questions stated in paragraph 1.2, it must solely be seen as a base tool to further formalizing the system analysis and not as a replacement for these research questions, which still are leading the direction of this report.

2. The Objectives and Criteria (outcomes of interest)

Recall of the problem formulation:

How can the ***efficiency*** of Airport Terminal Operations experienced by passengers be increased without diminishing the ***security process*** and without (too much) increasing effect on the ***security costs***?

By having the dilemma formalized in a problem formulation, a first level objective is stated, which describes what has to be achieved and what should be avoided. This problem formulation is translated into the following root objective:

"responsible improvement of the Airport Terminal Efficiency experienced by passengers",

which encompass both the desired and the to be avoided issues:

To create operational criteria from this root objective, the root objective is specified in more details. The term 'responsible' is further defined as low increasing effect on costs and no diminishing security process, while 'higher efficiency experienced by passengers' is defined as a higher Level of Services for the passengers. In figure A3 one can see how these three descriptions have further be lined out into operational criteria.

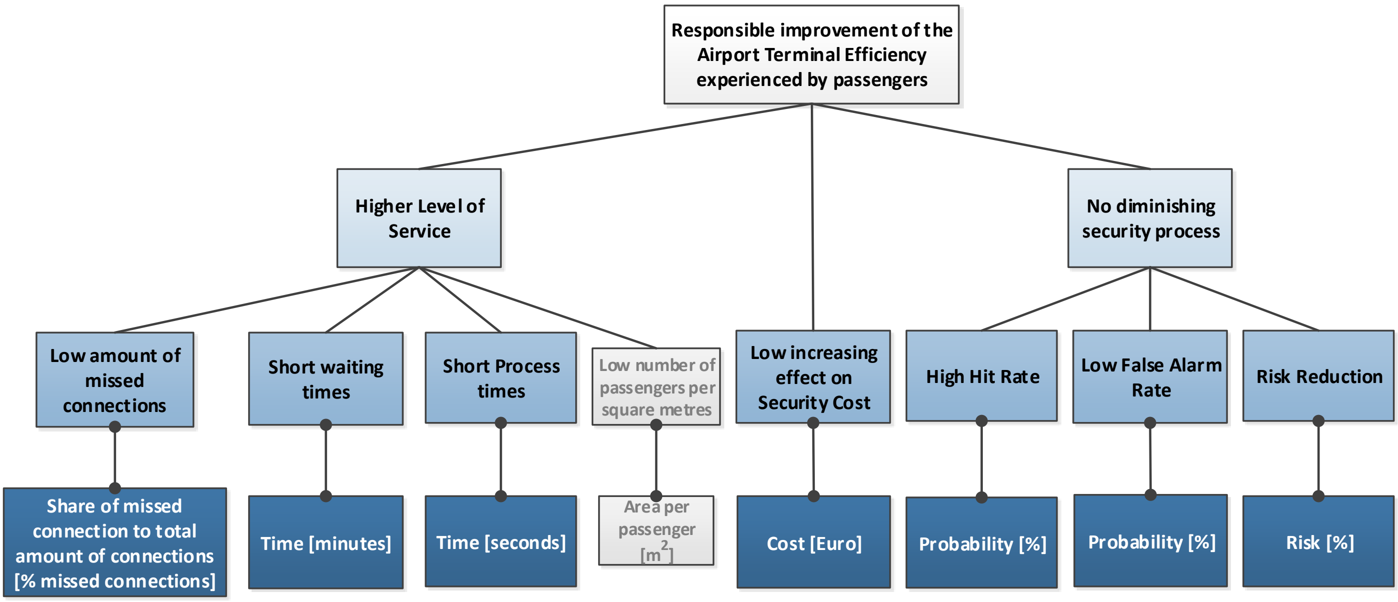


Figure A3: Objective Tree leading to operational criteria

3. The Means, Causal Relations and their influence on the outcomes of interests

Although the means and criteria already provide insights on what should be the outcomes of the system and what means can be used to achieve these outcomes, it is very sensible to provide the causal chains between the means and the criteria. With this the relations within the systems are made more explicit. A Causal Relation Diagram/Causal Map can be used to map out these causal chains. This map provides the causal relations between the factors that are relevant to the problem.

In figure A4 a Causal Map of the airport security operational system is shown. In this map one can note how the number of security lanes for instance can influence, via the queue lengths, the waiting times and the probability of missed connections. Security risk, can be influenced by the number of hit rates, which is dependent on the screening accuracy and with this the quality and training of security personnel. These factors also influence the false alarm rate, based on the screening accuracy of security personnel. However, the number of trainings of security personnel also influences the security costs of airports. Furthermore, the number of passengers via different causal chains also has influence on the outcomes of interests.

Interpretation of causal relations by using '+' and '-' signs

- Note that a '+' is a positive relation meaning that an increase of factor X results in an increase of factor Y or the other way, a decrease in factor X also results in a decrease of factor Y.
- A '-' is defined as a negative relation meaning that an increase in factor X results in a decrease of factor Y or the other way, a decrease in factor X results in an increase in factor Y.

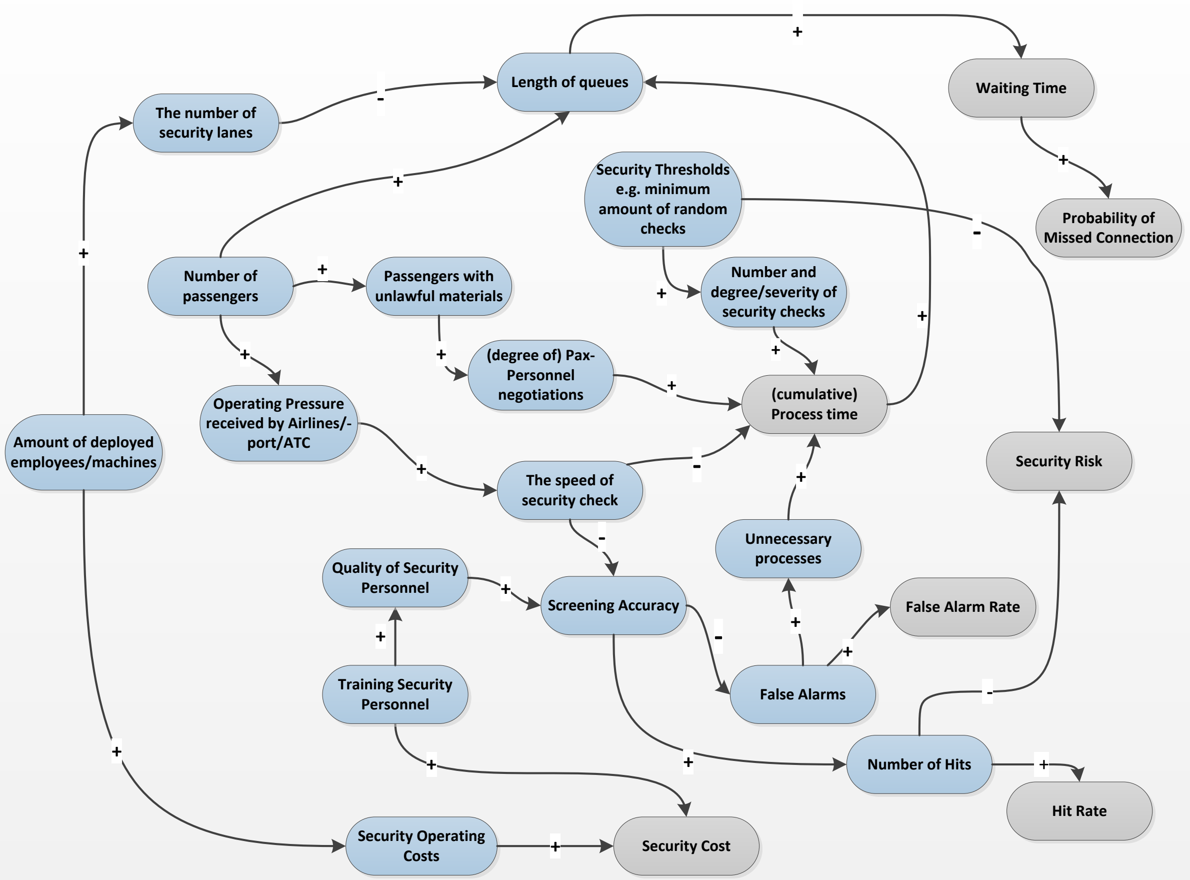


Figure A4: Causal Map indicating the causal chains within the security operational system

4. The system Diagram indicating the problem area

By combining the results of the different steps in the four-steps approach provided by Enserink et al. (2010) a system diagram can be constructed (see figure A5). In this system diagram the means of the Means-ends Diagram can be seen at the left side of the diagram, while the criteria of the Objective Tree are attached to the right side of the system diagram. The causal chains derived from the Causal Map are placed in the System Diagram, connecting the means and the criteria and with this also forming a causal link between these two factors. With this construction, one can assess (qualitatively) the influence of the decisional instruments (i.e. the means) that security operational decision-makers have on the outcomes of interest (i.e. the criteria of the system).

Although the external effects are out of control of the operational decision-makers, they play an important role as they influence the system and with this the outcomes of interest. The amount of trainings for example is not seen as an operational decision, which security operational decisions-makers (frequently) take, but rather a more tactical decision. Although, these decisions can influence different outcomes of interest such as the security costs, false alarm rate, hit rate etc. The same phenomenon counts for the number of passengers, which also is denoted as an external factor in this system.

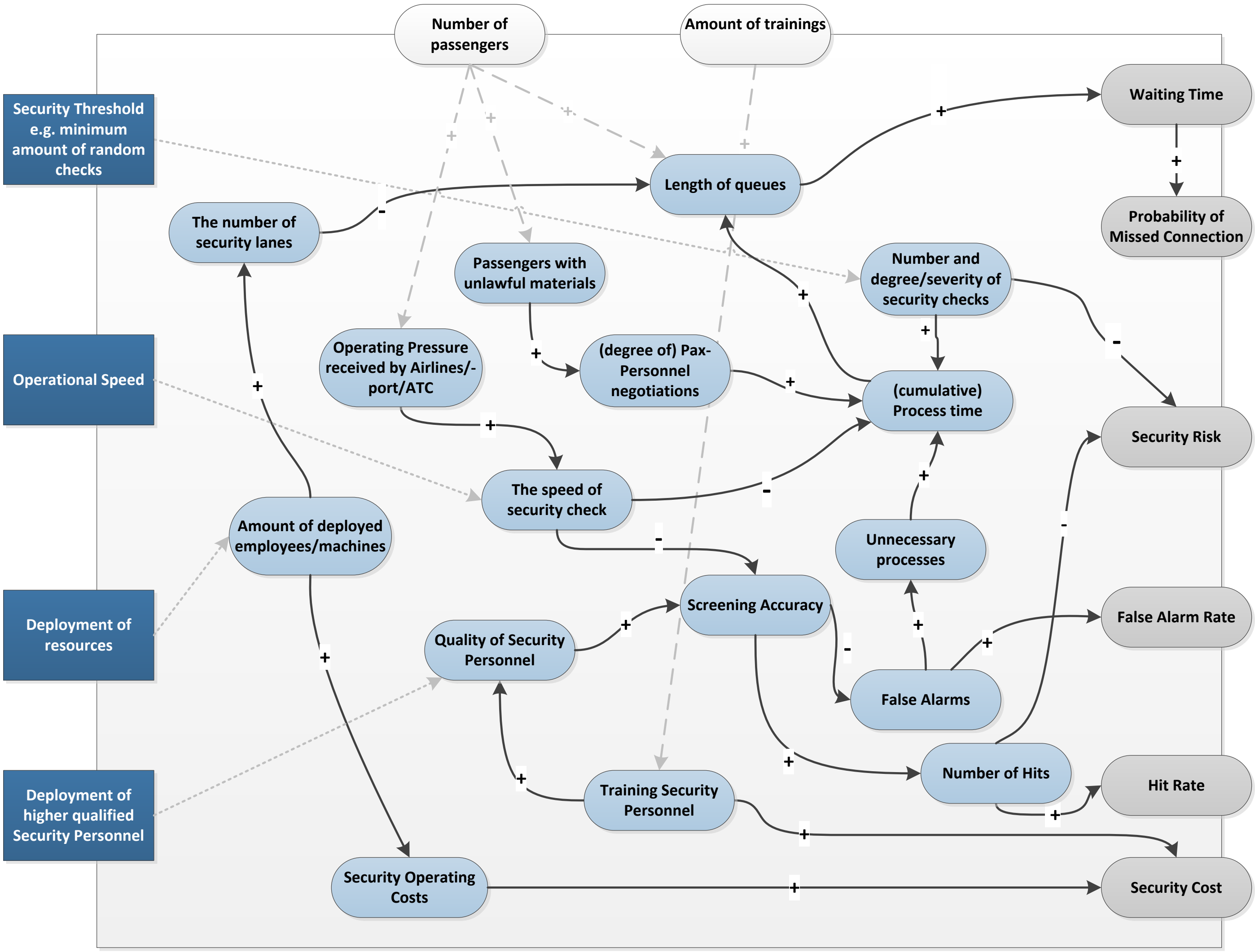


Figure A5: System Diagram of the Security Operational Systems of Airports.

Appendix B: Random Regret Minimization Models

Rather than maximizing utility, a feature of RUM-models, RRM-models assume decision-makers are aimed to minimize regret by choosing the alternative with minimum regret. RRM further assumes that the regrets attached to a certain alternative are derived from the regret summation of comparing the considered alterative attributes with the attributes of the other alternatives in the choice set. This regret calculation is computed with the following equation.

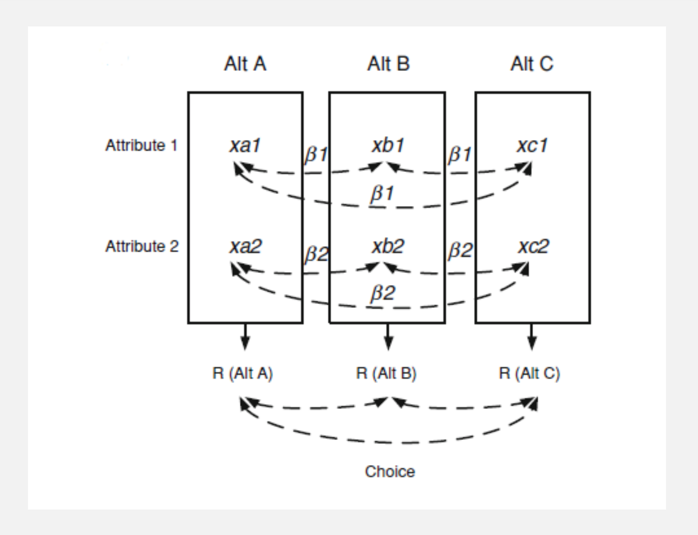
$$RR_i = R_i + \varepsilon_i = \sum_{j \neq i} \sum_{m} ln(1 + exp[\beta_m . (x_{jm - x_{im}})] + \varepsilon_i \qquad (B.1)$$

where,

RR_i	denotes the random (or: total) regret associated with a considered alternative i
R_i	denotes the 'observed' regret associated with i
ε_i	denotes the 'unobserved' regret associated with i
β_m	denotes the estimable parameter associated with attribute x_m
x_{im}, x_{jm}	denote the values associated with attribute x_m for, respectively, the considered alternative i and another alternative j.

The equation part "$ln(1 + exp[\beta_m . (x_{jm - x_{im}})]$" also known as the binary attribute-regret function; forms the heart of the RRM and measures the regret of an alternative by comparing the attribute of the considered alternative with the attributes of the other alternatives in the choice set as explained above. By repeating and summing this over all the attributes and competing alternatives; the observed (systematic) regret associated with alternative i can be found (i.e. R_i.) The ε_i again refers to the random error introduced due to uncertainty and lack of information of the analyst.

The binary attribute-regret function allows the RRM to take choice set-dependency of preferences into account, a feature that is ignored in RUM. Choice set-dependency means that the attractiveness of an alternative depends on the availability and performance of other alternatives and refers to the principle that a preference structure is not independent of the choice set (Orhun, 2005). According to Orhun (2005) different research in Marketing and Psychology have shown that the choice set can influence the utility of an alternative in the choice set. The utility of an alternative in RUM is not dependent of the availability and performance of other alternatives in the choice set (recall the choice process of the RUM-models in the previous section). In RRM this dependency feature (with the introduction of the binary attribute-regret function) has been taken into account. In figure B1, with the upper dashed arrows, this dependency in the determination of regret of an alternative is shown.



(Chorus, 2012a)

Figure B1: Choice set-dependency in the choice process of RRM-models

Another property of RRM is that it gives more value to regret that rejoice. This assumption is made with the idea that avoiding poor performance in comparison to the other alternatives is much more important than performing better. This property together with the feature that the performance of other alternatives plays a role, results into these RRM-models to capture compromise effects. Compromise effect is the situation where a decision-maker tends to choose an alternative that perform not to bad but also not to good compared to the other alternatives, but choses the middle options which performs reasonable on the different attributes. Following Simonson (1989); people have a tendency to choose middle options due to their distaste for and the uncertainty of the extreme performance of the attributes of the outside alternatives. (Chorus, 2012b)

Appendix C: Choice Experiment Construction

In this appendix the steps to generate the Orthogonal in the Difference Fractional Factorial Design are covered. Step 1 provides the syntax that is used in the software programme Ngene, which resulted in the optimality measure of 100%. The design itself can be seen in step 3. To minimize the number of dominant choice sets; different coding schemes have been considered. The final coding scheme that minimized the number of dominant profiles can be seen in step 4. In step 5 the labelling of the attributes is provided that also minimizes the amount of dominant profiles. In step 6 and 7 the attributes and choice sets are repositioned and reorganized resulting in the questionnaire that can be seen in step 8. Note that none of the steps treated above has influence on the properties of the Orthogonal in the Difference Fractional Factorial Design.

1. Syntax Code

```
Design
;alts = alt1, alt2, alt3
;rows = 9
;orth = ood
;model:
U(alt1) = b1 * A[0,1,2] + b2 * B[0,1,2] + b3 * C[0,1,2] + b4 * D[0,1,2]  /
U(alt2) = b1 * A        + b2 * B        + b3 * C        + b4 * D /
U(alt3) = b1 * A        + b2 * B        + b3 * C        + b4 * D $
```

2. OOD optimality measure

D optimality 100%

3. Design

Choice situation	alt1.a	alt1.b	alt1.c	alt1.d	alt2.a	alt2.b	alt2.c	alt2.d	alt3.a	alt3.b	alt3.c	alt3.d
1	0	0	0	0	1	1	1	1	2	2	2	2
2	2	1	1	0	0	2	2	1	1	0	0	2
3	1	2	2	0	2	0	0	1	0	1	1	2
4	1	1	0	1	2	2	1	2	0	0	2	0
5	0	2	1	1	1	0	2	2	2	1	0	0
6	2	0	2	1	0	1	0	2	1	2	1	0
7	2	2	0	2	0	0	1	0	1	1	2	1
8	1	0	1	2	2	1	2	0	0	2	0	1
9	0	1	2	2	1	2	0	0	2	0	1	1

Scenario 1

	alt1	**alt2**	**alt3**
a	0	1	2
b	0	1	2
c	0	1	2
d	0	1	2
Choice question:			

4. (Re-) Coding

	0	1	2
No. of Pax. Missed Flights	0 pax.	1 pax.	2 pax.
False Alarm Rate	10%	20%	30%
Hit Rate	70%	80%	90%
Average Pax. Waiting Time	2 min.	13 min.	24 min.

5. (Re-) Labling

Scenario 1

	alt1	alt2	alt3
No. of Pax. Missed Flights	0 pax.	1 pax.	2 pax.
False Alarm Rate	10%	20%	30%
Hit Rate	70%	80%	90%
Average Pax. Waiting Time	2 min.	13 min.	24 min.
Choice question:			

6. (Re-) Positioning

Scenario 1

	alt1	alt2	alt3
Hit Rate	70%	80%	90%
False Alarm Rate	10%	20%	30%
Average Pax. Waiting Time	2 min.	13 min.	24 min.
No. of Pax. Missed Flights	0 pax.	1 pax.	2 pax.
Choice question:			

7. (Re-) Ordering

Scenario 7

	alt1	alt2	alt3
Hit Rate	70%	80%	90%
False Alarm Rate	10%	20%	30%
Average Pax. Waiting Time	2 min.	13 min.	24 min.
No. of Pax. Missed Flights	0 pax.	1 pax.	2 pax.
Choice question:			

Note that an addition choice question is attached to the survey in order to provide the analyst extra information (on e.g. the fill behaviour of the respondents).

8. Questionnaire – Airport Security vs. Airport Efficiency

This questionnaire is about how security screeners trade-off different indicators of airport security and airport efficiency. During this questionnaire, you are asked to make choices between sets of 'airport security operational performance indicators' which has your preference for the operations of small airports. The provided sets of performance indicators are measurements that indicate how the security operation performs in terms of airport security and efficiency.
After each choice, you are also asked to indicate with a number between 0 and 10 how certain you are about the choice you made. With a 0 indicating completely not certain about your previous choice and a 10 indicating completely certain about your previous choice.

This questionnaire consists of 10 choice questions; each one directly followed by 10 questions about your (un-) certainty corresponding to the choice you made.

The data gathered from this questionnaire is completely anonymous and therefore will and can in NO form be used hereafter to bind any consequences to you.

The questionnaire will take approximately 5 minutes.

The role of security at airports is to check departing passengers and their luggage with detection tools. Based on observations security screeners will, if needed, explore the passengers and/or their luggage through more thorough investigations. They are expected to do this in a rapid and secure manner. However, their work behaviour can lead to a set of 'airport security operational performance indicators', namely Hit Rate, False Alarm Rate, Average Passengers Waiting Time and Number of Passenger Missed Flights.

Note **-legal bags and passengers do not carry/contain prohibited items** **- Illegal bags and passengers carry/contain prohibited items**
Hit Rate [%] The percentage of illegal bags-passengers that are intercepted by you as a security screener A Hit Rate of 70% means that 7 out of each 10 illegal bags-passengers are intercepted.
False Alarm Rate [%] The percentage of legal bags-passengers that is judged as 'not ok' by the security screener; unnecessarily going through more thorough investigations. A False Alarm Rate of 20% means that 2 out of each 10 legal bags-passengers unnecessarily is judged as illegal, which unnecessarily leads to more security processes.
Average Passengers Waiting Time [Minutes] The average waiting time in minutes in an average workday that passengers are standing in the queue before passing through security
Number of Passenger Missed Flights [passengers] The number of passengers that at the end of an average workday unnecessarily have missed their flights as a consequence of the security process or the work behaviour (i.e. the work process, -actions and/or -decisions) of you as a security screener.

Used Abbreviations

Pax. = Passengers

No. = Number

Questions

Make a choice between the following sets of 'airport security operational performance indicators' which has your preference for the operations of airports.

It can be that some choice situations do not seem completely logic. However, for our information; you are asked to assume that these choice situations can happen.

Consider a workday at a small (regional) airport such as ………………….. Airport.

The following question is an example question to give you an idea how the choice questions work.

Choice example

	Set A	Set B	Set C
Hit Rate	70%	90%	80%
False Alarm Rate	30%	10%	20%
Average Pax. Waiting Time	13 minutes	2 minutes	24 minutes
No. of Pax. Missed Flights	2 passengers	0 passengers	1 passenger
Choice	○	◉	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

------->

Choice 1

	Set A	Set B	Set C
Hit Rate	80%	90%	70%
False Alarm Rate	20%	30%	10%
Average Pax. Waiting Time	2 minutes	13 minutes	24 minutes
No. of Pax. Missed Flights	2 passengers	0 passengers	1 passenger
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 2

	Set A	Set B	Set C
Hit Rate	90%	70%	80%
False Alarm Rate	30%	10%	20%
Average Pax. Waiting Time	2 minutes	13 minutes	24 minutes
No. of Pax. Missed Flights	1 passenger	2 passengers	0 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 3

	Set A	Set B	Set C
Hit Rate	70%	80%	90%
False Alarm Rate	20%	30%	10%
Average Pax. Waiting Time	13 minutes	2 minutes	24 minutes
No. of Pax. Missed Flights	1 passenger	2 passengers	0 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 4

	Set A	Set B	Set C
Hit Rate	80%	90%	70%
False Alarm Rate	30%	10%	20%
Average Pax. Waiting Time	13 minutes	24 minutes	2 minutes
No. of Pax. Missed Flights	0 passengers	1 passenger	2 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

------->

Choice 5

	Set A	Set B	Set C
Hit Rate	90%	70%	80%
False Alarm Rate	10%	20%	30%
Average Pax. Waiting Time	13 minutes	24 minutes	2 minutes
No. of Pax. Missed Flights	2 passengers	0 passengers	1 passenger
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 6

	Set A	Set B	Set C
Hit Rate	70%	80%	90%
False Alarm Rate	10%	30%	20%
Average Pax. Waiting Time	24 minutes	2 minutes	13 minutes
No. of Pax. Missed Flights	2 passengers	0 passengers	1 passenger
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 7

	Set A	Set B	Set C
Hit Rate	70%	80%	90%
False Alarm Rate	10%	20%	30%
Average Pax. Waiting Time	2 minutes	13 minutes	24 minutes
No. of Pax. Missed Flights	0 passengers	1 passenger	2 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 8

	Set A	Set B	Set C
Hit Rate	80%	90%	70%
False Alarm Rate	10%	20%	30%
Average Pax. Waiting Time	24 minutes	2 minutes	13 minutes
No. of Pax. Missed Flights	1 passenger	2 passengers	0 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

-------> -------> ------->

Choice 9

	Set A	Set B	Set C
Hit Rate	90%	70%	80%
False Alarm Rate	20%	30%	10%
Average Pax. Waiting Time	24 minutes	2 minutes	13 minutes
No. of Pax. Missed Flights	0 passengers	1 passenger	2 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Choice 10

	Set A	Set B	Set C
Hit Rate	90%	70%	80%
False Alarm Rate	10%	30%	20%
Average Pax. Waiting Time	2 minutes	13 minutes	24 minutes
No. of Pax. Missed Flights	0 passengers	1 passenger	2 passengers
Choice	○	○	○

How certain are you about this choice, you made?
- 0: I am completely not certain about my choice
- 10: I am completely certain about my choice

0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

Thank you for participating in this experiment. 

Appendix D: Choice Models and Parameter Distributions

Multinomial Logit (MNL) model

For this study a MNL model has been estimated by using the software programme Biogeme. Four parameters were estimated, namely Hit Rate modelled as B_HITRATE, False Alarm Rate modelled as B_FALSALARM, Average Passenger Waiting Time modelled as B_WAITINGTIME and Missed Flights as B_MISSEDFLIGHT. The utilities, expressed as linear-in-parameter, were specified as follows:

B_HITRATE * HIT_RATE_A + B_FALSALARM * FALSE_ALARM_RATE_A + B_WAITINGTIME * WAITING_TIME_A + B_MISSEDFLIGHT * MISSED_FLIGHT_A

B_HITRATE * HIT_RATE_B + B_FALSALARM * FALSE_ALARM_RATE_B + B_WAITINGTIME * WAITING_TIME_B + B_MISSEDFLIGHT * MISSED_FLIGHT_B

B_HITRATE * HIT_RATE_C + B_FALSALARM * FALSE_ALARM_RATE_C + B_WAITINGTIME * WAITING_TIME_C + B_MISSEDFLIGHT * MISSED_FLIGHT_C

The parameter results (with t-test between parentheses) of the MNL model for Hit Rate, False Alarm Rate, Waiting Time and Missed Flights are respectively 0.0851 (13.87); -0.0131 (-2.27); -0.0324 (-6.16) and -0.657 (-11.25). In figure D1 one can note how the part utility responds to changes in attribute levels based on the parameter results of the MNL model.

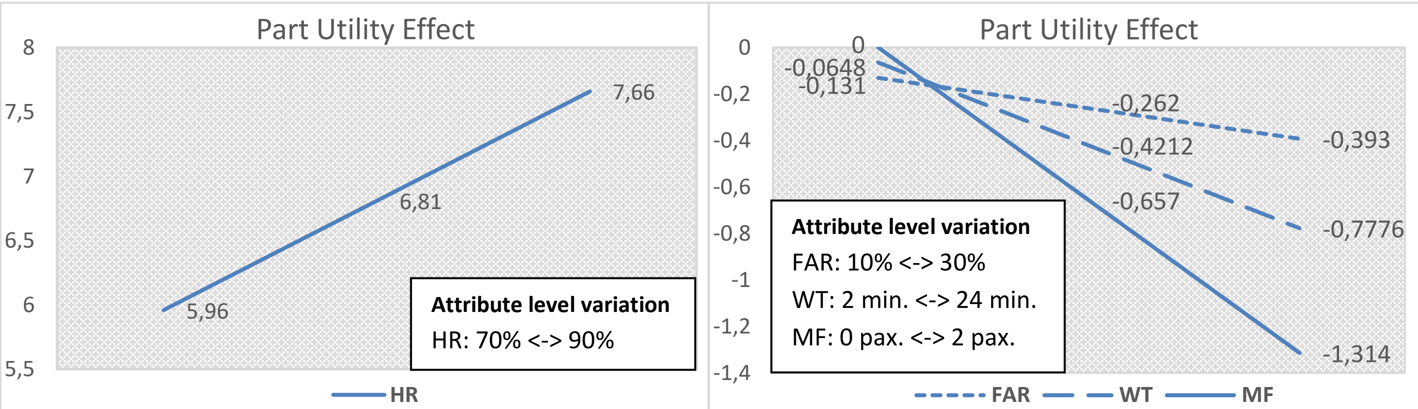


Figure D1: Part Utility effect of the different attributes based on the MNL parameter results

Latent Class (LC) Model

For this study LC Models have also been estimated. A three Latent Class Model was estimated as the best fit out of several class models, namely a two class, a three class and a four class model. Although a four Latent Class Model has been estimated, the model with three classes has been chosen since the four class model could not be interpreted well, while the majority of the parameters also became insignificant. In this (three) Latent Class Model 14 parameters were estimated, namely 12 taste parameters (of which 4 parameters per class) and 2 class membership parameters. Note that the third class membership parameter (of the third class) has been fixed and therefore was not estimated. To improve the log-likelihood optimum, different starting values were experimented with. The best estimate parameters gathered are based on the four class model parameter results as starting values for the third class model. This procedure was used as a measure, to clear the three class model from a local log-likelihood optimum based on starting values of parameters which were specified as zero. The utilities of the three different classes, where B_HR was modelled for the Hit Rate attribute, B_FAR for the False Alarm Rate attribute, B_WT for the Waiting Time attribute and B_MF for Missed Flights, were expressed as follows:

CLASS 1
B_HR_1 * HIT_RATE_A + B_FAR_1 * FALSE_ALARM_RATE_A + B_WT_1 * WAITING_TIME_A + B_MF_1 * MISSED_FLIGHT_A

B_HR_1 * HIT_RATE_B + B_FAR_1 * FALSE_ALARM_RATE_B + B_WT_1 * WAITING_TIME_B + B_MF_1 * MISSED_FLIGHT_B

B_HR_1 * HIT_RATE_C + B_FAR_1 * FALSE_ALARM_RATE_C + B_WT_1 * WAITING_TIME_C + B_MF_1 * MISSED_FLIGHT_C

CLASS 2
B_HR_2 * HIT_RATE_A + B_FAR_2 * FALSE_ALARM_RATE_A + B_WT_2 * WAITING_TIME_A + B_MF_2 * MISSED_FLIGHT_A

B_HR_2 * HIT_RATE_B + B_FAR_2 * FALSE_ALARM_RATE_B + B_WT_2 * WAITING_TIME_B + B_MF_2 * MISSED_FLIGHT_B

B_HR_2 * HIT_RATE_C + B_FAR_2 * FALSE_ALARM_RATE_C + B_WT_2 * WAITING_TIME_C + B_MF_2 * MISSED_FLIGHT_C

CLASS 3
B_HR_3 * HIT_RATE_A + B_FAR_3 * FALSE_ALARM_RATE_A + B_WT_3 * WAITING_TIME_A + B_MF_3 * MISSED_FLIGHT_A

B_HR_3 * HIT_RATE_B + B_FAR_3 * FALSE_ALARM_RATE_B + B_WT_3 * WAITING_TIME_B + B_MF_3 * MISSED_FLIGHT_B

B_HR_3 * HIT_RATE_C + B_FAR_3 * FALSE_ALARM_RATE_C + B_WT_3 * WAITING_TIME_C + B_MF_3 * MISSED_FLIGHT_C

The parameter results (with t-test between parentheses) of the LC model for Hit Rate, False Alarm Rate, Waiting Time and Missed Flights for the different classes can be found in table D1. In table D1 one can also note how the part utility responds to changes in attribute levels based on the parameter results of the different classes.

Table D1: Part Utility effect of the different attributes based on the LC parameter results

Attributes	Parameter [t-test]		Attribute Levels	Part Utility		
Hit Rate - Class 1	0.0197	(1.27)	[70% - 80% - 90%]	1.379	1.576	1.773
Hit Rate - Class 2	0.148	(6.76)	[70% - 80% - 90%]	10.36	11.84	13.32
Hit Rate - Class 3	0.0174	(0.52)	[70% - 80% - 90%]	1.218	1.392	1.566
FAR - Class 1	0.000397	(0.03)	[10% - 20% 30%]	0.00397	0.00794	0.01191
FAR - Class 2	-0.0361	(-3.03)	[10% - 20% 30%]	-0.361	-0.722	-1.083
FAR - Class 3	-0.947	(-12.94)	[10% - 20% 30%]	-9.47	-18.94	-28.41
WT - Class 1	-0.0913	(-4.85)	[2 – 13 – 24 min.]	-0.1826	-1.1869	-2.1912
WT - Class 2	-0.0149	(-2.11)	[2 – 13 – 24 min.]	-0.0298	-0.1937	-0.3576
WT - Class 3	-0.86	(-13.57)	[2 – 13 – 24 min.]	-1.72	-11.18	-20.64
MF - Class 1	-0.818	(-3.48)	[0 – 1 – 2 pax.]	0	-0.818	-1.636
MF - Class 2	-0.445	(-3.19)	[0 – 1 – 2 pax.]	0	-0.445	-0.89
MF - Class 3	-12.2	(-34.03)	[0 – 1 – 2 pax.]	0	-12.2	-24.4

Panel Mixed Logit (ML) Model

For the Panel Mixed Logit Model four taste parameters, namely Hit Rate modelled as B_HITRATE, False Alarm Rate modelled as B_FALSALARM, Average Passenger Waiting Time modelled as B_WAITINGTIME and Missed Flights as B_MISSEDFLIGHT were estimated together with four extra parameters to test taste heterogeneity among respondents. These four extra parameters were modelled as SIGMA_HITRATE, SIGMA_FALSALARM, SIGMA_WAITINGTIME and SIGMA_MISSEDFLIGHT. The Mixed Logit Model has first been estimated with 100 Halton Draws, whereafter the draws were increased to provide a better representation of the probability density function. The final model was estimated with 1000 Halton Draws after continuously testing for stability when the number of draws was increasing. This model was furthermore estimated by using the DONLP2 optimization algorithm instead of the BIO default optimization algorithm, which was not able to converge. The utilities, expressed as linear-in-parameter, were specified as follows:

B_HITRATE [SIGMA_HITRATE] * HIT_RATE_A + B_FALSALARM [SIGMA_FALSALARM] * FALSE_ALARM_RATE_A + B_WAITINGTIME [SIGMA_WAITINGTIME] * WAITING_TIME_A + B_MISSEDFLIGHT [SIGMA_MISSEDFLIGHT] * MISSED_FLIGHT_A

B_HITRATE [SIGMA_HITRATE] * HIT_RATE_B + B_FALSALARM [SIGMA_FALSALARM] * FALSE_ALARM_RATE_B + B_WAITINGTIME [SIGMA_WAITINGTIME] * WAITING_TIME_B + B_MISSEDFLIGHT [SIGMA_MISSEDFLIGHT] * MISSED_FLIGHT_B

B_HITRATE [SIGMA_HITRATE] * HIT_RATE_C + B_FALSALARM [SIGMA_FALSALARM] * FALSE_ALARM_RATE_C + B_WAITINGTIME [SIGMA_WAITINGTIME] * WAITING_TIME_C + B_MISSEDFLIGHT [SIGMA_MISSEDFLIGHT] * MISSED_FLIGHT_C

The mean parameter results (with t-test between parentheses) of the ML model for Hit Rate, False Alarm Rate, Waiting Time and Missed Flights are respectively 0.136 (7.29); -0.0367 (-3.09); -0.0493 (-4.66) and -1.00 (-7.28). In figure D2 one can note how the part utility responds to changes in attribute levels based on the mean parameter results of the ML model.

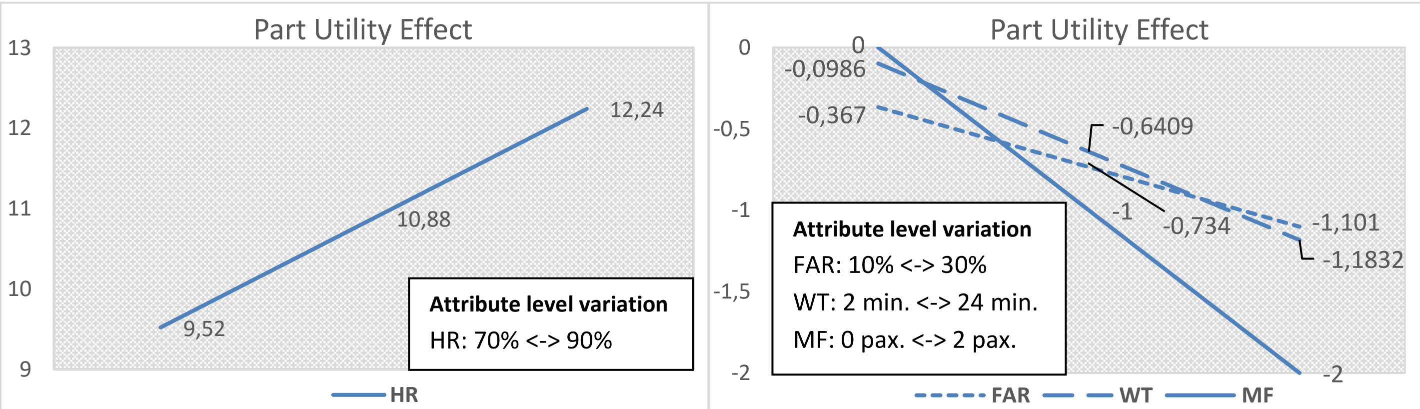
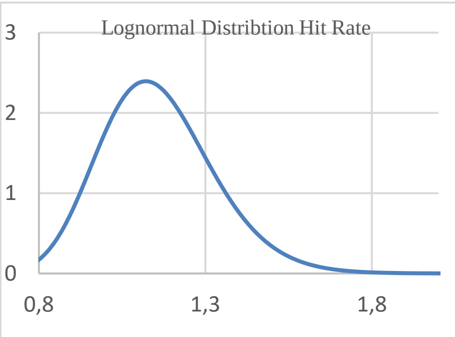


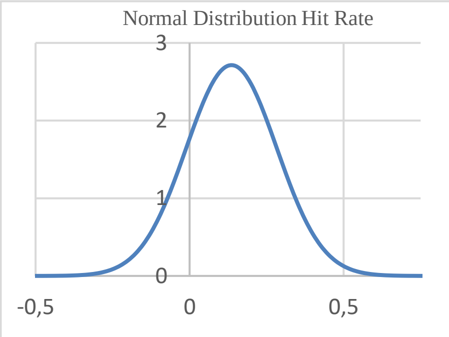
Figure D2: Part Utility effect of the different attributes based on the ML parameter results

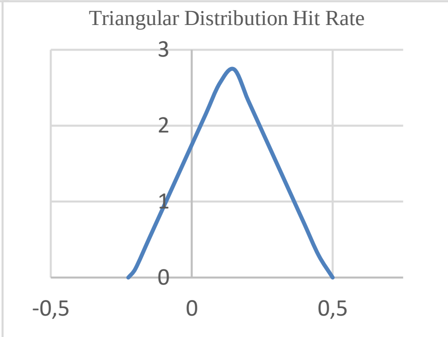
Parameter Distributions

A Mixed Logit model consists of two parts, namely a logit specification dependant on a parameter and a specification of the distribution, also called the mixing distribution and is denoted as f (β). The mixing distribution can be discrete, with (β) taking a finite set of distinct values. However, in mixed logit the mixing distribution f(β) is generally specified to be continuous, with the parameter distribution to be specified as normal, lognormal, uniform, triangular, gamma, Johnson's Sb or any other distribution. According to Train (2016) the vast majority of studies have used normal and lognormal distributions and a few have been using Johnson's Sb, gamma, and triangular distributions.

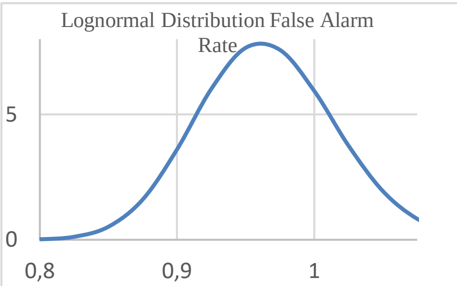
The lognormal distribution is useful when coefficients are considered to have the same sign for every decision-maker, such as price parameters known to be negative for everyone (Train, 2009). The same is considered for the parameters of this study. Therefore, this study has specified the parameter distributions as Lognormal with $\ln(\beta) \sim N(\beta,\sigma)$ with estimated parameters β and σ (recall table 4 for the estimated parameters). This results in the following mixing distribution f(β) for respectively Hit rate, False Alarm Rate, Waiting Time and Missed Flights. Beside the Lognormal distribution, other distributions that can be assumed like the normal and triangular distributions are shown next to the lognormal distribution.
Note that these are examples that indicate what form the distributions of the corresponding parameters can take, which are dependent of the assumed distribution and parameter specifications.

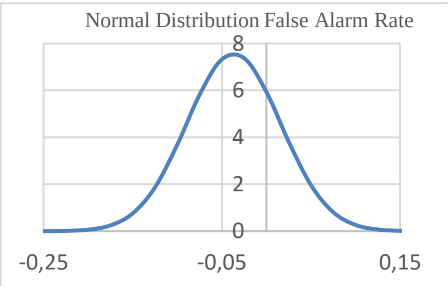


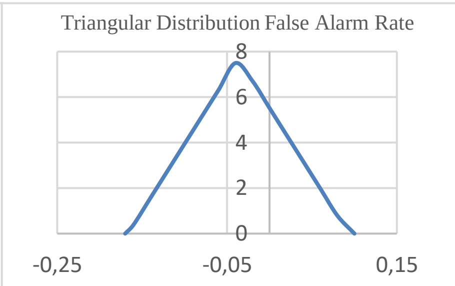




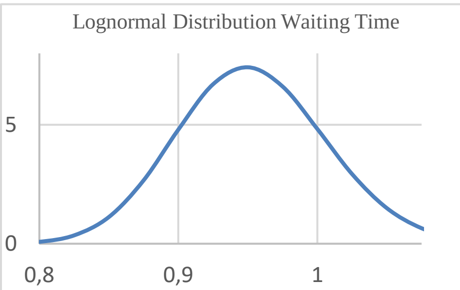
$\ln(\beta_{Hit\_Rate}) \sim N(0.136, 0.147)$	$N(\beta_{Hit\_Rate}, \sigma_\beta) = \mathrm{N}(0.136{,}0.147)$	a = -0.214; b = 0.136; c = 0.486

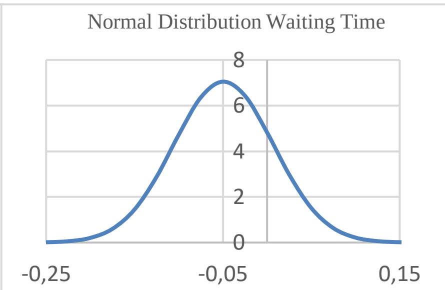


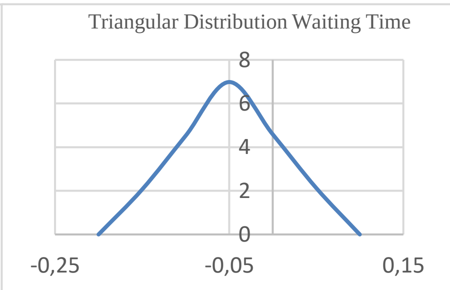




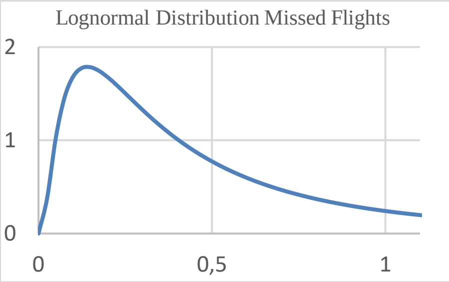
$\ln(\beta_{False\_Alarm\_Rate}) \sim N(-0.0367{,}0.0528)$	$N(\beta_{False\_Alarm\_Rate}, \sigma_\beta) = N(-0.0367{,}0.0528)$	a = -0.167; b = -0.0367; c = 0.093

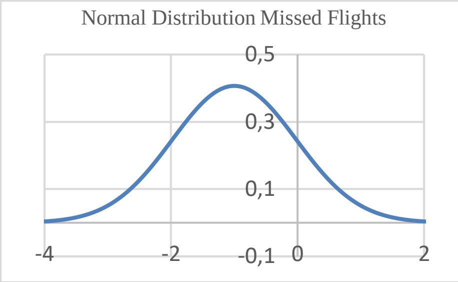


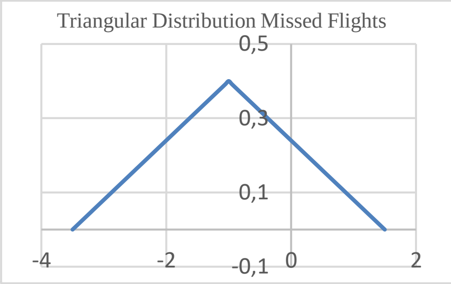




$\ln(\beta_{Waiting\_Time}) \sim N(-0.0493, 0.0566)$	$N(\beta_{Waiting\_Time}, \sigma_\beta) = N(-0.0493, 0.0566)$	a = -0.191; b = -0.049; c = 0.093







$\ln(\beta_{Missed\_Flights}) \sim N(-1.00, 0.981)$	$N(\beta_{Missed\_Flights}, \sigma_\beta) = N(-1.00, 0.981)$	a = -3.50; b = -1.00; c = 1.50

Appendix E: Value of Security and Efficiency Derivation

Since the utility is a linear function of the different attributes; the Value of Security (VoS) and the Value of Efficiency (VoE) can be calculated by looking at the ratio of partial derivatives of the different attribute parameters.

In this section Hit Rate (HR) is used as base unit to express the Value of Efficiency.

The Value of Efficiency, which can be derived from the Value of the three efficiency attributes (i.e. Value of False Alarm Rate (FAR), Value of Waiting Time (WT) and Value of Missed Flights (MF) can be calculated as follows:

$$VoFAR = \frac{\frac{\partial V}{\partial FAR}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{FAR}}{\beta_{HR}} \qquad VoWT = \frac{\frac{\partial V}{\partial WT}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{WT}}{\beta_{HR}} \qquad VoMF = \frac{\frac{\partial V}{\partial MF}}{\frac{\partial V}{\partial HR}} = \frac{\beta_{MF}}{\beta_{HR}}$$

The Value of Security on its turn, which can be derived from the Value of Hit Rate (HR) can be expressed in Missed Flights, Waiting Time and False Alarm Rate and can be calculated respectively as follows:

$$VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial MF}} = \frac{\beta_{HR}}{\beta_{MF}} \qquad VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial WT}} = \frac{\beta_{HR}}{\beta_{WT}} \qquad VoHR = \frac{\frac{\partial V}{\partial HR}}{\frac{\partial V}{\partial FAR}} = \frac{\beta_{HR}}{\beta_{FAR}}$$

Note that this approach only holds for non-continuous models like the MNL and the MNL Latent Class models. Therefore, this section provides the VoS and VoE based on the parameters derived from the MNL and MNL Latent Class models.

In the tables E1 till E4 the VoS and VoE are expressed for respectively the MNL and the three LC models.

Table E1: Value of Security and Efficiency derived from the MNL model

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	6.50 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	2.63 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.13 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	7.73 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	0.38 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	0.15 Percentage Points Hit Rate

Table E2: Value of Security and Efficiency derived from class 1 of the LCM

Note that these values are based on one or more non-significant parameters

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	49.62 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	0.22 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.024 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	41.52 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	4.63 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	0.020 Percentage Points Hit Rate

Table E3: Value of Security and Efficiency derived from class 2 of the LCM

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	4.10 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	9.93 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.33 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	3.01 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	0.10 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	0.24 Percentage Points Hit Rate

Table E4: Value of Security and Efficiency derived from class 3 of the LCM

Note that these values are based on one or more non-significant parameters

Value of Security (VOS)	**Value**
Value of Hit Rate (VoHR)	0.02 Percentage Points False Alarm Rate
Value of Hit Rate (VoHR)	0.02 Minutes Avg. Passengers Waiting Time
Value of Hit Rate (VoHR)	0.001 Passengers Missed Flights
Value of Efficiency (VOE)	**Value**
Value of Passengers Missed Flights (VoPMF)	701.14 Percentage Points Hit Rate
Value of Avg. Passengers Waiting Time (VoWT)	49.4 Percentage Points Hit Rate
Value of False Alarm Rate (VoFAR)	54.4 Percentage Points Hit Rate

Appendix F: Interviews Overview

In this section the different interview that were held during the project are provided in a table overview (see table F1). This table overview provides information on the main outcomes of each interview.

Table F1: Interviews Overview during the MSc. Thesis Project

Interview no.	Date	Interviewee	Topic
001	23/05/17	**Dr.ir. E.J.L. (Emile) Chappin** Assistant Professor Simulations of Energy Infrastructure Systems at Delft University of Technology (faculty of TPM)	First Insights on combining Discrete Choice Modelling with Agent Based Modelling
Main Outcome	A framework for combining DCM and ABM methodology (see paragraph 3.4 and figure 7)		
002	14/07/17	**dhr. A. (Alexander) Dilweg** Airport Security Advisor Afd. Security, Safety & Support	Trade-offs between security and efficiency factors which govern airport security operational decisions
Main Outcome	New insights on operational trade-off attributes.		
003	4/09/17 – 13/09/17	**S.A.M. (Stef) Janssen MSc.** PhD Candidate at the faculty of Aerospace Engineering section Air Transport and Operations	Empirical insights on passengers waiting times at a local airport
Main Outcome	Empirical inter-arrival, process and waiting times of the security operations at a local airport		
004	20/09/17	**Dr.ir. Y. (Yashar) Araghi** Junior Researcher at Significance	Deeper insights on combining Discrete Choice Modelling with Agent Based Modelling
Main Outcome	New ideas on how to evaluate security and efficiency trade-offs (as outputs of Discrete Choice Modelling technique) in Agent Based Models.		
005	17/10/17	**Several Security Screeners/Team leaders** at a local airport	Security operations at a local airport and trade-offs between security and efficiency
Main Outcomes	- New insights on trade-offs being made during security operations. - Personal experience during the operations of security such as (waiting times and experienced missed flight)		
006	23/10/17-26/10/17	**Several Security Screeners/Team leaders** at a local airport	Security operations at a local airport and Trade-offs between security and efficiency
Main Outcomes	- Personal experience during the operations of security such as (waiting times and experienced missed flights) - Qualitative value of the Security and Efficiency attributes being presented in the choice experiment - Insights on the difference in the valuation of security and efficiency attributes across the security screeners (mainly on 2 attributes i.e. Hit Rate and Passenger Missed Flights.		