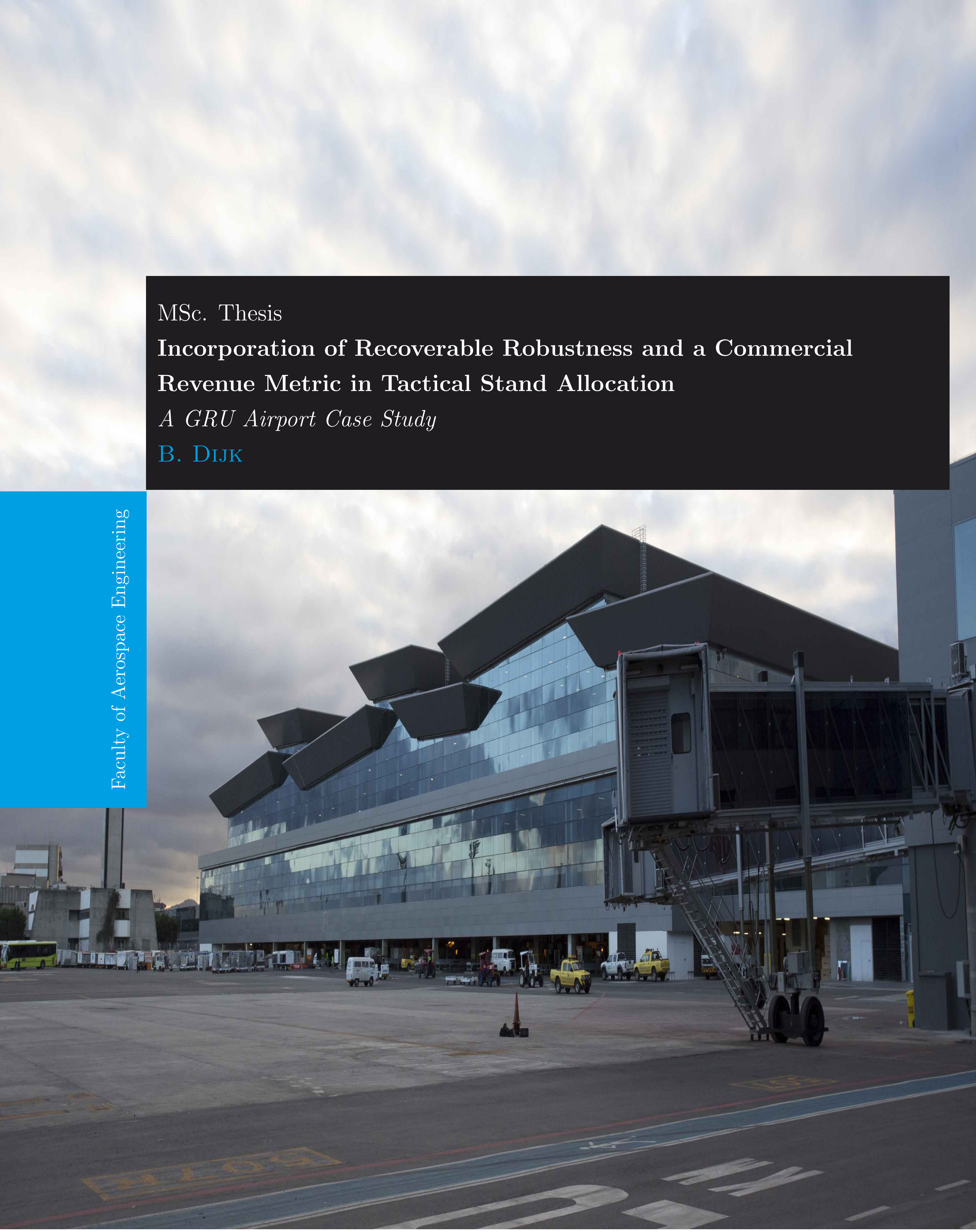

MSc. Thesis

Incorporation of Recoverable Robustness and a Commercial Revenue Metric in Tactical Stand Allocation

A GRU Airport Case Study

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Challenge the future

Delft University of Technology

Incorporation of Recoverable Robustness and a Revenue Framework into Tactical Stand Allocation

Master Thesis

In partial fulfilment of the requirements for the degree of MSc. Aerospace Engineering

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Executive Summary

Aircraft stands at airports are scarce resources and should therefore be utilised as effective as possible. Consequently, airport stand allocation has been a well-researched optimisation problem since the 1980s. Recent research in stand allocation has focused on the incorporation of robustness in the stand allocation plan. Often a tactical stand allocation plan, created the day before operations, can not be maintained during actual operations. Aircraft might arrive early or tardy and influence the stand allocation plan significantly. Therefore, a robust tactical stand allocation plan, insensitive to small time deviations, is desired. This thesis project extends this research direction with the application of a new robustness concept in the stand allocation context: recoverable robustness. The created recoverable robustness stand allocation model generates a set of feasible allocation plans, which are testing against several scenarios and recovered if necessary. The recoverable robust solution to the stand allocation problem can, at least, be recovered in all tested scenarios. A recoverable robust tactical allocation plan limits the required schedule changes which can simplify the operations at the airport.

In addition to the concept of recoverable robustness, this research project focuses on commercial revenues at an airport. Privatisation and competition effects cause airports to focus more on non-aeronautical revenues. This research project includes an objective function based on commercial revenues in the stand allocation model, with the aim to stimulate expenditure at the airport. For both the robustness and commercial revenue aspect of this research project, an extensive literature review is conducted and specific objectives are defined. To highlight the industrial applicability of the recoverable robust stand allocation model a case study with Guarulhos International Airport São Paulo is performed.

Literature Review

Initial research on airport stand allocation started in the 1980s by solving a simplistic model with basic capacity and allocation constraints [1, 2, 3]. The early models can be extended with, for example, towing possibilities for long-stay flights, stand compatibility and adjacency constraints [4, 5, 6]. The objectives used for stand allocation can be divided into passenger-oriented objectives (minimum walking distance) and airport-oriented objectives [7]. The stand allocation problem is commonly formulated as a (mixed) integer or binary linear program, due to the nature of the

allocation and capacity constraints [1, 7].

Research on robustness in airport stand allocation has progressed from fixed buffer time constraints to robustness objectives [7, 8, 9]. Another methodology to include uncertainty in the stand allocation problem is a stochastic approach [10, 11]. Robustness approaches from other industries typically fall in the general classes of robust optimisation and stochastic programming. Robust optimisation takes into account the range for the variables, aiming to satisfy the worst case scenario [12]. Stochastic programming optimises a solution based on different parameter realisations (scenarios) [13]. Based on the foundations of both a new robustness concept was developed: recoverable robustness [14]. Recoverable robustness allows for limited recovery in tested scenarios and has been successfully applied to, amongst others, the timetabling problem [15] and the tail assignment problem [16].

Besides the operational focus of stand allocation, this research project aims to include a business perspective as well. Non-aeronautical revenues are becoming more important for airports due to privatisation and competition [17]. One aspect is to characterise airport shoppers, who are especially influenced by time pressure, proximity of the store, culture and variation of goods [18, 19]. Another revenue metric is the trading area of specific stores, to obtain information on where passengers shop [20]. These aspects, in combination with revenue data analysis, could provide useful input for the framework to establish an objective function based on historical commercial revenue data.

Research Objectives

From the literature review and initial scope three objectives for the research project are defined:

- **Objective 1** Create a stand allocation model that effectively incorporates the concept of recoverable robustness
- **Objective 2** Develop a framework to include air-side commercial revenues into the tactical stand allocation context
- **Objective 3** Demonstrate the industrial applicability of the recoverable robust stand allocation model in a case study with Guarulhos Airport

The first two objectives are academic objectives and comply with the contributions stated in the literature section. The last objective aims to highlight the applicability of the recoverable robust stand allocation model in the air transport industry with a case study. The performance of the recoverable robust model is relevant for the research and will therefore be compared with a strict robust stand allocation model. The strict robust stand allocation model has to satisfy the all scenarios without recovery possibilities. The hypothesis of the research project is related to the comparison between the recoverable robust stand allocation model and the strict robust stand allocation model:

Hypothesis 1: *The recoverable robust solution to the stand allocation problem has a lower cost of robustness relative to the strict robust solution*

The cost of robustness is defined as the deviation from the optimum objective function value for the stand allocation problem.

For the commercial revenue framework no hypothesis is established. In the time-frame of the research project it is rather complex to measure, for example, the impact on air-side commercial revenues. Rather, the applicability of the objective function based on the commercial revenue framework is evaluated and recommendations are provided.

Recoverable Robust Stand Allocation Model

The recoverable robust stand allocation model consists of an optimisation module and a recovery module (See Figure 1). The optimisation module generates a set of feasible allocation plans to the stand allocation problem. The stand allocation problem in the optimisation module is formulated as a binary program with capacity, allocation, adjacency and towing constraints. The objective function is set to maximise affinity, based on a commercial revenue framework. The output of the optimisation module is a set of feasible allocation plans, the input for the recovery module.

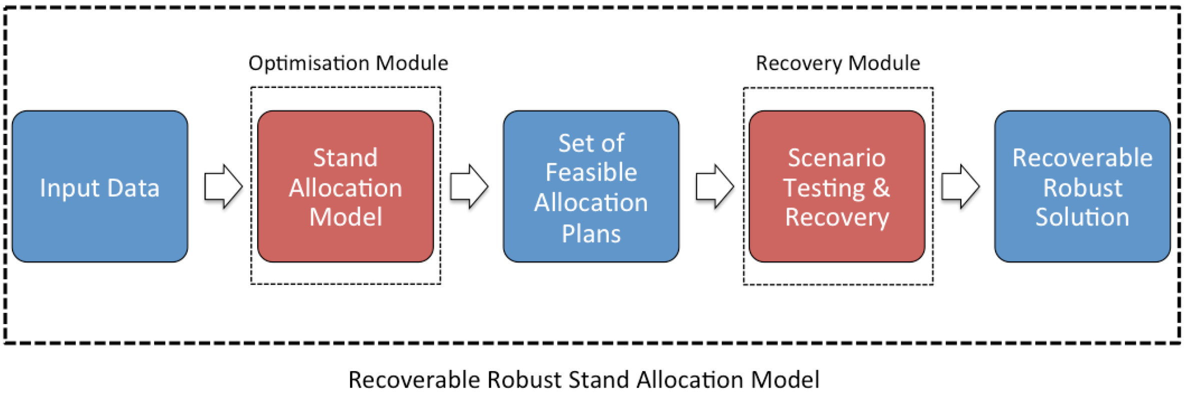

Figure 1: High-level Overview of the Components of the Recoverable Robust Stand Allocation Model

In the recovery module, the generated feasible allocation plans are tested against a number of scenarios and aimed to be recovered if necessary. The scenarios for scenario testing are determined with historical arrival time distributions and relations between aircraft visits with similar arrival times. The allowed recovery strategies in the recovery module are: limited waiting, re-allocation to a free stand and tow of a long-stay aircraft. The final output of the recoverable robust stand allocation model is a recoverable robust solution to the stand allocation problem. The recoverable robust solution provides a tactical stand allocation plan that can, at least, be recovered by limited means in all tested scenarios. Moreover, it provides additional information for the controllers on critical flights and recovery possibilities in the tactical plan.

Results

The recoverable robust stand allocation model is tested in a case study with Guarulhos International Airport of São Paulo, focused on the international terminal: Terminal 3. The terminal consists of 10 wide-body contact-stands, which each can be split into two narrow-body contact-stands. In total 73 stands are considered and in the case study the number of aircraft visits per day varies between 64 and 70. To limit the runtime of the model, 60 feasible allocation plans were generated and tested against 40 scenarios. All cases were solved within 60 minutes on a 8 GB RAM Mac OS X computer.

An objective the of the research was to compare the recoverable robust solution with the solution that has to satisfy all scenarios without recovery (strict robust solution). The results for the objective to maximise affinity demonstrated an increase in average objective function value for the recoverable robust solution of 0.8 to 4.5 percent relative to the strict robust solutions. Furthermore, the average percentage of passengers allocated to a contact-stand over all scenarios was 2.0 to 6.3 percent higher in the recoverable robust solution. For several cases the worst case scenario for the recoverable robust solution still maintained a higher percentage of passengers allocated to a contact-stand than the strict robust solution. It highlights the capability of recoverable robust solution to provide a less conservative, yet robust solution to the stand allocation problem.

In comparison to the allocations of GRU Airport, an increase in affinity of 14.4 to 27.1 percent was achieved. The difference in percentage of passengers allocated to a contact-stand was between -1.3 to 3.6 percent. However, GRU Airport allocated several operations to contact-stands at different terminals. The recoverable robust solution is capable of allocating these operations (6.8 - 10.8 percent of the passengers) to the international terminal. An overall increase of passengers allocated to a contact-stand at the international terminal of of 6.9 - 13.8 percent could be achieved.

The objective function of the recoverable robust stand allocation model, maximisation of affinity based on a commercial revenue framework, was compared with minimisation of total walking distance, minimisation of tows and maximisation of passengers allocated to a contact-stand. The comparison indicated that the airport could focus on either of the objectives at a cost of up to 10 percent of the affinity generated with the maximisation of affinity objective. The minimisation of tows and maximisation of percentage of passengers allocated to a contact-stand both resulted in a significant increase of total walking distance. Therefore, the objectives with best overall characteristics for both the airport and passenger are the maximisation of affinity and the minimisation of walking distance.

Conclusion and Limitations

With regard to the research project several conclusions were established:

- The recoverable robust solution outperforms the strict robust solution in terms of average objective function value and average percentage of passengers allocated to a contact-stand
- The recoverable robust stand allocation model is capable of obtaining a robust solution with an objective function value that approximates the optimum
- The affinity objective results in a relatively good solution in terms of walking distance and percentage of passengers allocated to a contact-stand

The main limitations to the research project were the limited available revenue data and the scope of one terminal. It is desirable to test the recoverable stand allocation robust model with a full airport case study and all required revenue data. Future research could focus on incorporating an operational stand allocation model, or to compare recoverable robustness with, for example, a robustness objective in a multi-objective approach.

List of Acronyms

Table 1: List of Acronyms [1]

Acronym	Definition
ARR	Arrival
at	Arrival time
AVG	Average
DEP	Departure
DOM	Domestic
dt	Departure time
EU	Europe
GRU	Guarulhos International Airport of São Paulo
INT	International
NA	North-America
NCT	Non-Central T Distribution
OF	Objective Function Value
Pax	Passenger(s)
PC	Percentage of Passengers allocated to a contact-stand
RR	Recoverable Robust
SA	South-America
T	Terminal
TA	Trading Area
WD	Walking Distance

[1] A list of used Airline and Airport abbreviations is provided in Appendix A

Contents

Chapter 1

Introduction

Over the past years air traffic has grown significantly, which resulted in the expansion of many airports. In the dynamic airport environment, planning is a crucial factor to make effective use of the scarce resources, such as contact-stands. Airport planning does not only affect passengers, but crews, catering, maintenance and other service providers as well. A well-known planning problem for an airport is the stand allocation problem. The stand allocation problem handles the allocation of aircraft to available stands.

The stand allocation problem has been widely studied since the 1980s. Most research solved the stand allocation problem without the consideration of time deviations in the flight schedule. The determined solutions were therefore not robust to flight disruptions and could lead to many required recovery actions on the day of operation.

This research project includes a recently developed robustness concept into the tactical stand allocation context: recoverable robustness. In recoverable robustness limited recovery is allowed to maintain an allocation plan in the tested scenarios. The recoverable robust solution to the stand allocation problem is then robust, yet relatively close to the optimum. The recoverable robustness concept has been proven effective in, for example, train timetabling [14]. This research project is the first application of recoverable robustness in a stand allocation context.

Furthermore, this thesis project aims to include an initial framework to include commercial revenues in a stand allocation model. Non-aeronautical revenues are becoming more important for airports due to privatisation and competition effects [17]. The title of the research project is:

Incorporation of Recoverable Robustness and a Revenue Framework into Tactical Stand Allocation

The research is conducted in collaboration with GRU Airport (International Airport São Paulo).

The academic contribution of the research is two-fold. Firstly, the concept of recoverable robustness will be applied in the stand allocation context, to create a recoverable robust stand allocation model. Secondly, an initial framework to incorporate air-side commercial revenues into the objective function of the stand allocation model is described. The academic contributions for the research project are translated into specific objectives:

- **Objective 1** Create a stand allocation model that effectively incorporates the concept of recoverable robustness
- **Objective 2** Develop a framework to include air-side commercial revenues into the tactical stand allocation context
- **Objective 3** Demonstrate the industrial applicability of the recoverable robust stand allocation model in a case study with GRU Airport

The first two objectives are related to the academic contribution of the research project, while the latter is focused on the industrial applicability. With these objectives in mind, an extensive literature study is conducted in Chapter 2. A more detailed project plan is provided in Chapter 3. The description of the recoverable robust stand allocation model is found in Chapter 4. Furthermore, an overview of GRU Airport and the performed data analysis are illustrated in Chapter 5. To demonstrate effective working of the recoverable robust stand allocation model, verification and validation are performed, as explained in Chapter 6. Finally, obtained results and concluding remarks are discussed in Chapter 7 and Chapter 8.

Chapter 2

Literature Review

To evaluate the current state of the art in airport stand allocation literature, an extensive review is conducted. Combined with a review of robustness and airport commercial revenue literature, the place of this research project in the body of knowledge is established. The remainder of this chapter will focus mainly on a state of the art representation of the relevant literature (Section 2.1). Different objectives, constraints, modelling approaches and solution techniques for the stand allocation problem will be outlined. Furthermore, both the robustness and the commercial revenue aspect will be covered. In Section 2.2 the results of the review will be analysed. Section 2.3 provides a discussion of the literature and identifies research gaps. Next to the main conclusions, the place of the thesis in literature is discussed in Section 2.4.

2.1 State of the art

Airport stand allocation is a well-researched optimisation problem due to its solving complexity and interesting context. Research has provided different formulations, modelling approaches and solution techniques for the problem. The literature review aims to provide an overview of these differences. Thereafter, concepts in related industries regarding robustness and commercial revenue are reviewed to highlight useful aspects for the research project.

Initial research on stand allocation started in the 1980s by solving simplistic models with basic constraints [1, 2, 3]. Often stand allocation is referred to as gate assignment, which is valid when a 1-to-1 mapping of stands and gates exist (i.e. for every stand an air-bridge is available to connect the stand with the airport terminal) [6]. At many European and South-American airports remote stands are apparent as well, therefore the correct term is stand allocation. The objective of the simplistic models was to minimise walking distance for passengers. The simplistic models covered two basic constraints: One stand can hold one flight per time instance (capacity constraints) and a flight can only be allocated to one stand (allocation constraints) [1]. Potential additional constraints as stand compatibility or airline specific areas are mentioned in early literature, but are not included in the simplistic models [1]. The stand allocation literature has built on the simplistic models with variations in constraints, objectives, modelling approaches and solution methods.

2.1.1 Constraints

As expansion of the simplistic models, other essential operational constraints might be included to improve applicability at the airports. For example, potential towing of a long-stay aircraft has been mathematically formulated for the stand allocation model [4, 5, 6]. The aircraft visit is split into an arrival and a departure part (optionally a part as well [6]) [4, 5]. The exact decision of when to tow and towing time are not yet modelled.

Another advanced constraint is stand compatibility (aircraft can only be serviced at suitable stands) [5]. This can be modelled as objective as well, to include airline preferences. For some airports adjacency constraints need to be included, where placement of two large aircraft next to each other not possible [21]. Adjacency constraints can also be referred to as shadow constraints [6]. A variation of the adjacency constraint is the Last-in First-out constraint [4]. A buffer constraint might be imposed to account for small variations in arrival/departure time [10, 22]. Moreover, a constraint can be in place to split international and domestic flights in the allocation.

2.1.2 Objectives

The objectives for stand allocation can roughly be split into passenger-oriented objectives and airport-oriented objectives [7]. As mentioned, early research focused on passenger service by aiming to minimise walking distance [1, 2, 3]. More recent models included transfer passengers [23, 24]. Other passenger-oriented objectives include minimising passenger "rush" [25], minimising passenger transit time [24, 26] and minimising passenger waiting time [10]. Although beneficial for passengers, this objective may lead to high utilisation of contact-stands in proximity of the main building [6]. Recent research included airport-oriented objectives for the stand allocation problem as well. The most common airport-oriented objective is the minimisation of unallocated turns [4, 8, 21, 24]. In some cases a dummy contact-stand is in place to "allocate" the unallocated turns [10, 24]. Other airport-oriented objectives are the minimisation of stand conflict durations [11, 22, 26], the maximisation of preferences [4, 8, 27] and minimisation of towing operations [4, 6, 8]. Operational stand allocation typically aims to minimise the deviation from a specified stand allocation plan [28].

A recent trend in stand allocation literature is the application of a multi-objective approach [4, 6, 8, 26]. In general this results in a trade-off between the objectives. Airport preference seems crucial in determining the objectives for the stand allocation model. Recent literature on tactical stand allocation included on towing and connecting passengers [4, 6, 25, 26]. Moreover, often a robustness objective is included to account for small time deviations during operations [4, 8, 26].

2.1.3 Mathematical Formulations

The mathematical formulation of the objectives and constraints in a stand allocation model can be described in various manners. Most research formulated the problem as a (mixed) integer or binary linear program [1, 7]. When only the basic constraints are considered, the model is naturally a binary integer program [3]. The 0,1 formulation can be extended with the mentioned advanced operational constraints [4, 28]. Integer formulations require all variables to be integer, while mixed integer only constrains some of the variables to be integer [6, 29].

Another modelling approach is the multi-commodity network model in which stands “flow” through the model from source to sink via various arcs (flight operations) [25]. A downside is the requirement for multiple model copies when heterogeneous stands are present at the airport [10]. A visualisation of the network model is provided in Figure 2.1.

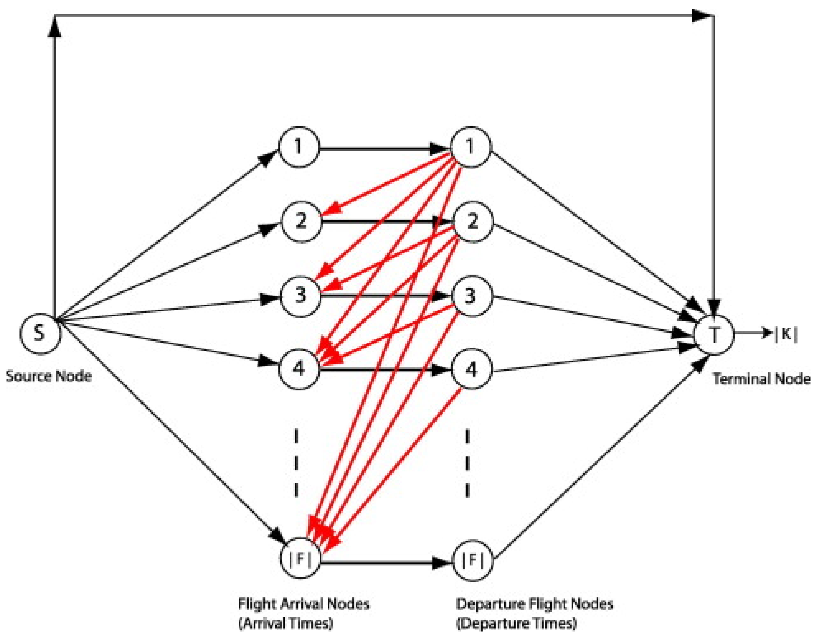

Figure 2.1: Illustration of the Multi-Commodity Flow Network Model [25]

The Clique Partitioning Problem has also been considered for stand allocation [8, 30]. Although relatively complex to set up due to the definition of edge weights, it has been successfully applied for a large airport case study [30]. Finally a dynamic programming formulation could be utilised [27]. Despite the successful application of the multi-commodity network model, clique partitioning model and dynamic programming to the stand allocation problem, addition of advanced constraints might complicate the model [10, 27]. Consequently, recent literature expresses the problem often as a (mixed) integer or binary program [4, 6, 9, 31].

2.1.4 Obtaining a Solution to the Stand Allocation Problem

Obtaining a solution for the stand allocation problem can be relatively complicated, since many of its formulations have been proven NP-hard [6, 27] or NP-complete [8]. This has led to the development of (meta)-heuristics that provide a solution technique to obtain a "good enough" solution in reasonable time. One of the solutions techniques is the greedy algorithm [32, 33]. The drawback of the greedy method is the potential for a large optimality gap [6].

Other popular methods are Tabu search, simulated annealing or a hybrid version of the two [23, 33]. Tabu search typically consists of a neighbourhood search with an exchange move, in which two flights-stand combinations are swapped, and an insert move, where a flight is removed from its stand and allocated to a different stand [11]. Tabu search tends to obtain a fast, reasonably good solution due to the storage of solution deteriorating moves [23]. Recent Tabu search algorithms ensure not getting stuck at a local minimum, however advanced neighbourhood searches are still desired [11]. Stochastic approaches for the stand allocation problem can exploit the Tabu search algorithm effectively as well [11].

Comparably, simulated annealing adopts neighbourhood searches as well, but utilises a probabilistic approach to determine whether to accept an improved solution [24]. For simulated annealing it is required to set a starting temperature, cooling factor, accept rate and stopping criteria, which can be complicated to determine [24, 33]. Simulated annealing obtains slower computation times and less accurate results for an equal problem size compared to the Tabu search algorithm [23].

Another solution method is a hybrid approach of Tabu search and simulated annealing [33]. The comparison between the hybrid version and Tabu search demonstrated a slight improvement in objective function for the hybrid model at the cost of a three times longer computation time [23]. The downside of both algorithms and the hybrid version is the unknown optimality gap.

Complementary to the methods stated above, other algorithms have been investigated. For example, a genetic algorithm can use mutation and cross-over operations of a population to create feasible solutions to the stand allocation problem [34, 35]. The Tabu search algorithm is demonstrated superior in both computational speed and solution quality with respect to the genetic algorithm [23]. Another algorithm, the ejection chain algorithm, was utilised to solve the clique partitioning problem [8]. Although computational speed is high, the algorithm introduces an optimality gap of approximately 8 percent for a large airport instance [6]. Literature still aims to provide new solution algorithms, exhibited by publications on the ant colony algorithm and bee colony algorithm [9, 31].

A more intuitive solution method to solve large scale problems is column generation [36]. A column generation approach solved a problem instance of 700 flights and 128 stands within 10 minutes [5]. Recently, a strengthened mixed integer formulation was proposed to solve the stand allocation problem to optimality [6]. A large airport instance including over 700 operations and more than 100 stands was solved to optimality within 35 seconds [6]. The computation time could even be further reduced by time decomposition or stand decomposition [6]. In comparison, the ejection chain algorithm and greedy algorithm demonstrated faster computational times, however optimality gaps of approximately 5 and 18 percent respectively are introduced [6]. The strengthened formulation has not been tested in a stochastic environment, but it questions the necessity of (meta)-heuristics as solution techniques for tactical stand allocation.

2.1.5 Robustness in Stand Allocation

The tactical allocation plan might suffer from uncertainty in arrival/departure times during actual operations. The tactical stand allocation model has to include measures to handle this uncertainty. As a consequence, research has focused on improving the robustness of the solutions for stand allocation. Here, the current state of robustness in stand allocation modelling is reviewed.

The robustness measures in stand allocation have progressed from fixed buffer time constraints to robustness objectives [7, 8, 9]. The idea of using a fixed buffer was recognised early in literature [1]. The fixed buffer introduces a minimum time between two consecutive flights at the same stand [1, 10]. The buffer can absorb small deviations in arrival/departure time during operation. However, a large fixed buffer time for all flights is considered relatively conservative [4]. As a result, robustness has recently been considered as one of the objectives in multi-criteria approaches for the stand allocation problem [4, 8]. Robustness objectives can be expressed as minimisation of desired stand rest [4], maximisation of overall buffer time [9] or minimisation of stand conflicts [11, 26]. Some formulations penalise the objective function when a certain buffer between flights is not achieved [4, 8]. Only one paper considers a flight-specific desired stand rests by taking the 95th percentile of historical delay [4].

Another methodology to handle uncertainty is a stochastic approach [10, 11]. Stochastic models include random parameters by means of scenarios [13]. For stand allocation, the random parameters can be determined by distributions of flight arrival/departure times [11]. Unfortunately only self-generated flight data is used to create the scenarios in the stochastic stand allocation models found in literature. A stochastic approach can be computationally expensive due to scenario expansion [13, 14]. To overcome this drawback often a limited set of scenarios is considered in stand allocation literature [11]. Furthermore, important advanced constraints as towing are typically not considered in the stochastic models described [11]. Nevertheless, stochastic programming does allow for more sophisticated incorporation of robustness and the modelling approaches are therefore of interest.

2.1.6 Other Robustness Approaches

In addition to the robustness approaches in stand allocation literature, other methodologies are available in related industries. Robustness approaches typically fall in the general classes of robust optimisation and stochastic programming [14]. Robust optimisation takes into account the range for the variables, aiming to satisfy the worst case scenario [12]. Stochastic programming optimises a solution based on different parameter realisations [13]. A popular approach is two-stage stochastic programming, a method that revisits the optimisation problem after initial data is obtained [14]. It could be applied to the operational stage of stand allocation, to allow for re-optimisation after several flights have arrived. Based on the foundations of robust optimisation and stochastic programming two new robustness concepts are considered: light robustness and recoverable robustness [14, 37].

Light robustness can be viewed as a compromise between the objective function value and handling the uncertainty of input data [37]. A maximum deterioration of the objective function is set, after which the most robust solution is obtained within the allowed objective value range [37]. Due to allowed constraint violations and a rather simplistic approach light robustness might not be suitable for all contexts: "it is not clear whether such a simple approach can deliver solutions that are comparable to those obtained through more involved stochastic programming or robust models" [37]. This uncertainty is a drawback for the method, although the method is successfully applied to a timetable information problem [38].

The goal of recoverable robustness is to combine stochastic programming with robust optimisation [14]. Limited recovery is admitted for the scenarios to obtain a less conservative solution [14]. Recoverable robustness has been successfully applied to, amongst others, the timetabling problem [15] and the tail assignment problem [16]. Although scenario expansion will remain an issue for recoverable robustness, an application to the stand allocation problem might provide a less conservative robust planning solution. The recovery strategies could follow from analysis at the airport and conversations with the airport controllers. The recoverable robust solution will not only provide a tactical stand allocation plan, but will express required recovery strategies for each of the scenarios as well. In contrast to light robustness and recoverable robustness, most other recent advances in robust optimisation under uncertainty focus on satisfying the worst-case scenario, which would be too conservative for the stand allocation problem.

2.1.7 Commercial Revenues

The second academic contribution of the research project covers the relation between air-side commercial revenues and stand allocation. Non-aeronautical revenues are becoming more important for airports due to privatisation and competition [17]. The location to which the aircraft is allocated may influence the spending behaviour of airport passengers. In stand allocation literature, commercial air-side revenue has not yet been considered. The goal of this research project is to provide an initial framework for handling air-side commercial revenue in the stand allocation context.

One aspect is to characterise airport shoppers, which can be divided into three categories: shopping lovers, mood shoppers and apathetic shoppers [19]. Shopping lovers were especially influenced by proximity of the store and variation of goods [19]. It has to be noted that the survey only contained Belgian citizens. Airport passengers tend to shop less under time pressure and culture influences shopping behaviour as well [18]. Other aspects of shopping behaviour are dwell time and taxes at origin [39].

Even though the passenger can reasonably be characterised, the link with stand allocation remains relatively unclear. To generate ideas on how to incorporate a revenue metric in stand allocation, related industries are reviewed. For example, shelves closer to the aisle in supermarkets tend to generate more sales due to higher customer traffic [40]. Moreover, in a shelf the first item encountered tends to be the most profitable one [41].

Another option would be to analyse the trading area of specific stores [20]. The trading area of retail stores with respect to stands could be determined and utilised to increase sales. A similar approach is defining the "Buying Association", which computes the correlation between product groups [42, 43].

Which of the above methods is suitable for stand allocation will depend on the retail revenue data available. A suitable methodology will be defined in collaboration with the airport to effectively incorporate an initial air-side commercial revenue framework into the stand allocation context.

2.2 Results and Analysis

The development of stand allocation research has progressed towards the involvement of more operational constraints and objectives, a direction that will likely continue in the future. Required operational constraints will depend on the terminal lay-out, but towing and adjacency constraints are demonstrated relevant for many airport case studies in literature. Recent literature mainly expresses the stand allocation problem with a binary or (mixed) integer formulation.

Furthermore, literature aims to increase the probability of feasibility for the tactical stand allocation plans during operations. This incorporation of robustness has been considered as constraint, objective or via a stochastic approach. A new robustness concept, recoverable robustness, has been successfully applied to train timetabling problems, but it has not yet been considered for airport stand allocation. The concept can be the next step for robustness incorporation into the stand allocation problem. The recovery strategies included in recoverable robustness should follow from discussions with airports.

Due to privatisation and competition effects, non-aeronautical revenues are becoming more important for airports. In this context, placement of specific flights to specific stands might have an impact on air-side commercial revenues generated. Literature on stand allocation does not cover this link with air-side retail revenues. The literature review of related industries provides initial ideas for an analysis framework, for example utilising buying association correlations or shelf allocation indicators. These ideas can be combined with extensive revenue data analysis to design an initial framework to handle air-side commercial revenues in the stand allocation context.

2.3 Discussion

Stand allocation has been a well-researched optimisation problem for multiple decades. Its solving complexity and interesting context have led to many variations in mathematical formulations and solution approaches. Objectives for the stand allocation problem range from minimising walking distance to minimising towing operations. Furthermore, literature considers towing, stand affinity, adjacency or buffer time constraints complementary to the basic constraints (maximum one flight per stand per time instance and a flight can only be assigned to one stand). Due to the solving complexity, many solution techniques have been applied to the stand allocation problem. A drawback of the variations, and different problem sizes, is the lack of comparison between the methods. Only recently some papers provided comparisons to analyse differences between solution techniques. The comparisons displayed a trade-off between optimality and computation time.

Robustness is often included in the stand allocation model as buffer time constraint. Incorporating robustness as an objective might be a less conservative approach, especially when using a flight-specific approach. A stochastic approach has been considered for the stand allocation problem as well, to handle the uncertainty in arrival/departure times better. Unfortunately literature only used self-generated scenarios for the problem, instead of historical flight data. The next step for incorporating robustness in stand allocation is still undefined and the recoverable robustness may be suitable. The concept can result in a less conservative yet robust solution due to allowed recovery strategies. The model might suffer from longer computational time due to scenario expansion, however for tactical stand allocation planning this may not be a critical issue.

On the commercial revenue aspect for stand allocation currently no literature is available. An initial framework for handling air-side commercial revenues in the stand allocation model will have to be designed based on extensive revenue data analysis and a literature review of related industries. The framework could lead to further research on the connection between air-side commercial revenue and tactical stand allocation.

2.4 Conclusion

The aim for stand allocation modelling should be to include most operational constraints like towing, gate affinity and adjacency, depending on airport lay-out and operations. Recent objectives for the stand allocation model consider maximisation of connecting revenues and minimisation of towing operations. Furthermore, a robustness objective is often apparent in multi-objective approaches. New objectives are still being developed to highlight new approaches for the problem. Binary or (mixed) integer program formulations are most common in stand allocation literature. The solving complexity of the stand allocation problem has led to the development of many advanced solution techniques ((meta-)heuristics). However recently, due to a strengthened mathematical formulation of the problem and improved computational possibilities, the necessity for advanced solution techniques is questioned.

Robustness in the stand allocation problem is often expressed with a fixed buffer time or an objective. A fixed buffer time is considered relatively conservative, although a flight-specific buffer time improves the methodology. Another measure to incorporate robustness is stochastic programming. Successful application to the stand allocation problem is demonstrated, but unfortunately self-created data sets are used and constraints regarding towing and stand compatibility are not included. A new robustness concept, recoverable robustness, can be the subsequent step for incorporating robustness in the stand allocation problem. The evaluation if the application of recoverable robustness results in a less conservative robust stand allocation solution due to allowed recovery is part of the scope of the thesis project. The placement of recoverable robust stand allocation relative to literature is visualised in Figure 2.2.

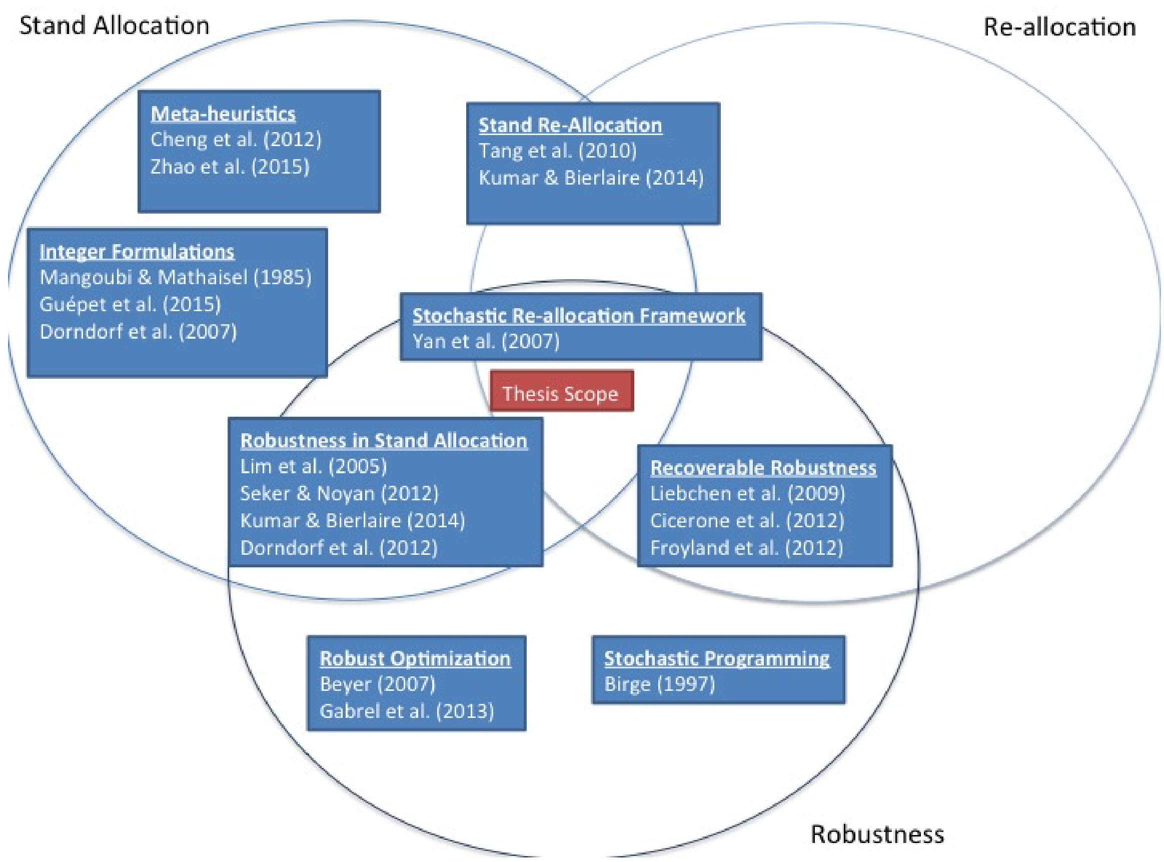

Figure 2.2: Location of the Thesis Scope Relative to Literature

In addition, air-side retail revenues have not yet been considered in the stand allocation context. Although airport shoppers can be characterised, the relation of air-side retail revenue and stand allocation is not yet considered in literature. Initial ideas to construct a framework for handling air-side commercial revenues within the stand allocation context might follow from extensive revenue data analysis and a literature review of related industries. Examples from related industries entail shelf allocation strategies and trading area estimations. Applicability of those ideas to the stand allocation problem will highly depend on the revenue data availability and resulting analysis. The placement of the thesis scope regarding commercial revenue is visualised in Figure 2.3.

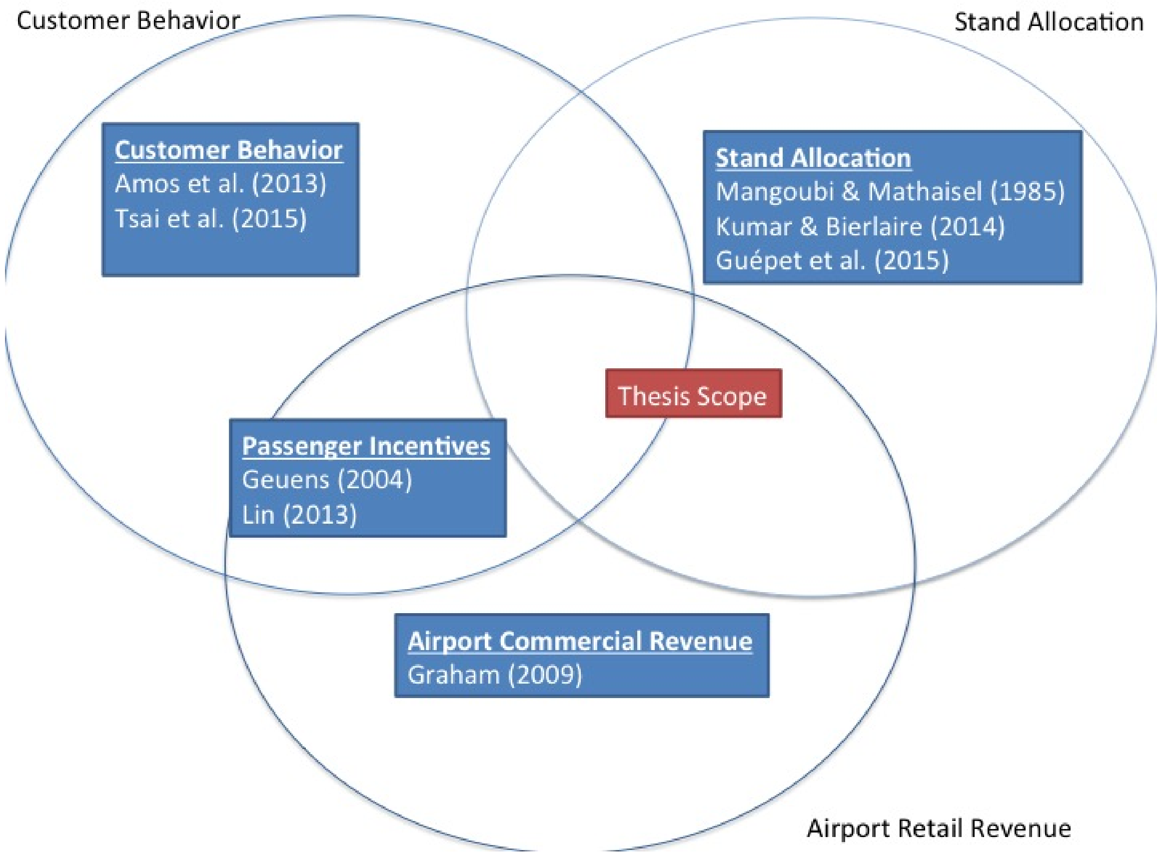

Figure 2.3: Location of the Thesis Scope Relative to Literature

The long-term impact of this thesis project will consist of both a robustness and a revenue aspect. Application of the recoverable robustness concept to the stand allocation problem provides a set of feasible allocation plans which will be tested against realistic scenarios. The objective is to evaluate if recoverable robustness can be the next step for robustness in the stand allocation context. The data analysis performed to generate scenarios for the recoverable robust model will provide useful insights for future research as well. Furthermore, a contribution of this thesis project is to provide an initial framework to include air-side retail revenue into the stand allocation model. Future research may utilise this framework and further investigate the benefit of including air-side retail revenue in stand allocation.

Chapter 3

Project Plan

3.1 Introduction

Based on the literature review and research objectives, a detailed project plan is created to further define the required steps and scope for the research project. The project plan further aims to provide hypotheses, conceptual ideas and experimental set-ups. Initial thoughts on the outcome of the project are included as well. An overview of the main research questions and objectives is provided in Section 3.2, complemented with a methodology part in Section 3.3. Moreover, the experimental set up and anticipated results are discussed in Sections 3.4 and 3.5. Finally some concluding remarks are provided in Section 3.6.

3.2 Research questions and objectives

Defining research questions will help to clarify the process of the research project and to relate the project to the research gaps found in literature. This section aims to provide an overview of the main research questions. Furthermore, a discussion of the novelty of the project will be provided. First the research questions for both the robustness and commercial revenue aspect are explained, followed by the objectives of the thesis project.

3.2.1 Research Questions

Since the thesis project has two distinct contributions to literature, this will be split for the research questions as well. The research question regarding the robustness aspect is formulated as:

Can the cost of robustness for tactical stand allocation be reduced by applying the concept of recoverable robustness?

The cost of robustness can be defined as the difference in objective function value between the optimal solution for the stand allocation problem and a sub-optimal solution which includes a robustness measure. Incorporating robustness in planning leads to deviations from the optimum, but the goal is to minimise these deviations, the so-called "cost". Reducing the cost of robustness would lead to a robust solution which is relatively close to the deterministic optimal solution of the stand allocation problem. The measurement of a reduction in cost of robustness will require the comparison of the recoverable robust solution with another stand allocation model. For the research project, the recoverable robust solution will be compared with the solution of a strict robust model. In a strict robust model, recovery is not allowed and therefore all scenarios have to be satisfied. The goal is to evaluate whether recoverable robustness is the next step for incorporating robustness in tactical stand allocation. Tactical is defined as the planning created the day before operations. Recoverable in this context refers to the possibility to recover the plan with limited actions.

For the commercial aspect of this thesis, a research question is formulates as well:

Can air-side retail revenues effectively be included in tactical stand allocation by incorporating an initial revenue-based framework?

Air-side retail revenues refer to the sales in the terminal of the airport, after clearing customs. It covers all types of retail as duty-free, food & beverages and jewelry. The form of the framework will have to follow from the data analysis and conversations with employees of the airport. Therefore, it is more viable to evaluate the framework established rather than the direct impact on air-side sales.

3.2.2 Objectives

Based on the research questions stated, objectives for the thesis project are defined. The objectives are used to further clarify the scope of the project. The objectives are formulated as:

- **Objective 1** Create a stand allocation model that effectively incorporates the concept of recoverable robustness
- **Objective 2** Develop a framework to include air-side commercial revenues into the tactical stand allocation context
- **Objective 3** Demonstrate the industrial applicability of the recoverable robust stand allocation model in a case study with Guarulhos Airport

The first two objectives are the academic objectives, while the third objective is to demonstrate industrial applicability. The industrial applicability will be assessed with a case study. The case study will have the scope of one terminal, the international terminal of Guarulhos Airport, the international airport of São Paulo in Brazil.

3.2.3 Novelty

A novelty of this research project is firstly the application of the concept of recoverable robustness to the tactical stand allocation problem. The resulting recoverable robust stand allocation model will generate a set of feasible allocation plans, which are tested against a number of scenarios. The aim is to find a recoverable robust solution, a solution that can, at least, be recovered over all specified scenarios by limited means. Second, commercial retail revenue has not yet been considered as objective in stand allocation literature. This research aims to provide an initial framework to include air-side retail revenue in the objective function for tactical stand allocation.

3.3 Theoretical Content/Methodology

This section will focus on the methodology to be used during the thesis project, utilising the research questions from the previous section. The following hypothesis can be defined:

Hypothesis 1: *The recoverable robust solution to the stand allocation problem has a lower cost of robustness relative to the strict robust solution*

In the hypothesis, the recoverable robust solutions is expected to be closer to the optimum objective value relative to the strict robust solution. In the strict robust solution no recovery actions are allowed and therefore the all scenarios have to be satisfied. For the commercial revenue framework no hypothesis is defined. The objective of the framework is to obtain indications whether high-revenue flights are allocated to prime locations for retail. To, for example, test an hypothesis based on measurements in sales data is not possible for the time-frame of the research project. Rather the applicability of the revenue framework will be assessed, to determine whether further research in this direction can be recommended. To test the mentioned hypothesis and to evaluate the commercial revenue framework, the following steps in the project can be described:

Step 1: Extensive data analysis of flight data and revenue data, to establish insights in uncertainty and retail revenue characteristics
In this step extensive data analysis is conducted on flight data and air-side commercial revenue data. For the flight data historical distributions will be established for the arrival time deviations. These distributions will be utilised to generate realistic scenarios for the recoverable robust stand allocation model. The revenue analysis aims to identify which flights contribute most to air-side retail revenue. If possible, this will be divided into specific product groups or stores in the terminal.

Step 2: Development of a stand allocation model with crucial operational constraints
The core part of the recoverable robust stand allocation model, a stand allocation model, will be established in this step. Recent literature will provide the basis for the stand allocation model, with constraints for towing, adjacency and overlap. The exact mathematical formulation will

depend on the constraints apparent at the airport. The stand allocation model will utilise a strengthened binary or mixed integer formulation, following recent literature.

Step 3: Establish a framework of how to handle revenue data in this model and incorporate the framework in the model

This step aims to incorporate the retail revenue data in a stand allocation model. An initial framework based on literature and the revenue data analysis will have to be established on which further research can be conducted. The framework will be part of the objective function for the stand allocation model.

Step 4: Transform the model to a recoverable robust stand allocation model

The stand allocation model has to be transformed into a recoverable robust stand allocation model by addition of recovery strategies and scenario testing. It entails an extensive study of the recoverable robustness concept and the definition of the recovery strategies. For the scenario testing a number of scenarios will be constructed based on the flight data analysis.

Step 5: Evaluate the cost of robustness of Recoverable Robustness and compare it with non-recoverable robust approaches

In a case study with GRU Airport, the recoverable robust stand allocation model will be be evaluated. A comparison with a strict robust model, which has to satisfy all scenarios without recovery, will be provided. This step should demonstrate added value of the recoverable robustness concept .

Step 6: Assess the applicability of the revenue framework within the stand allocation context

A final step is to assess the applicability of the revenue framework. The conclusion should establish whether to pursue further research in this direction.

3.4 Experimental Set-up

The experimental set-up for the thesis project will be in a computer environment. The initial data analysis will be performed using Microsoft Excel and/or Python. The decision will depend on the availability, type and quantity of data available. Excel might not be sufficient when large data-sets need to be analysed. Since the data is from an external source (the airport) care has to be taken when analysing the data, there might be errors or unexpected outliers which need to be investigated.

For the flight data analysis, probability sampling will be used to obtain the error between scheduled time and actual. Moreover, a "best-fitted" theoretical distribution will established by using a fit function, available in the statistic SciPy package in Python.

Data analysis for the commercial revenue data will highly depend on the data available at the airport. A sales per passenger combined with historical stand allocations should provide useful insights. Furthermore, a dwell time analysis will be performed using data from electronic boarding pass scanners.

The recoverable robust stand allocation model will be developed in Python coupled with Gurobi. Gurobi will perform the optimisation part of the model. The choice for Python is based on its available work-packages and efficient interaction with optimisation software. The Gurobi module is chosen for its compatibility with object-oriented programming and its computational speed. For the optimisation a computer with Mac OS environment will be used, with a 2.7 Ghz processor and 8 Gb RAM. The set-up of the conceptual model is provided in Figure 3.1.

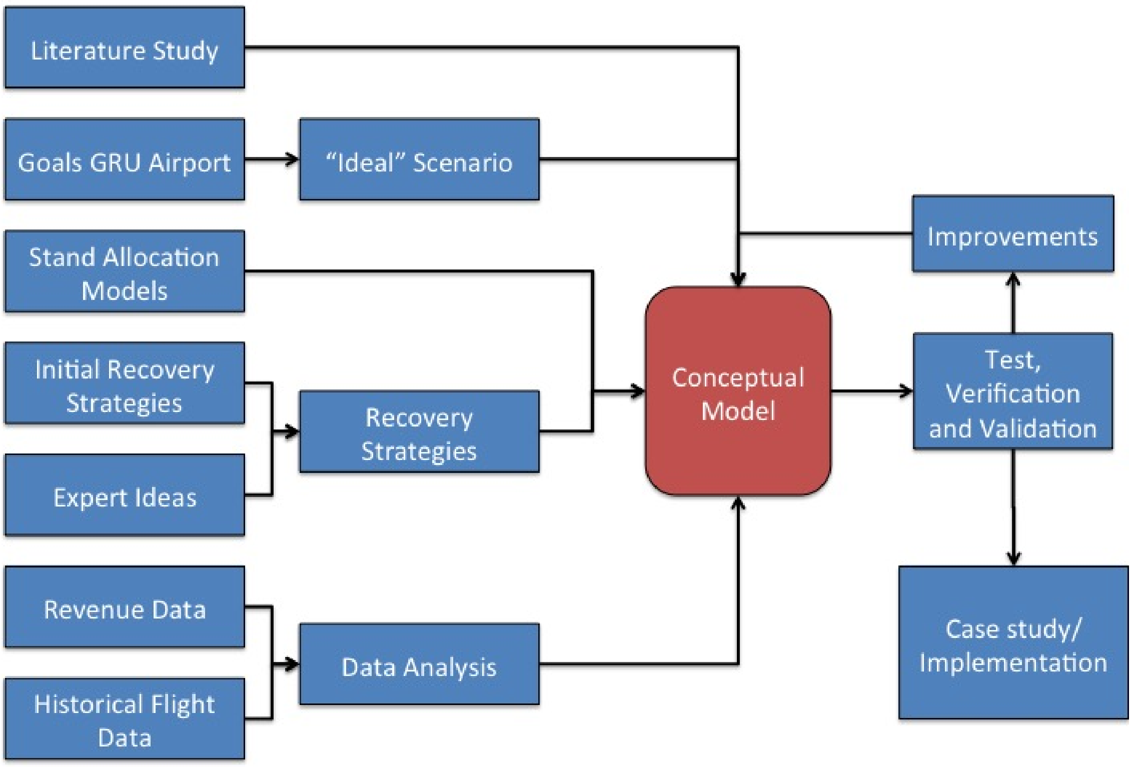

Figure 3.1: Flowchart of the Set-up of the Conceptual Model

The verification of the recoverable robust stand allocation model will be performed using small test data-sets. The flight times and stand compatibility will be chosen such that specific constraints can be tested. For example, specific flights can only be handled at one stand and it can be verified if the model works accordingly. The runtime during verification and validation is of crucial importance to enable fast adjustments to the code if necessary. Similarly the test-scenarios will be generated to test the working of the recovery algorithms.

Literature review of related industries will provide ideas for commercial revenue integration in the recoverable robust stand allocation model. Extensive data analysis on revenue data will be performed in a computer environment using Microsoft Excel and/or Python. Together the data analysis and available literature will be combined into an initial framework. The framework will be incorporated in the Python/Gurobi recoverable robust stand allocation model.

3.5 Results, Outcome and Relevance

The outcome of the recoverable robust stand allocation model should be a recoverable robust solution with corresponding objective value. Furthermore, recovered flights in the scenarios will be indicated. Visual results will be presented to simplify the analysis. The current airport solution and the strict robust solution can be compared with the recoverable robust solution. Since contact-stands are scarce resources, the recoverable robust solution can be highly relevant for airports to provide a less conservative yet robust solution.

Anticipated output of the utilisation of a commercial revenue framework into the stand allocation model is placement of high-revenue passengers in spending stimulating locations. The main relevance is identification of the framework as a first attempt to integrate air-side retail revenue into the stand allocation context. Main outcome should be to identify whether future research in this direction is desired.

Regarding the controllers at the airport the relevance of the results is two-fold. The recoverable robust stand allocation model should provide a robust stand allocation solution. Such a solution should reduce the number of required recoveries and therefore the workload for the controllers. Furthermore, for every scenario evaluated in the recoverable robust stand allocation model the flights that cause conflicts and the alternative stands are identified. This provides valuable information for the controllers and simplifies the recovery process.

3.6 Conclusions

In this research project, two research gaps in tactical stand allocation will be addressed: improvement of the robustness of the stand allocation and implementation of commercial revenues in the stand allocation model. To increase the robustness of the tactical stand allocation plans, the concept of recoverable robustness will be included in the stand allocation model. The recoverable robust stand allocation model will generate a set of feasible allocation plans, which will be tested against a number of scenarios. The overall goal of the incorporation of recoverable robustness is to assess whether this concept may be a next step for robustness in tactical stand allocation models. Effectiveness of the concept will be measured by the cost of robustness and computational speed.

The revenue framework included in the recoverable robust stand allocation model will be based on extensive data analysis of revenue data and a literature review of related industries. The framework will determine the basis for the objective function of the optimisation part in the recoverable robust stand allocation model. The revenue framework may spark future research in this area.

Both aspects of this thesis, the implementation of recoverable robustness into tactical stand allocation modelling and the implementation of an air-side commercial revenue framework into the stand allocation context, are highly relevant for airports. Furthermore, the recoverable robust stand allocation model provides valuable information to the controllers for the day of operation. Potential conflict flights in the selected schedule are available to the controllers and therefore problems can be identified and solved earlier and faster. To illustrate the applicability, a case study with GRU Airport is performed. Similarly, further research on implementation of an air-side commercial revenue into stand allocation models may be based on the initial framework established in this project. With the described project plan, a detailed framework was established to develop and test the recoverable robust stand allocation model.

Chapter 4

Recoverable Robust Stand Allocation Model

This chapter will discuss the development of the recoverable robust stand allocation model. The development consists of two main modules: an optimisation module and a recovery module. The optimisation module consists of a stand allocation model and a solution generation methodology. The recovery module includes a scenario generation methodology and a recovery algorithm.

A schematic overview of the modules in the recoverable robust stand allocation model and their respective inputs and outputs is provided in Figure 4.1. The modules of the recoverable robust stand allocation model are highlighted in red, while the inputs and outputs are in blue. Please note that detailed information on each module and their respective inputs and outputs will be provided later in this chapter.

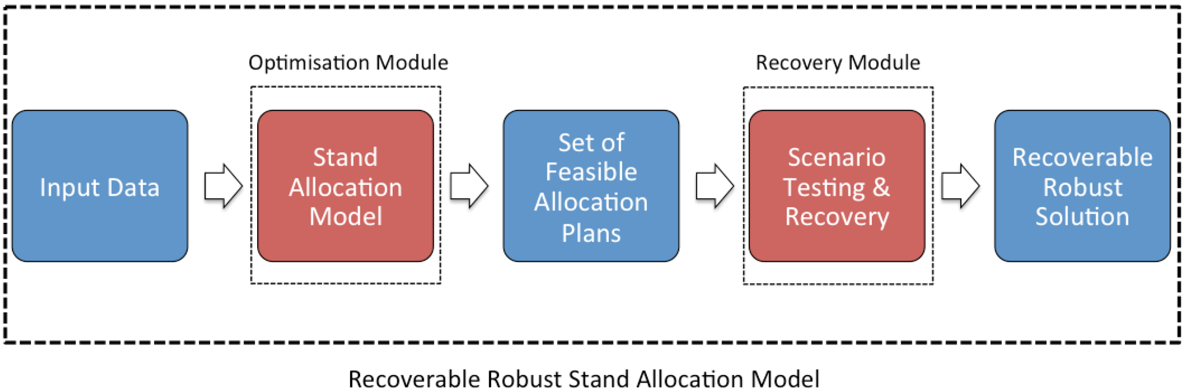

Figure 4.1: Overview of the Modules of the Recoverable Robust Stand Allocation Model

The recoverable robust stand allocation model loads the flight schedule and airport lay-out as input data. The optimisation module generates feasible allocation plans for the flight schedule and stores the plans into a set of feasible allocation plans. The plans are tested against a number of scenarios in the recovery module. The scenarios are generated based on historical arrival time deviation distributions. If a feasible allocation plan can, at least, be recovered by the recovery algorithm in the recovery module for all scenarios, the allocation plan is a recoverable robust solution to the stand allocation problem. Furthermore, the recovery module will indicate crucial aircraft in the flight schedule, which can aid airport controllers to maintain the allocation plan during operations.

In Section 4.2 the optimisation module will be explained in detail, with the mathematical formulation of the stand allocation model. Section 4.3.1 will focus on the methodology to generate the scenarios for the recoverable robust stand allocation model, as first part of the recovery module. Furthermore, Section 4.3.2 will describe the recovery algorithm as included in the recovery module. Finally, Section 4.4 will highlight the expected output of the recoverable robust stand allocation model.

4.1 Definitions

This section aims to describe some important definitions used in the recoverable robust stand allocation model to ensure the terms are interpreted correctly. When possible, a graphical representation is provided as well.

4.1.1 Gate vs. Stand

Often literature refers to gate assignment rather than stand allocation, therefore it is important to understand the difference between stands and gates. Typically a gate provides access to the bridge-way to board the aircraft. A stand is a parking position for an aircraft, which can be a contact-stand (with bridge-access to the terminal), a remote stand (bus access to the terminal) or a parking-only stand (no boarding allowed). In the United States remote boarding is not allowed, leading to a 1-to-1 mapping of stands and gates. There, gate assignment would be an appropriate term, however in most other airports this is not the case and therefore the term stand allocation is used throughout this document.

4.1.2 Operation

For this research project, an operation can be viewed as a stand-still of an aircraft. The stand-still can be for different purposes: disembarkation after arrival, embarkation before departure, parking or a combination. The combination occurs when the aircraft only stays a short time at the airport, the operation will then consists of both disembarkation and embarkation (i.e. arrival and departure). Therefore, an aircraft that visits the airport can have a single or multiple stand-stills (i.e. operations) at the airport, depending on the length of the stay of the aircraft.

4.1.3 Visit

An aircraft visit starts with an arriving flight of an aircraft and ends with a departure flight of the same aircraft. Therefore a visit typically contains two flight numbers. An aircraft visit can be classified as either short-stay or long-stay, depending on the stay time of the aircraft. As mentioned, a short-stay visit consist of only 1 operation, with both disembarkation and embarkation included. However, to avoid that a long-stay aircraft visit occupies a contact-stand for a long time, the long-stay aircraft visits are split into three operations: disembarkation, parking and embarkation. In between the operations, the aircraft is towed if it can not stay at its stand. For the parking operation parking-only stands might be available at the airport. The operations of a short-stay and a long-stay visit are exemplified Figure 4.2.

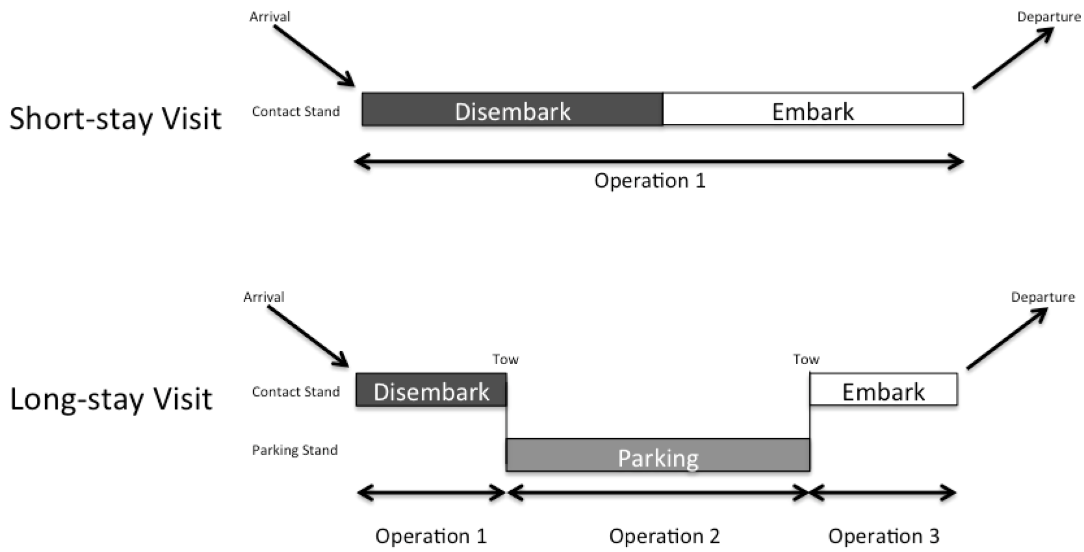

Figure 4.2: Example of a Short-stay Aircraft Visit and a Long-stay Aircraft Visit

4.1.4 Successor

A definition related to only the long-stay visits is successor. A successor needs to be defined in the operations of a long-stay visit to keep track of required tows. For example, the parking operation of Visit 1 is the successor of the arrival operation of Visit 1 and the departure operation of Visit 1 is the successor of the parking operation of Visit 1. The operations in the long-stay visits are connected with the successor concept. In Table 4.1.4 an example of the operations and corresponding successors for a long-stay visit are provided.

Operation	Successor
Visit 1 Arrival	Visit 1 Parking
Visit 1 Parking	Visit 1 Departure
Visit 1 Departure	-

Table 4.1: An Example of the Successor Definition

4.1.5 Overlap

An overlap between two visits or operations can be identified by the arrival and departure time of the visit/operation to a stand. In Figure 4.3 an example of two visits with overlap is provided.

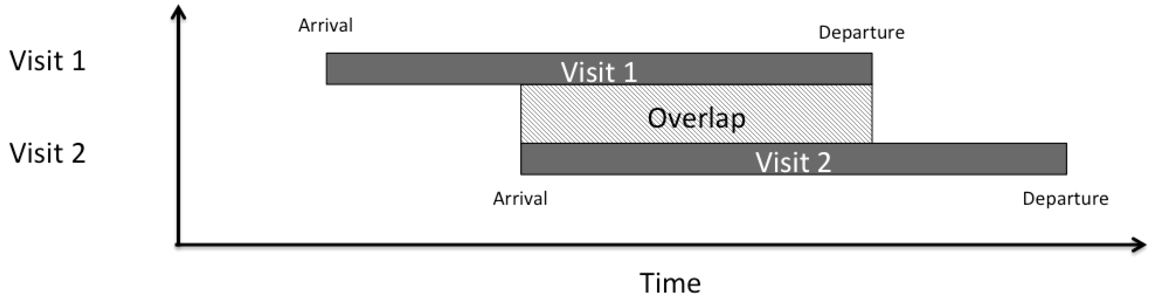

Figure 4.3: Example of Visits with Overlap

4.1.6 Adjacency

Adjacency is an important operational consideration for stand allocation. Adjacency indicates overlap between specific stands. In this research project adjacency is defined as: a stand can either be used for 1 wide-body aircraft or 2 narrow-body aircraft. This case is visualised by Stand 1, Stand 1L and Stand 1R (see Figure 4.4). If Stand 1 is occupied by a wide-body aircraft, Stand 1L and Stand 1R can not be occupied and vice-versa.

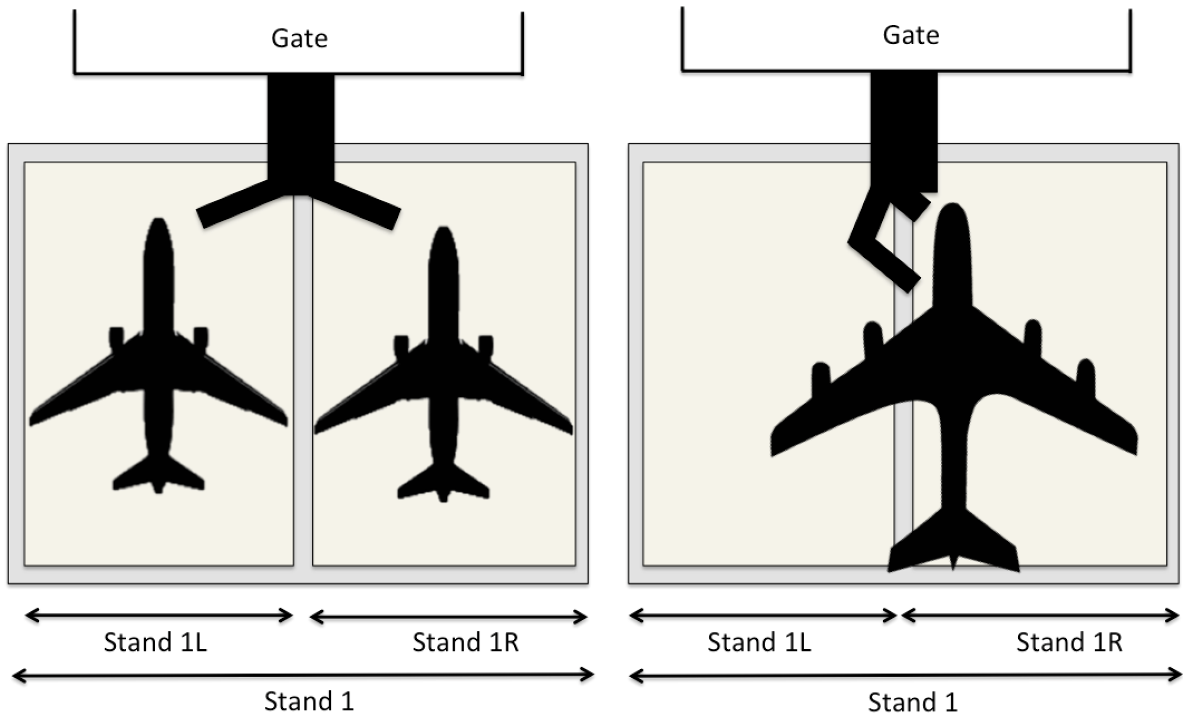

Figure 4.4: Example of Adjacent Stands 1, 1L and 1R with 2 narrow-body aircraft (left) or 1 wide-body aircraft (right)

4.1.7 Affinity

Affinity is related to the preference of a specific operation-stand combination. In the recoverable robust stand allocation model the affinity for each operation-stand combination is based on a revenue framework. Non-aeronautical revenues are becoming increasingly important for airports due to privatisation and competition between hubs [17]. Furthermore, proximity to stores might influence the shopping behaviour of airport passengers [18, 19]. The combination of these two aspects indicated that the allocated stands for passengers may influence the commercial revenue income of the airport. Therefore, a commercial revenue framework that determines the affinity in the recoverable robust stand allocation model can improve the stand allocation from a revenue perspective.

In this research project the affinity is determined for a pier-shaped terminal and expressed in dollars. The affinity calculation of each operation-stand combination is based on historical sales in both the terminal stores (i.e. close to security control) and the pier stores (i.e. close to gates), as well as estimated passenger numbers. The objective of the recoverable robust stand allocation model will be to maximise the overall affinity. From a commercial revenue perspective, the historical high-revenue aircraft visits will then be placed to a preferred revenue position with the aim to stimulate further expenditure.

The terminal stores of the airport are typically at locations where all passengers pass, for example close to security control. The affinity calculation for the terminal stores consists of three parts: historical sales per passenger data, estimated passenger number and a weighting factor for each contact-stand. The weighting factor for the terminal stores represents the distance factor; if the allocated stand is further from the terminal stores, a reduction in terminal store expenditure is expected.

A similar approach is utilised for the pier stores. However, the weighting factor for the pier stores represents the importance to have an operation at a specific stand for a specific store. The importance is determined per adjacent gate pair in the pier. Historical sales data and historical stand allocations can provide insights to determine the weighting factor.

The affinity for each operation-stand combination is calculated as the sum of the terminal and pier affinities. The operations with both high expenditure at the terminal stores and high number of passengers will be preferred close to the terminal. High sales at specific pier stores will increase the value of the affinity close the store. The usage of affinity as objective function will allocate passengers to their revenue-preferred locations and can therefore positively influence the non-aeronautical income for the airport.

4.2 Optimisation Module

The first module of the recoverable robust stand allocation model is the optimisation module. The optimisation module consists mainly of the stand allocation model with respective objective function and constraints. Furthermore, the methodology to generate a set of feasible allocation plans is described.

4.2.1 Stand Allocation Model

In this section the stand allocation model is described, which is the optimisation part in the recoverable robust stand allocation model. First, the optimisation module loads the input data for the stand allocation model. The stand allocation model is formulated as a binary problem, which includes towing, adjacency constraints and stand affinity. Firstly, the data-sets and the variables will be described to simplify understanding of the stand allocation model. After the mathematical formulation will be discussed in detail.

4.2.1.1 Data-sets

The required input data and related generated data-sets form the basis of the stand allocation model. The following input data-sets are essential to the model:

- Set of Aircraft Visits **F**
- Set of Stands **S**

These data-sets are obtained from the airport, in the form of a flight schedule and terminal lay-out map. The data-sets provide the stands and the aircraft visits to be allocated in the stand allocation model. Based on the input data-sets, the following data-sets are computed by the stand allocation model:

- Set of Operations **O**
- Set of Successors $\mathbf{U_i}$ for operation i
- Set of Adjacent Stands **Q** of size $S{*}S$
- Set of Compatible Stands $\mathbf{S_i}$, a subset of **S** for each operation i
- Set of overlapping operations $\mathbf{O_{ov_i}}$ a subset of **O** with overlap with operation i
- Set of Affinity **A** of size $O{*}S$

The set of operations $\mathbf{O}$ is composed by checking the stay time for each visit in the schedule (set $\mathbf{F}$). If the visit is considered a long-stay visit, it will be split into three operations (disembarkation, parking and embarkation). The set $\mathbf{O}$ is the combination set of the short-stay operations and the operations of the split long-stay visits. The successors for the operations in the long-stay visits are determined in the process as well and stored in the set $\mathbf{U_i}$.

The set of adjacent stands $\mathbf{Q}$ handles overlap in the stands at the airport. The set contains, per stand, the information if it overlaps with another stand. The matrix $\mathbf{Q}$ contains a 1 for adjacent stands, while a 0 is stored for non-adjacent stands.

Due to aircraft and stand classifications it has to be ensured a specific operation and stand combination is compatible. Therefore, for each operation i a subset of $\mathbf{S}$, $\mathbf{S_i}$, is determined. $\mathbf{S_i}$ contains the compatible stands for operation i.

Subset $\mathbf{O_{ov_i}}$ contains the operations that overlap with operation i. Normally one would define Visit 1 in overlap with Visit 2 and Visit 2 in overlap with Visit 1 as well. However, from a mathematical perspective it is sufficient to only consider 1 of the 2. This methodology reduces the total number of constraints in the model. Therefore an operation i overlaps with operation *i'* if:

$$at_{i'} \leq at_i \leq dt_{i'} \tag{4.1}$$

in which at and dt represent the arrival time and departure time respectively. The extension of this evaluation over all operations results in a sub-set $\mathbf{O_{ov_i}}$ of operations that overlap with operation i.

Finally, the set of affinities $\mathbf{A}$ defines the preference of each operation-stand combination. For the stand allocation model the affinities are based on commercial revenue data. Each preference in $\mathbf{A}$ is the sum of terminal affinity $\mathbf{A^t_{i,j}}$ and pier affinity $\mathbf{A^p_{i,j}}$ for each operation-stand (i,j) combination. The affinities are included in the objective function calculation to determine an optimal stand allocation from a commercial revenue perspective.

4.2.1.2 Variables

The variables used in the stand allocation model can be split into two: decision variables and parameters. The decision variables will be established by the model during optimisation. Parameters are values which are defined by the airport/user. In addition, the variables for the affinity determination are described in this section.

Decision Variables: The stand allocation model will decide on the decision variable values during optimisation. For the stand allocation model the following decision variables are defined:

- $x_{i,j}$ binary variable to describe whether operation i is allocated to stand j

- y_i binary variable to indicate whether operation i is towed

The choice for binary $x_{i,j}$ and y_i variables is logical, since the decision to allocate an operation to a stand or to tow an operation is a yes/no decision.

Parameters: For the stand allocation model several parameters can be set by the airport. Changing these parameters might result in different allocation plans for the same set of aircraft visits.

- Minimum time to tow: Minimum stay time of a visit specified by the airport to allow a towing operation.
- (Dis)embarkation time: Time required to (dis)embark the passengers, used to determine the minimum length of the arrival and departure operations for long-stay visits.
- Buffer time: A time between two consecutive operations to allow for short stand servicing and to handle small schedule deviations. The buffer time will be included in the visit time and hence in the determination of the overlap.

Affinity Variables: In the objective function the set of affinities $\mathbf{A}$ is utilised. The affinity for each operation-stand combination is the sum of terminal stores affinity A^t and pier stores affinity A^p. The variables in the affinity calculations are:

- sp_i: The sales per passenger for operation i
- Pax_i: The estimated passenger number for operation i
- α_j: Weighting factor representing the effect of distance on terminal sales
- $\beta_{i,j,z}$: Weighting factor representing the effect on the sales of a store in location z due to operation i allocated to stand j

The values of the variables are determined by revenue data analysis. Both weighting factors will need to be determined based on the relation between historical stand allocations and historical revenue data.

4.2.1.3 Mathematical Formulation

The set-up of the stand allocation model used in the optimisation module follows from the defined variables and data-sets. The model is subject to certain constraints and aims optimise an objective function. Firstly, the full mathematical formulation will be provided. Thereafter the objective function and its components will be explained. Finally the constraints will be described one-by-one. The full mathematical formulation of the stand allocation model is provided below.

$$\begin{aligned}
\underset{x}{\text{maximise}} \quad & \sum A_{i,j} * x_{i,j} && (4.2)\\
\text{subject to} \quad & \sum_{j \in S_i} x_{i,j} = 1, \ \forall\, i \in O, && (4.3)\\
& \sum_{i \in O_{ov_i}} x_{i,j} \leq 1, \ \forall\, i \in O, \forall\, j \in S_i, && (4.4)\\
& x_{i,j} - x_{U_i,j} \leq y_i, \ \forall\, i \in O, \forall\, U_i \neq 0, \forall\, j \in S_i && (4.5)\\
& x_{i,j} + \sum_{i' \in O_{ov_i}} x_{i',j'} \leq 1, \ \forall\, i \in O, \forall\, j, j' \in S, \forall\, Q_{j,j'} = 1, && (4.6)\\
& x_{i,j} \in \{0, 1\} && (4.7)\\
& y_i \in \{0, 1\} && (4.8)
\end{aligned}$$

Objective Function: The optimisation module to generate feasible solutions to the stand allocation problem considers the objective to maximise affinity:

$$\underset{x}{\text{maximise}} \ \sum A_{i,j} * x_{i,j} \tag{4.9}$$

The determination of $A_{i,j}$ follows from the sum of the terminal and pier affinities which are determined with the equations below.

$$A^t_{i,j} = \alpha_j * sp_i * Pax_i \tag{4.10}$$

$$A^p_{i,j} = \sum_z \beta_{i,j,z} * sp_{i,z} * Pax_i \tag{4.11}$$

Finally, the two affinities are summed together and included in the objective function.

$$A_{i,j} = A^t_{i,j} + A^p_{i,j} \tag{4.12}$$

Allocation constraints: The first set of constraints covers the aspect that each operation needs to be allocated to a stand, but not more than once. This is mathematically formulated as:

$$\sum_{j \in S_i} x_{i,j} = 1, \ \forall\, i \in O \tag{4.13}$$

It ensures that every operation i in $\mathbf{O}$ will be allocated to a compatible stand j of sub-set $\mathbf{S_i}$.

Capacity Constraints: The second set of constraints aims to avoid overlap for the stands. A stand can only handle one operation per time instance. This is formulated as:

$$\sum_{i \,\in\, O_{ov_i}} x_{i,j} \leq 1, \ \forall\, i \in O, \forall\, j \in S_i, \tag{4.14}$$

This formulation ensures that the sum of all overlapping operations for operation i and compatible stand j is at most one. The stand to which operation i is allocated will have $x_{i,j} = 1$ and will therefore not get another overlapping operations allocated.

Tow constraints: To include the long-stay visits efficiently in the stand allocation model they are split into three operations, and a towing decision variable keeps track of the tows. To indicate the tows decision variable y_i is introduced, and will be required to be 1 if i is allocated to stand j but its successor $\mathbf{U_i}$ is not. This is mathematically included by the following constraint:

$$x_{i,j} - x_{U_i,j} \leq y_i, \ \forall\, i \in O, \forall\, U_i \neq 0, \forall\, j \in S_i \tag{4.15}$$

The $\mathbf{U_i} \neq 0$ ensures the constraint is only enforced if the operation has a successor.

Adjacency constraints: Adjacency constraints for stand utilisation form an important factor in the stand allocation. In general an adjacency constraint can be explained as: if operation i is allocated to stand *j*, operation *i'* can not be allocated to stand *j'*. For the model this is formulated as:

$$x_{i,j} + \sum_{i' \,\in\, O_{ov_i}} x_{i',j'} \leq 1, \ \forall\, i \in O, \forall\, j, j' \in S, \forall\, Q_{j,j'} = 1 \tag{4.16}$$

The sum of x for operation i and overlapping operations $\mathbf{O_{ov_i}}$ for adjacent pair j, k should be less or equal to 1, as expressed in the formulation.

4.2.2 Generation of Feasible Allocation Plans

The described stand allocation model can be solved to optimality and provide a feasible allocation plan to the stand allocation problem. However, the desired output of the optimisation module is a set of feasible plans to the stand allocation problem.

To generate the set of feasible allocation plans the model is solved numerous times, depending on the number of desired allocation plans set by the user. Different feasible allocation plans are ensured by the addition of a constraint after every solving iteration.

To formulate the constraint the previous found feasible allocation plan is expressed by the decision variables $x_{i',j'}$. The next feasible allocation plan to be determined has the decision variables $x_{i,j}$. For the previous found feasible allocation plan the decision variables are split into two sets; one set with operation-stand combinations that were allocated in the previous found plan (i.e.

$x_{i',j'} = 1$) and one set with the unallocated combinations (i.e. $x_{i',j'} = 0$). The following constraint is enforced for finding the next feasible allocation plan:

$$\sum x_{i,j} \left[x_{i',j'} = 0\right] + \sum (1 - x_{i,j}) \left[x_{i',j'} = 1\right] \geq 1 \tag{4.17}$$

The constraint ensures that the number of changes in the plan for $x_{i,j}$ has to be at least one with respect to the previous plan $x_{i',j'}$ (since otherwise the sum would equal 0). For every solving iteration to find a new feasible plan, a new constraint is added (i.e. in the generation of the fifth plan, 4 of the above constraints are included in the model). All the generated feasible allocation plans are stored together in a set of feasible allocation plans. The set of feasible allocation plans is the output of the optimisation module and provides the input for the next module: the recovery module.

4.3 Recovery Module

The recovery module consists of two parts: the generation of scenarios and the recovery algorithm. The scenario generation will be described first, with the determination of the historical arrival time deviation distributions will as well as the methodology to relate flight pairs. Thereafter, the recovery algorithm will be described with the allowed recovery actions.

4.3.1 Scenario Generation

From the optimisation module a set of feasible allocation plans is used as input to the recovery module. To ensure a robust plan, the feasible plans will be tested against scenarios. In literature often normally distributed scenarios are utilised, without consideration of historical data. The aim for the recoverable robust stand allocation model is to take advantage of historical flight data for the scenarios. Ideally two aspects of the historical flight data are included: the historical distribution of the arrival time deviation and the relation of the arrival time deviations between aircraft visits.

The first step for the scenario generation is to determine the historical arrival distribution function for every aircraft visit. In the historical flight data, the arrival time deviation is grouped per flight number. The theoretical best-fit distribution per flight number is then established by a distribution fit-function and the $Kolmogorov - Smirnov$ test, considering 23 possible theoretical distributions. The historical arrival distributions will be utilised to determine the quantity of the arrival time deviation for the aircraft visits in the scenarios.

To include the relation between aircraft visits in the scenario generation correlation calculations could be utilised. High correlations between visits can help determine the quantity of the arrival time deviation with respect to previous arrived visits. However, as will be demonstrated in Chapter 5, correlations between visits may be relatively low. The low correlations did not provide enough confidence to continue with a correlation approach.

Therefore, the metric to describe a relation between two visits is the arrival time deviation sign: positive arrival time deviation or negative arrival time deviation. The metric is expressed as the percentage of days two visits had a similar sign (i.e. positive or negative) in arrival time deviation. These percentages are determined for all flight number pair combinations and are utilised in the scenario generation.

To highlight the methodology for the scenario generation, arriving visit i is considered. Two criteria are used to determine the methodology for the scenario generation:

1. Amount of visits from the same region as visit i that have arrived in the hour before the arrival of visit $i \geq 3$
2. Amount of visits that have arrived in the hour before arrival of visit $i \geq 3$

If either of the two criteria is met, visit i will be handled as a dependent visit. The previously arrived visits in the last hour (and potentially from same region) will be evaluated with regard to visit i. The number 3 is chosen to ensure visit i does not depend or a single or two previously arrived visit(s), which would introduce a relatively large bias.

The previously arrived visits will be annotated with *i'*, *i"* etc., in order of arrival. Two indicators of the previous arrived visits are of importance:

- Historical percentage of the same arrival time deviation sign (positive/negative) between visit i and previously arrived visit *i'*, noted as P(S)
- In the current scenario, did the previous visit *i'* arrive early or late?

The two indicators provide information for the generation of the arrival time deviation for dependent visit i. For dependent visit i two probabilities will be calculated: early arrival $P(Early)_i$ and late arrival $P(Late)_i$. These probabilities will be based on the arrival of the previous visits and their percentage of the same sign for early/late arrival with visit i, noted as P(S).

The methodology is exemplified with an example of 3 previously arrived visits (*i"'*,*i"* and *i'*, in order of arrival). In the case the visits have arrived <u>early</u>, <u>early</u> and <u>late</u> respectively the probabilities for early arrival and late arrival are calculated as:

$$P(Early)_i = P(S)_{i'''} * P(S)_{i''} * (1 - P(S)_{i'}) \tag{4.18}$$

$$P(Late)_i = (1 - P(S)_{i'''}) * (1 - P(S)_{i''}) * P(S)_{i'} \tag{4.19}$$

This method is extended to the general case for an unknown number of available visits, adding $P(S)_{i^n}$ to the multiplication of the probabilities if the previous visit arrived with the same sign as the probability to be calculated (i.e. for P(Early) if visit i^n arrived early or for P(Late) if visit

i^n arrived late) and $(1 - P(S)_{i^n})$ otherwise.

After the calculation of the probabilities, a random number is generated to determine whether visit i's arrival time deviation is positive or negative, with consideration of the calculated probabilities for early arrival and late arrival. The random number provides the sign of the arrival time deviation for dependent visit i, but not yet the quantity.

The quantity of the arrival time deviation follows from the determined historical arrival time deviation distribution in the first step of the scenario generation methodology. To exclude extreme early and tardy deviations, the confidence bounds are set to 0.1 and 0.9 respectively. A random number n determines a probability *p(n)* for the quantity of the arrival time deviation with:

$$\Delta at_i = p(n)\ 0.1 \leq n \leq lim \tag{4.20}$$

$$\Delta at_i = p(n)\ lim \leq n \leq 0.9 \tag{4.21}$$

for earliness and tardiness respectively. Which of the two equations has to be utilised follows from the pre-determined sign of the arrival time deviation for dependent visit i. In the equations at_i represents the arrival time for visit i, and *lim* the limit where $p(lim) = 0$. The probability *p(n)* relates to a quantity of arrival time deviation on the historical arrival time deviation distribution. The deviation for the arrival time at_i will then be added to the nominal arrival time of visit i for the specific scenario.

The visualisation for the determination of the quantity of arrival time deviation for dependent visit i with an early arrival (i.e. sign = negative arrival time deviation), is provided in Figure 4.5, which also highlights the early/late regions, the cumulative arrival time deviation distribution, the confidence bounds and the limit.

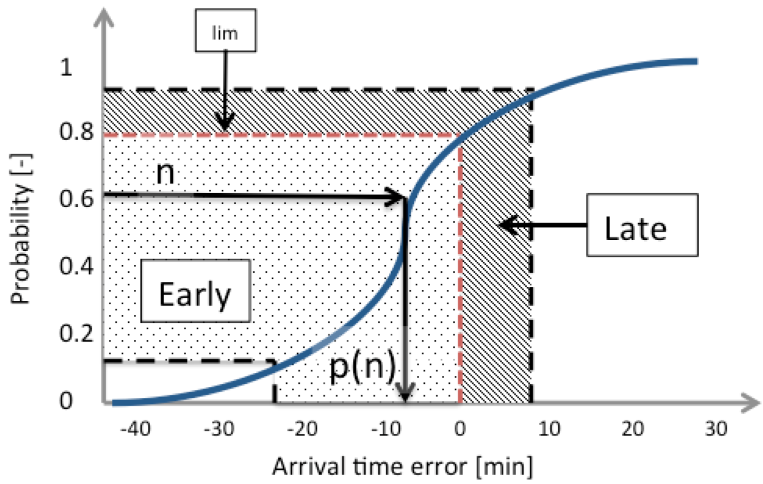

Figure 4.5: Determination of Arrival Time Deviation for an Early Visit Based on the Historical Cumulative Arrival Time Distribution

In case both criteria for a dependent visit can not be met, the visit will be handled as an independent visit. The arrival time deviation of independent visits utilises the historical arrival time deviation distribution determined in the first step of the scenario generation as well. Again, a random number n between 0.1 and 0.9 determines probability $p(n)$. The corresponding arrival time deviation is added to the original arrival time of the visit. Please note that for an independent visit the sign (positive/negative) of the arrival deviation is not pre-determined. In Figure 4.6 an example of the arrival time deviation is provided, with dotted lines as the confidence bounds.

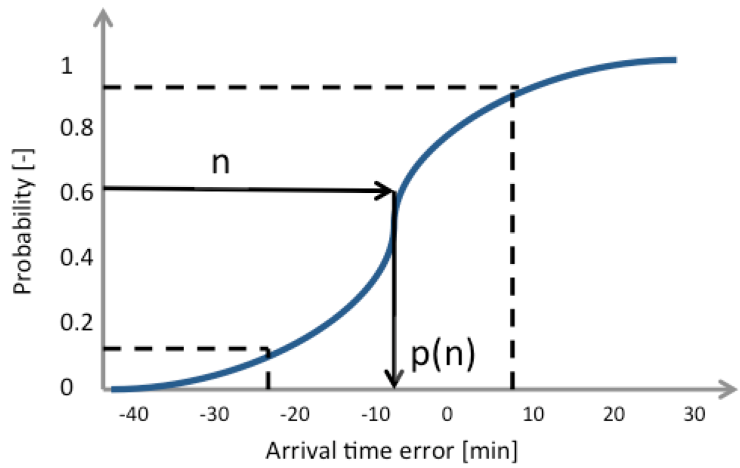

Figure 4.6: Determination of Arrival Time Deviation for an Independent Visit Based on the Historical Cumulative Arrival Time Distribution

The scenario generation methodology aims to include the effect of the relation between aircraft visits if enough previously arrived visits are available. It aims to ensure a realistic arrival time deviation based on historical data. The incorporation of relation between the aircraft visits in the scenario generation methodology and the effective utilisation of historical data improve the robustness of the final recoverable robust stand allocation solution. The scenarios, together with the set of feasible allocation plans, are inputs for the next part of the recovery module: the recovery algorithm.

4.3.2 Recovery Algorithm

The recovery algorithm aims to find recoverable robust solutions to the stand allocation problem. The set of feasible allocation plans is tested against the generated scenarios in the recovery algorithm. The recoverable robust solutions are a sub-set of the set of feasible allocation plans, the recoverable robust solutions are the feasible allocation plans that can, at least, be recovered by limited means in all created scenarios.

The recovery algorithm contains of two parts: an algorithm to recover a schedule conflicts and a selection mechanism for the final solution. In the first part of recovery algorithm three recovery actions are allowed to recover the feasible allocation plans: Waiting, re-allocation to a free stand and tow of a long-stay visit. In the scenarios, a schedule conflict (i.e. overlap in time) can occur due to the shifted arrival times. If a conflict occurs, the three recovery actions will be tried to recover the allocation plan. The allowed recovery actions are described as:

- **Waiting:** Let an aircraft wait until its allocated stand is free. Obviously, it is not acceptable to make an aircraft wait extensively therefore a limit is set (5 minutes in the algorithm).
- **Re-allocate to a free stand:** If the conflict-time is larger than the allowed waiting time, it is tried to find a free compatible stand for the operation that causes the conflict.
- **Tow a long-stay parking operation:** If a conflict occurs and there is no free compatible stand, but a long-stay visit is parked at a contact or remote stand, the long-stay visit is considered for a towing operation to an available parking-only stand. The freed stand can then be utilised for (dis)embarkation.

The second part of the recovery algorithm is a selection mechanism for the final recoverable robust solution. The selection can be based on, for example, the lowest number of recovered scenarios, the average percentage of passengers allocated to a contact stand over all scenarios or other performance indicators as average walking distance over the scenarios or average required towing operations. A similar selection procedure is in place for the case that none of the feasible allocation plans is recoverable robust. A non-recoverable robust will then be selected, for example based on the lowest number of non-recoverable scenarios or one of the other performance indicators listed.

The complete recovery algorithm, with the three recovery actions, is described as:

Algorithm 1: Recovery Algorithm

```
Result: Recovery of Feasible Allocation Plans in Scenario Testing
Start at First Scenario and Feasible Plan;
while Untested Feasible Allocation Plan Exist do
    while Untested Scenario Exist do
        while Conflict Exists do
            Find conflict time ;
            if conflict-time ≤ 5 minutes ;
            then
                Let aircraft wait ;
                Move to next conflict
            else
                Find free, compatible stands ;
                if Free compatible stand is available then
                    Allocate conflict operation to free compatible stand ;
                    Update recovery variables ;
                    Move to next conflict
                else
                    Find Towable Operations and Free Parking Stands;
                    if A long-stay towing operation at a compatible stand and parking stand available then
                        Tow long-stay parking operation to parking stand ;
                        Allocate conflict operation to freed stand ;
                        Update recovery variables ;
                        Move to next conflict
                    else
                        Indicate Allocation Plan as Non-Recoverable;
                        Move to next conflict ;
                    end
                end
            end
        end
        Go to next Scenario
    end
    Go to next Feasible Allocation Plan
end
if Recoverable Robust Solutions Found then
    Print best Recoverable Robust Solution
else
    Print best Non-Recoverable Solution
end
```

To keep track of the recovery applied in a certain scenario, recovery variables are introduced. The recovery algorithm alters the feasible allocation plan for a specific scenario and therefore it is important to store the utilised recovery actions. The recovery actions are stored with recovery variables:

$$r_{i,j}^{s,c} \begin{cases} \text{1 if operation } i \text{ is re-allocated to stand } j \text{ in scenario } s \text{ for feasible allocation plan } c \\ \text{-1 if operation } i \text{ is removed from stand } j \text{ in scenario } s \text{ for feasible allocation plan } c \\ \text{0 otherwise} \end{cases} \tag{4.22}$$

To highlight the application of recovery variables further an example for the allocation constraints is provided. Operation i can only be allocated once per scenario in every solution and therefore the following constraints can be described (Please note the set of scenarios $\mathbf{T}$, noted by s and the set of feasible allocation plans $\mathbf{C}$, noted by c):

$$\sum_{j \in S_c} (x_{ij} + r_{i,j}^{s,c}) = 1, \; \forall\, i \in O, \; \forall\, s \in T, \; \forall\, c \in C \tag{4.23}$$

The other constraints in the stand allocation model are extended similarly for the recovery algorithm. The recovery variables represent information about the recovery in a specific scenario and can be provided to the airport controllers if desired. After a recovery move is in place, the same scenario needs to be re-tested to ensure no other conflicts are apparent in the scenario. In the re-testing of the scenario variable r might not be equal to 0, but also be 1 or -1, depending on the recovery in the previous iterations. The variable r indicates the difference between the original feasible allocation plan c and the recovered allocation plan for a specific scenario.

The recovery algorithm evaluates the set of feasible allocation plans against the scenarios and indicates the plans that are recoverable robust solutions to the stand allocation problem. The output of the recovery module, a recoverable robust solution, is then selected by a criteria chosen by the airport. This concludes the recovery module in the recoverable robust stand allocation model. The expected output for the airport controllers will be highlighted in the next section.

4.4 Expected Output

The expected output of the recoverable robust stand allocation model is a recoverable robust solution to the stand allocation problem. The recoverable robust solution can be visualised with the respective decision variable values. An example of the visualisation is provided in Figure 4.7, where the stands are plotted relative to the time. The output for the airport controllers is an html-plot similar to the figure, with zooming options and labels to provide more detailed information. In the figure, blue squares indicate (dis)embarkation operations while light-blue squares indicate parking operations. If a (dis)embarkation operation is allocated to a remote stand the square would be highlighted in orange.

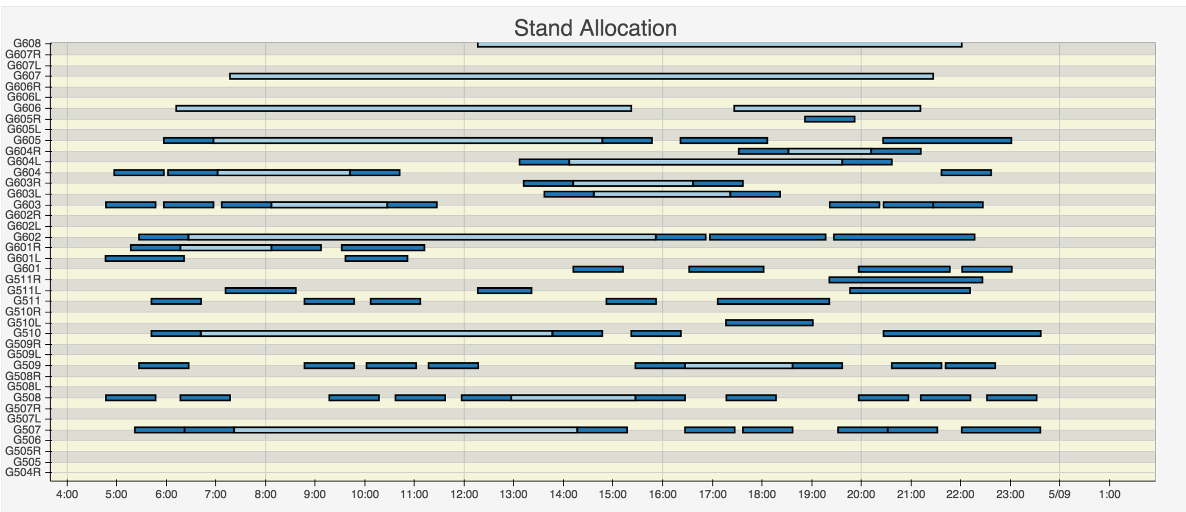

Figure 4.7: Example of the Visualisation of the Recoverable Robust Solution, with Allocations per Stands

Furthermore, the recovery per scenario of the recoverable robust solution is stored with the recovery variables. A visualisation of the values of the recovery variables is provided in Figure 4.8. The figure highlights one operation (red dot) in 5 scenarios, with 3 stands. The superscripts for the scenario number and the solution number are neglected to enhance readability. In the nominal scenario (0), the operation is allocated to stand 2 ($x_{1,2} = 1$). For scenarios 1 and 4 the operation is assumed to require recovery due to a conflict and is therefore re-allocated to another stand. The original decision variable in the solution is not changed, however the recovery variables for the specific scenario are updated.

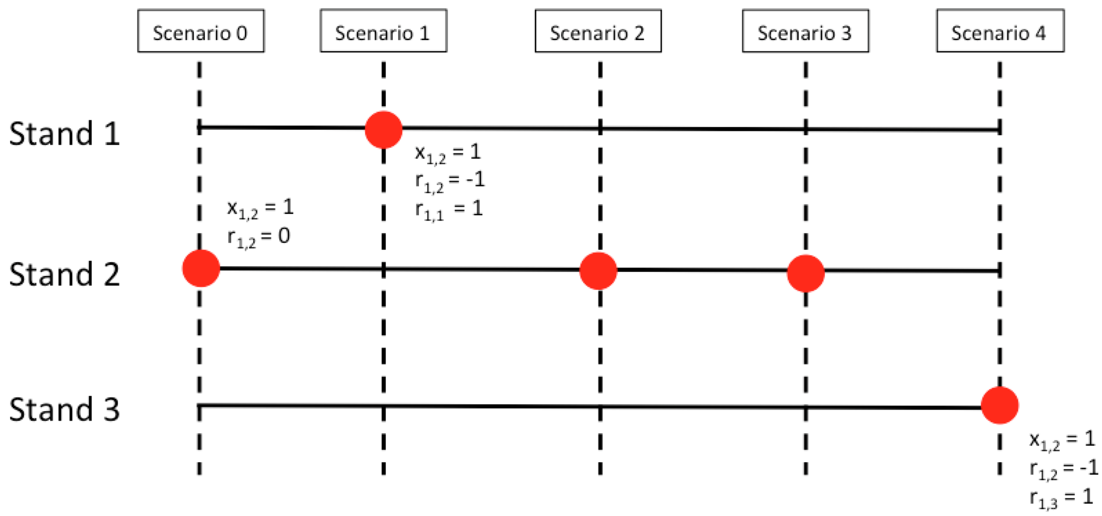

Figure 4.8: Example of the Recovery Variables Values in Different Scenarios

Detailed information will be provided to the airport controllers in the form of the number of re-allocations per stand and the alternative stand used for specific operations. Special attention can be given to the conflict operations to spot potential conflicts early during actual operations. The controller can re-allocate operations effectively with the information on the alternative stands.

Chapter 5

Case Study

To demonstrate the industrial applicability of the recoverable robust model, a case study is performed in collaboration with Guarulhos International Airport São Paulo (GRU). In this chapter first, GRU and their stand allocation methodology is introduced. Thereafter, the flight data analysis is explained. The flight data analysis aims to generate the inputs for the scenario generation of the recoverable robust stand allocation model: historical arrival time deviation distribution per flight number and percentage of equal arrival time deviation sign per flight number pair. Finally, the revenue data analysis is described. In the revenue data analysis the inputs for the affinity calculation of the objective function of the recoverable robust stand allocation model are determined.

GRU is the largest airport in South-America, handling around 40 million passengers per year and is operated by GRU Airport. In 2012, GRU Airport won the bid for the concession to operate GRU for 30 years. This not only led to large investments, but raised profit awareness inside the company as well.

GRU consists of 4 passenger terminals and a cargo terminal. Terminal 1/2 are both domestic and international terminals, and are undergoing a huge retrofit. In 2014 a new international terminal was opened, Terminal 3, adding a capacity of 12 million passengers per year. Finally Terminal 4 is a linear terminal, solely for domestic operations. The lay-out of GRU is presented in Figure 5.1 (Terminal 4 is located left of the apron 1). Outside of the figure, there are parking-only stands for long-stay aircraft visits located on the right of apron 6.

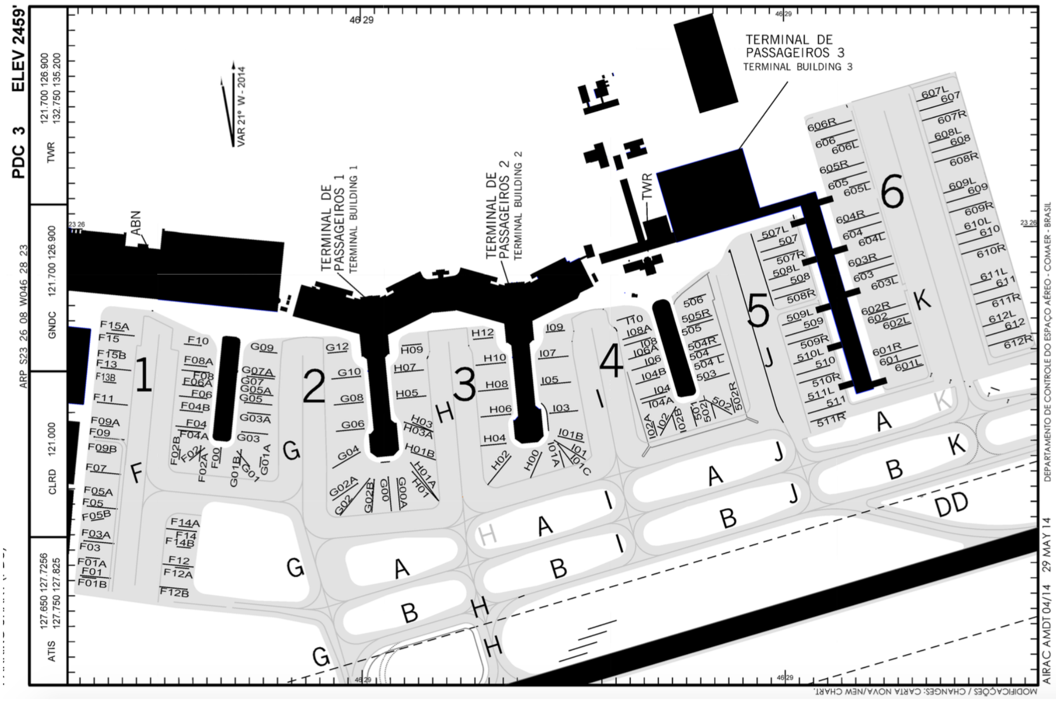

Figure 5.1: Lay-out of GRU Airport, with Terminal 3 between Apron 5 and 6

For the research project the focus is on Terminal 3, with 10 wide-body contact stands (each can be split into 2 narrow-body contact stands). The long-stay visits can be parked both at remote stands in zone 5 (3 wide-body) and 6 (7 wide-body), and the parking-only stands in zone 9 (13 wide-body). The parking stands are necessary since most international visits arrive early morning and do not depart until late afternoon.

The current process for stand allocation at GRU Airport is semi-automatic and based on a number of criteria. Before every day most flights are allocated to an arrival stand, but the departure stand is not yet determined. In practice, schedule disruptions cause coordinators to re-allocate operations to different stands, deviating from the initial schedule. As stated by one of the coordinators: "often there is no view of the future, only the current problem is solved. This often results in quite some unnecessary re-allocations due to previous actions of the controllers". In the actual allocation, this is confirmed since typically operations are allocated to Terminal 2 at the end of the day, when Terminal 3 is congested. The controllers can not find a suitable stand at Terminal 3 and allocate operations to Terminal 2 instead. GRU Airport uses certain criteria for their stand allocation (in order of importance):

- International vs. Domestic
- Number of Passengers
- Short stay vs. Long stay
- Connectivity

The criteria are utilised to determine which aircraft visits have preference for a contact-stand. For example, an international aircraft visit is preferred over a domestic aircraft visit. Typically the international visits have a higher passenger number as well, a further indication of the preference for international visits. For GRU Airport an international, short-stay aircraft visit with high connectivity and passenger number would have the highest preference. However, no clear metrics exist to determine the preference of one aircraft visit over another. The coordinators can drag-and-drop operations in the stand allocation system, where free available stands are highlighted. It is possible to input preference scores into this system to simplify the picking process for the coordinators, but this is not used. In the current system of GRU Airport, the estimated time of arrival of an aircraft can be inserted as well. The source can be either the airline, air traffic control or online sources as FlightRadar. The insertion is a manual process. When the estimated arrival time deviates too much from the planned arrival time it can be indicated as overlap in the system. If the overlap is large, the coordinator needs to recover the schedule manually. Without knowledge on the impact of a re-allocation, the recovery actions might result in even more required recovery.

The top two criteria for stand allocation at GRU Airport follow from Brazilian legislation, which requires an average of 95% of all international passengers to be allocated to a contact-stand. Penalties might be enforced by the Brazilian government if the 95% is violated. GRU Airport expressed a desire to aim for this percentage in the tactical stand allocation. Therefore, in the optimisation module of the recoverable robust stand allocation model the following constraint is added for the case study:

$$\sum_{i \in O} \sum_{j \in S_{ct}} x_{i,j} * Pax_i \,/ \sum_{i \in O} Pax_i \geq 0.95 \tag{5.1}$$

In the equation S_{ct} represents the set of contact-stands, a sub-set of $\mathbf{S}$. Pax_i contains the estimated passenger number for operation i. It has to be noted that according to GRU Airport the 95% can not always be achieved without compensation of international visits allocated to the other terminals.

As mentioned in Chapter 4, the recoverable robust stand allocation model can obtain results with multiple recoverable robust solutions. A selection mechanism is included in the recoverable robust stand allocation model to select the final solution. The percentage of passengers allocated to a contact stand is an important performance indicator for GRU Airport, therefore the selection of the final recoverable robust solution will be based on the average percentage of passengers allocated to a contact-stand over all the scenarios tested.

Another outcome of the recoverable robust stand allocation model is no recoverable robust solution. All feasible allocation plans could not be recovered in the recovery module, however a tactical stand allocation for GRU Airport is still required. GRU Airport could decide to allow allocation to more parking stands to increase the number of remote stands, or to allocate operations to other terminals. In the recoverable robust allocation model, the non-recoverable robust solution with the highest average percentage of passengers allocated to a contact stand will be selected, following the desire for a high percentage of passengers allocated to a contact-stand.

To support the research, two data sources are analysed; flight data and revenue data. In collaboration with GRU Airport, the required data-sets were determined and collected if possible. The following data is provided by GRU Airport:

- Historical Flight Data and Stand Allocations (1 year, August 2014 - July 2015)
- Stand lay-outs and Classifications
- Flight Schedules with Aircraft Classifications (July 2015, November 2015)
- Planned and Actual Allocations (November 2015)
- Minimum times required for (Dis-) Embarking
- Duty-free Revenue Data (August 2014 - July 2015)
- Pier Stores Revenue Data (July 2015)
- Terminal Lay-out and Store Locations
- Boarding-pass Data from Electronic Boarding Pass Scanners (1 week, March 2015)

These data-sets will be input into several parts of the recoverable robust stand allocation model. The flight data will aid the scenario generation and the revenue data will be analysed for the affinity calculation in the objective function of the stand allocation model. Please note that a list of airlines and their respective codes used in the data analysis is found in Appendix A.

5.1 Flight Data Analysis

The flight data analysis will be utilised in the scenario generation of the recoverable robust stand allocation model and consists of historical flight data and passenger numbers. The data is used to create historical arrival time deviation distributions per flight number. The distributions are input to the scenario generation methodology in the recoverable robust stand allocation model. Moreover, insights in the correlations and percentages of equal arrival time deviation sign (positive/negative) between flight number pairs are provided.

5.1.1 Data Description and Methodology

For the flight data analysis a full year of historical flight data (August 2014 - July 2015) is available. An example of the data format is provided in Figure 5.2. For each flight the scheduled time and actual time are provided, as well as the allocated stand and number of passengers.

Type	Flight ID	Acft_Type	Schedule Data	Schedule Time	Real Data	Real Time	Category	Pax DOM	Pax INT	Pax Conex DOM	Pax Conex INT	Pax Transit	Gate/Belt	Terminal	Qualifier	Box	From/To
DEP	AAL0930	B77W	3/1/15	1:10:00 AM	3/1/15	1:21:00 AM	INT	0	162	0	1	0	30	3	J	508	MIA
DEP	UAE0262	B773	3/1/15	1:25:00 AM	3/1/15	1:38:00 AM	INT	0	294	0	37	0	42	3	J	603	DXB
DEP	QTR0772	B77L	3/1/15	3:15:00 AM	3/1/15	3:21:00 AM	INT	0	120	0	15	105	38	3	J	605	DOH

Figure 5.2: Example of the Available Flight Data

The flight data analysis is performed using the SciPy library in Python. For every flight number with an occurrence higher than 30 an historical arrival time deviation distribution is generated, to ensure representative distributions. The historical arrival time deviations are divided into a high number of bins and a theoretical best-fit is determined by the $Kolmogorov - Smirnov$ test, with the evaluation of 23 theoretical distributions. In addition, arrival time deviation distributions are generated for each airline. These distributions will be used in the scenario generation methodology of the recoverable robust stand allocation model in case a distribution based on flight number can not be found. To avoid generalisation of the home-carrier of the airport (TAM airlines), the home-carrier's arrival time deviation distribution is split per region.

For the correlation analysis, Pearson's R, Spearman's Rank or Kendall's Tau correlation methodology can be utilised. The selection of the method will depend on the data. Both the correlations and percentage of equal arrival time deviation sign (positive/negative) is determined between flight number pairs.

5.1.2 Results

Based on the historical flight data, first the historical arrival time deviation distributions are determined. The correlation analysis and percentage of equal arrival time deviation sign analysis are described at the end of this section.

In Figure 5.3 the cumulative arrival time deviation distributions of TAM visits at GRU Airport is presented, both per region and overall. The regions are South-America (SA), Europe (EU) and North-America (NA). It is visible that the majority of the visits arrive before the scheduled time. From the division it shows that specifically the TAM aircraft from Europe arrive early. These aircraft visits could impact a non-robust tactical stand allocation significantly. The best fit theoretical distribution covering all arriving TAM visits is a non-central t (NCT) distribution (parameters: v = 2.90, $\mu = 1.01$, loc = -39.31, scale = 16.39).

The same analysis is performed per flight number and for the other airlines, to identify their arrival time deviation distributions. The distributions per flight number are provided in Appendix B. In Table 5.1 the results are displayed per airline, for both the percentiles of the arrival time deviations (i.e. 10th percentile presents the arrival time deviation for 10 percent of the arriving visits) and best-fitted theoretical distribution.

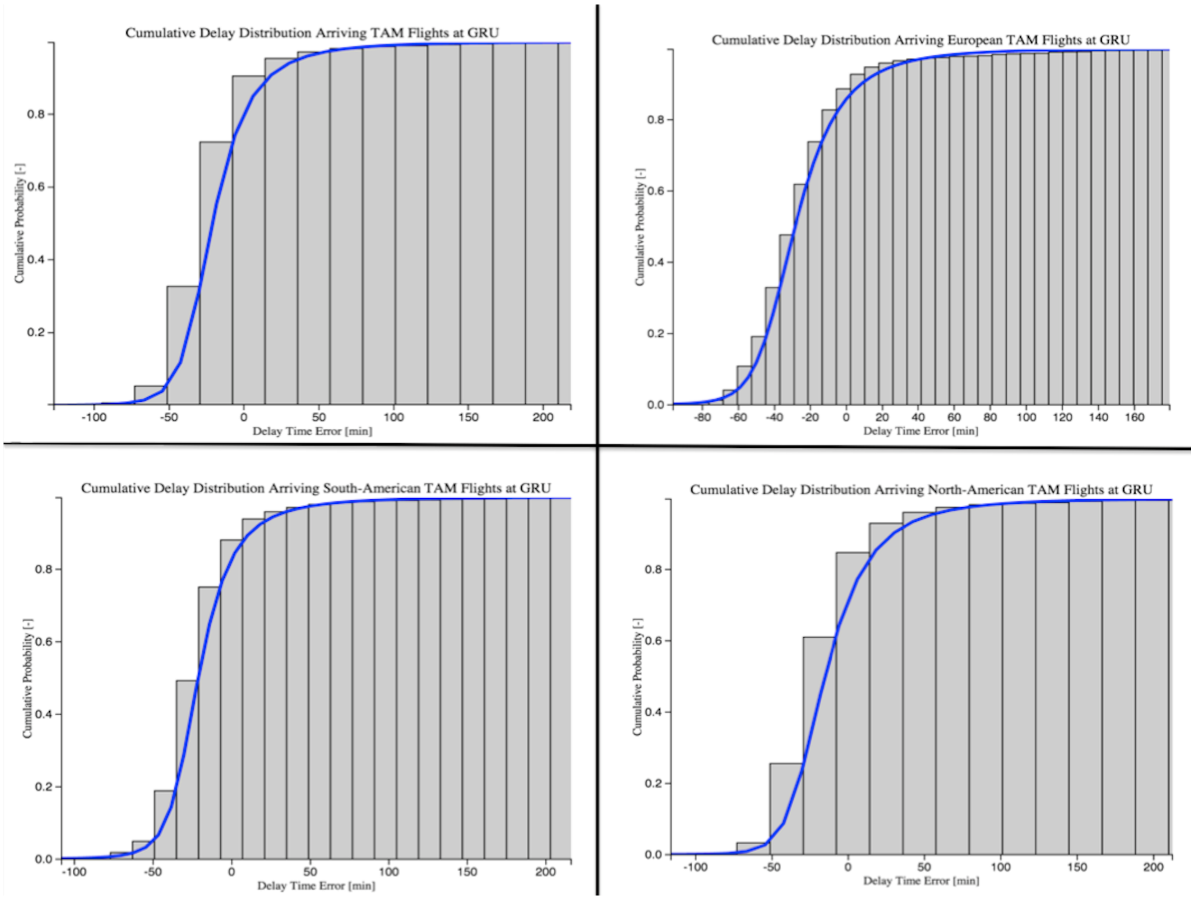

Figure 5.3: Cumulative Arrival Time Deviation Distribution of TAM Visits at GRU Airport

Airline	10th	20th	30th	40th	50th	60th	70th	80th	90th	Best Fit	Parameters
	Percentile [min]										
SWR	-21	-14	-8	-5	-1	2	6.8	11	21	nct	v = 2.24 mu = 0.42 loc = -7.14 scale = 11.66
IBE	-42	-34	-27	-21	-16	-10	-5	1	16	nct	v = 2.26 mu = 0.73 loc = -30.44 scale = 16.28
BAW	-25	-18	-12	-8	-4	3	10	20	39.4	nct	v = 2.02 mu = 1.11 loc = -21.68 scale = 14.61
TAP	-13.8	-4	3	8.8	14	20	27	35	48	nct	v = 3.30 mu = 0.67 loc = -0.12 scale = 19.28
AFR	-28	-20	-13	-7	-3	2	9	18	29	nct	v = 2.30 mu = 0.89 loc = -19.56 scale = 15.94
KLM	-21	-14	-10	-6	-3	0.8	5.1	12	24	nct	v = 2.41 mu = 0.87 loc = -14.45 scale = 11.91
DLH	-31.9	-23	-17	-12	-8	-2	3	10	22	nct	v = 1.76 mu = 0.74 loc = -20.50 scale = 14.08
AZA	-34	-20.8	-14	-7	-1.5	5	14	23	39.8	nct	v = 2.41 mu = 0.80 loc = -20.13 scale = 20.75
SAA	-53	-45	-37	-31	-23	-17	-11	-2	8	t	v = 1.80 loc = -24.98 scale = 18.75
QTR	-37	-30	-26	-22	-19	-15	-11	-5	5	nct	v = 2.69 mu = 0.70 loc = -28.22 scale = 12.21
ETD	-23.5	-13	-4	2	8	16	25.5	40	61.5	nct	v = 3.33 mu = 1.82 loc = -34.20 scale = 21.50
THY	-36	-28	-23	-16	-9.5	-2	5	18	34.5	genextreme	c = -0.10 loc = -18.10 scale = 23.47
CCA	-40.4	-33	-31	-27	-22	-18.2	-11.9	-3	4.7	nct	v = 2.51 mu = 1.08 loc = -37.93 scale = 12.94
KAL	-31	-23	-18	-13.4	-10	-5.6	-1	6.2	14.1	genlogistic	c = 1.49 loc = -15.79 scale = 11.89
SIA	-42	-35	-28	-23	-17.5	-12	-4.5	2	9.5	dgamma	a = 1.19 loc = -16.47 scale = 16.21
UAE	-39.7	-30	-22.1	-17	-10	-4	2	11	31	nct	v = 4.97 mu = 1.60 loc = -45.38 scale = 20.34
LAN	-25	-20	-15	-10	-6	-1	4	13	29	nct	v = 3.02 mu = 2.07 loc = -34.81 scale = 12.32
LAP	-55.4	-45	-39	-34.6	-30	-26	-22	-17	-6	t	v = 2.48 loc = -30.74 scale = 13.72
AAL	-32	-25	-20	-14	-9	-2	7	21	55	nct	v = 1.52 mu = 1.27 loc = -32.03 scale = 15.04
DAL	-29	-22	-18	-14	-10	-5	4	13	43.3	nct	v = 1.53 mu = 1.21 loc = -27.97 scale = 12.50
UAL	-34	-24	-17	-12	-6	0	8	21	47	nct	v = 3.58 mu = 2.51 loc = -54.07 scale = 17.59
ACA	-18.8	-10	-4	1	7	12	20	34.6	64	nct	v = 2.42 mu = 2.38 loc = -32.54 scale = 14.28
TAM SA	-42	-35	-30	-25	-21	-16	-11	-3.2	10	nct	v = 2.66 mu = 0.85 loc = -35.00 scale = 14.58
TAM NA	-42	-33	-27	-20.2	-15	-8	-1	9	24	nct	v = 3.19 mu = 1.43 loc = -43.95 scale = 18.32
TAM EU	-54	-44	-38	-33	-28	-22.4	-16	-8	5	nct	v = 3.46 mu = 1.21 loc = -50.64 scale = 16.86

Table 5.1: Arrival Time Deviation Percentiles and Theoretical Best Fit per Airline

Please consult Appendix A for a list of airlines and airports, and their abbreviations. Interestingly, for most airlines and flight numbers the NCT distribution provides the best fit for the arrival time deviation distributions. Most stochastic stand allocation models in literature assumed normally distributed flight data for their scenario generation. The distributions for GRU Airport indicate the importance of flight data analysis. The application of the recoverable robust stand allocation model to another airport will require a similar flight data analysis.

To indicate which airlines have a similar historical arrival time deviation distribution, a hierarchical cluster methodology is applied. Relative distances between the clusters are determined based on their centroid. Inputs are the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th and 90th percentiles of the historical data. The distance D for a percentile n is calculated as:

$$D_{al_{1_n},al_{2_n}} = ||c_{al_{1_n}} - c_{al_{2_n}}|| \tag{5.2}$$

in which al_1 and al_2 can represent any airline or cluster. The variable c stands for the centroid. The distance is calculated between each percentile. The resulting distance vector therefore is 9-dimensional. The magnitude of the distance vector between two airlines or cluster is then calculated as:

$$||\mathbf{D_{al_1,al_2}}|| = \sqrt{}(D^2_{al_{1_{10}},al_{2_{10}}} + \ \ldots \ + D^2_{al_{1_{90}},al_{2_{90}}}) \tag{5.3}$$

In Figure 5.4 the clusters created with the hierarchical clustering methodology are presented. On the y-axis the relative distance between the distributions is plotted. Most North-American airlines (i.e. DAL, AAL, UAL) are clustered relatively close, as well as some European airlines (KLM and SWR, BAW and AZA).

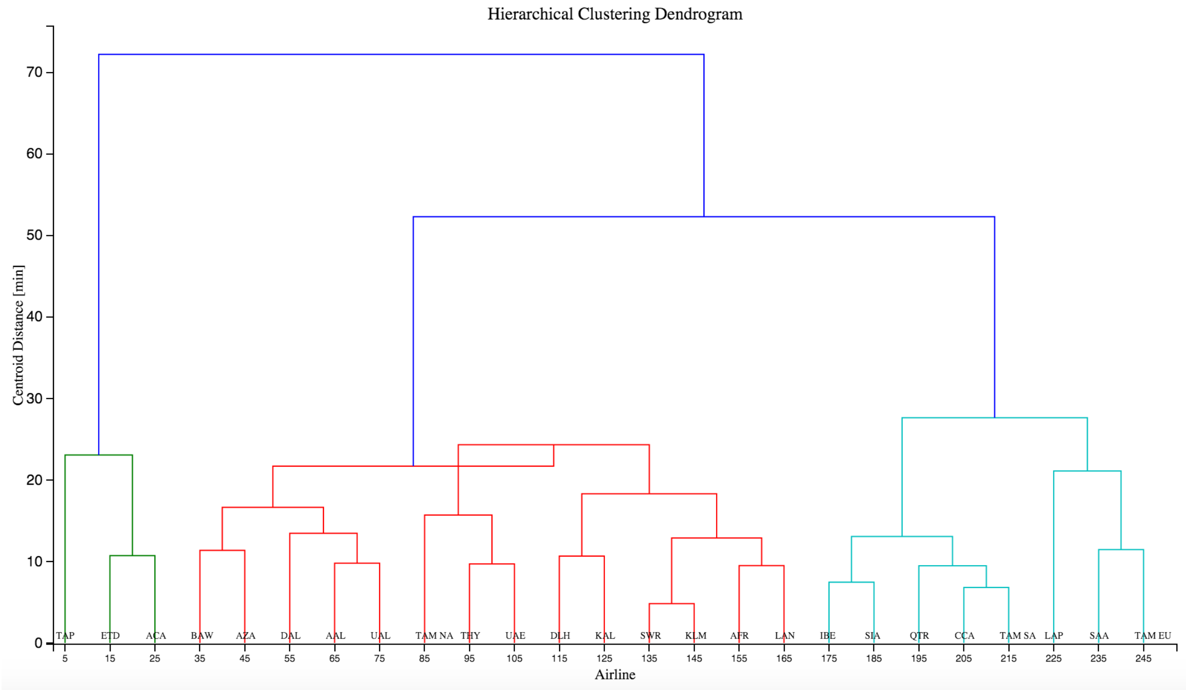

Figure 5.4: Centroid Clustering of Airlines Based on Arrival Time Deviation Distributions

Besides the arrival time deviation distributions, the scenario generation methodology requires another input: the percentages of same sign (positive/negative) arrival time between flight number pairs. The percentages are utilised to calculate the relative probability if an arriving visit will arrive early or late, depending on previously arrived visits in the last hour (and region, if possible).

However first, a correlation analysis is provided. As mentioned in Chapter 4 correlations are not utilised in the scenario generation methodology. High correlations between flight number pairs would enable the scenario generation methodology to relate the quantity of the arrival time deviation as well, and not only the sign (positive/negative).

Correlations can be calculated with Pearson's R correlation, the Spearman's Rank correlation or the Kendall-Tau correlation. Since the arrival time deviation is not normally distributed and the Spearman's Rank requires monotonic related data and is more sensitive to error and discrepancies in data, the Kendall-Tau correlation is selected. The Kendall-Tau checks whether a data pair is concordant or discordant. A concordant data-pair in the arrival time deviations has a deviation in a similar direction relative to the previous day (i.e. both greater than the previous day or both smaller than the previous day).

The calculated Kendall-Tau correlations for the flight number pairs demonstrated relatively low correlations. Only 0.3 percent of the flight-pairs showed a correlation above 0.5 or below -0.5, commonly accepted limits for a moderate relationship between data-sets. Figure 5.5 provides an overview of distribution of the found correlations. Most flight pairs demonstrate a low correlation and therefore the correlations are not used to relate the quantity of delay of one aircraft visit to another.

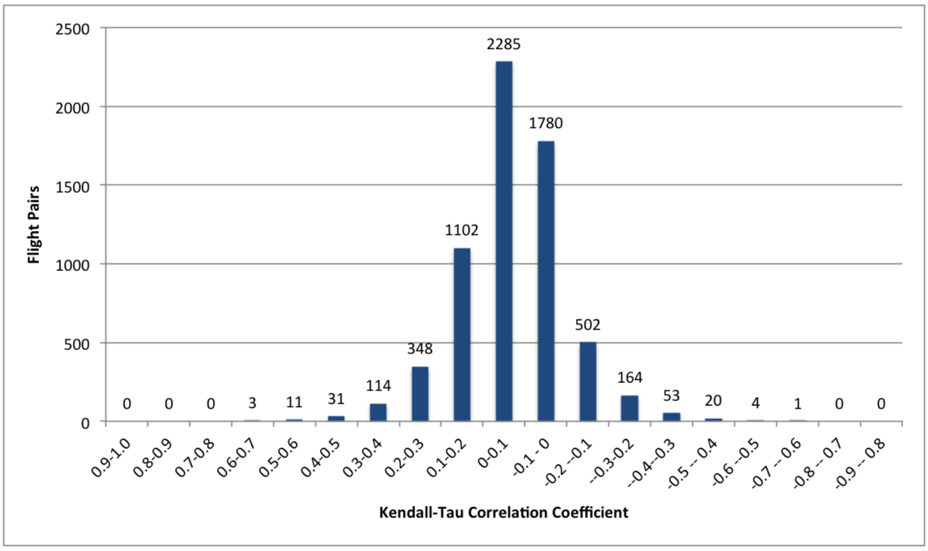

Figure 5.5: Overview of Occurrence of Correlations between Flight Pairs

Instead of the correlations, the determination of arrival time deviation sign (positive/negative) will be used in the scenario generation methodology. For every flight pair the percentage is calculated and stored for the recoverable robust stand allocation model. Figure 5.6 provides an overview of the occurrence of percentages for the flight pairs. The percentages are used as input to the scenario generation methodology to calculate the probability of an early or late arrival for a specific visit based on previously arrived visits.

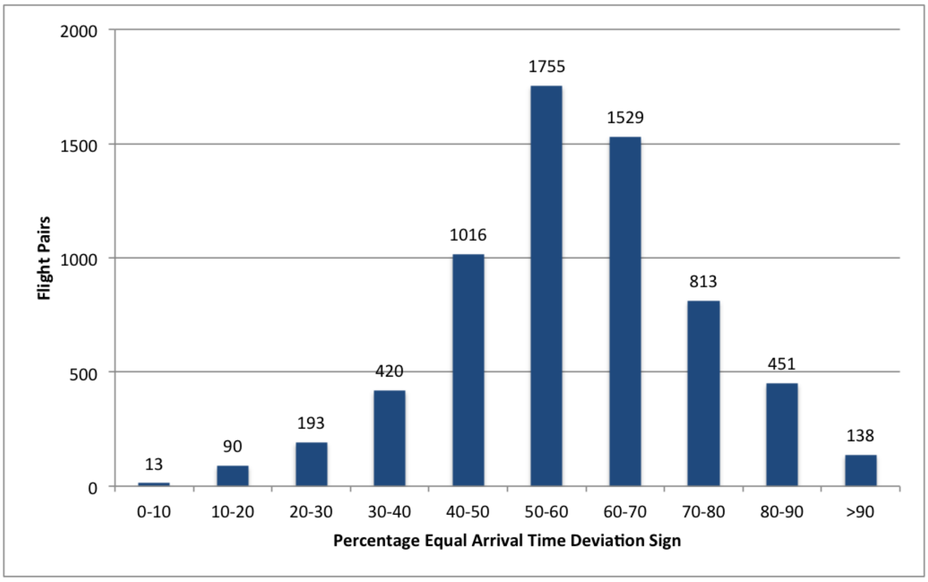

Figure 5.6: Overview of Occurrence of the Percentages Equal Arrival Time Deviation Sign between Flight Pairs

For other airports it is encouraged to perform similar data analysis, potentially correlations can be used effectively for other airports to relate the quantity as well. The performed flight data analysis will be included in the recoverable robust stand allocation model, to generate realistic scenarios for the scenario testing in the recovery module.

5.2 Revenue Data Analysis

The second part of the data analysis covers revenue data analysis. The revenue data analysis is utilised to determine the variables of the affinity calculations. The affinities are included in the objective function of the recoverable robust stand allocation model. Commercial revenue is becoming more important for airports, especially due to privatisation and competition effects [17]. In Chapter 4 the general idea of affinity (Section 4.1) and the required variables for the application of affinity in the stand allocation model (Section 4.2.1) were described. This section will describe the revenue data available at GRU Airport and the results obtained from the data analysis. The results will be included in the recoverable robust stand allocation model in the calculation of the affinity. Please recall the scope is the international terminal at GRU Airport (Terminal 3).

The revenue data consists of two parts: the terminal stores data and the pier stores. The main terminal store is a large duty-free store. Inside the pier several stores and restaurants are located, which will be included in the revenues analysis as well. The store locations are highlighted pink in Figure 5.7, the restaurants/bars blue. The terminal stores are located before the entrance of the pier, therefore they are not visible in the figure.

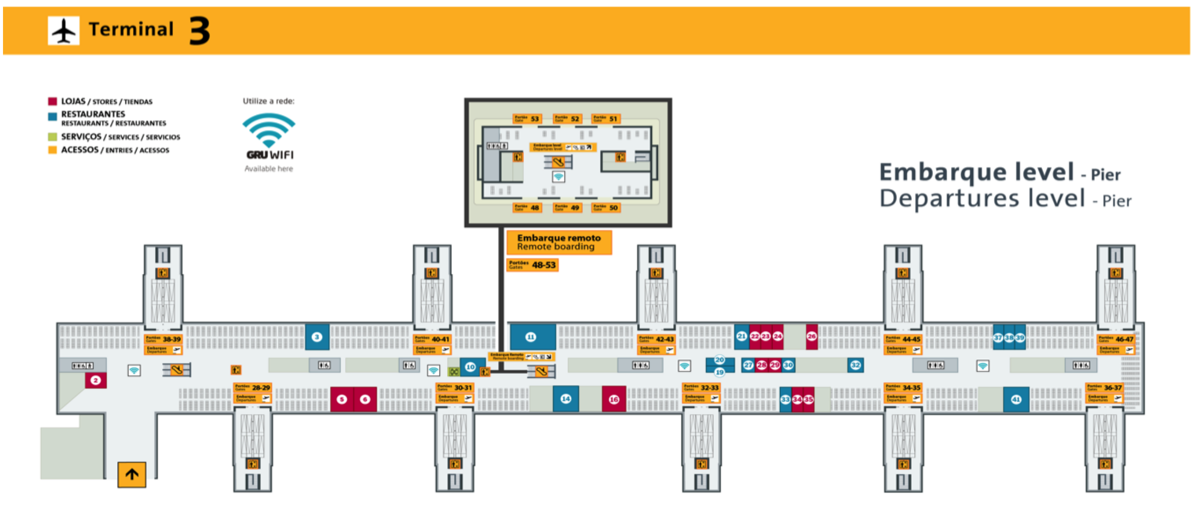

Figure 5.7: Pier Terminal 3 of GRU Airport

To complement the revenue data analysis, a dwell-time analysis is performed. Dwell-time is often considered to be an important characteristic for airport expenditure. However, it is not included in the affinity calculation of the revenue framework in the recoverable robust stand allocation model. To highlight the reasoning, a dwell-time analysis is provided in sub-section 5.2.3.

5.2.1 Data Description and Methodology

The data for the terminal stores consists of one year sales per passenger data (August 2014 - July 2015, in dollars), available per month per airline. The pier store data is very limited, only total revenue data per store for a month (July 2015) is available. To be applicable to stand allocation, the pier revenue data needs to be related to locations inside the pier. To simplify the locations the pier of Terminal 3 at GRU is divided into 5 zones, 1 per each opposing pair of gates (See Figure 5.7, a zone stops after the 2nd gate of the pair). The objective is to determine the influence of each zone on the revenue, for both terminal and pier stores. The main data-link is historical stand allocation, with data on passenger numbers and airlines allocated to the respective zones. Unfortunately, extensive passenger tracking data is not available. It will therefore not be possible to accurately determine the sales per passenger and the β weighting factors.

5.2.2 Results

The objective of the revenue analysis is to be able to perform the affinity calculations. Consequently, the average sales per passenger needs to be estimated for both the terminal and the pier stores, as well as the α and β weighting factors.

5.2.2.1 Terminal Stores

The data for the terminal stores is split per airline and month. Almost all passengers have to pass the terminal stores in order to walk to their gate. The average sales per passenger (in dollars) per airline over August 2014 - July 2015 is provided in Figure 5.8. The category "Others" represents airlines as Turkish Airlines and Qatar Airways, for which no separate data is available. The other acronyms can be found in the list of airlines in Appendix A

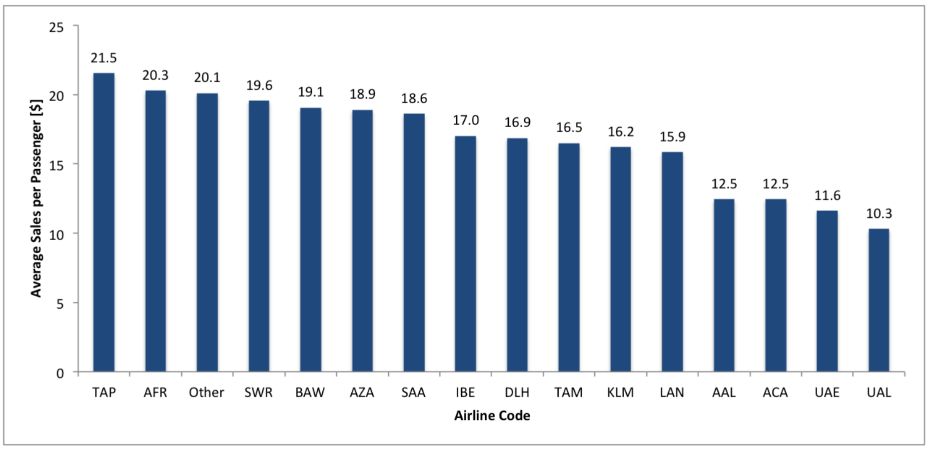

Figure 5.8: Average Sales per Passenger at Departure in the International Terminal (August 2014 - July 2015)

For the airlines TAM, LAN and SAA the average is computed for the period October 2014 - July 2015, these airlines started operations in the international terminal only in October 2014. On average, the European carriers spend more compared to the North-American carriers. The average sales per passenger per airline will be a direct input in the affinity calculation for the objective function of the recoverable robust stand allocation model.

Ideally, it should be possible to compute the average sales per passenger per origin, destination and even per day. It would enable more detailed conclusions from the commercial revenue at the airport. Furthermore, it is recommended to perform a detailed forecast of the sales per passenger including, amongst others, the dollar exchange rate and seasonality. Due to the large time gap in data availability between the sales data (up to July 2015) and planned allocations (November 2015), the average sales per passenger as demonstrated in Figure 5.8 will be utilised in the affinity calculation for the case study.

The next step is the estimation of the relative importance of each zone for the duty-free store in the terminal (the α weighting factor in the affinity calculation).

5.2.2.2 α-Calibration

The α weighting factors in the terminal stores affinity calculation are determined by combining the average sales data with historical stand allocation and passenger numbers. The α factors represent the importance of each zone for the total revenue of the airport. The assumption is that the importance decreases with the increasing distance from the terminal. To simplify the determination of the α factors, the pier terminal is divided into several zones. In Figure 5.9 an overview of the zones inside the pier is provided.

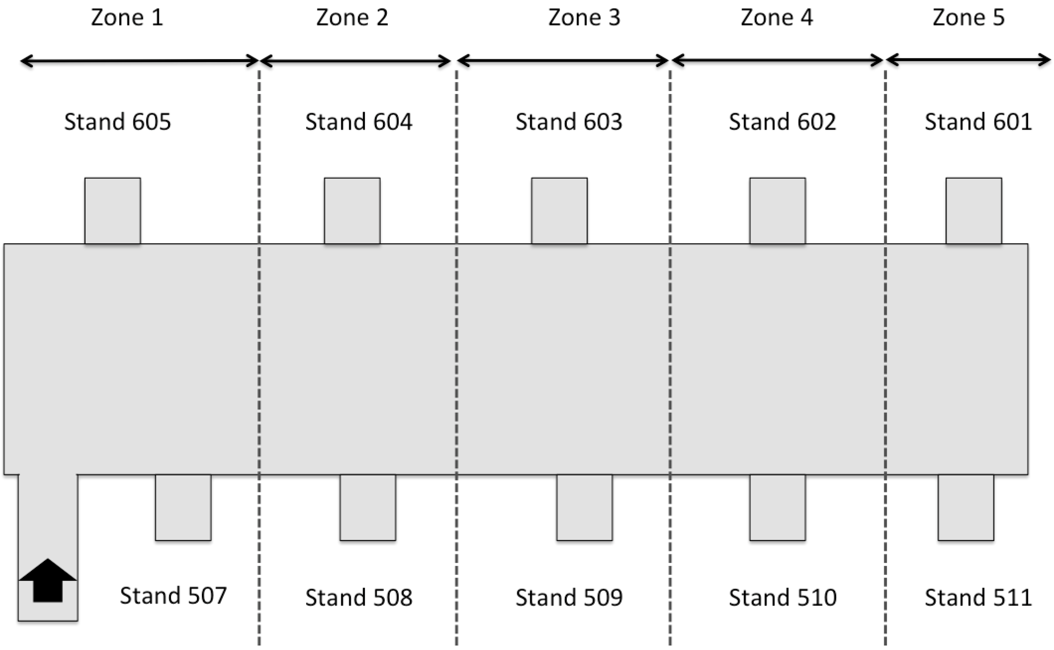

Figure 5.9: Overview of the Pier Zones

For each month in the period August 2014 - July 2015 the total sales per zone (in dollars) for the terminal stores is calculated. The calculation consists of the evaluation of all visits in the month, with the computation of their average sales per passenger for that month for the airline multiplied by the passenger number of the aircraft visit. The resulting value is then added to the sub-total for the zone at which the aircraft visit was allocated. For example, if Visit 1 is allocated in Zone 4 the average number of passengers of the aircraft visit is multiplied by the average sales per passenger for the respective airline and added to the subtotal of Zone 4. Ideally, the variation between days would be included in this analysis to derive more detailed conclusions.

For all five zones the percentage of the sales with respect to the total sales (dollars) is determined for each month in the period August 2014 - July 2015. In Figure 5.10 an overview of the sales percentage per zone is provided. The assumption is a linear decreasing effect towards the end of the pier, visualised by a linear trend-line.

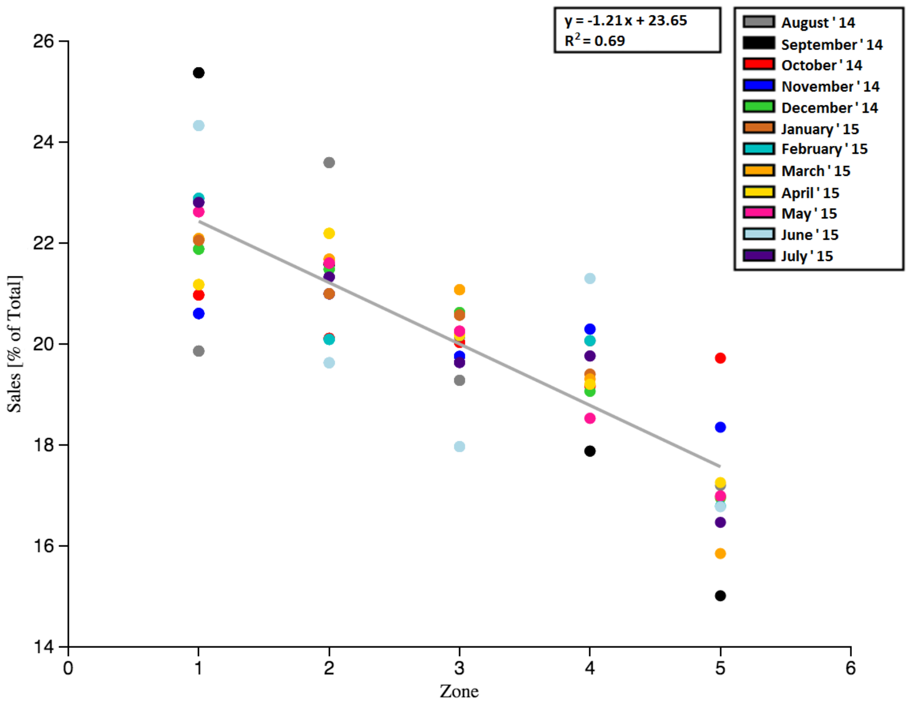

Figure 5.10: Percentage of Terminal Sales per Zone per Month

The R^2-value (0.69) demonstrates that a linear relationship seems a reasonable assumption. The sales percentages per zone are affected by the airlines allocated to the zone and the number of visits allocated to each zone. This effect, and other factors (variation in spending per day, passenger behaviour, dollar exchange rate), introduce deviations which can explain the R^2 value. However, since GRU Airport has no fixed airline preferences for specific stands and aims to include variation in their allocations, it should provide a relatively realistic view.

The linear trend-line ($y = -1.21x + 23.65$) is used to determine an estimated sales (dollars) percentage for each of the zones. With Zone 1 as reference value, since it is closest to the terminal stores, a respective weighting factor for the other zones is determined. Table 5.2 provides an overview of the estimated sales percentages and α weighting factors for the respective zones.

Zone	Sales [% of Total]	α_j [-]
1	22.44	1.0
2	21.23	0.95
3	20.02	0.89
4	18.81	0.84
5	17.60	0.79

Table 5.2: Estimated Sales Percentages and α Weighting Factors per Zone

For the terminal stores affinity, the α factors provide the final input for the calculation. The factors are combined with the sales per passenger (dollars) and estimated passenger number for an aircraft visit. As example, the terminal stores affinity for a SWR visit with estimated 200 passengers allocated to Zone 5 will generate a terminal affinity of:

$$A^t_{i,j} = \alpha_5 * sp_i * Pax_i = 0.79 * 19.6 * 200 = \$3097 \tag{5.4}$$

5.2.2.3 Pier Stores

The second part of the affinity in the objective function of the stand allocation model, the affinity calculation for the pier stores was not straightforward due to limited data. Some assumptions were required in order to calculate the pier affinities. The two aspects required for the pier affinity calculation are the average sales per passenger and the β weighting factors. With one month of total sales in dollars per store available (July 2015), it was relatively complicated to split the total sales into sales per passenger.

An aspect that could help to split the monthly total sales is the passenger flow inside the terminal. If the amount of passengers to which the store is exposed can be determined, an adjusted sales per passenger can be calculated. Advanced tracking systems can provide data on the passenger flow based on Wi-Fi and Bluetooth. Unfortunately, these type of systems are not in place at GRU Airport.

A first step to obtain a realistic assumption for the passenger flow is to determine the number of passengers that are certain to pass specific zones, due to their stand allocation. These passengers would need to pass the store in order to walk to their gate. Based on historical stand allocation and passenger numbers a distribution along the terminal can be made. This is visualised for July 2015 in Figure 5.11, where each number in the zone represents the percentage of total passengers that is required to pass through the zone. For example, all passengers need to pass through Zone 1 to walk to their gate, hence the 100%. Furthermore, 17.8 % of the passengers had a gate allocated in Zone 5 and therefore had to walk through all zones. Please note that only operations allocated to a contact-stand are included in this analysis.

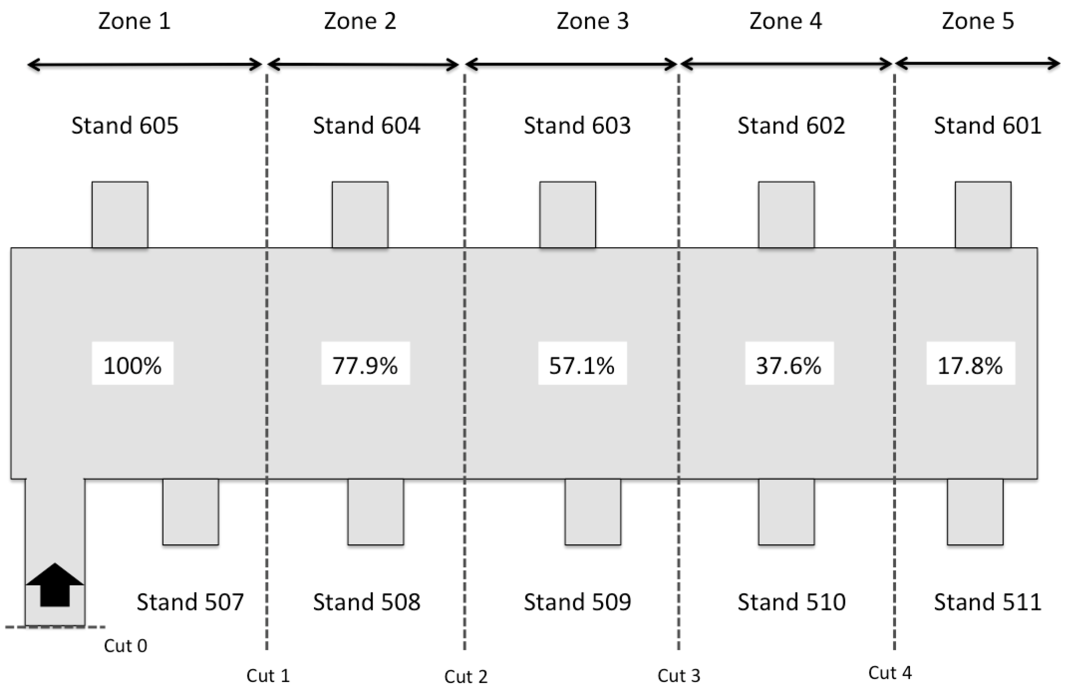

Figure 5.11: Overview of the Pier Zones and Respective Percentage of Passengers that need to pass the Zone

The second step in the passenger flow estimation is to include the behaviour of passengers. Passengers may not walk straight to their gate and stay there waiting, but may wander around the pier. It is tried to estimate the area of the terminal in which passenger wander, the trading area of passengers. For example, a passenger allocated to Zone 1 may visit stores in the other zones of the pier. Without the availability of advanced tracking systems, the trading area of passengers is estimated by measuring the flows in the pier. The flows inside the pier were estimated by experimental measurements, counting passengers on several locations inside Terminal 3 of GRU Airport. Both passengers moving towards the end of the pier (Pax In) and passengers walking back to the terminal (Pax Out) were counted at every zone border (a cut). An overview of the measurements is provided in Table 5.3, for the locations of the cuts please refer to Figure 5.11.

Measurement	Date Time	Cut	Pax In	Pax Out	Pax Out / Pax In [%]
M1	October 12th 14:30 - 15:30	Cut 1	456	94	20.6
M2	October 12th 15:45 - 16:45	Cut 1	340	124	36.5
M3	October 12th 17:00 - 18:00	Cut 2	463	212	45.8
M4	October 12th 18:15 - 19:15	Cut 0	1028	193	18.8
M5	October 12th 19:45 - 20:45	Cut 0	1410	293	20.8
M6	November 17th 17:30 - 17:45	Cut 3	69	20	29.0
M7	November 17th 17:45 - 18:00	Cut 2	44	28	63.6
M8	November 17th 18:00 - 18:15	Cut 2	43	41	95.3
M9	November 17th 18:15 - 18:30	Cut 1	73	34	46.6
M10	November 17th 18:30 - 18:45	Cut 1	78	26	33.3
M11	November 25th 15:45 - 16:00	Cut 3	41	28	68.3
M12	November 25th 16:00 - 16:15	Cut 4	20	14	70.0
M13	November 25th 16:15 - 16:30	Cut 4	27	19	70.4
M14	November 25th 16:30 - 16:45	Cut 3	31	48	64.6

Table 5.3: Passenger Flow Measurements at GRU Airport

The measurements could only be performed in October and November, but will be utilised for the July 2015 pier revenue data. It limits the validity of the pier affinity calculations, but should still provide an overall indication of the passenger flows. Measurements M4 and M5 at Cut 0 were performed to obtain an indication if passengers would walk back to the terminal stores. This backward flow was around 20 percent, a further indication the importance of the terminal affinity in the revenue framework.

From the measurements, the goal is to obtain an assumption for the additional flow due to passenger movements, on top of passengers that are simply walking towards their respective gate. The assumption is based on the ratio between the Pax In and Pax Out for all respective cuts in Table 5.3. Moreover, the additional flow a zone will be expressed as a percentage of the passengers allocated to the previous zone.

Based on the measurements, an additional passenger flow of 33 percent between Zone 1 and Zone 2 is assumed. This indicates that 33 percent of the passengers allocated to Zone 1 will enter Zone 2. The percentage of Zone 1 passengers is added to the passengers required to pass through Zone 2 to reach their gate. For the border between Zone 2 and Zone 3 an additional flow of 50 percent will be assumed (i.e. 50 percent of the passengers from Zone 2 will enter Zone 3, although in practice it will be a mix of passengers allocated to Zone 1 and Zone 2). Please note that measurement M8 is neglected because of the extreme high value compared due to a proximate boarding process.

For the end of the pier, the measurements show a larger variation due to a lower passenger flow. At the measurement time of M6 the aircraft allocated at Stand 602 started their boarding process, leading to a relative high number of passengers entering the zone. Therefore the approximation of 30 percent back-flow is considered too low. Considering the other measurements at the end of the pier and extrapolating from the measurements of the previous zones, the additional for Zone 4 and Zone 5 is assumed to be 67 and 75 percent of the passengers allocated to the previous zone (3 and 4 respectively). Advanced passenger tracking systems could provide more detailed and accurate data and it is encouraged to implement such systems to improve the available data for the affinity calculations.

Table 5.4 provides an overview of the estimated number of passengers that are required to pass the zone (Pax Pass) and the assumed additional flow (Extra) per zone. The total number of passengers that is exposed to a store (Pax TA) is then determined for every zone z as:

$$Pax\ TA_z = Pax\ Pass_z + Extra_z * Pax_{z-1} \tag{5.5}$$

in which Pax_{z-1} the number of passengers allocated to the previous zone, expressed as a percentage of the total number of passengers. To exemplify, the Pax TA for Zone 2 is calculated as: 77.9 + 0.33 * (100-77.9) = 85.2 percent. In Table 5.4 the values for all zones are displayed.

Zone	Pax Pass$_z$ [% of Total]	Extra [%]	Pax TA$_z$ [% of Total]
1	100	0	100
2	77.9	33	85.2
3	57.1	50	67.5
4	37.6	67	50.7
5	17.8	75	32.7

Table 5.4: Percentage of Passengers in Trading Area (Pax TA) determined with the Passenger Flow Estimations

It has to be noted that the values in the table are considered rough estimates, ideally one would have a large database with realistic passenger tracking to validate the passenger flows. The total sales in dollars per store is translated to a sales per passenger value with the estimated passenger number in the trading area for July 2015 of the specific store. The results are summarised in Table 5.5.

Name	Segment	Sales [$]	Sales per Pax [$]	Zone
365 DELI	Cafeteria	195324.96	0.52	1
CAFE DO PONTO	Cafeteria	38126.02	0.10	1
H STERN	Boutique	138094.50	0.43	2
TRACK & FIELD	Fashion	48731.10	0.15	2
CAFFE PASCUCCI	Cafeteria	70089.91	0.22	2
PIOLA PIER	Fast food	116953.00	0.37	2
V.CAFE	Cafeteria	94871.92	0.38	3
MARGARITA VILLE	Restaurant	129236.30	0.51	3
GO FRESH	Cafeteria	16103.85	0.06	3
BRUNELLA	Fast food	8106.00	0.03	3
CHILLIBEANS	Convenience	11062.35	0.06	4
PUKET	Fashion	25421.82	0.13	4
SCARF ME	Fashion	24322.62	0.13	4
LIZ LINGERIE	Fashion	7388.28	0.04	4
FOM	Convenience	35274.71	0.19	4
EMPORIO DO MEL	Cafeteria	12058.73	0.06	4
BACIO DI LATE	Cafeteria	39966.14	0.21	4
HAVAIANAS	Fashion	60426.74	0.32	4
TOSTEX	Fast food	52674.41	0.28	4
BRASIL SOUVENIRS	Boutique	38650.48	0.20	4
KONI/ SPOLETO	Fast food	72128.25	0.59	5
ON THE ROCKS	Restaurant	63233.54	0.52	5
CASA DO PDQ PIER	Cafeteria	110102.01	0.90	5

Table 5.5: Overview of Pier Stores Sales, Sales per Pax and Zone

The determination of the sales per passenger per store is important for the pier affinity calculation. The only unknowns left are the β weighting factors. The β factors indicate the relative importance of allocating a specific visit to a specific stand with respect to the sales in the zones. Unfortunately, the level of detail of the available data (only total store revenue data for one month, no realistic passenger tracking) does not allow for a reasonable estimation of the β weighting factors for GRU Airport. Consequently, for this case study the weighting factors are initially set to 1 for the zone where the store is located and 0 otherwise. As result, an aircraft visit only generates pier affinity inside the zone it is allocated.

To continue with the example of the SWR aircraft in Zone 5 the pier affinity will be:

$$A^p_{i,j} = \sum_z \beta_{i,j,z} * sp_{i,z} * Pax_i = 1 * (0.59 + 0.52 + 0.90) * 200 = \$402 \tag{5.6}$$

Clearly, the affinity generated at the pier is significant lower than the terminal store affinity. A detailed estimation of the β-factors would improve the pier affinity calculation. The combined terminal and pier affinity for allocating the SWR flight to Zone 5 (Stand 601 or 511) is:

$$A_{i,j} = A^t_{i,j} + A^p_{i,j} = \$3097 + \$402 = \$3499 \tag{5.7}$$

Extension of the affinity calculation for all operations, provides the affinity for each operation-stand combination. The affinities and the results of the flight data analysis provide the required inputs for the recoverable robust stand allocation model.

5.2.3 Dwell-time

Dwell-time is commonly accepted as an important parameter for expenditure in airport terminals. This section aims to highlight why dwell-time is not directly included in the revenue framework to determine the affinities for the objective function of the recoverable robust stand allocation model.

GRU Airport provided boarding pass scan data for the week March 22th - 29th 2015, with which a dwell-time for every passenger is calculated. It has to be noted that after the boarding pass scan, the passenger still needs to clear security and pass the federal police. The effective dwell-time of the passenger will thus be lower than the dwell-time reported in this section.

Since only boarding pass data for March 2015 is available, revenue data from the terminal stores for March 2015 is utilised as well. In Figure 5.12 the relation between dwell-time and terminal stores sales per passenger is plotted. Although for some airlines a longer dwell-time seems to lead to a higher expenditure per passenger, this is not the case for all. For example, LAN and AFR had a relatively high expenditure per passenger with a relatively short dwell-time.

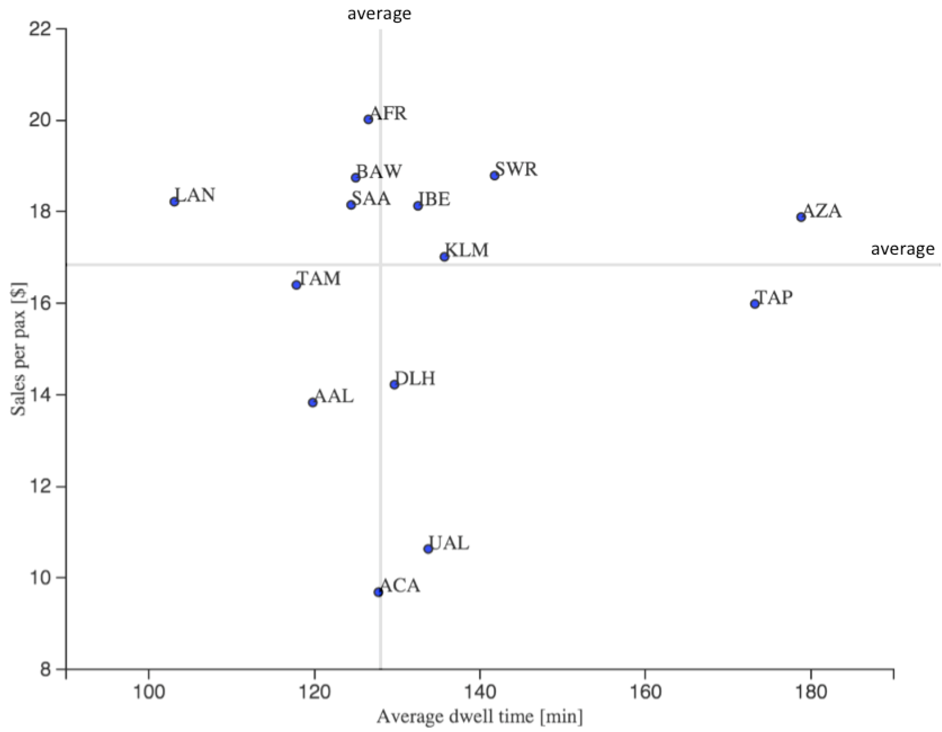

Figure 5.12: Dwell-time versus Average Expenditure Per Passenger March 2015

Unfortunately, a more detailed division (flight number, destination) can not be made due to a lack of data. In the recoverable robust model, affinities for stands close to the terminal building are higher due to the higher sales at the terminal stores. As result, aircraft visits with high passenger numbers or high sales per passenger are preferred for stands close to the terminal. If a longer dwell-time would always result in higher sales, the visits with long dwell-time would generate a higher affinity. However, visits with a low dwell-time and high sales are preferred in the revenue framework as well. Effectively, this increases the potential shopping time for these high-revenue passengers due to a limited walking distance to their stand.

Chapter 6

Verification and Validation

Verification and validation are a crucial part of the research project, especially in the development of a mathematical model. Verification demonstrates the correct working of a model, while validation assesses if the appropriate model is built. Verification for the recoverable robust stand allocation model will be executed by means of simple test cases, while the validation test will consist of the examination of a flight schedule of the airport to check if it works according to the standards of GRU Airport. Extensive discussions with the responsible employees at GRU Airport are required to ensure the correct model is built.

6.1 Verification

Verification prevents mistakes in the final results and makes potential bugs in the model easier to spot. For the recoverable robust stand allocation model the two main parts to be verified are the optimisation module and recovery module. The split between the modules allows for the testing of multiple requirements in the same test case. Three tests were developed to demonstrate the working of the constraints and recovery strategies.

Test 1: The first test focuses on demonstrating the working of the constraints of the stand allocation model in the optimisation module. Constraints regarding towing, adjacency and stand classifications are evaluated. The test set consists of 7 visits, 12 contact stands (4 wide-body) and 1 parking position. All visits except 1 are wide-body. The narrow-body visit has a high affinity with stand G509L and adjacency constraints should prevent the usage of stand G509 (other visits have a preference for this stand as well) at the same time. Furthermore, the visits are given specific flight times to ensure a tow for the long-stay visit to the parking position (G913) is required. Finally, the scenarios (5 generated) are described to generate overlap, to force the recoverable robust stand allocation model to return a non-recoverable robust solution due to no recovery possibilities. The allocation of Test 1 is provided in Figure 6.1.

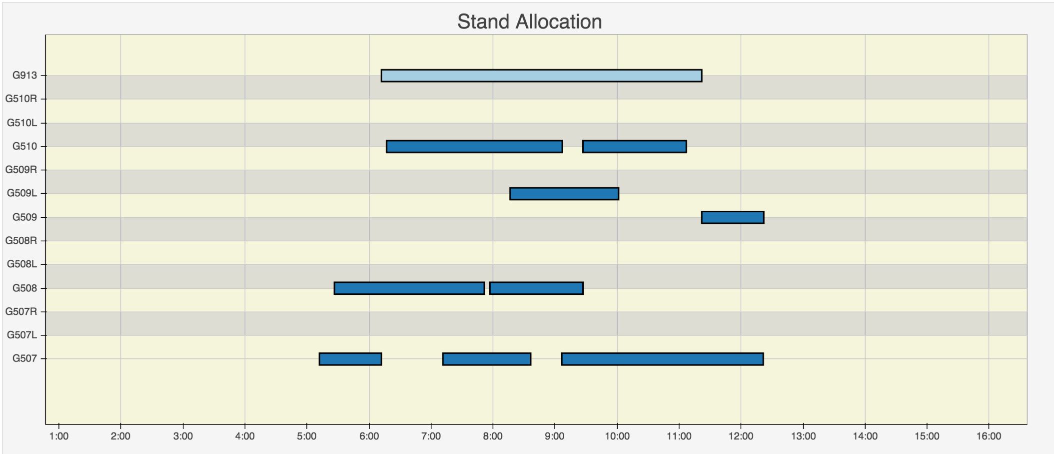

Figure 6.1: Results of Verification Test 1

The result shows the long-stay visit has been split, which confirms the working of the tow constraints. The consideration of affinity is demonstrated as well (the narrow-body visit is allocated to G509L). Moreover, the adjacency constraint is effective since G509 is not used when G509L is occupied.

When checking the log, it is found that solution 0 is selected even though it is not a recoverable robust solution, as expected. In one of the scenarios, the overlap between the two flights located at stand 508 is too large and there are no options to recover. The result indicates the crucial flights for this planning (at stand G508) as information for the controller.

Test 2: The second test focuses on two of the recovery strategies in the recovery module; recovery by waiting and towing of a long-stay parking operation. It takes the simplistic case of 2 contact stands and a parking stand, combined with 3 visits (1 long stay, 2 short). Initially the 2 short term visits do not have time overlap. Two specific scenarios are generated, one which creates an overlap less than 5 minutes and a scenario where the two short-stay visits have a longer overlap. These specific scenarios will require recovery by waiting and by towing a long-stay parking operation. The resulting allocation for the nominal scenario is showed in Figure 6.2.

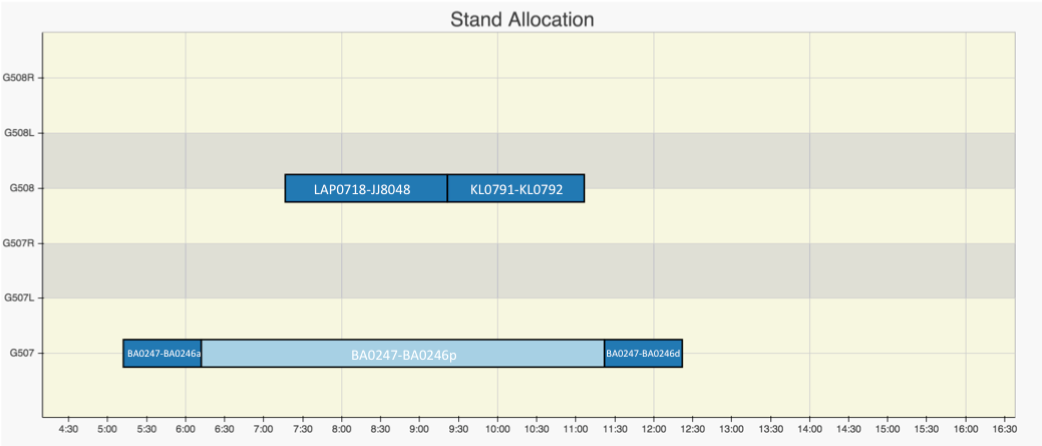

Figure 6.2: Results of Verification Test 2

The initial result shows the long-stay visit at G507 and the two short stays at G508. The allocation results for the respective scenarios are summarised in Table 6.1.

Name	Scenario 0	Scenario 1	Scenario 2
LAP0718-JJ8048	G508	G508	G508
KL0791-KL0792	G508	G508	G507
BA0247-BA0246a	G507	G507	G507
BA0247-BA0246p	G507	G507	G901
BA0247-BA0246d	G507	G507	G507

Table 6.1: Allocation for the Scenarios in Verification Test 2

For Scenario 1 no recovery was needed even though there existed a small overlap, the test adhered to the expectations. In the second scenario the KL0791-KL0792 operation is re-allocated to G507, which requires the tow of BA0247-BA0246p to parking stand G901. Both recovery types proved to work correctly in the verification test.

Test 3: Finally, the remaining recovery of the recovery module needs to be verified: re-allocation to a free stand. The test consists of two short-stay visits (LAP0718-JJ8048 and KL0791-KL0792) and two contact-stands, with both a high affinity for the same stand (G507). Initially there is no overlap between the visits i.e. they can be allocated to the same stand. A scenario is generated with overlap between the visits and recovery is required. The result is summarised in Table 6.2.

Name	Scenario 0	Scenario 1
LAP0718-JJ8048	G507	G507
KL0791-KL0792	G507	G508

Table 6.2: Allocation for the Scenarios in Verification Test 3

The overlap is correctly solved by re-allocating one of the visits to another stand. This provides confidence in the working of the recovery algorithm and allows for continuation towards validation of the complete model with real flight schedules.

6.2 Validation

Validation ensures the model simulates the operational situation at Guarulhos International Airport of São Paulo (GRU) correctly. Validation of the model consists of operational and revenue aspects, therefore it is crucial to involve experts from all involved departments at GRU Airport. Main points of contact at GRU Airport during validation process were the strategic planning department and the planning & performance department. Moreover, conversations with employees from the commercial department provided useful insights for the revenue framework validation. Validation of the recoverable robust stand allocation model was a continuous, iterative process. Topics in the validation process were:

- Objectives for the stand allocation at GRU Airport
- Revenue objectives at GRU Airport
- Constraints for stand allocation apparent at GRU Airport
- Working process of the controllers at GRU Airport
- Lay-out of the model output

In the conversations, the model and current project status was actively discussed. Points for improvements were incorporated in the model as good as possible. The final model is validated based on a validation test and several statements from the employees at GRU Airport that aim to highlight the applicability for GRU Airport. Firstly the results of the validation test will be discussed.

6.2.1 Validation Test

For the validation test of the model, a real day-schedule from GRU Airport is tested. Since the revenue data is available up to July 2015, it is decided to use a busy day in July, July 9th. The schedule consists of 66 aircraft visits, with a total of 142 operations.

The goal is to evaluate the recoverable robust solution provided by the recoverable robust stand allocation model and compare it with an actual day of operations at GRU Airport. The recovery moves required will be highlighted and should demonstrate the effectiveness of a recoverable robust solution. For the test 30 feasible allocation plans will be generated and tested against 20 scenarios.

The recoverable robust solution is further described with some important indicators; objective function value (OF) and percentage of passengers assigned to a contact stand (both for the nominal flight schedule and average over all scenarios). The running time and number of recoverable robust (RR) solutions found will be discussed as well.

The initial step in the validation test is to generate the 30 feasible allocation plans. However, an initial run with the 95% passenger to contact-stand constraint indicated that it is not feasible to satisfy the constraint for the flight schedule of July 9th. The responsible managers mentioned that the 95% for Terminal 3 is usually unachievable but it is compensated by international flights serviced at contact-stands at the other terminals. This improves the overall percentage for international passengers at a contact-stand to above the required 95 percent. After discussion with GRU Airport, it is decided that relaxation of the 95% is acceptable, however the aim for the deterministic problem should be to approximate the 95%. When possible, the constraint will be enforced in the case study in the generation of the feasible allocation plans. Otherwise, the constraint will be automatically relaxed by the recoverable robust stand allocation model.

After the relaxation of the 95% constraint, a re-run of the model did not obtain a recoverable robust solution from the feasible allocation plans generated. A review of the provided non-recoverable robust solution demonstrated a high occupancy of the remote and parking-only stands, resulting in few recovery possibilities. GRU Airport tends to utilise other stands outside Terminal 3 if they require extra capacity, both for parking and boarding operations. The addition of extra parking stands would increase the recovery possibilities during the scenario testing for the recoverable robust stand allocation model. However, GRU Airport expressed that ideally the aircraft are parked in the areas for Terminal 3. To provide the recoverable robust stand allocation model with more recovery possibilities, it is decided to offer 3 extra parking-only stands for the case study, at the cost of a penalty. For July 9th, 2 parking positions outside Terminal 3 were utilised by GRU Airport. Furthermore, GRU Airport allocated 5 operations to Terminal 2 for embarkation/disembarkation operations. For the additional parking stands a penalty of $ 648 is imposed (equivalent to the cost of 2 towing operations [44]).

After including the additional parking stands, 27 out of the 30 feasible allocation plans were found to be recoverable robust solutions to the stand allocation problem (see Table 6.3). Over all the scenarios an average of 90.4 percent of the passengers is allocated to a contact stand. The allocation can be found in Appendix C. Due to the higher affinity relatively close to the terminal, many (dis)embarkation operations are allocated to nearby stands (G507, G508, G604, G605). In Table 6.3 the percentage of passengers allocated to a contact-stand for both the nominal solution and average over the scenarios (PC and PC AVG respectively) and number of recoverable robust solutions are provided.

From the recoverable robust solution to the stand allocation problem the controllers can extract more information. The number of changes per operation and alternative stands used during recovery are indicated (see Appendix C). The tactical allocation could be coupled with an operational

Test	OF [$]	PC [%]	PC AVG [%]	Time [s]	# RR sols
July 9th	348198	92.8	90.4	728	27

Table 6.3: Characteristics of the Recoverable Robust Solution of the Validation Test of July 9th

allocation system minimising the deviation from the allocation. However, this is not part of the scope of the research project.

6.2.1.1 Comparison Operations July 9th

To further validate the obtained recoverable robust solution for the allocation of July 9th, it is exposed to the actual operating times of the aircraft visits on July 9th. For the operations the blocks-on time and blocks-off time for the aircraft are utilised. In case this information is not available (since the recoverable robust stand allocation model and GRU Airport might split the long-stay visits differently) the landing or take-off time is utilised.

For the recoverable robust solution of July 9th, 10 operations had to be re-allocated during operations due to schedule conflicts larger than 5 minutes. The operations, initial allocated stand, new allocated stand and reason for the conflict are provided in Table 6.4.

Operation	Initial Stand	Re-allocated to	Reason
TP0087-TP0082a	G507	G511	Arrives early
AA0951-AA0930a	G507	G504	Over 12 hours late
IB6827-IB6824a	G508	G602	Arrives early
AC0090-AC0091a	G510	G505	Previous departs late
JJ8095-JJ8070	G603	G607	Arrives Early
JJ8085-JJ8108a	G603	G610	Arrives Early
JJ8081-JJ8090a	G604	G608	Arrives early
JJ8111-JJ8110a	G605	G603	Arrives Early
JJ8129-JJ8032a	G605R	G507R	Over 3 hours late

Table 6.4: Recovered Operations and Allocated Stands for July 9th

With the recoverable robust solution, five operations had to be re-allocated to a remote stand (G504, G505, G607, G608 and G610) during actual operations. Two operations suffered from a large time deviation relative to the provided schedule. Other re-allocations were mainly due to early arrivals in the peak hours. GRU Airport could decide to send several TAM (JJ) operations Terminal 2 to increase the percentage of passengers allocated to a contact-stand. The recoverable robust solution maintained a passenger-to-contact percentage of 86.2 percent. If the remote TAM operations would be allocated to a contact-stand in Terminal 2, the overall percentage would be above 91 percent. Furthermore, the percentage could be further increased by towing IB6827-IB6824p from contact-stand G511 and allocating AC0090-AC0091a to G511. In comparison, on July 9th GRU Airport only allocated 78.5 percent of the passengers to a contact-stand at Terminal 3. The recoverable robust stand allocation model demonstrated to provide an effective stand allocation solution for the validation test.

6.2.1.2 Limitations

The validation test demonstrated the effectiveness of the recoverable robustness approach in the stand allocation problem. The solution found complies with the most important operational constraints, and can be recovered easily in all scenarios. Furthermore, the methodology showed capable of handling real-time changes in operations for July 9th. However, there are still some factors that limit the validity of the solution:

- **Preference parking:** In the optimisation model parking positions are considered homogeneous. Parking an aircraft at a remote stand or a parking position has no effect on the objective function value. Some shorter parking operations are allocated to the stands 901-913, while in practice this is not desired due to the longer tow time. The issue can be resolved by controllers and is relatively complicated to include in the model without compromising the objective function, therefore the current solution is sufficient. As a future improvement detailed towing costs or towing time could be included as a factor in the optimisation model.
- **Contact Stand Utilisation:** Due to the strong influence of the terminal stores in the affinities, contact-stands close to the terminal are used more often indirectly leading to more conflicts in the scenarios. Furthermore, shops at the end of the pier might be less satisfied when only few are allocated to their zones. However, the nature of the objective will not change for the thesis project and therefore the current method is satisfactory for the project. The revenue analysis has to be revisited with all required data before implementation at GRU Airport.
- **High Demand:** There might be infeasible flight schedules for the optimisation model, due to a lack of stands available for the amount of visits. GRU Airport has the possibility to send some of these visits to other terminals, however the model does not. Since the scope focuses on Terminal 3, the model stays within the scope, however the flight schedule will require manual adjustment in case of exceeding demand. To provide more recovery possibilities and enhance capacity, three extra parking positions can be utilised during the scenario testing.
- **Parameter Estimation:** Currently the model uses one (dis)embarkation time for all aircraft. The 60 minutes used seems reasonable since the average disembarkation time on July 9th was 69 minutes, with a standard deviation of 17 minutes. As a model improvement the average historical (dis)embarking time could be used or at least split per aircraft class. GRU Airport emphasised that for the international aircraft a single value is acceptable.
- **Variation in Allocations:** At peak hours, GRU Airport typically needs to board some international flights at remote stands. If the model is run 10 times, the same flights will be allocated to the remote stands. GRU Airport expressed a desire for more variation in the solution, which could be a good improvement for the model but given the scope of the project it does not compromise the validity of the model.

- **Runtime:** Although the test for July 9th tested 30 solutions with 20 scenarios within 15 minutes, ideally more scenarios and solutions are tested. GRU Airport expressed the importance for a valid stand allocation is more important than the runtime. After discussion with GRU Airport, the goal is to not exceed a runtime of 1 hour for the other tests.

6.2.2 Statements

In addition to the validation test, the following statements should further highlight the validity of the created model for GRU Airport. The statements are based on requirements stated by GRU Airport employees. Per statement an explanation will be provided to what extend the statement is met.

Statement 1: ***"The model provides a feasible stand allocation for GRU Airport"*** The solution generated by the recoverable robust stand allocation model should be feasible for the operations at GRU Airport. The assessment of feasibility was an iterative process, with discussions about the operational constraints, aircraft classifications and stand classifications. For the recovery module, the recovery actions were discussed, and the feasibility was assessed by checking the recovery variables and log of the model. After discussing multiple results and demonstrating the validation test, GRU Airport expressed confidence in the feasibility of the model for their operational situation at Terminal 3.

Statement 2: ***"The stand allocation output has to be generated in a reasonable time"*** Although runtime is of less importance in tactical stand allocation, still the allocation should be provided in a reasonable time. It might be better to evaluate more feasible solutions to obtain a more robust solution. The runtime of the recoverable robust stand allocation model is dependent on the number of scenarios and number of solutions. The validation test demonstrated possibility to generate a fast output. However, to obtain more (and potentially better) recoverable robust solutions GRU Airport accepts a longer runtime.

Statement 3: ***"Recovery strategies simulate the decision process of the controllers"*** Due to the iterative process, this statement is validated. The recovery strategies are in fact based on the discussions and the decision process of the controllers. Currently 3 strategies are included in the model, which are used by the controllers during daily operations. In future research other strategies could be included, such as a swap of two operations.

Statement 4: ***"Spending at the airport is stimulated by the stand allocation"*** The stimulation of spending behaviour of passengers can focus on already existing customers or on the other passengers. After meetings with the retail manager, strategic planning executives and other commercial representatives, it was decided to focus on current high-spending aircraft visits. Therefore, to stimulate spending these passengers should be allocated close to their favourite shops or restaurants. This is validated in the stand allocation, airlines with high expenditure at the terminal stores are allocated close to these stores.

Statement 5: ***"Even if no solution can be recovered, the model should still output a feasible solution"*** This statement can be viewed as a specific addition to statement 2. As explicitly specified by the airport, it is unacceptable when the recoverable robust stand allocation model does not return a solution (assuming sufficient stand capacity). The limited recovery might not always be sufficient for the scenarios hence the model would not be able to provide a recoverable robust solution. In that case, it was decided in collaboration with GRU Airport to provide the non-recoverable solution with the highest average percentage of passengers allocated to a contact-stand over the scenarios.

6.3 Conclusion

Given the scope of the project and after discussion with the employees of GRU Airport, it is concluded that the recoverable robust stand allocation model is valid for the research project. An adjustment is made to include extra parking positions in the recovery stage, at the cost of a penalty, to increase recovery possibilities. This is in line with current GRU procedure, where other parking positions are utilised if necessary. The verification tests provided confidence in the working of the model, both operational constraints and objectives are implemented well.

The recoverable robust stand allocation model provided an acceptable solution for the operations at GRU Airport. Some factors, like parking preferences and variation in the allocations, limit the validity of the recoverable robust stand allocation model. The aim of GRU Airport to maintain a 95% passenger-to-contact ratio for international flights is usually not feasible with the capacity at Terminal 3. In case the optimisation module does not obtain feasible allocation plans with the 95% constraint, it is decided to relax the constraint.

Furthermore, GRU Airport expressed the desire to test more than 30 feasible allocation plans as well as to test more than 20 scenarios. The runtime for the recoverable robust stand allocation model should not exceed 1 hour. A runtime analysis should provide insights in a reasonable problem size for the time-frame of an hour. To allow for enough recovery possibilities, three additional parking-only stands are included in the recoverable robust stand allocation model. In case of limited capacity, GRU Airport utilises parking stands outside of the international terminal as well. The addition of the extra parking possibilities increases the probability to find a recoverable robust solution.

Chapter 7

Results

This chapter evaluates the results of the recoverable robust stand allocation model and compares the outcomes with the allocations of GRU Airport. The allocations from GRU Airport consist of the real allocations at the day of operations, since GRU Airport only plans a limited number of operations the day before (i.e. the tactical planning is not complete). After discussion with GRU Airport, the initial buffer time in the recoverable robust stand allocation model is set to 15 minutes for the case study.

Moreover, the outcomes of the recoverable robust stand allocation model will be compared with the results of a strict robust stand allocation model. In the strict robust stand allocation model recovery is not allowed, therefore the strict robust solution satisfies all generated scenarios. A strict robust model is comparable to most stochastic stand allocation models found in stand allocation literature, in which all scenarios were required to be satisfied.

The goal of the comparison is to evaluate if the recoverable robust stand allocation model is capable of providing a robust, yet less conservative solution to the stand allocation problem relative to the strict robust stand allocation model.

In addition to the comparison between recoverable and strict robustness, the objective function of the recoverable robust stand allocation model, maximisation of affinity, is compared with other objectives for stand allocation to highlight the trade-off an airport can make. The objectives considered are: minimisation of walking distance, minimisation of tows and maximisation of passengers allocated to a contact stand.

However, first the problem size determination for the case study will be explained based on a runtime analysis. Section 7.2 provides a detailed explanation of one case (November 19th) of the case study, while Section 7.3 provides an overview of all tested days in the case study. The deviation from the optimum, the objective function comparison and the comparison with GRU planning will be provided in this section as well. Finally, Section 7.4 highlights the impact of the

95% constraint, the buffer time, the scenario generation approach and provides insights in the number of recovery changes per stand.

7.1 Problem Size

To ensure a reasonable runtime for the recoverable robust stand allocation model, a runtime analysis is performed. The goal of the runtime analysis is to obtain a reasonable problem size for the runtime of one hour. Two important factors for the problem size are the number of feasible allocation plans generated and number of scenarios to be tested. Both impact the final recoverable robust solution and runtime of the recoverable robust stand allocation model. A higher number of feasible allocation plans increases the probability of obtaining a (better) recoverable robust solution, while a higher number of scenarios limits this probability. In contrast, a recoverable robust solution that satisfies more scenarios is considered more robust.

To analyse the impact, the schedules of November 19th and November 20th are subjected to various numbers of scenarios and feasible allocation plans.

7.1.1 Number of Feasible Allocation Plans

Firstly, the number of scenarios is set to 20 and the model is run with several numbers of feasible allocation plans. Furthermore, the tests are repeated for three different seeds of the random number generator, to include variation in the scenarios. The results for 19/11 and 20/11 are highlighted in Figure 7.1.

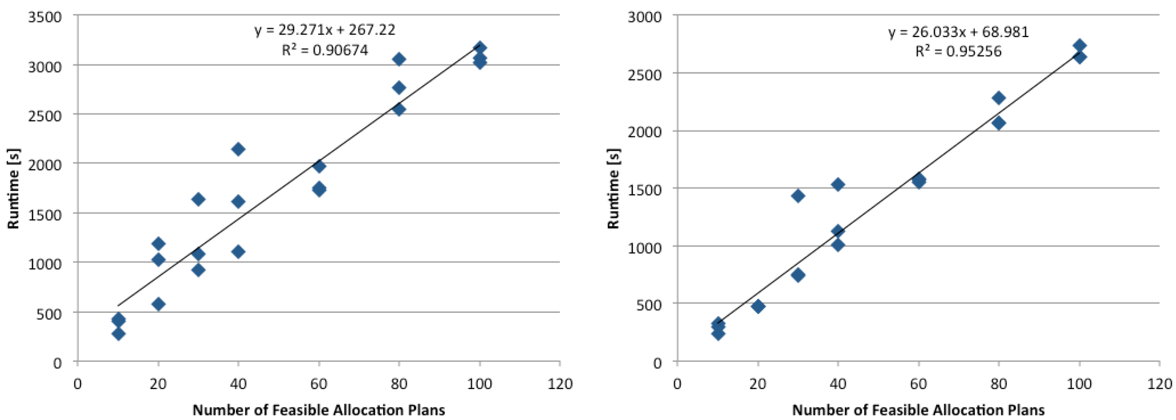

Figure 7.1: Impact of Number of Feasible Allocation Plans on Runtime for 19/11 (left) and 20/11 (right)

The number of feasible allocation plans has a linear impact on the runtime of the model. For generation of the set of feasible allocation plans the recoverable robust stand allocation model has to be solved as many times as the number of feasible allocation plans specified. A problem size with 100 feasible allocation plans and 20 scenarios seems achievable within the time limit of an hour. In Figure 7.2 the number of recoverable robust solutions is plotted against the number feasible allocation plans for three different seeds of the random generator.

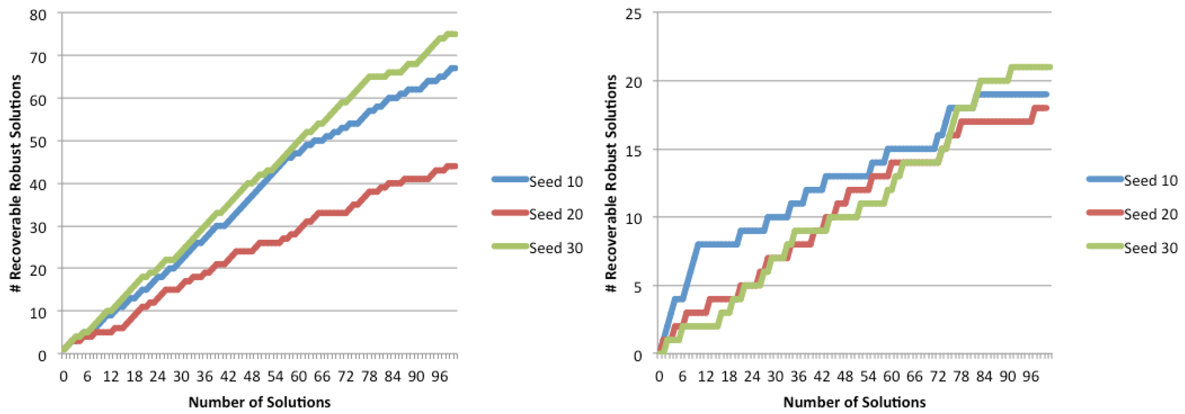

Figure 7.2: Number of Feasible Allocation Plans vs. Number of Recoverable Robust Solutions for Different Seeds for 19/11 (left) and 20/11 (right)

The number of recoverable robust solutions increases with the number of feasible allocation plans generated. A larger number of recoverable robust solutions increases the probability of obtaining a solution with a higher average percentage of passengers allocated to a contact-stand in the solution selection mechanism of the recoverable robust stand allocation model.

7.1.2 Number of Scenarios

For the number of scenarios a similar runtime analysis was performed with the number of feasible allocation plans set to 40. Again, the test was executed for three different seeds of the random generator. The effect of the number of scenarios on the runtime is shown in Figure 7.3

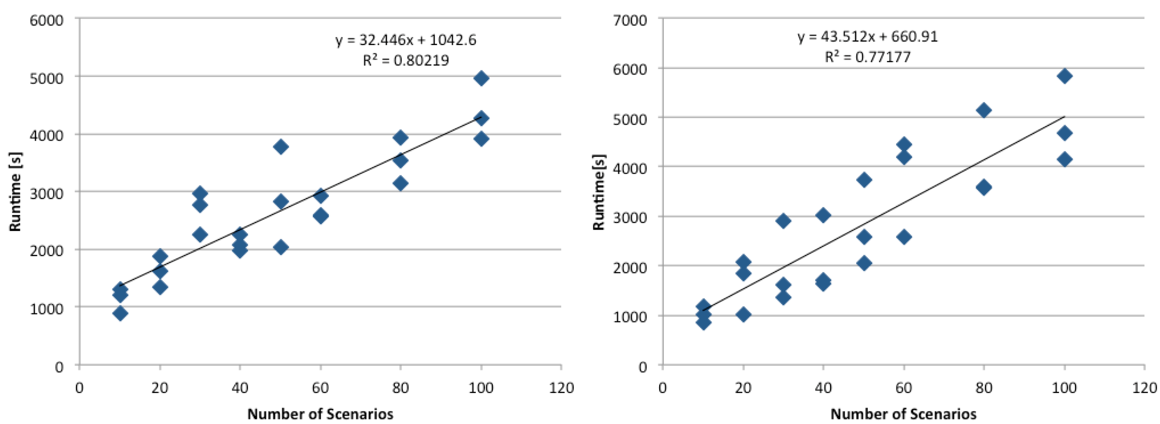

Figure 7.3: Impact of Number of Scenarios on Runtime for 19/11 (left) and 20/11 (right)

The number of scenarios has a linear relationship with the runtime of the recoverable robust stand allocation model as well. The number of recoverable robust solutions found is plotted against the number of scenarios in Figure 7.4.

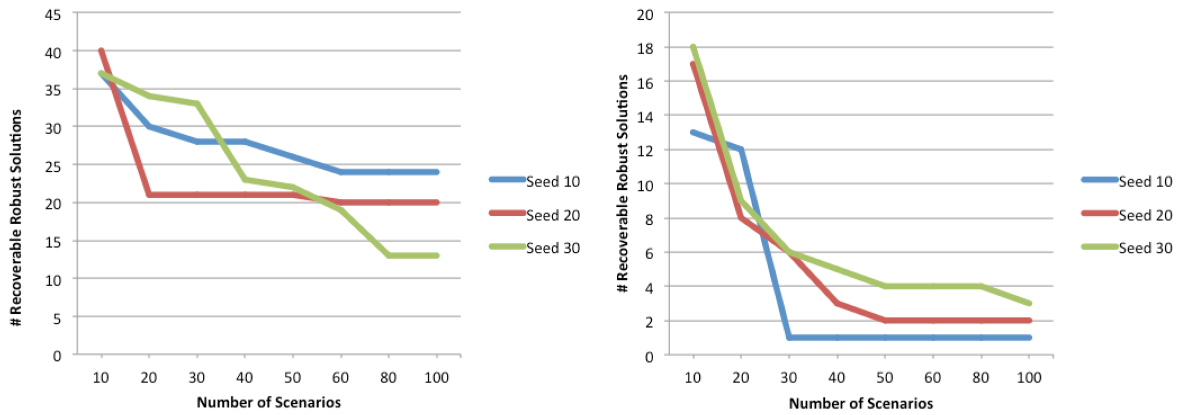

Figure 7.4: Number of Scenarios vs. Number of Recoverable Robust Solutions for Different Seeds for 19/11 (left) and 20/11 (right)

First, the number of recoverable robust solutions decreases sharply with increasing scenario numbers. After a certain amount of scenarios the number of recoverable robust solutions tends to remain relatively constant. It is therefore recommended to at least maintain a scenario number between 40 and 60 scenarios for the case study.

7.1.3 Conclusion

The goal of the recoverable robust stand allocation model is to determine a less conservative, yet robust solution. Consequently, the focus for the test cases is slightly on the generation of feasible allocation plans. The number of scenarios is recommended to be at least 40 to obtain a robust solution. The runtime of the model should remain close to an hour, therefore the parameters for the case study are set to 60 feasible allocation plans and 40 scenarios.

7.2 Solution November 19th

This section explains the solution for the case of November 19th. The flight schedule of November 19th consists of 70 aircraft visits, with a total of 158 operations. At the airport 73 stands are considered, of which 13 parking-only stands. For the scenarios in the recovery module 3 extra parking-only stands may be utilised, but only if no other option exists and at a cost of $648 per usage.

The stand allocation of the recoverable robust solution for November 19th and the list of alternative stands per operation are provided in Appendix D. The list provides insight in the total number of changes for an operation and the alternative stands used in recovery.

In Figure 7.5 and Figure 7.6 a part of the allocations for two scenarios of November 19th are provided. Parking operations are coloured light-blue and (dis)embarkation operations dark-blue. Please note that the vertical axis represents the names of stands available at the airport. In practice the recoverable robust stand allocation model produces an html plot with zooming options and labels to aid the airport controllers.

The allocations of operations AF0454-AF0457a (green), 4C3505-4C3506a (pink) and JJ8103-JJ8114a (yellow) are highlighted for the nominal scenario (i.e. scheduled times) and Scenario 5 respectively in Figure 7.5 and Figure 7.6. These operations had to be recovered in Scenario 5 due to schedule conflicts and are therefore re-allocated to different stands.

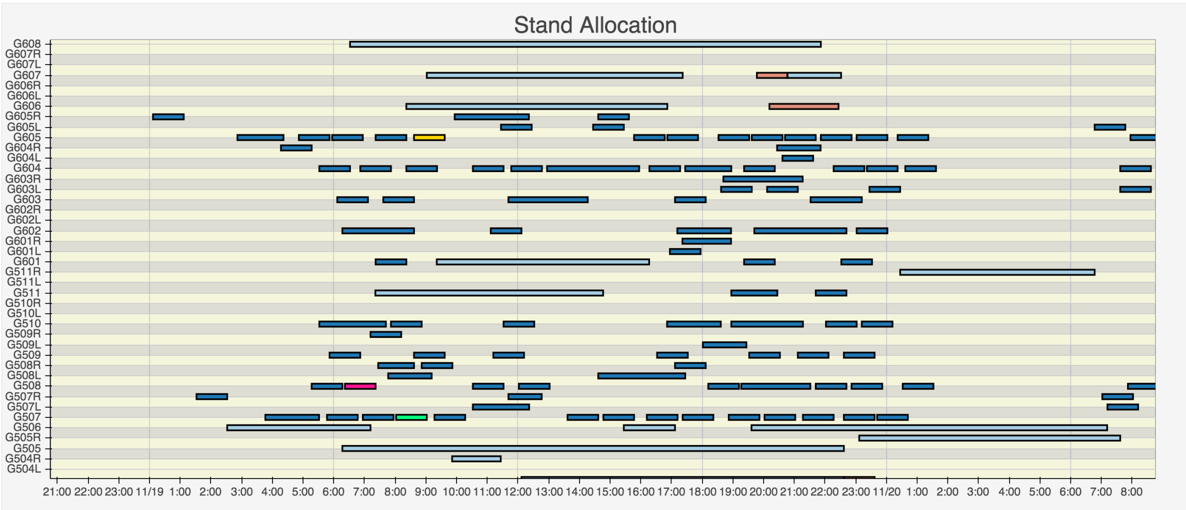

Figure 7.5: Location of AF0454-AF0457a (green), 4C3505-4C3506a (pink) and JJ8103-JJ8114a (yellow) in the Stand Allocation Solution of November 19th, Nominal Scenario

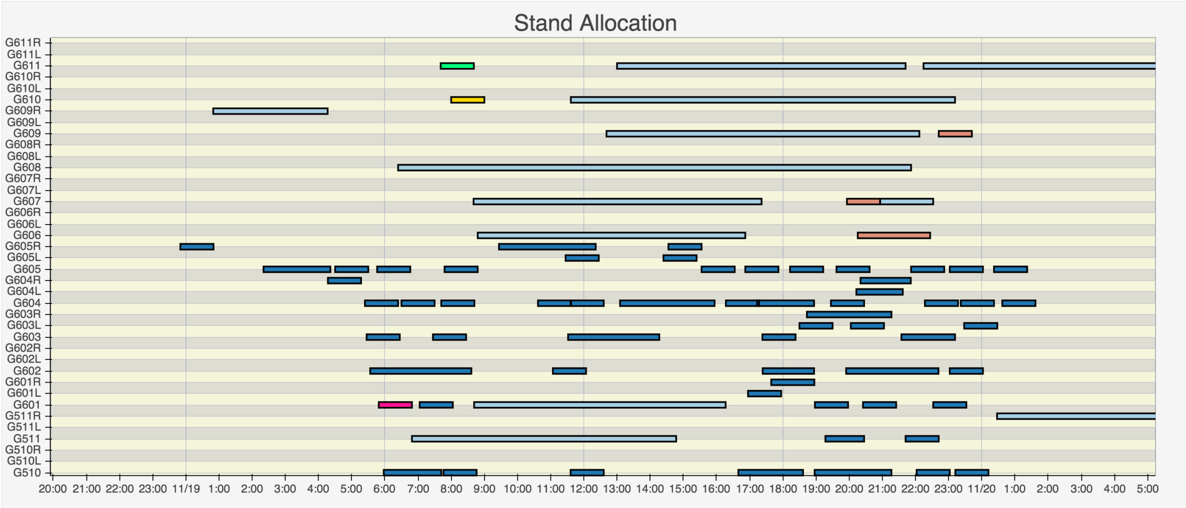

Figure 7.6: Location of AF0454-AF0457a (green), 4C3505-4C3506a (pink) and JJ8103-JJ8114a (yellow) in the Stand Allocation Solution of November 19th, Scenario 5

With the list of alternative stands provided in Appendix D the controller could determine a suitable alternative stand for these operations. The key is that the controller now has the information in advance and can take appropriate action if recovery is required. With the knowledge of alternative stands, airport controllers would know how to re-allocate the operations.

The characteristics of the solution obtained for November 19th are summarised in Table 7.1. The nominal objective function (OF), the nominal percentage of passengers allocated to contact-stand (PC) and the average percentage of passengers allocated to a contact-stand over the scenarios (AVG PC) are provided for the selected recoverable robust solution.

Case	Visits	Runtime [s]	OF [$]	PC [%]	AVG PC [%]
19/11	70	3100	382042	95.7	93.9

Table 7.1: Characteristics of the Recoverable Robust Solution for November 19th

The recoverable robust solution demonstrated a high percentage of passengers allocated to a contact-stand for both the nominal flight schedule (PC, 95.7%) and on average over the scenarios (PC AVG, 93.9%). For November 19th, 26 out of the 60 solutions were recoverable robust. Total penalty for the usage of the additional parking stands equalled $54 432 (84 times in 40 scenarios). The minimum and maximum objective function value found in the scenarios deviate less than $30 000.

An objective of the research project is to compare recoverable robustness (RR) with strict robustness and the current allocation as performed at GRU Airport. The allocation for strict robustness has to satisfy all scenarios and recovery is not allowed. Table 7.2 highlights the comparison of the average objective function value over the scenarios for the recoverable robust solution with the objective function value of the strict robust solution and objective function value for the allocation of GRU Airport for November 19th.

Case	AVG RR OF[1] [$]	Strict OF[2] [$]	$\Delta_{1,2}$ [%]	GRU OF[3] [$]	$\Delta_{1,3}$ [%]
19/11	372026	356142	4.5	292620	27.1

Table 7.2: Average Objective Value (OF) Comparison Recoverable Robustness (RR), Strict Robustness (Strict) and GRU Airport

Firstly, it has to be noted that GRU Airport does not focus on maximising affinity during their stand allocation. The higher average objective function value of the recoverable robust solution relative to the strict robust solution indicated a lower cost of robustness for the recoverable robust solution. The recoverable robust solution is therefore closer to the optimum allocation from a commercial revenue perspective (i.e. affinity).

Moreover, the strict solution required the three extra recovery parking stands to be used 4 times. The difference in total penalty due to the usage of the additional parkin stands, $54 432 for the recoverable robust solution and $103 680 for the strict robust solution, is close to $50 000.

In addition to the objective function value, an important performance indicator for the stand allocation is the percentage of passengers allocated to a contact-stand. Table 7.3 indicates the average percentage of passengers allocated to a contact-stand for the recoverable robust solution over all scenarios (AVG PC RR) and the percentage of passengers allocated to a contact-stand for the strict robust solution (Strict PC). Please note that the Δ-value is the relative difference between the recoverable robust solution and the strict robust solution in percent points, and similarly for the recoverable robust solution and the percentage of passengers allocated to a contact stand in the allocation of GRU Airport (GRU PC).

Case	AVG PC RR[1] [%]	Strict PC[2] [%]	$\Delta_{1,2}$ [%.]	GRU PC[3] [%]	$\Delta_{1,3}$ [%.]
19/11	93.9	87.6	6.3	90.3	3.6

Table 7.3: Comparison of Average Percentage of Passengers Allocated to a Contact-stand (PC) for the Recoverable Robust (RR), Strict and GRU Airport solutions

The recoverable robust solution outperformed the strict robust solution in terms of passengers allocated to a contact-stand over the scenarios tested. The gap with GRU Airport seems small, however GRU Airport allocated 14 (dis)embarkation operations to contact-stands at terminals outside the project scope. With the recoverable robust solution GRU Airport would be able to increase the number of passengers allocated to the international terminal by an average of 13.8 percent points for November 19th.

7.3 Overview Results

This section aims to provide an overview of the results obtained from the recoverable robust stand allocation model for 6 full-day case studies. The results of the recoverable robust stand allocation model will be compared with the strict robust results and the allocations of GRU Airport. Furthermore, a discussion of the deviation from the optimum and a comparison with the planning of GRU Airport is provided. Finally, the applicability of the affinity objective is assessed with a comparison with three other objective functions: minimisation of walking distance, minimisation of tows and maximisation of passengers allocated to a contact-stand.

Firstly, Table 7.4 indicates the number of recoverable solutions found and parameters of the selected recoverable robust solution for each case. Please recall that PC stands for the percentage of passengers allocated to a contact stand, provided for both the nominal scenario and as average over all scenarios.

Case	Visits	Runtime [s]	OF [$]	PC [%]	PC AVG [%]	RR Solutions
19/11	70	3100	382042	95.7	93.9	26
20/11	66	3304	368574	92.2	90.1	4
23/11	68	2992	376250	95.1	93.0	21
25/11	60	1914	356520	95.2	91.4	56
26/11	70	2669	378880	93.5	92.0	11
27/11	64	2150	365721	92.9	89.8	45

Table 7.4: Overview of Solution Parameters of Test Cases

For three cases (20/11, 26/11 and 27/11), the optimisation module could not obtain feasible allocation plans due to the 95% passenger-to-contact constraint. Therefore, the constraint was automatically relaxed for these case studies to obtain the results. GRU Airport can consider allocating some operations to Terminal 2 to achieve the desired 95 percent. All case studies returned a solution in less than an hour.

An objective of the research project is to compare the recoverable robust solutions with the strict robust solutions. The objective function value comparison between the recoverable robust solutions (RR AVG OF) and the strict robust solutions (Strict OF) is provided in Table 7.5. The average recoverable robust objective function value over all tested scenarios is utilised in the comparison with the strict robust solution.

Case	RR AVG OF[1] [$]	Strict OF[2] [$]	$\Delta_{1,2}$ [%]	GRU OF[3] [$]	$\Delta_{1,3}$ [%]
19/11	372026	356142	4.5	292620	27.1
20/11	358061	351049	2.0	295746	21.1
23/11	367132	364305	0.8	306020	20.0
25/11	341147	333445	2.3	298253	14.4
26/11	371532	355678	4.5	297677	24.8
27/11	351945	341346	3.1	297742	18.2

Table 7.5: Objective Function Value Comparison between the Average Recoverable Robust solution (RR AVG OF), the Strict Robust solution (Strict OF) and the allocation of GRU Airport (GRU OF)

It can be seen that the recoverable robust solution maintained a higher average objective function value than the strict robust solution. Therefore the relative cost of robustness for the recoverable robust solutions was lower compared to the strict robust solutions. The recoverable robust stand allocation model provided a robust yet less conservative solution relative to the strict robust stand allocation model.

Furthermore in Table 7.5, the difference between the objective function value of the recoverable robust solutions and the objective function value for the allocations of GRU Airport (GRU OF) indicated that GRU Airport can improve their allocation from a commercial revenue perspective.

Another comparison between the recoverable robust solutions and the strict robust solutions is the total penalty for the utilisation of the extra parking positions outside of the international terminal (see Table 7.6).

Case	RR Penalty [$]	Strict Penalty [$]	AVG RR Usage	Strict AVG Usage
19/11	54432	103680	2.1	4.0
20/11	58968	181440	2.3	7.0
23/11	34992	103680	1.4	4.0
25/11	14256	155520	0.6	6.0
26/11	41472	129600	1.6	5.0
27/11	24624	129600	1.0	5.0

Table 7.6: Comparison of Penalty Values and Average Usage of the Extra Parking Positions for the Recoverable Robust solution (RR) and Strict Robust solution (Strict)

The penalties and average usage of the extra stands were significantly lower for the recoverable robust solution relative to the strict robust solution. In the strict robust solution several operations were allocated to the extra stands for all scenarios (due to the necessity to satisfy all scenarios in the strict robust solution). The recoverable robust has more freedom to only utilise the extra stands when no other recovery possibility is available, which reduces the total penalty.

The next comparison between the recoverable robust solution and the strict robust solution was based on the percentage of passengers allocated to a contact-stand (Table 7.7). The percentage of passengers allocated to a contact-stand is an important performance indicator for GRU Airport. In Table 7.7 the average percentage of passengers allocated to a contact-stand over all the scenarios in the recoverable robust solution (AVG RR PC) is compared with the percentage of passengers allocated to a contact-stand for the strict robust solution (Strict PC). Furthermore, the worst-case scenario as found in the recoverable robust solution is provided (RR WC PC). Finally, a comparison with the allocation of GRU Airport (GRU PC) is provided, with an indication of the amount of passengers allocated to Terminal 2 (T2), outside of the scope of this research project, within that percentage.

Case	AVG RR PC[1] [%]	RR WC PC [%]	Strict PC[2] [%]	$\Delta_{1,2}$ [%.]	GRU PC[3] [%] (T2 [%])	$\Delta_{1,3}$ [%.]
19/11	93.9	90.0	87.6	6.3	90.3 (10.2)	3.6
20/11	90.1	87.5	87.7	2.4	87.3 (7.7)	2.8
23/11	93.0	90.8	90.3	2.7	92.5 (6.8)	0.5
25/11	91.4	87.8	87.8	3.6	92.7 (8.2)	-1.3
26/11	92.0	89.3	88.9	3.1	90.3 (10.8)	1.7
27/11	89.8	87.0	87.8	2.0	88.5 (7.9)	1.3

Table 7.7: Average Percentage of Passengers at Contact Stand (PC) Comparison for Recoverable Robustness (AVG RR), Strict Robustness (Strict) and GRU Airport (GRU), and the worst case for Recoverable Robustness (WC RR)

The comparison between the percentages of passengers allocated to a contact-stand further indicated the less conservative solution obtained by the recoverable robust stand allocation model relative to the strict robust solution. Even the worst case (WC) scenario in the recoverable robust solution had a higher or equal percentage of passengers allocated to a contact-stand than the strict solution for most of the cases.

In the comparison with GRU Airport the percentage of passengers serviced at a contact-stand is close to the recoverable robust solution. However, in the case study period GRU Airport allocated 6.8 to 10.8 percent of the passengers to a contact-stand out of the scope of the research project, at Terminal 2 (T2). The recoverable robust solution can service all those passengers at Terminal 3 for the respective case studies. On average, an improvement of 6.9 to 13.8 percent points of passengers allocated to contact-stands at Terminal 3 compared to the GRU Airport allocation can be achieved.

7.3.1 Deviation from Optimum

The comparison with strict robustness has provided insights that the recoverable robust solution is less conservative than the strict robust solution to the stand allocation problem. However, the level of conservatism in the recoverable robust solution relative to the optimal deterministic solution is not yet discussed.

In Table 7.8 the minimum and maximum objective function value found in the scenarios of the recoverable robust solution for all cases is provided. Furthermore, the optimal objective function value is provided.

Case	Optimum [$]	RR OF_{max} [$]	RR OF_{min} [$]	Gap [%]
19/11	382042	382042	355526	-6.94 - 0.00
20/11	368574	368574	343727	-6.74 - 0.00
23/11	376274	376250	358968	-4.60 - -0.01
25/11	356520	356520	322432	-9.56 - 0.00
26/11	379176	379176	358310	-5.43 - 0.00
27/11	365732	365721	339631	-7.14 - 0.00

Table 7.8: Comparison of Objective Function Value for the Optimal Solution and Recoverable Robust Solution

The comparison indicated that the worst case cost of robustness for the recoverable robust solution is less than 10 percent of the optimal objective function value.

7.3.2 GRU Planning

In Section 7.3, the results from the recoverable robust model were compared with the real GRU allocation. This allocation is only known after the day of operations. However, GRU Airport tends to only plan most (not all) arriving visits, which complicates a comparison between the tactical allocation plan of GRU Airport with the recoverable robust solution. For completeness, the affinities of the planned arrival operations are compared with the affinities obtained in the solution of the recoverable robust model (Table 7.9).

Case	RR^1 [$]	GRU^2 [$]	$\Delta_{1,2}$ [%]
19/11	182732	166795	9.55
20/11	191035	164595	16.06
23/11	228531	192091	18.97
25/11	182069	158338	14.99
26/11	192786	174632	10.40
27/11	185265	164215	12.82

Table 7.9: Comparison of Recoverable Robustness and GRU Allocation for Planned Operations

The operations planned in the recoverable robust solution generate a higher total affinity than the operations planned by GRU Airport. The difference in planned affinity indicates that GRU Airport can improve their tactical stand allocation from a revenue perspective.

7.3.3 Objective Function Variation

In literature, other objectives such as minimising walking distance for passengers are often used as objective for the stand allocation model. Maximising affinity based on commercial revenues has not yet been considered, and a comparison with other objectives can provide useful insights. This section provides firstly a comparison between the maximisation of affinity and minimisation of walking distance objectives. Thereafter, the minimisation of tows and maximisation of percentage of passengers allocated to a contact stand will be included in the comparison.

The affinity calculation for the objective to maximise affinity includes passenger numbers and tends to be higher closer to the terminal due to high expenditure at the terminal stores, reducing walking distance for high-revenue passengers. To compare the maximisation of affinity objective with the objective to minimise walking distance, the model is run with an objective to minimise walking distance.

The objective function for the minimisation of walking distance is formulated as:

$$min \sum_{i \in O} \sum_{j \in S} WD_j * Pax_i * x_{i,j} \tag{7.1}$$

In which WD_j represents the walking distance from the entrance of the pier to the stand and Pax_i the estimated passenger number for operation i. Please note that transfer-passengers are not included in the objective function, since nearly all transfer passengers at GRU Airport need to walk to a different terminal (out of the scope of the research project) for their connections.

In Table 7.10 the average walking distance (in minutes) in the recoverable robust solution over all scenarios with the objective to maximise affinity (AVG AF WD) is compared with the average minimum walking distance in the minimisation of walking distance solution (AVG Min WD). Following related literature, the minimum walking distance is expressed in minutes. The walking speed is assumed to be 4 km/hour [45]. The units for the relative differences are percentages and per passenger average walking time.

Case	AVG AF WD[1] [min]	AVG Min WD[2] [min]	$\Delta_{1,2}$ [%]	$\Delta_{1,2}$ per pax [min]
19/11	82403	76984	-6.58	0.19
20/11	83502	78972	-5.43	0.16
23/11	81842	77028	-5.88	0.17
25/11	76938	72992	-5.13	0.15
26/11	85184	80607	-5.37	0.16
27/11	83420	76977	-7.72	0.23

Table 7.10: Comparison of Average Walking Distance for the Objectives: Maximisation of Affinity (AVG AF WD) and Minimum Walking Distance (Min WD)

The average walking distance found with the maximisation of affinity can be reduced up to 8 percent when focusing solely on minimisation of walking distance. The average reduction is less than a quarter of a minute per passenger. The objective function focuses on the overall walking distance therefore for some passengers the walking distance can still be significant. However, the scope of one terminal should not result in extreme walking distances. If the scope is extended to all terminals of the airport a ratio to limit the extreme walking distances could be included.

To further indicate the trade-off airport controllers can make for a tactical stand allocation plan four objectives for the stand allocation problem are compared: maximise affinity, minimise walking distance, minimise number of tows and maximise the percentage of passengers allocated to a contact-stand.

The minimisation of number of tows focuses on the towing operations that are needed in the tactical stand allocation plan. In practice, minimisation of tows will try to maintain the long-stay aircraft visits at the same stand. To avoid excessive remote boarding operations, the minimisation of tows has a constraint of 90% of the passengers to a contact-stand, if the 95% constraint can not be satisfied. A lower percentage is not acceptable for GRU Airport due to the risk of not being capable to compensate the percentage enough with the operations in the other terminals. Please recall the tow indicator y_i, which leads to the objective function formulation for the minimisation of tows:

$$min \sum_{i \in O} y_i \tag{7.2}$$

The last objective, maximisation of the passengers allocated to a contact-stand, is chosen with regard to the 95% required by Brazilian legislation. With maximisation of the percentage allocated to a contact stand as an objective, it is possible to view to what extend GRU Airport can achieve the 95%. The objective function is formulated as:

$$max \sum_{i \in O} \sum_{j \in S_{ct}} Pax_i * x_{i,j} / \sum_{i \in O} Pax_i \tag{7.3}$$

in which Sct is the set of contact-stands, a sub-set of $\mathbf{S}$. For the comparison between the different objectives, the recoverable robust solution found with the maximisation of affinity objective is utilised as reference solution. The metrics included in the comparison are: Average affinity over the scenarios (Affinity), average walking distance over the scenarios (AVG WD), the number of tows in the recoverable robust solution (Tow) and average percentage of passengers allocated to a contact-stand (AVG PC).

In Table 7.11 the relative differences between the different objective functions and the maximisation of affinity are provided. The differences are expressed as ranges, as found by the assessment of all six days in the case study. For every case a day-specific table can be found in Appendix E.

Objective	Δ Affinity [%]	Δ AVG WD [%]	Δ Tow [%]	AVG PC [%.]
Max Affinity	-	-	-	89.8 - 93.9
Min WD	-2.0 - 0.2	-7.7 - -5.1	-1.1 - 0	90.8 - 94.3
Min Tow	-10.3 - -3.4	28.7 - 38.8	-40.2 - -22.6	87.0 - 92.4
Max PC	-4.4 - -2.4	32.2 - 41.2	0 - 1.3	91.1 - 94.6

Table 7.11: Ranges of Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of Passengers Allocated to a Contact-Stand (PC) for Four Objectives

At relative low loss of affinity the walking distance for passengers can be reduced between 5 to 8 percent in the case study. Similarly the number of tows can be reduced around 40 percent, although the objective has a negative effect on the percentage of passengers to contact-stand and the walking distance for passengers. Moreover, the percentage of passengers allocated to a contact-stand can be slightly improved when used as objective, but also at a cost of affinity and an increase in walking distance for passengers.

The visualise the variation in the scenarios for the four tested objectives, the walking distance and affinity of the objectives are plotted for every scenario in November 19th (Figure 7.7). Please note that an ideal stand allocation plan would maintain a low walking distance with high affinity (i.e. strive for the bottom right corner in the figure). The plots for the other case studies can be found in Appendix E.

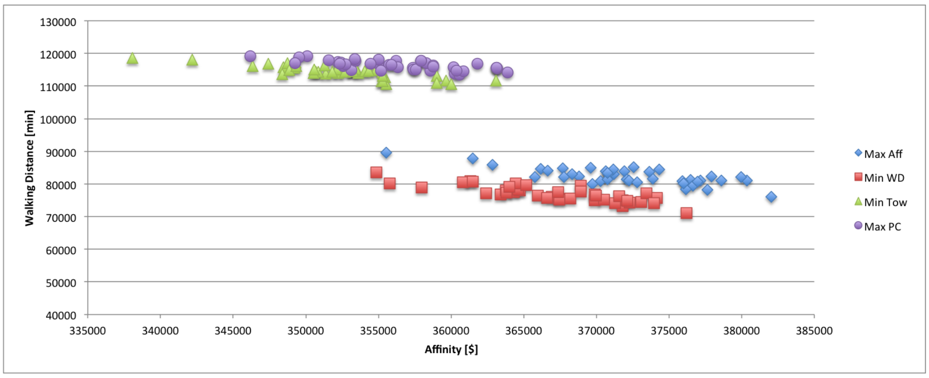

Figure 7.7: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 19th

In general, the scenarios cause a loss of affinity and higher walking distance, due to required recovery actions. Both the minimisation of walking distance objective and maximisation of affinity objective maintain a relatively low walking distance combined with a relatively high affinity. The other two objectives obtained a significantly higher walking distance and lower affinity, since walking distance and affinity are not the objectives in their optimisation.

The airport could decide to focus on the maximisation of affinity, and therefore their commercial revenue income, at the cost of a limited increase in walking distance for the passengers. If the amount of tow operations or the amount of passengers allocated to a contact-stand is absolutely critical, it could be the objective of the stand allocation. However, this may reduce the commercial revenue income of the airport and the walking distance of the passengers.

7.4 Sensitivity Analysis

In the recoverable robust stand allocation model several parameters are utilised that influence the recoverable robust solution found. Firstly, the effect of the 95% constraint for percentage of passengers allocated to a contact-stand is analysed. Thereafter, the sensitivity of the solution with respect to the chosen buffer time is highlighted. Furthermore, the influence of the scenario generation methodology and the stand changes during recovery are discussed in this section.

7.4.1 95% Constraint

One of the additions in the recoverable robust stand allocation model for GRU Airport is the 95% passenger-to-contact constraint. To comply with Brazilian legislation, this constraint is ideally met for GRU Airport. As demonstrated in the cases, it is not always possible to obtain feasible allocation plans with a percentage of passengers allocated to a contact-stand higher than 95%. Since the objective in the case study is to maximise affinity, the 95% constraint can be a limitation to achieve the maximum possible affinity. For three cases (20/11, 25/11 and 27/11) the 95% constraint was relaxed in the case study. The impact of the 95% constraint on the affinity for the other cases (19/11, 23/11 and 26/11) is highlighted in this section.

In Table 7.12 the comparison between cases with the 95% constraint and without the 95% constraint is provided in terms of average objective function value for the recoverable robust solution (AVG RR OF).

Case	AVG RR OF[1]	AVG RR OF[2]	$\Delta_{1,2}$ [%]
19/11	373195	372026	0.31
23/11	371759	367132	1.26
25/11	344961	341147	1.12

Table 7.12: Comparison of Objective Function Value (OF) for Case Studies without 95% constraint[1] and with the 95% constraint[2]

The average affinity generated for the model without the 95% constraint is slightly higher. However, the other relevant comparison is the impact on the percentage of passengers allocated to contact-stands. In Table 7.13 the comparison between percentage of passengers allocated to a contact-stand is provided, for both the nominal solution and the average over all the scenarios.

Case	RR PC[1]	RR PC[2]	$\Delta_{1,2}$ [%.]	RR PC AVG[1]	RR PC AVG[2]	AVG $\Delta_{1,2}$ [%]
19/11	95.7	95.7	0.0	93.9	94.1	0.2
23/11	95.1	94.7	-0.4	93.0	93.6	0.6
25/11	95.2	94.6	-0.6	91.4	92	0.6

Table 7.13: Comparison of the Percentage of Passengers allocated to a Contact-stand (PC) for Case Studies with 95% constraint[1] and without the 95% constraint[2]

In the table, the nominal percentage of passengers allocated to a contact-stand is higher with the 95% constraint (RR PC[1] is higher than RR PC[2]). However, the average percentage of passengers allocated to a contact-stand over all the scenarios is lower with the 95% constraint included (RR PC AVG[2] is higher than RR PC AVG[1]). It questions the necessity for the constraint on the percentage of passengers allocated to a contact-stand. In the affinity objective, preference is given to favourable contact-stands and will therefore allocate a high percentage of the passengers to a contact-stand without the 95% constraint as well.

7.4.2 Buffer time

In collaboration with GRU Airport an initial buffer time of 15 minutes was selected for the case study. The impact of the buffer time is assessed relative to the required stand changes (see Figure 7.8 for November 19th and 20th). The stand changes are the sum of all changes over the scenarios.

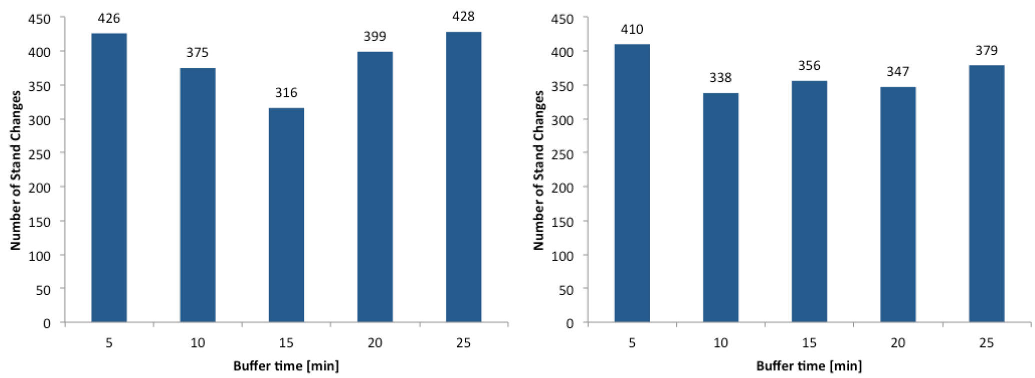

Figure 7.8: Number of Stand Changes vs. Buffer time for November 19th (left) and November 20th (right)

For November 19th and November 20th, the lowest number of stand changes over all scenarios is achieved for a buffer time of 10 or 15 minutes. Similar results are obtained for the other cases, except for the solution of November 26th, where a 5 minute buffer time results in the lowest number of stand changes in the solution. A low buffer time can increase the probability of a conflict in the allocation plan and therefore increase the number of stand changes. In contrast, a high buffer time results in a more conservative solution and therefore to more required stand changes as well, due to longer occupancy of the contact-stands. A buffer time between 10 to 20 minutes is therefore recommended to absorb small schedule deviations.

7.4.3 Scenario Generation

The goal of the scenario generation in the recovery module of the recoverable robust stand allocation is to create realistic scenarios by considering the relation between aircraft visits. More specifically, the visits that have arrived in the last hour (and from the same region if possible) can impact the arrival time deviation of a visit for a specific scenario. This section aims to compare the proposed scenario generation methodology with a random approach. The difference will be analysed based on the number of switches from an early/late arrival in the random approach to a late/early arrival in the proposed methodology.

In Figure 7.9 the time of the day is plotted against the amount of switches from an early/late arrival in the random approach to a late/early arrival in the scenario generation methodology for the aircraft visits. The periods without switches indicate no difference between the scenario generation methodology and a random approach, as expected for the visits that are handled as independent visits.

However, in the peak periods (highlighted in the plot) the scenario generation influences the arrival time deviation of the visits relative to a random approach. Sufficient previously arrived visits in the last hour (from the same region) are available and impact the arrival time deviations of the aircraft visits. For the visits of November 19th, up to 16 scenarios can have a different arrival time deviation sign (i.e. positive/negative).

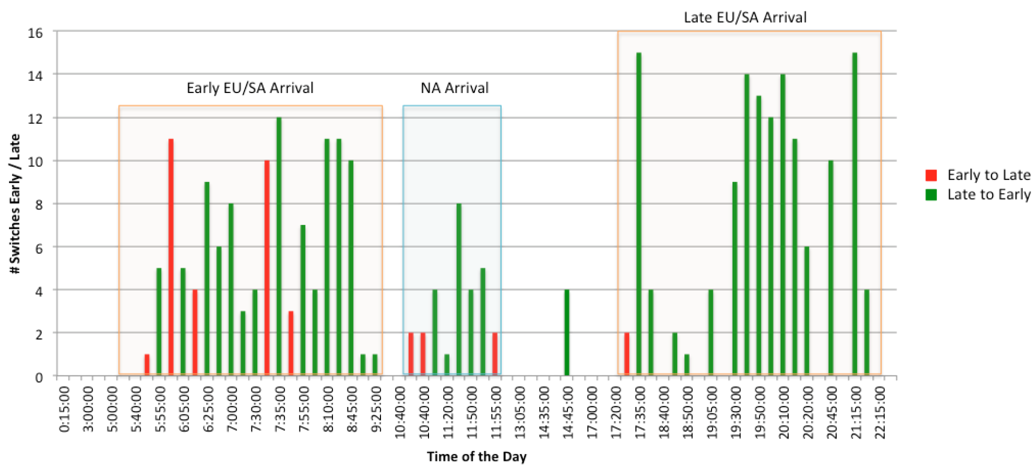

Figure 7.9: Analysis of Arrival Time Deviation Sign Switches due to Scenario Generation Methodology

Dominant is the switch between an early arrival in the random approach to a late arrival in the scenario generation methodology (red bars). The green bars represent the number of changes from a late random arrival to an early arrival. The scenario generation methodology in the recoverable robust stand allocation model ensures that, although the historical distributions are skewed towards an early arrival, some aircraft visits in the peak periods also obtain a late arrival time deviation due to previously arrived visits. It increases the variation in the scenarios generated in the recovery module of the recoverable robust stand allocation model.

7.4.4 Stand Changes

A final analysis is performed to check the stands at which most operations had to be recovered. Due to the nature of the objective function to maximise affinity, contact-stands close to the terminal building are preferred in the allocation. As visualised for November 19th in Figure 7.10, these stands (G507, G508, G604, G605) require more recovery actions as well.

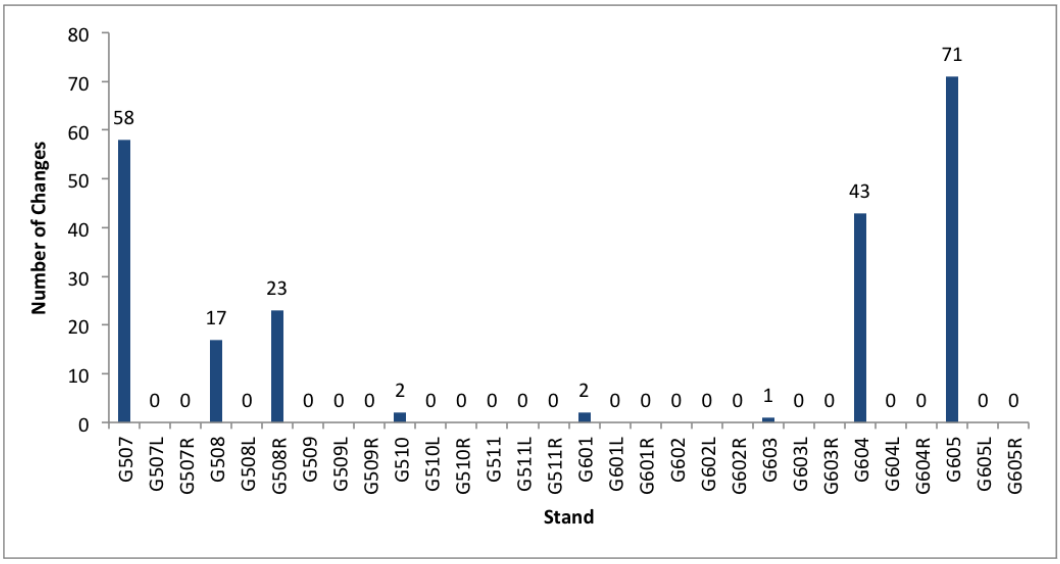

Figure 7.10: Amount of Required Recovery Actions at Contact-stands for November 19th over all Scenarios

The number of required recovery actions for the other stands for November 19th and the other case studies are provided in Appendix F. The objective function set results in an uneven utilisation of the contact-stands, comparable to a minimise walking distance objective function. The effect could be limited with other objective functions, however this would likely decrease affinity and increase total walking distance as demonstrated by the maximisation of percentage of passengers allocated to a contact-stand objective.

Chapter 8

Conclusion

To finalise the research project, an overview of the conclusions and further recommendations for future research are provided. Firstly, the results obtained in the research project are discussed in Section 8.1. Second, contributions of this project to the body of knowledge are highlighted. Thereafter, limitations of the model and recommendations for future research will be provided (Section 8.3). Finally, the initial objectives and hypothesis of the project are reviewed in Section 8.4.

8.1 Results

An objective the of the research is to compare the recoverable robust solution with a solution that has to satisfy all scenarios (strict robust solution). The results demonstrated an increase in objective function value for the recoverable robust solutions of 0.8 to 4.5 percent relative to the strict robust solutions. Furthermore, the average percentage of passengers allocated to a contact-stand over all scenarios was 2.0 to 6.3 percent points higher in the recoverable robust solution. For most cases the worst case scenario for the recoverable robust solution still maintained a higher percentage of passengers allocated to a contact-stand than the percentage found by the strict robust solution. It highlights the capability of recoverable robust solution to provide a less conservative, yet robust solution to the stand allocation problem.

In comparison to GRU Airport, the difference in percentage of passengers allocated to a contact-stand was between -1.3 to 3.6 percent points. However, GRU Airport allocated several operations to contact-stands at different terminals. The recoverable robust solution is capable of allocating these operations (6.8 - 10.8 percent of the passengers) to the international terminal. An overall increase of passengers allocated to a contact-stand at the international terminal of 6.9 - 13.8 percent points could be achieved. All cases were solved within 60 minutes on a 8 GB RAM Mac OS X computer.

The objective function of the recoverable robust stand allocation model, maximisation of affinity based on a commercial revenue framework, was compared with three other objectives: minimisation of walking distance, minimisation of tows and maximisation of passengers allocated to a contact-stand. The airport can decide to accept a loss of affinity up to 10 percent to either reduce walking distance by up to 8 percent or reduce towing operations between 20 to 40 percent. The latter also resulted in a lower passenger-to-contact percentage. The maximisation of passengers allocated to a contact-stand provided an increase of 0.7 - 1.9 percent points relative to the maximisation of affinity in the case study. However, the generated affinity decreased up to 5 percent and walking distance increased 30 - 42 percent. The comparison between objectives highlighted applicability of a commercial revenue framework incorporated in tactical stand allocation and the trade-off airports can make when generating a tactical stand allocation plan.

8.2 Contributions to Literature

The research project has contributed to stand allocation literature from both a robustness and an objective function perspective. This section highlights the main contributions of the research project to literature.

- **Recoverable Robustness** This research project is the first application of recoverable robustness in the stand allocation context. It includes the three parts of a recoverable robust model: the original optimisation model, the imperfection of information (scenarios) and the recovery algorithm. Firstly, a set of feasible allocation plans for the stand allocation problem is generated. The feasible allocation plans are tested against scenarios and recovered if required. A recoverable robust solution is obtained if, at least, the allocation plan can be recovered in all scenarios. The results of the case study demonstrated robust solutions relative to the stand allocation problem, with an objective function value close to the optimum. Furthermore, the recoverable robust solutions outperformed the strict robust solutions in terms of objective function value and percentage of passengers allocated to a contact-stand.
- **Revenue Framework** The second contribution focuses on a new objective for the stand allocation problem: affinity based on air-side commercial revenues. This research project provides an initial framework to include these revenues in the stand allocation problem and demonstrated the applicability. A lack of data limited the validity and therefore follow-up research is recommended.
- **Airport Data Analysis** Another distinction of this research project is the generation of realistic scenarios for the model. Previous stochastic models considered normal distributed delays. This research project provides insights in flight data analysis of an airport and applies the results in the scenario generation for the recoverable robust stand allocation model.

8.3 Limitations and Recommendations

Although the research project obtained promising results, there are several recommendations and limitations that should be considered for future research.

8.3.1 Recommendations

The first recommendation is the addition of an operational stand allocation model or system. A study on when arrival time information is obtained at the airport and implementation of an operational stand allocation model in a combination model for both tactical and operational planning could be a future research direction. Moreover, the recovery algorithm could be extended, for example with an algorithm to allow a swap between operations.

Second recommendation is to further assess the applicability of the affinity objective function based on the commercial revenue framework. Firstly to include other airport lay-outs, since the affinity calculations are established for a pier-shaped terminal and adjustments to the framework might be required for other shapes. Secondly, due to the limited data availability for the case study in the research project. Furthermore, effect on air-side commercial revenue at the airport due to the stand allocation based on the affinity calculation would be interesting to evaluate, although the effect will be complex to isolate.

The application of the revenue-based affinity objective in a multi-objective approach is an interesting research direction. It is advised to examine the runtime of the recoverable robust stand allocation model with a new objective function before testing large instances of the multi-objective approach.

The comparison of recoverable robustness with, for example, deterministic models with a robustness objective is not assessed in this research project. A research direction to compare several robustness methodologies is recommended, to provide guidance for future research in the robust stand allocation context.

8.3.2 Limitations

One limitation of the research project is the scope of only one terminal. The scope of the recoverable robust stand allocation model should be extended to cover all terminals, which would obsolete the additional parking-only stands included in the current model. The scope extension might require more operational constraints and an extension of the revenue framework.

The extension can have a significant effect on the runtime of the model due to the increased problem size. Time or space decomposition, other decomposition methods (like Bender's) or special heuristics can be included to limit the runtime, or the number of solutions and scenarios can be reduced. It is advised to analyse the runtime of a case study with limited number of solutions and scenarios, and linearly determine a reasonable problem size.

Preference parking locations and variation in allocation are not included this thesis project. Preference parking could improve the stand allocation from an operational perspective, to maintain the shorter parking operations closer to the terminal. It is desirable for airlines to include variation in the tactical allocation, to limit excessive remote boarding for specific airlines.

The results of the revenue data analysis form a second limitation for the project. The lack of detailed revenue data and passenger tracking data complicated the estimation of desired parameters for the revenue framework. Consequently, the affinity calculation is not as accurate as desired. It is recommended to re-evaluate the affinity calculations based on commercial revenue with all required data.

8.4 Review Objectives and Hypothesis

The hypothesis related to the research project was described in the project plan as:

Hypothesis 1: *The recoverable robust solution to the stand allocation problem has a lower cost of robustness relative to the strict robust solution*

For all test cases the average objective function value of the recoverable robust solution is closer to the optimum compared to the strict robust objective function value. Consequently, the hypothesis is accepted for the case study. Moreover, the recoverable robust solution maintains a higher percentage of passengers allocated to a contact-stand as well. The recoverable robust stand allocation model provides a less conservative yet robust solution to the stand allocation problem.

At the start of the research project three objectives were established:

- **Objective 1** Create a tactical stand allocation model that effectively incorporates the concept of recoverable robustness
- **Objective 2** Develop a framework to include air-side commercial revenues into the tactical stand allocation model
- **Objective 3** Demonstrate the industrial applicability of the model in a case study with GRU Airport

The first objective focuses on the development of the recoverable robust stand allocation model. The recoverable robust stand allocation model effectively incorporates the recoverable robust concept in the stand allocation context. The three steps; an optimisation model, the imperfect information (the scenarios) and recovery with limited means (recovery algorithm) are included in the recoverable robust stand allocation model developed. Therefore, the objective is successfully achieved.

Objective 2 focuses on the air-side commercial revenues at an airport. The objective is met, since a framework to handle these revenues in combination with stand allocation is constructed to calculate the preference (affinity) for each operation-stand combination. However, the revenue framework is only evaluated with limited data for the case study. Future research and more data could improve the methodology and further evaluate the applicability of commercial revenue in the stand allocation context.

Finally, the industrial applicability is demonstrated with a case study at the international terminal of GRU Airport. The recoverable robust stand allocation model provided a recoverable robust solution to the stand allocation problem in reasonable time for GRU Airport. The case study indicated potential to increase both the revenue perspective and passengers allocated to a contact-stand at the international terminal of GRU Airport significantly. An extension of the scope to all four terminals is required before the implementation of the model. Furthermore, a coupling with an operational stand allocation model/system is recommended to maintain the schedule during the day of operations.

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Appendix A: List of Airlines & Airports

Table A.1: List of Airlines Part 1

IATA-code	ICAO-code	Name
4C	LCO	LAN Colombia
4M	DSM	LAN Argentina
AA	AAL	American Airlines
AC	ACA	Air Canada
AF	AFR	Air France
AM	AMX	Aeromexico
AR	ARG	Aerolineas Argentinas
AT	RAM	Royal Air Maroc
AU	AUT	Austral Lineas Areas
AV	AVA	Avianca
AZ	AZA	Alitalia
BA	BAW	British Airways
CA	CCA	Air China
CM	CMP	Copa Airlines
DL	DAL	Delta Airlines
EK	UAE	Emirates
EQ	TAE	TAME
ET	ETH	Ethiopian Airlines
EY	ETD	Etihad Airways
G3	GLO	GOL Linhas Aereas
H2	SKU	Sky Airline
HP	AWE	US Airways
IB	IBE	Iberia
JJ	TAM	TAM Airlines
KE	KAL	Korean Airlines
KL	KLM	KLM Royal Dutch Airlines
LA	LAN	LAN Airlines
LH	DLH	Lufthansa
LP	LPE	LAN Peru Airlines
LX	SWR	Swiss Airlines
M3	TUS	ABSA Cargo Airline

Table A.2: List of Airlines Part 2

IATA-code	ICAO-code	Name
OB	BOV	Boliviana de Aviacion
PZ	LAP	TAM Airlines Paruguay
QR	QTR	Qatar Airways
SA	SAA	South-African Airways
SQ	SIA	Singapore Airlines
TK	THY	Turkish Airlines
TP	TAP	TAP Portugal
UA	UAL	United Airlines
UX	AEA	Air Europa

Table A.3: List of Airports Part 1

Code	Country	Region	City
AEP	Argentina	South America	Buenos Aires-Newbery
AGT	Paraguay	South America	Ciudad Del Este
AMS	Netherlands	Europe	Amsterdam
ASU	Paraguay	South America	Asuncion
ATL	United States	North America	Atlanta
AUH	United Arab Emirates	Middle East	Abu Dhabi
CCS	Venezuela	South America	Caracas
CDG	France	Europe	Paris-De Gaulle
COR	Argentina	South America	Cordoba
CUN	Mexico	North America	Cancun
DFW	United States	North America	Dallas/Fort Worth
DOH	Qatar	Middle East	Doha
DXB	United Arab Emirates	Middle East	Dubai
EWR	United States	North America	Newark
EZE	Argentina	South America	Buenos Aires
FCO	Italy	Europe	Rome-Da Vinci
FRA	Germany	Europe	Frankfurt
IAD	United States	North America	Washington-Dulles
IAH	United States	North America	Houston-Intercontinental
ICN	South Korea	Asia	Seoul
IST	Turkey	Europe	Istanbul
JFK	United States	North America	New York-JFK
JNB	South Africa	Africa	Johannesburg
LAX	United States	North America	Los Angeles

Table A.4: List of Airports Part 2

Code	Country	Region	City
LFW	Togo	Africa	Lome
LHR	United Kingdom	Europe	London-Heathrow
LIM	Peru	South America	Lima
LIS	Portugal	Europe	Lisbon
MAD	Spain	Europe	Madrid
MCO	United States	North America	Orlando
MEX	Mexico	North America	Mexico City
MIA	United States	North America	Miami
MUC	Germany	Europe	Munich
MVD	Uruguay	South America	Montevideo
MXP	Italy	Europe	Milan-Malpensa
OPO	Portugal	Europe	Porto
ORD	United States	North America	Chicago-O'Hare
ORL	United States	North America	Orlando-Metro
PEK	China	Asia	Beijing
ROS	Argentina	South America	Rosario
SCL	Chile	South America	Santiago
SIN	Singapore	Asia	Singapore
YYZ	Canada	North America	Toronto
ZRH	Switzerland	Europe	Zurich

Appendix B: List of Distributions per Flight Number

Please note: Param1, Param2 etc. are the parameters of the distribution in the order as found in the SciPy documentation of Python.

Table B.1: Historical Arrival Time Deviation Distribution per Flight Number

Flight nr.	Destinations	# Observations	Distribution	# Param	Param1	Param2	Param 3	Param 4
AAL0215	LAX	364	nct	4	1.53	1.33	-30.05	11.81
AAL0233	MIA	260	nct	4	2.05	1.10	-30.16	14.38
AAL0907	MIA	123	nct	4	2.28	1.09	-27.12	13.41
AAL0919	JFK	66	nct	4	2.79	1.29	-26.41	16.28
AAL0929	MIA	362	nct	4	1.95	1.69	-36.84	15.87
AAL0951	JFK	360	nct	4	1.37	1.04	-38.15	18.53
AAL0963	DFW	363	nct	4	1.51	2.03	-37.94	13.27
AAL0995	MIA	361	nct	4	1.28	1.47	-34.21	14.56
ACA0090	YYZ	361	nct	4	2.86	2.64	-36.04	14.34
AEA0057	MAD	275	nct	4	3.87	2.54	-43.98	18.02
AFR0454	CDG	356	nct	4	1.79	1.14	-30.16	13.61
AFR0456	CDG	317	nct	4	3.01	1.15	-12.72	13.51
AZA0674	FCO	365	nct	4	2.28	0.86	-19.67	20.01
AZA0678	FCO	66	t	3	5.43	-8.52	26.03	
BAW0241	LHR	133	nct	4	2.58	1.64	-29.63	17.38
BAW0247	LHR	360	nct	4	1.91	0.98	-19.90	13.20
CCA0907	PEK	104	nct	4	2.51	1.08	-37.93	12.94
DAL0053	DTW	357	nct	4	1.89	1.30	-31.09	11.65
DAL0059	ATL	345	nct	4	1.50	1.34	-24.72	9.56
DAL0105	ATL	342	nct	4	1.61	0.85	-23.12	13.11
DAL0471	JFK	360	nct	4	1.66	2.08	-43.89	15.52
DLH0504	MUC	346	nct	4	1.55	0.81	-16.55	14.20
DLH0506	FRA	356	nct	4	2.04	0.59	-21.90	13.19
ETD0191	AUH	365	nct	4	3.31	1.80	-33.82	21.44
ETH0506	LFW	154	nct	4	2.27	1.30	-7.78	21.96
IBE6821	MAD	180	nct	4	2.20	0.96	-27.24	14.88
IBE6823	MAD	34	genlogistic	3	0.90	-14.56	19.50	
IBE6827	MAD	363	nct	4	2.29	0.85	-34.67	15.20
KAL0061	ICN	180	genlogistic	3	1.49	-15.79	11.89	
KLM0791	AMS	364	nct	4	2.41	0.87	-14.45	11.91
LAN0750	SCL	365	nct	4	2.92	2.42	-35.91	11.22
LAN0752	SCL	365	nct	4	3.68	3.24	-36.75	9.90
LAN0756	SCL	157	nct	4	2.94	1.88	-36.08	10.32
LAN0758	SCL	188	nct	4	2.81	1.65	-35.98	10.92
LAN0760	SCL	363	nct	4	2.72	2.12	-33.87	12.50
LAP0706	AGT	301	t	3	3.89	-38.19	18.03	
LAP0712	ASU	35	nct	4	1.76	2.86	-60.47	6.20
LAP0716	ASU	127	nct	4	1.98	0.74	-32.58	10.09
LAP0721	EZE	84	t	3	2.11	-25.94	7.33	
LPE2765	LIM	160	nct	4	4.37	1.96	-30.11	11.34
LPE2767	LIM	365	nct	4	2.97	1.01	-29.70	14.52
QTR0771	DOH	727	dgamma	3	1.39	3.41	15.52	
QTR0772	EZE	726	logistic	2	0.21	16.74		
SAA0222	JNB	361	nct	4	5.75	-0.85	0.01	20.17
SAA0224	JNB	169	nct	4	1.08	1.02	-55.81	13.64
SIA0068	SIN	156	dgamma	3	1.19	-16.47	16.21	
SWR0092	ZRH	362	nct	4	2.44	0.42	-7.10	11.23
SWR2694	ZRH	70	t	3	3.25	-1.12	16.87	
TAM8005	AEP	358	nct	4	4.72	3.32	-55.36	11.83
TAM8009	AEP	360	nct	4	2.63	1.56	-31.02	8.68
TAM8015	AEP	361	nct	4	4.07	3.26	-54.14	11.77
TAM8016	ASU	56	t	3	1.48	-10.14	15.20	
TAM8019	EZE	363	t	3	3.48	-28.23	11.89	

Table B.2: Historical Arrival Time Deviation Distribution per Flight Number Part 2

Flight nr.	Destinations	# Observations	Distribution	# Param	Param1	Param2	Param 3	Param 4
TAM8027	SCL	364	gengamma	4	10.82	0.62	-54.55	0.83
TAM8029	SCL	360	nct	4	3.74	1.29	-42.47	13.65
TAM8031	MVD	345	nct	4	3.24	1.84	-43.52	8.25
TAM8035	MIA	145	t	3	3.75	-2.62	18.84	
TAM8041	MVD	315	beta	4	7.31	13706175447335.80	-69.78	102121685332109.00
TAM8045	MVD	313	genextreme	3	-0.08	-26.72	13.03	
TAM8047	MVD	193	nct	4	3.22	1.86	-46.88	9.14
TAM8051	CCS	76	nct	4	5.57	3.93	-70.48	18.00
TAM8063	MXP	360	nct	4	3.13	1.03	-52.24	15.93
TAM8065	MAD	366	nct	4	4.49	1.35	-44.61	16.42
TAM8067	LIM	345	nct	4	7.20	3.21	-85.14	17.96
TAM8071	FRA	360	dweibull	3	1.10	-24.63	16.22	
TAM8073	SCL	196	nct	4	3.81	1.56	-32.47	11.20
TAM8081	JFK	356	nct	4	2.95	1.88	-53.58	21.73
TAM8085	LHR	362	nct	4	3.87	1.05	-50.83	16.42
TAM8087	MCO	359	nct	4	3.98	1.75	-41.42	16.12
TAM8091	MIA	364	nct	4	5.68	2.29	-48.39	13.87
TAM8095	MIA	365	nct	4	3.73	1.78	-48.52	14.70
TAM8097	EZE	98	nct	4	1.55	1.61	-42.37	8.81
TAM8101	CDG	361	nct	4	2.73	2.12	-66.54	15.25
TAM8103	JFK	321	nct	4	3.06	1.89	-71.29	22.96
TAM8107	COR	179	nct	4	2.73	0.93	-31.92	9.47
TAM8111	ORL	289	nct	4	4.48	3.45	-75.63	15.52
TAM8113	MEX	360	genlogistic	3	299.73	-146.97	20.47	
TAM8117	COR	118	nct	4	3.80	2.22	-34.88	10.84
TAM8122	ASU	84	genlogistic	3	971.73	-142.57	17.00	
TAM8124	ASU	93	beta	4	8.93	2827.43	-62.85	12540.29
TAM8129	ROS	105	t	3	2.81	-43.63	20.17	
TAM8131	ROS	227	logistic	2	-42.92	12.17		
TAM8135	ASU	107	t	3	2.40	-28.27	10.90	
TAM8147	SCL	31	genlogistic	3	2.46	-18.80	11.25	
TAM8161	CUN	41	nct	4	8.98	7.99	-76.35	10.53
TAM8183	JFK	36	powerlognorm	4	0.01	0.01	-203.93	135.55
TAM9600	SCL	54	nct	4	1.77	0.53	14.22	19.91
TAM9601	FRA	44	t	3	1.90	3.26	24.87	
TAM9611	MIA	37	powerlognorm	4	0.01	0.02	-127.45	84.05
TAM9623	MCO	49	nct	4	1.28	0.15	-30.69	13.32
TAM9716	ASU	30	nct	4	1.64	6.06	-54.19	3.79
TAP0081	OPO	105	t	3	2.38	-5.35	17.24	
TAP0083	LIS	40	nct	4	5.14	7.60	-32.70	6.54
TAP0085	LIS	170	genlogistic	3	811.54	-134.25	22.29	0.00
TAP0087	LIS	277	nct	4	3.82	0.20	7.47	17.19
TAP0089	LIS	84	dweibull	3	1.21	27.48	18.14	
THY0015	IST	726	logistic	2	19.05	19.58		
THY0016	EZE	726	t	3	2.37	4.36	22.88	
UAE0261	DXB	364	nct	4	4.97	1.60	-45.38	20.34
UAL0021	IAH	114	nct	4	4.01	4.00	-50.86	12.76
UAL0031	EWR	295	nct	4	4.03	2.61	-54.67	15.08
UAL0148	EWR	58	genextreme	3	-0.39	-10.44	31.95	
UAL0845	ORD	352	nct	4	7.07	8.78	-104.88	10.05
UAL0861	IAD	357	nct	4	2.83	1.52	-35.43	14.04
UAL0979	IAH	243	nct	4	2.82	2.27	-34.28	17.45

Appendix C: Validation Test Allocation

Table C.1: Allocation and Alternative Stands for Validation Test July 9th Part 1

Name	Allocation	Changes	Alternative Stands	Name	Allocation	Changes	Alternative Stands
JJ8015-JJ8148	G604R	0		UA0845-UA0844a	G508	6	G601 G611
QR0772-QR0772	G605	0		AC0090-AC0091p	G611	0	
TK0016-TK0016	G507	0		AC0090-AC0091d	G510	0	
JJ8071-TAM9601p	G902	0		AC0090-AC0091a	G510	6	G606 G508 G511
JJ8071-TAM9601d	G508	0		JJ8031-JJ8010	G605L	0	
JJ8071-TAM9601a	G603	0		AA0963-AA0906p	G905	0	
LH0506-LH0507p	G502	2	X001	AA0963-AA0906d	G604	0	
LH0506-LH0507d	G605	0		AA0963-AA0906a	G602	3	G511 G508 G611
LH0506-LH0507a	G507	0		KE0061-KE0062	G509	3	G508
SA0224-SA0225p	G913	0		AA0215-AA0216p	G606	0	
SA0224-SA0225d	G603	0		AA0215-AA0216d	G510	0	
SA0224-SA0225a	G509	1	G606	AA0215-AA0216a	G604	4	G511 G601 G508
AZ0674-AZ0675p	G607	1	X002	LA0750-LA0751p	G511	0	
AZ0674-AZ0675d	G507	0		LA0750-LA0751d	G603	0	
AZ0674-AZ0675a	G604	0		LA0750-LA0751a	G605	0	
BA0247-BA0246p	G609	0		LA0760-LA0761p	G501	0	
BA0247-BA0246d	G507	0		LA0760-LA0761d	G501	0	
BA0247-BA0246a	G508	1	G610	LA0760-LA0761a	G605L	0	
JJ8065-JJ8000	G505	0		CA0907-CA0908p	G610	0	
LAP0712-JJ8044	G501	0		CA0907-CA0908d	G610	0	
JJ8091-JJ8026	G510	0		CA0907-CA0908a	G509	0	
LH0504-LH0505p	G907	0		LP2767-LP2766p	G907	0	
LH0504-LH0505d	G605	0		LP2767-LP2766d	G605	0	
LH0504-LH0505a	G511	0		LP2767-LP2766a	G604	11	G602
TP0087-TP0082p	G610	2	X002	SQ0068-SQ0067	G510	0	
TP0087-TP0082d	G508	0		EK0261-EK0262p	G609	0	
TP0087-TP0082a	G605	0		EK0261-EK0262d	G510	0	
LX0092-LX0093p	G912	0		EK0261-EK0262a	G508	0	
LX0092-LX0093d	G508	2	G608	SA0222-SA0223	G503	0	
LX0092-LX0093a	G601	0		EY0191-EY0190p	G607	0	
AF0454-AF0457p	G608	0		EY0191-EY0190d	G605	1	G611
AF0454-AF0457d	G605	0		EY0191-EY0190a	G507	5	G604 G608 G509
AF0454-AF0457a	G507	3	G606 G502	QR0771-QR0771	G511	0	
IB6827-IB6824p	G601	3	X002	TK0015-TK0015	G602	0	
IB6827-IB6824d	G604	0		AF0456-AF0459	G509	0	
IB6827-IB6824a	G604	4	G606 G608 G607	KL0791-KL0792	G604	0	
JJ8081-JJ8090p	G908	0		TP0081-TP0080	G603	0	
JJ8081-JJ8090d	G605	0		LA0752-LA0759p	G502R	0	
JJ8081-JJ8090a	G508	6	G606 G604 G608 G610	LA0752-LA0759d	G507R	0	
JJ8147-JJ8066	G605R	0		LA0752-LA0759a	G601R	0	
JJ3158-JJ8046	G507L	0		TAM9751-JJ8008	G601L	0	
AA0929-AA0234	G509	0		IB6821-IB6820p	G912	0	
LP2765-LA0757	G605L	0		IB6821-IB6820d	G604	0	
JJ8129-JJ8032p	G501	0		IB6821-IB6820a	G507	6	G608 G508
JJ8129-JJ8032d	G507R	0		AA0233-AA0950	G507	1	G610
JJ8129-JJ8032a	G605R	15	G507R G604R	JJ8095-JJ8070	G603	6	G610
UA0148-UA0149p	G902	0		JJ3749-JJ8086p	G907	0	
UA0148-UA0149d	G602	0		JJ3749-JJ8086d	G507	0	
UA0148-UA0149a	G510	1	G511	JJ3749-JJ8086a	G508	0	
AA0951-AA0930p	G910	0		LA0758-LA0753	G511R	0	
AA0951-AA0930d	G602	0		JJ8009-TAM9716	G605R	0	
AA0951-AA0930a	G507	0		JJ8117-PZ0707	G509L	0	
UA0021-UA0020p	G906	0		JJ8101-JJ8094p	G905	0	
UA0021-UA0020d	G601	0		JJ8101-JJ8094d	G507	4	G602 G502 G511
UA0021-UA0020a	G602	0		JJ8101-JJ8094a	G602	0	
UA0861-UA0860p	G909	0		JJ8085-JJ8108p	G901	0	
UA0861-UA0860d	G511	0		JJ8085-JJ8108d	G507	0	
UA0861-UA0860a	G511	0		JJ8085-JJ8108a	G509	4	G606 G608
JJ8103-JJ8086	G603	0		JJ8165-JJ8164p	G904	0	
AA0995-AA0962p	G505	0		JJ8165-JJ8164d	G604	0	
AA0995-AA0962d	G508	0		JJ8165-JJ8164a	G605	0	
AA0995-AA0962a	G604	0		JJ8063-JJ8112p	G911	0	
4M4540-4M4541	G605R	0		JJ8063-JJ8112d	G508	0	

Table C.2: Allocation and Alternative Stands for Validation Test July 9th Part 2

Name	Allocation	Changes	Alternative Stands	Name	Allocation	Changes	Alternative Stands
UA0845-UA0844p	G504	0		JJ8063-JJ8112a	G610	0	
UA0845-UA0844d	G602	0		JJ8161-TAM9614	G611	0	
JJ8113-JJ8034p	G903	0		JJ8111-JJ8110p	G906	2	X002
JJ8113-JJ8034d	G509	0		JJ8111-JJ8110d	G507	0	
JJ8113-JJ8034a	G603	0		JJ8111-JJ8110a	G605	6	G604 G602
4C3505-4C3506p	G503	0		JJ8097-JJ8148p	G905	0	
4C3505-4C3506d	G508	0		JJ8097-JJ8148d	G507R	0	
4C3505-4C3506a	G504	0		JJ8097-JJ8148a	G509R	0	

Appendix D: Allocation Results 19/11

Table D.1: Allocation and Alternative Stands 19/11 part 1

Name	Allocation	Changes	Alternative Stands				
LA0756-LP2764p	G609R	0					
LA0756-LP2764d	G604R	0					
LA0756-LP2764a	G605R	0					
JJ8015-JJ8014p	G506	0					
JJ8015-JJ8014d	G509R	0					
JJ8015-JJ8014a	G507R	0					
QR0774-QR0774	G605	0					
TK0016-TK0016	G507	0					
JJ8071-JJ8026p	G913	0					
JJ8071-JJ8026d	G605	0					
JJ8071-JJ8026a	G605	6	G603	G508			
JJ8065-JJ8090p	G505	32	X001	G502L			
JJ8065-JJ8090d	G507	0					
JJ8065-JJ8090a	G508	0					
LA0701-LA0701	G510	0					
JJ8091-JJ8064p	G608	11	X002	G502L			
JJ8091-JJ8064d	G605	0					
JJ8091-JJ8064a	G604	0					
JJ8101-JJ8024p	G910	0					
JJ8101-JJ8024d	G509	0					
JJ8101-JJ8024a	G507	24	G601	G602	G509	G603	
JJ8161-JJ8140p	G902	0					
JJ8161-JJ8140d	G604	0					
JJ8161-JJ8140a	G509	0					
JJ8085-JJ8070p	G907	0					
JJ8085-JJ8070d	G507	4	G601				
JJ8085-JJ8070a	G605	16	G601	G602	G511	G509	G603
JJ8081-JJ8102p	G909	0					
JJ8081-JJ8102d	G605	0					
JJ8081-JJ8102a	G603	0					
JJ8113-JJ8140	G602	0					
4C3505-4C3506p	G511	0					
4C3505-4C3506d	G507	0					
4C3505-4C3506a	G508	5	G601	G611	G605		
LH0506-LH0507p	G901	0					
LH0506-LH0507d	G507	0					
LH0506-LH0507a	G604	5	G605	G611	G601		
BA0247-BA0246p	G912	0					
BA0247-BA0246d	G509	0					
BA0247-BA0246a	G507	2	G601	G611			
AA0929-AA0950p	G906	0					
AA0929-AA0950d	G604	0					
AA0929-AA0950a	G601	0					
TP0087-TP0082p	G606	0					
TP0087-TP0082d	G605	0					
TP0087-TP0082a	G605	0					
PZ0712-JJ8116	G508R	0					
AZ0674-AZ0675p	G903	0					
AZ0674-AZ0675d	G507	0					
AZ0674-AZ0675a	G603	1	G611				
LP2765-LA0757	G508L	0					
LX0092-LX0093p	G911	0					
LX0092-LX0093d	G605	19	G505				
LX0092-LX0093a	G510	2	G611	G610			
AF0454-AF0457p	G607	0					
AF0454-AF0457d	G507	0					
AF0454-AF0457a	G507	12	G611	G510	G603		
IB6827-IB6824p	G601	2	X003				
IB6827-IB6824d	G604	0					
IB6827-IB6824a	G604	3	G611	G610	G507		
JJ8103-JJ8114p	G905	0					
JJ8103-JJ8114d	G602	0					
JJ8103-JJ8114a	G605	15	G611	G601	G610	G604	G507
TAM8129-JJ8144p	G504R	0					
TAM8129-JJ8144d	G605L	0					
TAM8129-JJ8144a	G508R	23	G610R	G611R	G609R	G510R	

Table D.2: Allocation and Alternative Stands 19/11 Part 2

Name	Allocation	Changes	Alternative Stands				
AA0995-AA0906p	G904	0					
AA0995-AA0906d	G604	0					
AA0995-AA0906a	G507	3	G602				
JJ8031-JJ8010	G605R	0					
4M4540-4M4541	G507L	0					
UA0861-UA0860p	G610	1	G502L				
UA0861-UA0860d	G510	0					
UA0861-UA0860a	G604	0					
UA0148-UA0149p	G609	0					
UA0148-UA0149d	G502	0					
UA0148-UA0149a	G508	2	G509	G503			
UA0105-UA0104p	G504	0					
UA0105-UA0104d	G504	0					
UA0105-UA0104a	G602	0					
AA0951-AA0930p	G611	0					
AA0951-AA0930d	G508	0					
AA0951-AA0930a	G509	0					
UA0845-UA0844p	G908	0					
UA0845-UA0844d	G609	0					
UA0845-UA0844a	G510	0					
KE0061-KE0062	G603	0					
JJ8029-JJ8072	G507R	0					
AC0090-AC0091p	G503	0					
AC0090-AC0091d	G511	0					
AC0090-AC0091a	G604	4	G505	G502	G508	G611	
AA0963-AA0962p	G502	0					
AA0963-AA0962d	G510	0					
AA0963-AA0962a	G508	6	G509	G602	G503	G505	
LA0750-LA0751	G604	15	G509	G602			
AA0215-AA0216p	G910	0					
AA0215-AA0216d	G604	0					
AA0215-AA0216a	G507	0					
JJ3558-TAM9770p	G506	0					
JJ3558-TAM9770d	G508R	0					
JJ3558-TAM9770a	G605L	0					
LA0760-LA0753	G508L	0					
JJ8009-JJ8096p	G501	0					
JJ8009-JJ8096d	G601L	0					
JJ8009-JJ8096a	G605R	0					
CA0907-CA0908p	G912	23	X003				
CA0907-CA0908d	G508	0					
CA0907-CA0908a	G605	0					
SA0222-SA0223	G510	0					
LP2767-LP2766p	G903	0					
LP2767-LP2766d	G509	0					
LP2767-LP2766a	G603	0					
SQ0068-SQ0067	G602	0					
LA0752-LA0761	G601R	0					
QR0773-QR0773	G604	15	G511				
JJ8145-TAM8008	G509L	0					
EY0191-EY0190p	G901	0					
EY0191-EY0190d	G509	0					
EY0191-EY0190a	G605	0					
JJ8005-JJ8014p	G506	0					
JJ8005-JJ8014d	G507L	0					
JJ8005-JJ8014a	G603L	0					
JJ3357-JJ8028	G603R	0					
TK0015-TK0015	G511	0					
KL0791-KL0792	G510	0					
AF0456-AF0459	G508	4	G608	G505			
EK0261-EK0262p	G911	0					
EK0261-EK0262d	G508	0					
EK0261-EK0262a	G601	0					
JJ8095-JJ8084p	G912	0					
JJ8095-JJ8084d	G508	0					
JJ8095-JJ8084a	G604	1	G606				
JJ8027-JJ8108	G602	0					
JJ8141-JJ8112p	G607	0					
JJ8141-JJ8112d	G601	0					
JJ8141-JJ8112a	G607	0					
IB6821-IB6820p	G903	0					
IB6821-IB6820d	G507	0					
IB6821-IB6820a	G507	13	G505	G508	G606	G608	G601
TAM8117-JJ8018p	G501	0					
TAM8117-JJ8018d	G507R	0					
TAM8117-JJ8018a	G603L	0					
LA0700-LA0700	G606	0					
JJ8019-JJ8030	G604R	0					

Table D.3: Allocation and Alternative Stands 19/11 Part 3

Name	Allocation	Changes	Alternative Stands					
JJ8045-JJ8128	G604L	0						
JJ8067-JJ8110p	G907	14	X003					
JJ8067-JJ8110d	G605	0						
JJ8067-JJ8110a	G605	15	G507	G505	G601	G608	G508	
JJ3409-JJ8066p	G611	7	X003	X002				
JJ3409-JJ8066d	G508	0						
JJ3409-JJ8066a	G509	0						
JJ8111-JJ8080	G603	0						
JJ8097-JJ8116p	G505R	0						
JJ8097-JJ8116d	G603L	0						
JJ8097-JJ8116a	G503	11	G601R	G610	G505	G608	G608R	G509R
JJ8073-JJ8044p	G511R	0						
JJ8073-JJ8044d	G605L	0						
JJ8073-JJ8044a	G603L	0						

Appendix E: Comparison Objectives

Table E.1: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectives for November 19th

Case & Objective	Δ Affinity [%]	Δ WD [%]	Δ Tow [%]	PC AVG [%]
19/11 Max Aff	-	-	-	93.9
19/11 Min WD	-1.33	-6.58	0.00	94.3
19/11 Min Tow	-5.30	38.79	-33.72	92.4
19/11 Max PC	-4.22	41.25	0.00	94.6

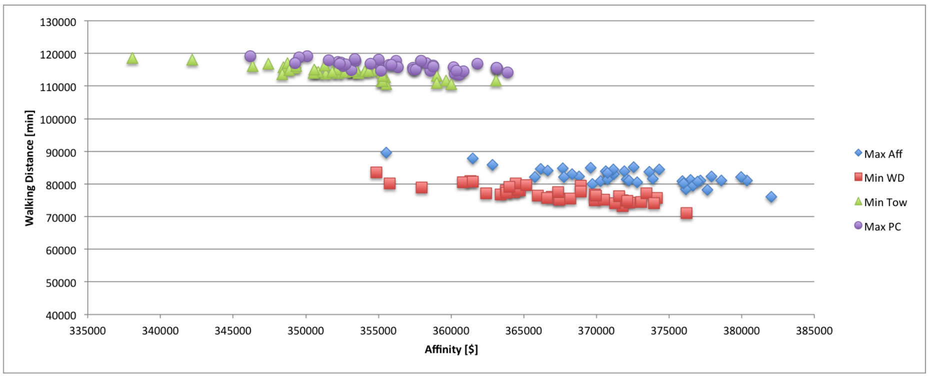

Figure E.1: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 19th

Table E.2: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectives for November 20th

Case & Objective	Δ Affinity [%]	Δ AVG WD [%]	Δ Tow [%]	Contact [%]
20/11 Max Aff	-	-	-	90.1
20/11 Min WD	-1.20	-5.43	0.00	90.8
20/11 Min Tow	-5.98	28.65	-38.82	87.8
20/11 Max PC	-4.06	39.27	1.18	91.1

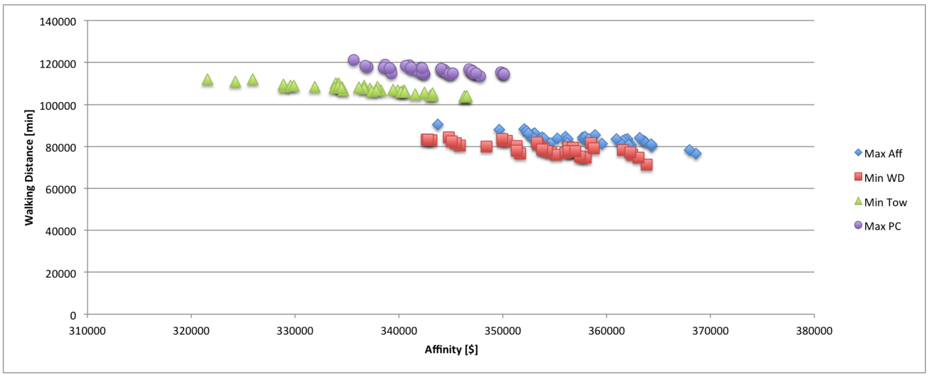

Figure E.2: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 20th

Table E.3: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectivesfor November 23th

Case & Objective	Δ Affinity [%]	Δ WD [%]	Δ Tow [%]	AVG PC [%]
23/11 Max Aff	-	-	-	93.0
23/11 Min WD	0.055	-5.88	0.00	93.9
23/11 Min Tow	-3.36	31.07	-22.62	92.7
23/11 Max PC	-2.36	34.74	0.00	94.3

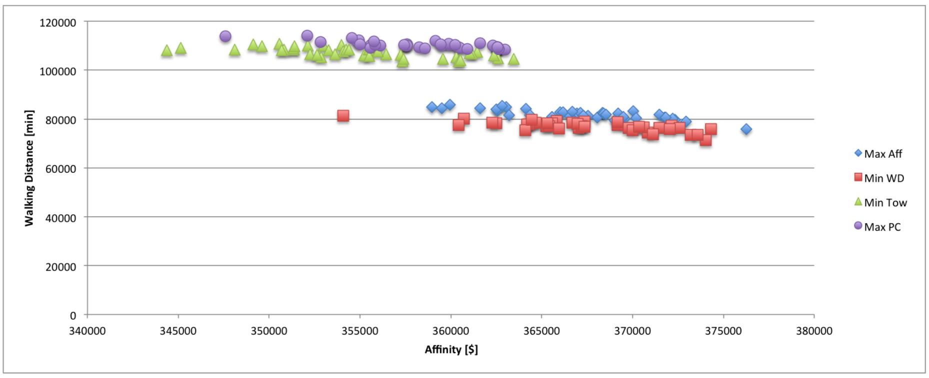

Figure E.3: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 23th

Table E.4: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectives for November 25th

Case & Objective	Δ Affinity [%]	Δ WD [%]	Δ Tow [%]	AVG PC [%]
25/11 Max Aff	-	-	-	91.4
25/11 Min WD	0.20	-5.13	0.00	92.2
25/11 Min Tow	-3.53	34.20	-31.65	91.4
25/11 Max PC	-2.92	41.09	0.00	92.7

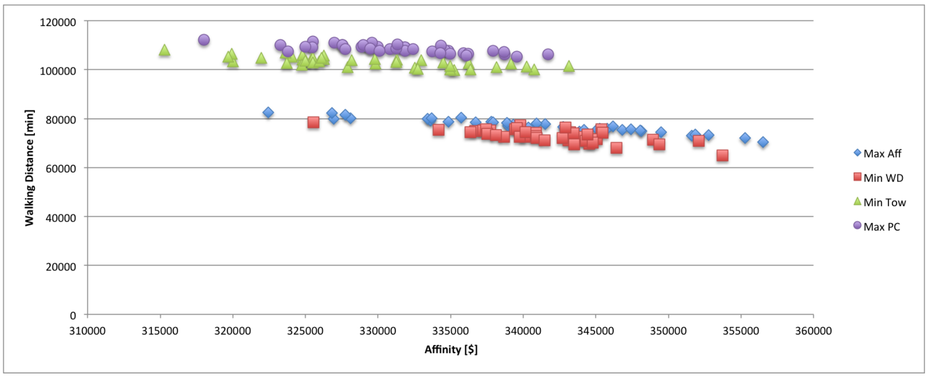

Figure E.4: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 25th

Table E.5: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectives for November 26th

Case & Objective	Δ Affinity [%]	Δ WD [%]	Δ Tow [%]	AVG PC [%]
26/11 Max Aff	-	-	-	92.0
26/11 Min WD	-2.04	-5.37	-1.15	92.2
26/11 Min Tow	-10.30	37.33	-40.23	87.2
26/11 Max PC	-4.39	32.20	0.00	92.8

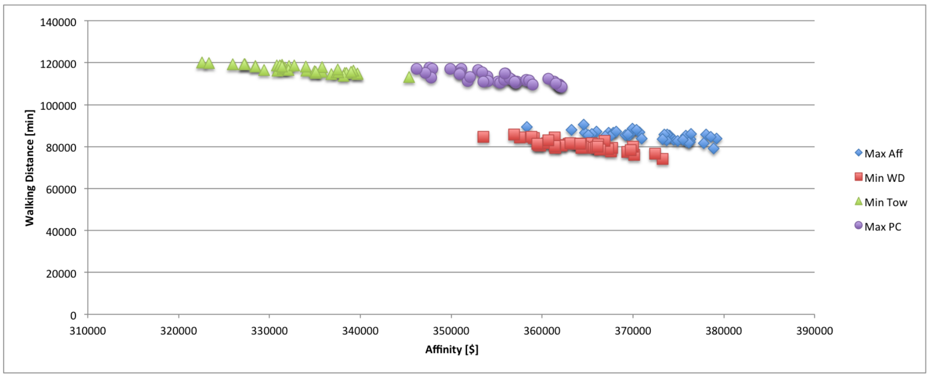

Figure E.5: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 26th

Table E.6: Relative Differences in Affinity, Walking Distance (WD), Towing Operations and Percentage of passengers allocated to a Contact-Stand (PC) for four Objectives for November 27th

Case & Objective	Δ Affinity [%]	Δ WD [%]	Δ Tow [%]	AVG PC [%]
27/11 Max Aff	-	-	-	89.8
27/11 Min WD	-0.89	-7.72	0.00	91.3
27/11 Min Tow	-8.23	35.72	-39.74	87.0
27/11 Max PC	-3.36	36.21	1.28	91.7

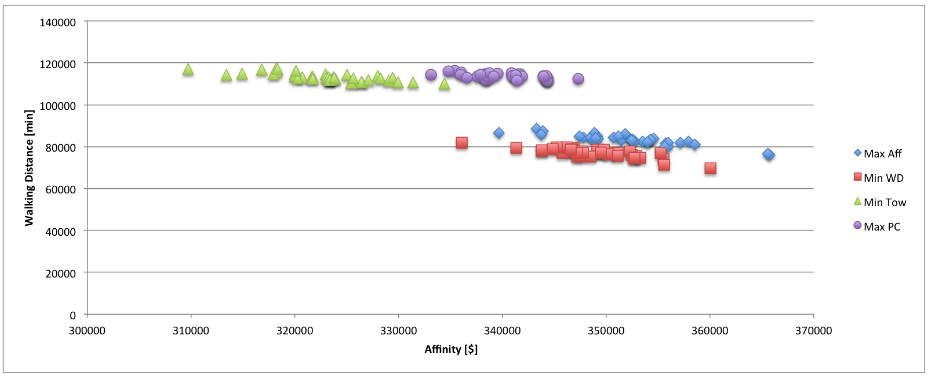

Figure E.6: Variation in Walking Distance and Affinity for the Four Objectives in the Scenarios for November 27th

Appendix F: Recovery per Stand

Table F.1: Required Recovery Actions per Stand Part 1

Stand	19/11	20/11	23/11	25/11	26/11	27/11
G501	0	0	0	0	20	0
G502	0	9	1	0	0	0
G502L	0	0	0	0	0	0
G502R	0	0	0	0	0	0
G503	11	0	8	0	29	6
G504	0	0	0	0	0	0
G504L	0	0	0	0	0	0
G504R	0	0	0	0	0	0
G505	32	0	0	0	0	4
G505R	0	0	0	0	0	0
G506	0	0	0	0	0	0
G507	58	52	34	72	83	51
G507L	0	0	0	0	0	0
G507R	0	0	0	0	0	0
G508	17	18	25	36	42	45
G508L	0	22	0	0	0	0
G508R	23	0	0	0	0	0
G509	0	2	43	0	5	9
G509L	0	0	0	1	0	0
G509R	0	0	0	0	0	0
G510	2	12	9	21	2	0
G510L	0	0	0	0	0	0
G510R	0	0	0	0	0	0
G511	0	0	0	0	0	0
G511L	0	0	0	0	0	0
G511R	0	0	0	0	0	0
G601	2	0	0	29	0	0
G601L	0	0	0	0	0	0
G601R	0	0	0	0	0	0

Table F.2: Required Recovery Actions per Stand Part 2

Stand	19/11	20/11	23/11	25/11	26/11	27/11
G602	0	3	8	4	23	25
G602L	0	0	0	0	0	0
G602R	0	0	0	0	0	0
G603	1	0	0	0	15	0
G603L	0	0	0	0	0	0
G603R	0	0	0	0	0	0
G604	43	81	29	12	27	60
G604L	0	0	0	0	0	6
G604R	0	0	17	0	0	0
G605	71	74	64	73	45	64
G605L	0	0	0	0	0	0
G605R	0	0	0	0	0	0
G606	0	25	0	2	4	0
G606L	0	0	0	0	0	0
G606R	0	0	0	0	0	0
G607	0	1	0	0	1	0
G607L	0	0	0	0	0	0
G607R	0	0	0	0	0	0
G608	11	0	0	0	4	28
G608L	0	0	0	0	0	0
G608R	0	0	0	0	0	0
G609	0	0	2	0	0	2
G609L	0	0	0	0	0	0
G609R	0	0	0	0	0	0
G610	1	0	26	0	0	0
G610L	0	0	0	0	0	0
G610R	0	0	0	0	0	0
G611	7	0	0	27	0	3
G611L	0	0	0	0	0	0
G611R	0	0	0	0	0	0
G901	0	21	3	0	0	0
G902	0	0	0	0	0	0
G903	0	20	0	0	0	0
G904	0	0	0	7	0	0

Table F.3: Required Recovery Actions per Stand Part 3

Stand	19/11	20/11	23/11	25/11	26/11	27/11
G905	0	0	0	0	0	0
G906	0	0	0	0	0	0
G907	14	0	0	4	0	0
G908	0	0	0	0	0	0
G909	0	0	1	0	18	0
G910	0	0	0	0	0	0
G911	0	16	15	0	0	0
G912	23	0	0	0	9	28
G913	0	0	0	0	2	0
X001	0	0	0	0	0	0
X002	0	0	0	0	0	0
X003	0	0	0	0	0	0