Master of Science Thesis

A Many-objective Tactical Stand Allocation: Stakeholder Trade-offs and Performance Planning

A London Heathrow Airport Case Study

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Challenge the future

Delft University of Technology

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Master of science thesis

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Dedication

To Mom and Dad, for being the best role models possible.

To Soma, for setting the bar high for me each and every day.

To Mesi, for teaching me humility and to never ever come up with excuses.

To Harriet, for teaching me how to find and express my strengths.

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[1] Cover page image: https://upload.wikimedia.org/wikipedia/commons/1/16/Heathrow_Airport_010.jpg

Executive summary

Airports are considered to be highly complex systems that are able to generate economic growth on their own. It means that the airport works in synergy with other stakeholders such as the airlines and their subcontractors, the government, the passengers, local businesses and the environment. Accordingly, airports take proactive actions to create a status quo between the stakeholders in both the master planning of the airport itself[1] and the operational adjustment of processes using Airport Collaborative Decision Making (A-CDM)[2]. While the master plans account for synergy on a system level(strategic decisions) and A-CDM mitigates disruptions on an operational basis, the interests of the stakeholders are not necessarily systematically taken into account on the planning of sub-systems such as the tactical allocation of aircraft to stands within the airport's stand infrastructure. Namely, the harmonization between the stakeholders' interests are either reactively accounted for or not considered at all which means that one cannot be certain that the objectives of the stakeholders are met. For that reason, a methodology is developed in the current research to proactively assess decision alternatives on the performance of the tactical stand allocation to identify how the different stakeholders can achieve their goals in (partial) synergy. As the methodology is also suitable for actually implementing the found consensus(since it is forecasted), the airport can apply the concept of empathetic negotiation on its subsystems which means that the interests of other stakeholders can be planned for while the airport's interests are not compromised, hence, a favorable status quo can be established.

The stand allocation problem at airports is a pressing issue, since aircraft stands are scarce and expensive resources and capacity problems often arise which leaves capacity planners to be only able to (most of the time) allocate each aircraft to a stand, hence only focus on complying with capacity requirements[3]. While this solves the original problem, the aircraft are assigned to stands in a sub-optimal way for which high costs are paid not necessarily by the airport itself, but by the other stakeholders. Therefore, this research investigates the Stand Allocation Problem(SAP) for tactical stand planning taking some of the objectives(goals) of the corresponding stakeholders into consideration. These stakeholders along with the airport are the airlines and the passengers. The interests of these stakeholders are numerous, however, trends in previous literature indicate a set of practical objectives for the three different stakeholders. Five of these objectives are deemed to represent the most characteristic objectives of the three stakeholders which makes the stand allocation model to be investigated a many-objective tactical stand allocation model. The objectives of the stakeholders are listed as:

- Minimization of non- and remote allocation of aircraft (airport objective)
- Maximization of effective stand use (airport objective)
- Minimization of aircraft taxi distance (airline objective)
- Minimization of the number of aircraft tows (airline objective)
- Minimization of passenger walking distance (passenger objective)

The balancing of the needs of all these stakeholders is considered a complicated task, since the above listed objectives(goals) have a complex (often conflicting) relationship with each other. It is also complicated to decide on a stand allocation policy and guide the generation of the tactical stand allocation to give an allocation performance that was previously agreed on by the stakeholders. In this way, this research investigates the degree to which suitable decision alternatives on the performance of the tactical stand allocation can be both generated, predicted and proactively be selected as a strategy for a future stand allocation.

Literature review

Complex policy decisions with multiple (conflicting) objectives often pose a degree of confusion on the decision makers regarding the effect of their decisions on the performance of the objectives and that of the overall

problem[4]. The fact that decision makers are not in possession of accurate information on the synergic or conflicting relationship between their objectives, they tend to make decisions based on alternative-focused thinking principles[5]. Namely, they first generate an alternative(scenario) which is then subject to revision and iterative readjustment. If the revision provides insufficient results, they tend to reactively adjust the alternative to meet their requirements or improve on the performance of the alternative. This is a very common approach in the tactical planning of the aircraft stand allocation at airports.

The aim of this research is to improve the awareness of airport decision makers (capacity planners) regarding their decisions on the performance of the tactical stand allocation problem. This requires a different way of decision making process, which is the method of value-focused thinking. Using this approach decision makers can proactively generate decision alternatives taking the objectives of the stakeholders into account and see the amount of value generated based on the decisions they make[6]. Accordingly, this methodology can be applied to the many-objective planning of the tactical stand allocation problem.

The scientific investigation of the stand allocation problem began in the 1980's when researchers aimed to model the allocations using simplistic constraints such as capacity constraints, allocation constraints, compatibility constraints and even stand adjacency constraints[7, 8]. Furthermore, the allocation of aircraft to gates(later on stands) was not only investigated, however, optimization of these allocations was performed using simplistic allocation objectives such as the minimization of passenger walking distance[9].

When it comes to subsequent research, a large variety of allocation objectives were developed to increase the control over the way the allocations are optimized. These objectives include the minimization of towing operations[10], aircraft taxi distance[11] and maximization of stand effectiveness[12] amongst others. Most of these objectives were developed independently, however, several attempts were made to investigate the degree of compromise one has to make when two of these objectives are used simultaneously for the allocation. It was discovered, that there is an underlying conflict between the objectives when it comes to the performance of the allocation[13]. Some other researches also attempted to investigate the degree of compromise in the performance of each objective as the importance of each (objective weight) is varied. It was concluded that the performance of an objective can be accurately manipulated using the Weighted Sum Method(WSM) on the representation of the stand allocation problem[10, 11]. Unfortunately, a direct correlation between the significance (weight) of an objective to its performance is only proven when the stand allocation problem uses less than 4 objectives.

Although, relationships between the objectives of the many-objective stand allocation problem (at least 4 objectives) were not investigated previously, other operations research fields developed techniques for identifying potential trade-offs between these objectives. One of these methods is an objective reduction technique which progressively lowers the number of objectives that are non-conflicting which ensures that both relationships between the objectives is found and the problem size is reduced[14]. Other methods aim to use correlation metrics, however, these methods appear inaccurate in a many-objective optimization framework[15]. S. H. Kim[11] revealed that the solution space generated by continuously varying the weights of the objectives is highly discontinuous which makes it hard for decision makers to deduct meaningful alternatives.

Robust techniques within the data mining domain are able to identify relationships in a many-dimensional solution space(at least 4 dimensions). A branch of interest is the clustering of solutions, however, several clustering techniques are present such as distribution-based clustering, density-based clustering, connectivity-based clustering and centroid-based clustering. While all of these techniques aim to relate(or to cluster) similar data points in all dimensions, the first 3 methods focus on separating and putting the focus on parts of the solution space. On the other hand, centroid-based clustering, namely, k-means clustering focuses on dividing the complete solution space up into regions that are suitable to work with[16].

However, as this present research discovered, k-means clustering prove to be suitable to solve this issue[16]. This would open up the possibility of performance planning. In this way, the research gap in the many-objective(weighted sum) tactical stand allocation framework combined with k-means clustering prove to be beneficial to establish the current research.

Research Objectives

In light of the above presented discussion, 3 research objectives are introduced that accurately describe the scope of the research:

- **Research objective 1:** Develop a many-objective tactical stand allocation model that both incorporates at least one interest of the airport stakeholders and also allows for the manipulation of the orders of these interests.
- **Research objective 2:** Develop a framework that provides a priori performance planning options to airport capacity planners on the many-objective tactical aircraft stand allocation.
- **Research objective 3:** Display the industrial applicability of the a priori performance planning framework in a London Heathrow Airport case study.

Research objectives 1 and 2 intend to lead to academic findings in the field of aviation. On the other hand, the 3^{rd} research objective aims to investigate whether the developed techniques can be implemented for industrial use. This is investigated through a case study that is carried out on the tactical stand allocation of Terminals 2 and 3 of London Heathrow Airport. It is important that the developed model provides clear and easy-to-understand performance design options to the decision makers a priori to carrying the allocation out. The research hypothesis therefore investigates the validity of the feedback to the decision makers, namely, the weights of the allocation objectives. The research hypothesis is formulated below.

- **Hypothesis 1:** The objective weight combinations of the many-objective tactical stand allocation model should provide an exact trade-off in the standardized KPI design space irrespective of the used flight schedule.

In this way, it will be examined whether the weight inputs to the stand allocation problem on the first hand provide direct Key Performance Indicators(KPI) of the allocation irrespective of the used flight schedule. If not, an approximation framework for relating the objective weights to the allocation KPIs is developed which is then used as a basis for providing objective weight options for decision makers to apply on their allocation model.

The Stand Allocation Performance Planning Framework

The Stand Allocation Performance Planning Framework for providing accurate feedback on the expected performance of the tactical stand allocation comprises of several modules and models. These modules can be seen in Figure 1. Module 1 consist of the many-objective tactical stand allocation model and the connected Weight Space Search algorithm to explore the variety of performance characteristics the allocation can have by using a large set of objective weight combinations. The large variety of KPI values (in multiple dimensions) creates the solution space of the many-objective tactical stand allocation problem. The model makes use of 5 allocation objectives. The first objective is the minimization of non- and remote allocation of flights. This objective is on top of the importance hierarchy, namely, it will be always optimized first regardless of the other objectives. Then, 4 objectives are competing(hence compromises can be made between them). These objectives are the minimization of aircraft taxi distances, towing operations, local transfer passenger walking distances and the maximization of effective stand use. It must be mentioned that the interests of transfer passengers were emitted, since that would have created more complex relationships between the objectives of the stakeholders which is out of the scope of this research.

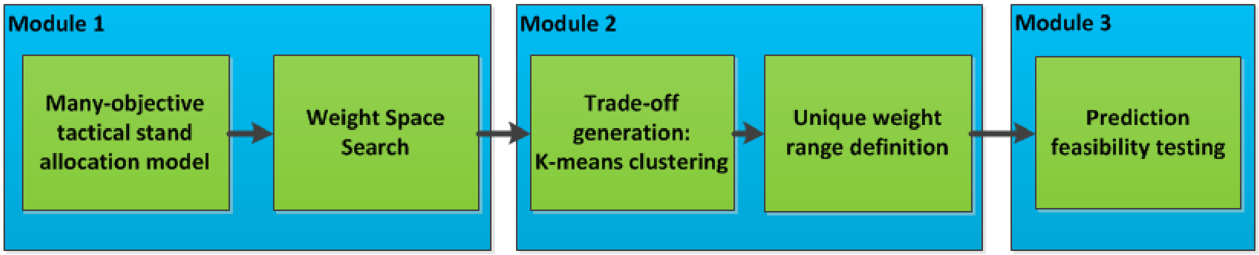


Figure 1: High-level overview of the components of the performance planning framework of a many-objective tactical stand allocation

Module 2 initially groups allocations that have similar performance characteristics for all allocation objectives (clusters) by making use of the k-means clustering algorithm. While the found clusters are distinguishable based on KPI values, it is possible that the connected objective weight ranges overlap with other clusters, therefore, reducing the size of the cluster (and the related weight ranges) is done in the unique weight range finder model. In this way, each cluster or in other words performance profile is defined uniquely. In order to test whether the created performance profiles can be re-used for an allocation to be created in the future(through the reuse of the related objective weights), the prediction accuracy of these performance profiles is carried out in Module 3 using London Heathrow Airport as a case study basis.

Research Results

The Stand Allocation Performance Planning Framework was tested by creating 10 performance profiles(clusters) for the tactical stand allocation of London Heathrow Airport's Terminal 3 on the 12^{th} of August, 2016 with an Easterly 1 runway configuration. The main reason for creating these performance profiles was proven by identifying the inability to unambiguously and directly relate the weight of an objective to the corresponding allocation's performance metrics. In certain cases, it was found that the weight of a single objective can lie anywhere within a 35 % range in its KPI range. It means that the accuracy of purely using the objective's own weight for predicting its performance provides very inaccurate results. It also means that the performance of an objective is dependent on the objective weights of all of the included objectives, therefore, their combined effect defines each objective's performance.

Furthermore, the number of performance profiles the solution space is broken up into was investigated and it was found that when one uses more performance profiles the expected KPI accuracy will be larger. While this is a desirable characteristic of the problem, one has to realize that as the number of performance profiles increases, the predicted KPI accuracy decreases, the airport decision maker is bombarded with a larger variety of choices. Unfortunately, that leads to the choice of paradox which makes it harder for decision makers to choose between the performance profiles. Also, it was discovered that as the number of performance profiles is increased, the predicted allocation performances are less and less accurate. While breaking the solution space up into a maximum of 10 clusters results in an average prediction accuracy of 90%, more performance profiles results in a prediction accuracy of 40-60%. For that reason, the decision maker has to make a balanced decision on the number of performance profiles used.

The above mentioned models were also analyzed by trying to provide performance planning decisions to London Heathrow Airport's Terminal 3 for the summer planning season. The analysis revealed that airports can ensure that their interests are completely satisfied while enabling other stakeholders to also improve on their processes that are linked to the stand allocation. It was found that while the non-allocation of flights and the stand effectiveness are optimized for the airport, either the passengers or the airlines can also improve on their processes to a certain extent. It was also found that when the airport is unable to have optimum performance, the other two stakeholders cannot have optimum performance simultaneously either. Furthermore, it was discovered that it is not possible to have the objectives of all stakeholders optimized at the same time. It was also suggested to LHR to use the discovered information to gain negotiating power when discussing the stand allocation with the other stakeholders in the form of empathetic negotiation. This could not only potentially enable the airport to gain new sources of revenues, but it would also enable them to improve on the overall performance of the apron of their airport.

Conclusions and limitations

With regard to the discoveries of the present research project, several conclusions can be drawn. These conclusions are listed below.

- The weights of the single objectives do not directly represent the allocation KPI values in the many-objective tactical stand allocation framework.
- By grouping allocations with similar performance characteristics(clusters or performance profiles) in the many-dimensional solution space, the related objective weights that created these allocations are also similar in all dimensions. Namely, these weights(for each objective) are grouped in continuous ranges.
- While the weight ranges of the performance profiles are continuous, they do not uniquely define the performance profile, therefore, the size reduction of these performance profiles was necessary to be able to describe them uniquely through their objective weights.
- The Stand Allocation Performance Planning Framework can effectively uses the uniquely defined performance profiles(through their weights) to provide an accurate performance forecast for airport decision makers for their future aircraft stand allocations, hence empowering airport decision makers with the tool of empathetic negotiation.

While the above listed conclusions provide value to the aviation society, it has to be pointed out that the presented research has limitations. Firstly, the Stand Allocation Performance Planning Framework was proven to work for the combination of the used objectives, however, other relevant allocation objectives need to be investigated. Furthermore, the granularity of the Weight Space Search algorithm should be increased to ensure that the found performance profiles are still stable when using a more refined weight space. Moreover, including an objective representing the interests of transfer passengers should be included to be able to control the performance of more processes at airports. Then, the number of performance profiles created from the solution space greatly effects both the expected and the predicted KPI accuracy. When the number of performance profiles is increased, one can define its goals more accurately, hence have more accurate expected KPI values. On the other hand, the accuracy of the predicted(resulting) KPI value is lowered.

All in all, the developed methods provide useful recommendations for the a priori performance planning of the tactical stand allocation, hence it fits well within the value-focused thinking methodology. Also, the developed methods could be applied and investigated in other research areas such as check-in desk allocation optimization, baggage reclaim belt allocation optimization or even airport financial budget allocation optimization.

List of Abbreviations

Abbreviations

A-CDM	Airport Collaborative Decision Making
ACTD	Aircraft Taxi Distance
ATC	Air Traffic Control
ATD	Arrival Taxi Distance
ADG	Aircraft Design Group
AWD	Arrival Walking Distance
B&B	Branch and Bound optimization algorithm
CA	Charter Airline
DTD	Departure Taxi Distance
DV	Decision Variable
DWD	Departure Walking Distance
FAA	Federal Aviation Administration
GB	Gigabite
GHz	Gigahertz
ICAO	International Civil Aviation Organization
ID	Identifier
KPI(s)	Key Performance Indicator(s)
LC	Legacy Carrier
LCC	Low Cost Carrier
LOS	Level of Service
MaOO	Many-objective Optimization
MARS	Multiple Aircraft Receiving System
MCDM	Multi-criteria Decision Making
MILP	Mixed Integer Linear Programming
MIQP	Mixed Integer Quadratic Programming
NRA	Non- and Remote Allocations
O&D	Origin & Destination Airport
PAX	Passengers
PWD	Passenger walking distance
RAM	Random Access Memory
SAP	Stand Allocation Problem
SE	Stand Effectiveness
SGA	Stand & Gate Allocation Problem
SM	Size Mismatch Between the Stand and the Operation
SLA	Service Level Agreement
TW	Tows
USA	United States of America
WCSS	Within-cluster Sum of Squares
WSM	Weighted Sum Method
WSS	Weight Space Search

Contents

1 Introduction

An airport is a highly complex system that does not only serve as the backbone of transportation for a certain area, but it also acts as a platform for other entities to either conduct their businesses or to prosper in symbiosis with the airport. Such entities are the stakeholders of the airport which include the airlines and their subcontractors, the passengers travelling through the airport, the government, local businesses and even the environment. Although, the airport's master plan accounts for the synergy of the stakeholders' objectives on a system level(strategic decisions) and Airport Collaborative Decision Making(A-CDM) mitigates disruptions on an operational basis, the interests of the stakeholders are not necessarily systematically taken into account on the planning of sub-systems such as the tactical aircraft stand allocation. Specifically, the harmonization between the stakeholders' interests are either reactively accounted for or not considered which means that it is not ensured that the objectives of the stakeholders are met. This becomes problematic, since the tactical decisions involving multiple stakeholders are made without the stakeholders which can result in sub-optimal processes and disruptions on an operational level.

This is especially true for the tactical planning of the aircraft stand infrastructure of an airport. Stand capacity planners at airports are facing capacity and service policy problems which can be partially attributed to their decision making processes that are based on alternative-focused thinking principles[5, 10, 11]. It means that the values of the stakeholders are either not discovered or are only taken into consideration in a non-structured way[5]. In other words the harmonization between the stakeholders' values are either reactively accounted for or not considered at all. Therefore, this research focuses on developing a framework which utilizes value-focused thinking that proactively assesses decision alternatives(opportunities) on the performance of the stand allocation problem[4]. This framework would help decision makers(capacity planners) to identify favorable decision alternatives and the degree to which the stakeholder objectives can be met a priori to generating the allocation plan.

Accordingly, a stand allocation model is built that accounts for 5 stand allocation objectives of different stakeholders, hence, this type of model is called a many-objective tactical stand allocation model. Furthermore, the allocations generated by this model are used to create performance alternatives on a tactical level, namely, days before the actual allocation plan has to be implemented. The stakeholders of the stand allocation are considered to be the airport, the airlines and the passengers. The objectives and the corresponding stakeholders are presented below:

- Minimization of non- and remote allocation of aircraft (airport objective)
- Maximization of effective stand use (airport objective)
- Minimization of aircraft taxi distance (airline objective)
- Minimization of the number of aircraft tows (airline objective)
- Minimization of passenger walking distance (passenger objective)

This model is built in such a way to not only account for these objectives simultaneously, but to also give capacity planners the opportunity to create a ranking between the allocation objectives. While this allows them to proactively influence the different performance metrics of the stand allocation and the compromises(trade-offs) the stakeholders have to make, it is still uncertain whether these trade-offs are realized and the desired performance is obtained. For that reason, a framework is developed that examines the relationships between the stakeholders' interests and their effects on the stand allocation's performance. This framework also identifies and forecasts promising decision opportunities that can be implemented for future allocations through recommended inputs when creating the allocation.

As a result, airports can apply the concept of empathetic negotiation also on a subsystem level which ensures that an acceptable status quo is achieved between the stakeholders[4]. Namely, while the airport aims to maintain the operation of its stand infrastructure at a desirable performance level, it can also provide direct value (improvement) to the remainder of the stakeholders. In other words, a prescriptive negotiating framework is established on the performance of the stand allocation of the airport.

Since the above mentioned framework allows decision makers to plan the performance (and status quo) of the tactical stand allocation, the title of this thesis follows as:

"A Many-objective Tactical Stand Allocation: Stakeholder Trade-offs and Performance Planning"

This research is conducted in co-operation with Beontra GmbH, a leading airport scenario planning firm to bridge the gap between academic and industrial advancements. Furthermore, London Heathrow Airport as Beontra GmbH's customer will serve as a case study basis to validate the industrial applicability of the developed methodology. It means that the objectives of this research consist of both academic and industrial objectives. The objectives of this research are listed below:

- **Research objective 1:** Develop a many-objective tactical stand allocation model that both incorporates at least one interest of the airport stakeholders and also allows for the manipulation of the orders of these interests.
- **Research objective 2:** Develop a framework that provides a priori performance planning options to airport capacity planners on the many-objective tactical aircraft stand allocation.
- **Research objective 3:** Display the industrial applicability of the a priori performance planning framework in a London Heathrow Airport case study.

The first and second research objectives are academic objectives while the third objective investigates the industrial relevance of the developed methodology. The above listed research objectives clearly outline the scope of this research. Therefore, a detailed literature review is presented in Chapter 2. It is followed by an elaboration on the extensive project plan in Chapter 3. In Chapter 4, the mathematical model of the many-objective tactical aircraft stand allocation is presented. Then, the framework for identifying the relationships between the allocation objectives and the objective Key Performance Indicators(KPIs) along with the performance planning framework is presented in Chapter 5. Furthermore, a case study is performed at London Heathrow Airport to investigate that the researched methods can indeed be used in realistic scenarios. The case study can be found in Chapter 6. Then, the verification and validation of the developed models are presented in Chapter 7. Lastly, Chapter 8 gives detailed analyses on the main findings and outcomes of this research.

2 Literature review

This chapter presents the general motivation behind conducting the current research through the presentation of the state of the art knowledge in the research framework. Firstly, general definitions related to the research framework are introduced in Section 2.1. Secondly, the stakeholders of the tactical stand allocation problem are presented in Section 2.2. It is followed by the discussion on strategic approaches used in decision making regarding Multi-criteria Decision Making(MCDM) problems in Section 2.3. Then, the current state of literature on the tactical Stand Allocation Problem(SAP) along with its links to many-objective optimization is presented in Section 2.4. Furthermore, the expected contribution of this research to science is described in Section 2.5.

2.1 General definitions of the research framework

This section introduces the general definitions that are used throughout this research. Although, these definitions are directly related to the SAP, they also will be used for the interpretation of the research results. Hence, it is important to clearly define these aspects in order to avoid confusion.

- **Tactical (Aircraft) Stand Allocation:** the allocation of flights or turnarounds to aircraft stands approximately 4-6 days prior to the use of the allocation to evaluate if all the flights can be (optimally) allocated.
- **Allocation objective:** an allocation objective expresses the interest of a certain stakeholder in the Stand Allocation Problem(SAP). The sum of all objectives(mathematical representation) make up the objective function of the SAP.
- **Relative significance (weight) of an objective:** the relative significance of an objective expresses the rank or the degree of certain stakeholder's influence on the tactical aircraft stand allocation. It is also referred to in this document as the allocation weight of a certain objective.
- **Objective KPI:** the KPI of an objective expresses the performance of the objective of the respective stakeholder in the optimized stand allocation. It is deducted(and transformed) from the optimal objective function value of the stand allocation. It means that the KPI value can be sub-optimal.
- **Solution space:** The set of multi-dimensional KPI values generated by solving the SAP iteratively with varying objective weights (creating different MIPs and hence allocations). The solution space contains the multi-dimensional KPI values, hence the solution space is also multi-dimensional.
- **Standardized solution space (standardized KPIs):** the normalized set of KPI values that make up the solution space. Namely, the adjustment of KPI values to be measured on a common scale.
- **Operational day:** the day for which the tactical stand allocation is performed.
- **Cluster (trade-off):** a sub-set of the solution space that contains KPI values that are similar in multiple dimensions. The clusters are created using the k-means clustering algorithm.
- **Cluster weight range:** the set of multi-dimensional relative significance (objective weights) that describe the KPIs belonging to a specific cluster.
- **Unique (cluster) weight range:** the sub-set of the cluster weight range for a specific cluster that contains weight values that uniquely define the cluster.

2.2 Stakeholders and their objectives in the stand allocation problem

The tactical aircraft stand allocation problem is considered complex task, since it is not only important to allocate each flight or turnaround to an aircraft stand, but it is also of great importance to allocate them in a way that both the airport's and other stakeholders' interests are met. This is an increasingly used concept and it is called Collaborative Decision Making(CDM)[2]. In CDM the airports work together with other stakeholders (that use the airport) in order to improve on the efficiency of the different processes at the airport. The tactical stand allocation at airports also can make use of the CDM concept, which means that the interests of multiple stakeholders are taken into account when creating the allocation plan. It is very well possible that some of the interests of the different stakeholders are of a conflicting nature. Thus, it is necessary to specify which stakeholders are relevant for the tactical stand allocation problem.

The airport

The most relevant and influential stakeholder in the tactical SAP is the airport itself. The airport provides the necessary infrastructure for the other stakeholders - such as the passengers and airlines - to conduct their operations. The infrastructure relevant for the SAP consists of the contact and remote stands, the taxiway and apron systems, the runways, Air Traffic Control(ATC) and aircraft ground support. It must be mentioned that ground support is often outsourced at most airports, hence, it is worth clearly defining whether ground support is considered a separate stakeholder or if it is part of the airport's or even the airlines' jurisdiction[1, 17]. For the current research, it is assumed that the airlines take responsibility of the operations of the ground support. This assumption is based on the operational standards at the airport used for the research case study, namely, London Heathrow Airport(LHR). At LHR, airlines are responsible for organizing their ground support.

The goal of the airport is to attract more and more traffic to maximize its aeronautical and non-aeronautical revenues. Aeronautical revenues are directly (but not necessarily linearly) proportional to the amount of aeronautical traffic (flight movements) that is at the airport[1]. On the other hand, non-aeronautical revenues are not directly proportional to the amount of aeronautical traffic (flight movements). It highly depends on the strategic decisions an airport makes[18]. These decisions include the operational structure of the airport, the industrial significance of the region where the airport is located, the possibility of the airport to grow, the local community and environmental measures or laws in place. These decisions can include non-aeronautical revenues such as retail, airport landside revenues and car parking revenues amongst others.

In this fashion, the current research differentiates between two airport types, namely, a large international hub airport such as Amsterdam Airport Schiphol or Frankfurt Airport and an origin and destination airport like Budapest Airport. The main reason for differentiating between the two airport types lies in the fact that the flight movement and passengers structures might be significantly different. Also, the interests and the hierarchy of the interests of the stakeholders might significantly differ.

International hub airports are the largest and most complex airports in the world. The main characteristic of such an airport is that it acts as a hub (of one or more airlines) where a significant amount of passengers are collected by airlines from smaller airports and these passengers are re-directed to other destinations. This strategy was induced by the influence of large airlines, since a hub airport provides a lot of destinations to the passengers while minimizing the amount of aircraft that are used for the airline's operations[1].

Origin and Destination(O&D) airports have a broader definition than international airports. These airports mostly feed the international hub airports with passengers. These airports are smaller in size (amount of passenger gates, aircraft stands and terminal size) and the amount of passengers are also less. This is due to the fact that these airports are (mostly) located in less populated regions and also the transfer passenger share is significantly lower (close to zero). The fact that these are not hub airports does not exclude the possibility of some smaller (low cost carrier) airlines use the airport as their hubs[1].

In light of the previous discussion, the airports have several interests(objectives) regarding the tactical stand allocation. First and foremost, it is of primary importance for airports to allocate each and every flight to a stand in order to provide adequate service to both the airlines and the passengers[3]. Furthermore, it is also of great importance to airports to maximize the amount of aircraft that are assigned to a contact stand, namely, to a stand which is directly connected to the terminal building through a passenger gate[1]. The main advantage for the airport of such an assignment is that contact stands are more expensive for airlines, hence, the airport can collect more aeronautical revenues. Furthermore, the service level provided to the passengers is higher, since the inconvenience of busing to and from a remote stand is avoided.

Another objective of the airports is to assign the aircraft to the available stands in an efficient way. It means that airports aim to allocate aircraft to stands that are not larger than the aircraft itself within the ICAO Aircraft Design Group classification(ICAO ADG) framework[12, 19]. The main motivation behind this objective is to ensure that the stand s are properly used and that the capacity for each Aircraft Design Group category is ensured throughout the day of allocation. It is especially important for large aircraft (type E and F), since the amount of such stands at an airport is significantly less than the smaller categories.

As the previous discussion suggests, there are significant differences in the working principles of the two airport types. It means that the set of trade-offs between the objectives might have a significantly different judgment by airport planners. Although, one can make subjective judgments on the importance of certain objectives for the airport types, it is yet to be proven which trade-offs are favorable to be carried out. This research aims at identifying these differences between allocation trade-offs per terminal.

The airlines

The main stakeholder that generates traffic at the airport are the airlines. Although, there are several different airline types, the most important ones that operate at airport that need automatized stand allocation are presented here: Legacy Carriers(LC), Low Cost Carriers(LCC) and charter airlines(CA)[20]. The airlines bring the traffic to the airport which is both beneficial for them and for the airport. Bringing passengers is not enough, since all the other competitors do the same, therefore, airlines try to edge each other out at every single airport. That is the reason why some airlines lease parts of the airport such as a few stands, a terminal or even the complete airport. One could argue that airports could prevent such a thing from happening, but they also have to realize that a certain airline might bring significantly more passengers to their airport than another one[21].

Airlines (mostly legacy carriers) also try to impose their gate preferences on the airport and the stand and gate allocation schedule to allow for shorter transfer time, higher passenger comfort and bigger non-aeronautical revenues (in case the terminal is leased by them)[21, 22]. Also, they might want to reduce taxi distances (or taxi times) and the related fuel burn, so they might opt for stands and gates that are close to the runways[1]. Furthermore, when an aircraft of an airline has a short turnaround time(is on the ground for a substantial amount of time), the airport might opt for the towing of the aircraft from a highly utilized (contact) stand to a remote stand to free up the stand for other passenger carrying flights to occupy it. As these towing operations are costly for airlines, it is of primary importance for them that the allocation is created in such a way as to minimize the amount of times their aircraft are towed[10].

The passengers

Although, passengers do not explicitly express their say in the distribution of resources, revenues and costs of airports, they have a very different but very significant interest, therefore, they have to be considered as a stakeholder in the SAP. The bigger the airport and the more the passengers are, the bigger the influence passengers have on the SAP. Airports must comply with Service Level Agreements(SLA) or in other words Level of Service (LOS) that are related to the timely processing of the passengers[23]. Some of these SLAs account for passenger comfort, for example terminal walking distances, transfer times between two flights or free dwell space. Accordingly, passengers exercise their stakeholder 'rights' through passenger comfort. This comfort can be expressed quantitatively through the rules and agreements mentioned in [23] and through passenger complaints and experiences. Such complaints include a missed flight, long walking distances, busing operations and long queues at gates or at security control[21].

Two types of passengers can be distinguished related to the current research framework. The first type of passengers are the local passengers. These passengers either commence or terminate their travel at the airport under consideration. It means that their passenger comfort (in connection to the stand allocation) is expressed through the minimization of walking distance. The other type of passenger is the transfer passenger. Such a passenger uses the airport to switch from one flight to another one, therefore, only uses the secured part of the terminal. Since operational delays are common place at most airports, the primary interest of transfer passengers is to minimize the transfer times. As it will be seen later on, the minimization of passenger walking distance does not provide (in general) significant value to the transfer passengers. However, transfer times are more critical to transfer passengers, since having a considerably large transfer time might result in missing the connecting flight[11].

Furthermore, passenger comfort can be expressed through the minimization of busing operations. A busing operation occurs when an aircraft serving a flight is located at a remote stand which is not directly connected to the terminal building. It means that the passengers have to be placed on a bus that transports the passengers to the aircraft stand. The additional busing operation in passenger processing introduces discomfort to the passengers, therefore, it needs to be ensured that the amount of bused passengers is minimal[21]. As the busing operations most of the time occur between a remote stand and a terminal, for the current research, it can be assumed that this passenger objective is expressed through one of the airport's objectives, namely, the minimization of remote allocations as presented before.

2.3 Decision making processes in complex systems

As the previous section revealed, the stakeholders of the stand allocation problem can formulate several different objectives which makes not only the stakeholders compete with each other for a better performance, but the objectives of a certain stakeholder can be conflicting. It means that the performance of a complex system has to both be decided on in a way to satisfy all parties involved and that it can be made sure that the decision(strategy) is realized.

Unfortunately, as the amount of aircraft stands at airports are low and investment costs are high[1], stand capacity planners are most of the time occupied by trying to assign each aircraft to a stand and they do not have the resources to create the allocation in such a way that each stakeholder can operate at an optimal performance. However, this does not disallow them to favor one or more stakeholder over the other. Capacity planners can implement the requests of certain stakeholders for a performance improvement. This is most of the time done through the consideration of an airline's preferences towards a certain set of stands[3]. Furthermore, the performance of the stand allocation can be modified through the assignment of different relative importance to the allocation objectives. This is done through the Weighted Sum Method(WSM)[11].

The main disadvantage of the above mentioned two methods is that decision makers(capacity planners) create alternatives first without actually assessing the effects of those decisions on the overall allocation performance. Secondly, the performance of the allocation is assessed a posteriori to creating the allocation, namely, decision makers reactively try to improve on a certain performance metric of the stand allocation by controlling the relative importance of the objectives. This problem-solving approach is called alternative-focused thinking[5]. In this way, decision makers are developing alternatives(allocations and their performances) and then assessing the allocation's values(performance metrics). Such developed alternatives seem attainable due to the straightforward representation of the priorities, however, such way of thinking prevents one from truly exploring all possible alternatives and also restricts one to only making reactive adjustments to already developed alternatives.

On the other hand, it is also possible to firstly articulate clearly the values(objectives) of the stand allocation problem and to later on create alternatives that try to comply with the expressed goals. This methodology is called value-focused thinking[6]. In this methodology, decision makers can proactively create and assess decision alternatives through the values(importance of objectives) specified previously. It means that for the present research scope, the performance of the tactical stand allocation can be decided on using empathetic negotiation[5]. It means that while the airport achieves an allocation performance that it finds suitable, it can ensure that allocations implemented in the future can have performance characteristics that are also favorable for the other stakeholders thereby creating a favorable status quo for the collective[4]. As the aim of this research is to ensure that the performance of the tactical stand allocation can be proactively assessed, the value-focused thinking methodology is discussed in detail in Chapter 5.

2.4 State of the art

This section provides information on the state of the art research on the stand allocation problem (SAP) as well as its link to many-objective optimization methods from other fields of operations research. It has to be mentioned that the current research will only focus on the stand allocation problem, but methods from the stand and gate allocation(SGA) problem will also be outlined here, since the SAP is a simplification of the SGA. The aim of this research is to include some of the relevant methods and techniques in a new method and to push the boundary of this research field further.

2.4.1 Stand allocation problem

The aircraft stand (and gate) allocation problem is has become a more and more pressing issue as the air transportation started to rapidly grow in the middle of the 20^{th} century[1]. This rapid growth fueled the need to investigate the gate allocation problem which produced significant results in the 1980's. These initial gate allocation models focused on developing and solving simple problems with simple constraints such as the allocation of each aircraft to one stand only and ensuring that two aircraft that are on the ground at the same time are not assigned to the same gate[7, 24]. Furthermore, simplistic gate allocation objectives such as the minimization of passenger walking distance were used to increase the value provided by the allocation[8]. These researches focus on gate allocation at airports which was apparent, since a specific passenger gate was directly linked to one aircraft stand at airports where the research was conducted. However, when these researched practices became widely used at airports using remote stands (which might not be directly linked to a single gate), the methods had to be extended to be the stand and gate allocation problem.

Constraints

As far as the constraints of the SAP are concerned, a large variety of constraints have been found to be suitable for the tactical stand allocation problem. The most commonly used constraints are essential constraints that make the optimization problem a stand allocation problem. Such constraints account for allocating each flight to a single stand(allocation constraint)[11], allocating aircraft to compatible stands(compatibility constraint)[12] and avoiding ground conflicts between a set of two flights at the same stand(capacity constraint)[12].

All of the above constraints are essential to be included in the optimization problem to make it a stand (and gate) allocation problem. Interestingly, the SAP can be customized based on the allocation requirements at airports to limit the crowdedness of the taxiway system[12, 25] as a consequence of the allocation, define which aircraft can be towed or not[10], express the allocation's flexibility due to schedule changes through a buffer time constraint[12] or to limit the number of tows. Furthermore, special stand configurations such as the use of MARS stands[12] can also be modelled.

Objectives

Most commonly, the SAP objectives include a combination of airport or airline and passenger related objectives, for example either the minimization of passenger walking distance[8, 9, 26], the maximization of airline preferences[27], maximization of effective stand use[12] or the minimization of towing operations[10].

Some other researches aim to introduce new objectives, such as the minimization of taxi distances[13] or the minimization of non- and remote allocations[3]. Additionally, some researches focus on developing 'exotic' objectives such as the minimization of the deviation from a past reference schedule[27] or the fair distribution of walking distance between the airlines' passengers[9].

While all of these objectives model important allocation aspects, not accounting for more (or all) of them simultaneously in creating the stand allocation can significantly overlook some crucial considerations regarding the allocation. Therefore, recent literature investigates the effects of including more than one objective in the tactical stand allocation model. As far as using multiple allocations parallel, the majority of state-of-the art research focuses on establishing relationships between two allocation objectives creating bi-objective optimization problems. Such researches discovered the synergy between the number of passengers assigned to a contact stand and the number of towing operations[10], the conflicting nature of minimizing overall and airline-based passenger walking distance[9] or the conflicting nature of passenger walking time and aircraft taxi distance[13]. All the above mentioned problems are deterministic problems, however, it is also possible to investigate multiple allocations in parallel by applying stochastic inputs to the model such as a stochastic robustness measure[28].

A group of researchers also aimed to identify the relationships of objectives in a tri-objective optimization problem[11, 29]. Although, S. H. Kim et al.[11] were able to identify a relationship between passenger transfer time, aircraft taxi time and the robustness of the schedule, these relationships are described visually and qualitatively. They also found that there is an identifiable (but not quantified) relationship between the objective weight and the obtained allocation KPI value, namely, as one increases the weight of an objective, the KPI value of that objective gets better.

Mathematical representation

Literature on the stand and gate allocation problem considers several types of mathematical representations. The most popular formulation is the Mixed Integer Linear Programming(MILP) problem[10, 12]. The MILP can consist of either only binary variables to account for a flight-stand combination [27], or a mix of binary and continuous variables[10] to truly harness the Mixed Integer Programming(MIP) nature of the problem. It can be said that the SAP in MILP representation is relatively easy to solve due to the fact that the constraints and the objectives are linear, however, a major limitation of such an approach is that certain stand allocation objectives or constraints cannot be accurately modelled. Such an objective is the minimization of transfer time of transfer passengers. That objective has to be modelled with quadratic variables to relate two flight-stand combinations[13]. The use of quadratic variables creates a Mixed Integer Quadratic Programming(MIQP) problem. This sort of problem in the SAP framework is considered to be hard to solve, since a large number of decision variables make up the objective functions.

The main disadvantage of the quadratic programming representation is the fact that solving such a problem is mathematically difficult due to the fact that this problem is NP-hard[30]. In order to reduce the problem complexity, the quadratic terms have to be linearized. While linearization solves the problem, a large number of additional constraints are introduced to the model to shift from quadratic to binary terms[31].

It is also possible to model the stand allocation problem as a multi-commodity network. This approach considers an arc between two flights in case the ground times of the two flights under consideration are not overlapping[31]. A major disadvantage of this approach is that the model has to be broken up into smaller sub-problems using different stand areas at the airport due to the long computational times of large problems.

Solver algorithms

One of the focus areas of researchers of the stand allocation problem is to find solver algorithms to speed up the allocation process[27, 32, 33]. The main motivation for such initiatives is due to the fact that it is hard to find a suitable heuristic solution within a reasonable time with current methods. Some of the researches focus on developing novel tabu search algorithms for obtaining a reduced computational time [32, 33], while other researches make use of an ejection chain algorithm[34], simulated annealing[35] or the branch-and-bound algorithm[13]. Although, this is a pressing issue, this current research does not aim at finding novel techniques related to solver algorithms.

2.4.2 Many objective optimization and the synergy of objectives

Most of the research on SAP that consider more than one optimization objective optimizes with the objectives having equal significance in the objective function[9]. On the other hand, it is also possible to give preference to one or more objectives over the remaining ones to express a hierarchy between the objectives. This is done using several different methods. One of these methods is the hierarchical (or lexicographic)[36] optimization where the objectives are sequentially optimized based on the hierarchy between them. As this method considers a strict hierarchy between the objectives, it is very inflexible for analyzing the relationships between the objectives. The other commonly used method is the Weighted Sum Method(WSM)[10]. Using this framework, one is able to assign a weight(significance) to each objective and by varying the weights of the objectives, one can create a large set of MIPs(and from those, allocations). The alternative solutions of those MIPs (the non-dominated solutions of each of the MIPs considered together) can then be analyzed to see if the weight of a certain objective has an effect on the performance of the objective. This method is called Weight Space Search and it is utilized in various forms in literature not related to the stand allocation problem[11, 37]. These researches proved the validity of creating trade-offs by using the weighted sum method.

Relationship discovery(trade-offs between objectives) techniques for optimization problems(and the SAP) in past research also include the use of different correlation techniques, such as the Pearson, Spearman and the Kendall correlation coefficients[38] between the KPIs of non-dominated solutions. The main limitation of such techniques is that they are only accurate in a low-dimensional space, namely, less that 3-dimensional space(less than 3 objectives)[15]. Also, these techniques provide linear relationships between the different objectives which is not necessarily accurate between two or more objectives.

As it was mentioned earlier, trade-offs in tactical stand allocation problem was not investigated previously when more than 3 objectives are present in the allocation model. Interestingly, it does not mean that many-objective optimization was not applied in any other field. The relationship between objectives in a many-objective optimization problem was investigated mostly through objective reduction techniques[39, 40]. These techniques aim to identify which objectives represent the same behavior(are in synergy) in the many-objective optimization problem. Since the amount of objectives quadratically increases the computational time of the optimization problem[14], it is favorable to exclude as many objectives as possible. In this way, only a subset of non-redundant objectives would be kept which are conflicting in nature. Other many-objective optimization methods aim to look at the ranks of the observed results. Namely, they try to find conflicting and redundant objectives based on the pattern in their relationships throughout the observations[41]. These methods are more suitable for the present many-objective approach, since their strengths lie in assessing the relationships between a large number of objectives[14]. However, these relationships are discovered by eliminating some objectives and approximating their Key Performance Indicator values which introduces a layer of uncertainty[39].

There are also other methods available for the assessment of the relationships between the different objectives. Machine learning data mining techniques are able to identify multi-dimensional patterns in the solution space by relating allocations to each other that are similar in performance for each objective[16]. This branch of machine learning is called cluster analysis. Cluster analysis consists of a set of algorithms that relate data points in a multi-dimensional space based on certain rules. There are 4 types of cluster analysis algorithms, which are Connectivity-based clustering (hierarchical clustering)[42], Distribution-based clustering, Density-based clustering and Centroid-based clustering (k-means clustering)[16].

Distribution-based clustering clusters (or groups) data points in a data set that have a similar distribution. The algorithm uses a set of distribution patterns (usually Gaussian distribution) to which the data points are attempted to be fitted while continuously updating the parameters of these distributions[43]. Although, this algorithm seems promising at first, since subsets of data points that are further away from other data points can be effectively captured, one has to point out that this method has major disadvantages. Firstly, the main disadvantage of this method is that it experiences overfitting which appears when a clustering model is very complex and when the model does not accurately catch the relationships, but it catches the random error instead[44]. It results in poor predictive performance. Additionally, it is highly likely that the data set cannot be related to any well defined mathematical distribution model, which means that the user has to investigate the possibilities of distribution patterns. Also, assuming e.g. Normal or Gaussian distributions for the model is rather constraining regarding the quality of the results. Accordingly, the Distribution-based clustering method is not suitable for the current research[44].

In Density-based clustering, the algorithms create clusters that are high in density[45]. Data points that are in not dense regions are assigned to either a separate cluster or are considered noise. For this current research, this is not an acceptable property, since all data points tell something about the behavior of the allocation. Density-based algorithms work based on connecting data points that are within a certain distance. In addition, these algorithms are aided by a density criterion that ensures the minimum number of data points that have to lie within a certain radius. Although, its complexity is low, it has disadvantages. In order for the algorithm to work properly, it expects a sudden drop in density on the border of the cluster[45]. In most cases and also in the current research, it cannot be ensured that there is a certain drop on the borders of the cluster. It means that using this technique, one cannot ensure that the found clusters are accurate.

Connectivity-based clustering (or hierarchical clustering) investigates whether certain data points are more correlated to near objects than to objects that are further away[46]. The clusters are formed based on the distance between the data points. In this way, the cluster is defined by the maximum distance between any two data points that are within the cluster. Since the distance between any two data points in the data space (solution space) is measured, the degree in which the data points are related can be expressed through a dendrogram[47]. This dendrogram represents the hierarchy between the emerging clusters, which is also a basis for the clustering method, hierarchical clustering. A disadvantage of this approach is that it does not produce a single unambiguous set of clusters to the user, but it presents a large combinations of possible clusters. It would mean that the user would have to apply a complex post processing step to include each data point in a cluster that seems acceptable. While an accurate post processing can be (automatically) done, there is a similar clustering algorithm (as it will be seen later on) that produces high quality clusters without the additional post processing steps necessary here.

The last branch of cluster analysis that is considered here is the Centroid-based clustering. In this method, the clusters are depicted using a central vector for which, it is not required to be a part of the set. Centroid-based clustering needs the definition of k (k-means clustering) which defines the amount of clusters and their centers a priori to the optimization[16]. Once the number of clusters are defined, the data points in the solution space are assigned to these clusters while ensuring that the squared Euclidean distances to the centers of these clusters is minimized. It means that data points that are similar to each other in multiple dimensions(i.e. their KPI values in all dimensions lie close to each other) are related to each other[43]. Thus, this algorithm is the most suitable for the present research.

2.5 Discussion and relevance to science and the industry

The aircraft stand allocation problem has been widely researched starting from allocation constraints such as the capacity, allocation, robustness and stand adjacency constraints to allocation objectives like the minimization of passenger walking distance and minimization of towing operations amongst others. Research has also been conducted on using multiple (conflicting) objectives simultaneously for the stand allocation problem. These objectives are guided for controlled trade-offs in their performance using the Weighted Sum Method. Although, researches were conducted investigating the trade-offs of objectives in pair[9] and even in a group of three[11], it is yet to be investigated what happens if at least 4 objectives of all of the three main stakeholders are present in the tactical stand allocation. S. H. Kim et al.[11] scrutinized the 3 main stakeholders simultaneously, but only in a multi-objective optimization framework. Namely, investigating the complexity of objective performance trade-offs of a many-objective tactical stand allocation(using at least 4 objectives) is recognized to be a research gap. This is visible in Figure 2.1. Furthermore, as most of the past research developed the objectives and constraints of the stand allocation model in a Mixed Integer Linear Programming(MILP) formulation, this formulation will also be used for the current research.

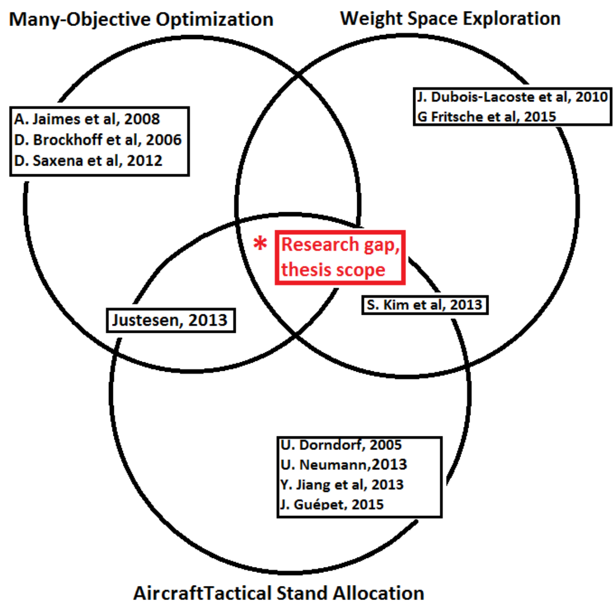


Figure 2.1: Research gap concerning operations research framework of the tactical stand allocation problem

It was shown earlier that the performance of the objectives can be guided through the Weighted Sum Method(WSM) representation. The WSM was solely used in stand allocation research for identifying the degree of trade-off between a certain set of objectives. However, it was also found that the performance of an allocation can be and should be influenced a priori to the allocation in the form of strategy selection(value-focused thinking). It means that a research gap is identified in utilizing the obtained performance trade-offs already researched and using it as a basis for objective performance planning(forecasting).

The above outlined objective performance trade-offs have been analyzed using regression analysis techniques when the amount of objectives in the problem did not exceed 3. Other research fields developed objective reduction techniques that are able to find trade-offs between objectives in a many-objective solution space. A third research brand also delivered promising results finding patterns in a many-dimensional solution space. Namely, k-means clustering provides the exploration of the solution space with controllability on the accuracy of the trade-offs created. Furthermore, this method allows for the user to investigate if the weights corresponding to the defined trade-offs are suitable for performance planning. As this method has not been used for the tactical stand allocation problem to identify trade-offs, the research gap of using k-means clustering for the establishment of performance trade-offs in the many-objective tactical stand allocation model is defined. It is also visible in Figure 2.2.

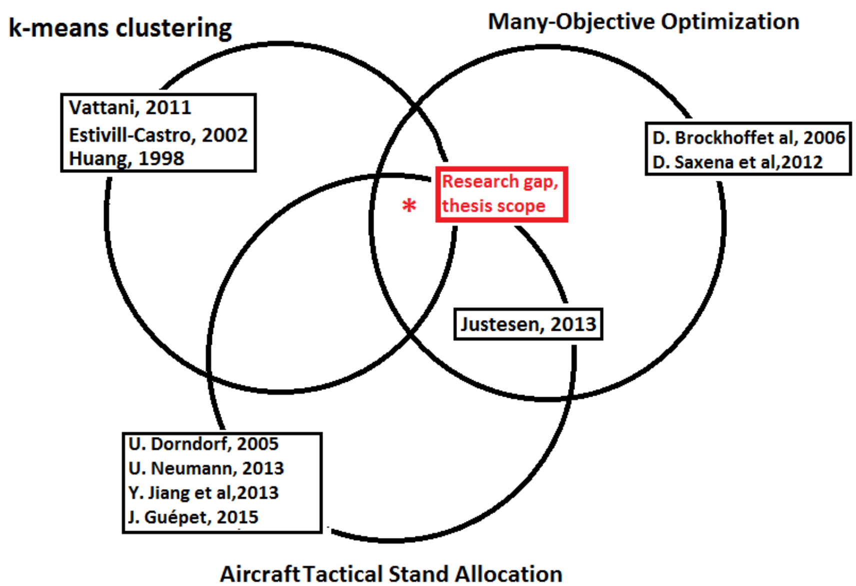


Figure 2.2: Research gap concerning the establishment of objective relationships (trade-offs) of the tactical stand allocation problem using data mining

The identified research gaps indicate that the current research has the potential to increase the awareness of capacity planners on the effects of their decisions on the other stakeholders. It means that capacity planners can create a set of allocation performance alternatives and can communicate these alternatives to the other stakeholders. It would allow for a concensus decision on the performance of the allocation using empathetic negotiation. As far as the academic potential of this research is concerned, it is expected that in filling the identified research gap, a new (more detailed) light can be put on the strengths of the Weighted Sum Method in controlling the trade-offs made in a many-objective optimization framework. The proposed k-means clustering algorithm is considered only one of many data mining techniques that seems promising in creating these trade-offs, therefore, it is hoped that this research can serve as a basis for future researchers. Lastly, future research may make use of the developed methodology to specify and control trade-offs in other many-objective allocation problems.

3 Project planning

This chapter proposes a detailed description of the general research framework. Namely, the research questions are detailed in Section 3.1. It is followed by the elaboration on the objectives of this research in Section 3.2. Then, the research hypotheses related to the many-objective tactical stand allocation along with the high level research setup and its step-by-step procedure are described in Section 3.3. Afterwards, a more detailed description of the research setup is given in Section 3.4. Finally, Section 2.5 describes the research gaps that this research aims to investigate along with its relevance to science and the aerospace industry.

3.1 Research questions

This section presents and elaborates on the research questions that are to be answered as a conclusion of this research. As it will be seen, there are three main research questions. Research question 1 has one sub-question and Research question 3 has two sub-questions which intends to increase the level of detail the main research question is answered. In addition, while Research question 1 investigates airport operations practices, research questions 2 and 3 explores the validity of modelling techniques and level of applicability of these methods for allocation performance planning (forecasting) purposes. It must be noted that the main research questions are shown with bold fonts, however, the sub-questions are shown with bold and italic fonts.

RQ1: Are the Key Performance Indicators representing the objectives of the airport, airlines and passengers conflicting in the many-objective tactical stand allocation problem regardless of the amount of included objectives?

Previous research discovered that the allocation objectives are conflicting in a bi- or tri-objective optimization framework. It means that the used objectives cannot be optimized at the same time. As for the tactical aircraft stand allocation problem, these previous statements were investigated for allocation models with less than or equal to 3 competing objectives. Accordingly, the present research aims to find sets of objectives that are conflicting and non-conflicting in nature. It also has to be mentioned that previous research investigated the Pareto-front of the SAP to discover the conflicting nature of the allocation objectives. On the contrary, this research investigates the set of alternative solutions generated by a large number of stand allocations (with different relative significance). It means that conflicts (or trade-offs) will be generated between subsets (clusters) of alternative solutions. Furthermore, the findings of other research fields prove that in the many-objective optimization framework, it is very well possible to identify objectives that work in symbiosis[14]. Accordingly, it will be evaluated whether the allocation objectives work in symbiosis or they create a conflict.

RQ1a: Do the relative significance(weights) of the allocation objectives directly predict their Key Performance Indicators in the many-objective tactical stand allocation problem?

As it was already mentioned in Subsection 2.4.2, when no more than 3 objectives are considered for the tactical stand allocation problem, the relative importance of the objectives are highly proportional to the KPI values of those objectives[11]. Namely, in case one increases the importance of one objective by a certain amount, then the KPI value of that objective proportionally gets better. State of the art research on the tactical aircraft stand allocation does not investigate this statement when more than 3 objectives are included. As a result, this present research aims to investigate whether the significance of a certain allocation objective directly predict the resulting objective KPI or if the weights of the other objectives play a significant role in determining the KPI value.

RQ2: Is it feasible to use the combination of weight space search and k-means clustering to identify relationships between the relative significance and the Key Performance Indicators of the objectives of the airport, airlines and passengers in the tactical stand allocation problem?

Subsection 2.4.2 revealed that the trade-offs between the KPI values of certain objectives are mostly determined by either regression analysis or by the investigation of the (linear) correlation between the different KPIs. Section 2.4 also discussed that these methods are effective when low dimensional problems are discussed, namely, when the number of allocation objectives are less than or equal to 3. Since these methods cannot be used for the evaluation of trade-offs between the different objective KPIs, the alternative method considered for this research will be examined. Namely, the feasibility of the combination of weight space search and k-means clustering for the development of trade-offs between the KPIs of a many-objective tactical stand allocation problem will be investigated.

RQ3: Is it possible to plan the KPI performance of a future tactical aircraft stand allocation by developing trade-off alternatives with different strengths and weaknesses?

Research Question 3 investigates the capabilities of translating the results of the combination of the weight space search method and the k-means clustering algorithm for the development of stable trade-offs between the KPIs of the objectives of the tactical SAP. Namely, it will be examined if the multi-dimensional cluster of certain allocations (establishing a trade-off) can develop feasible alternatives for the stakeholders of the stand allocation problem. In case this research question would be positively answered, then the developed method would be suitable for the a priori planning of the performance of a tactical stand allocation.

RQ3a:Does the type of terminal (international hub or origin and destination) have an influence on the mapping accuracy of the Key Performance Indicator trade-offs?

As the inputs to the tactical SAP originate from different sources, it is expected that changing one input source (e.g. the apron infrastructure) will also change the arrangement of the KPIs of the objectives in the solution space. Thus, the effects of changing the apron infrastructure to which the flights or turnarounds will be allocated is examined by Research Question 3a.

RQ3b: Does the structure of the flight schedule (number of turnarounds, number of passengers and ground demand) have an influence on the mapping accuracy of the Key Performance Indicator trade-offs?

Research Question 3b investigates the effects of changes in the inputs similarly to RQ3a, however, for this current research question, the effects of the variability in the flight schedules will be investigated. Changes in the flight schedules alone are a direct indication of the degree of predictability of the trade-offs between the objective KPIs. It means that the findings of this research question greatly define whether the developed methods are useful for the performance planning of the tactical stand allocation.

3.2 Research objectives

Section 2.5 in the previous chapter indicated the research gaps in the investigation of the trade-offs between the stand allocation objectives. It is not only important to identify the research gaps and the derived research questions, it is also of paramount importance to translate these considerations into research objectives. Therefore, the objectives of this research are outlined below.

- **Research objective 1:** Develop a many-objective tactical stand allocation model that both incorporates at least one interest of the airport stakeholders and also allows for the manipulation of the orders of these interests.

- **Research objective 2:** Develop a framework that provides a priori performance planning options to airport capacity planners on the many-objective tactical aircraft stand allocation.
- **Research objective 3:** Display the industrial applicability of the a priori performance planning framework in a London Heathrow Airport case study.

It can be seen that the first two research objectives are academic objectives. Namely, they aim to prove the validity of novel academic findings. On the other hand, Research Objective 3 addresses the applicability of these methods to the aviation industry. This is done by conducting a case study on the tactical stand allocation of London Heathrow Airport. By reaching all 3 research objectives, the novelty of being able to plan the KPI performance of a tactical aircraft stand allocation would result. It would mean that airport decision makers such as the stand and capacity planners would be able to decide on the strengths and weaknesses of the allocation. This would also give airport decision makers the power to negotiate with the other stakeholders on the performance of the allocation.

3.3 Research methodology

As it was mentioned in Chapter 2 above, the research aims to investigate the possibility of shifting from alternative-focused thinking to value-focused thinking when it comes to the tactical stand allocation of an airport. Namely, it aims to investigate the possibility of providing trade-off alternatives to decision makers a priori to allocating the flights to stands. Therefore, this section presents the value-focused thinking methodology and the way it is utilized in the present research framework.

3.3.1 Value-focused thinking

Contrary to many conventional approaches, value-focused thinking guides the decision makers of problems with multiple (conflicting) objectives to firstly define what value means to them[5]. This approach also focuses on creating alternatives that are feasible regarding the compromises that need to be made between the objectives. It is an essential consideration since most of the time, decision makers cannot set a quantifiable hierarchy between a set of conflicting objectives and hence they are not able to perceive the real effects of their decisions on the actual materialization of the decision[4].

The value-focused thinking(VFT) methodology provides an ideal framework for setting up the step-by-step procedure of the current research. Therefore, the main characteristics of VFT and their connection to the present research are listed below.

Preference elicitation

Preference elicitation is the first step in the value-focused thinking methodology. The goal here is to ensure that the goals of the decision maker (and the other stakeholders) are discovered and listed. These objectives are determined qualitatively, namely, each stakeholder lists their preferences[6]. Although, it is possible to create a hierarchy between the listed objectives that are to be considered, this hierarchy is determined on a rather high level. There are several techniques available to discover the objectives regarding any decision made. This procedure includes brainstorming and applying techniques such as Value Operation Methodology on the selected objectives for creating the hierarchy[5].

As far as the current research is concerned, the literature study presented in Section 2.4.1 reveals that a total of 5 stand allocation objectives can be regarded to represent the three stakeholders accurately well. These objectives are listed as:

- Minimization of non- and remote allocation of aircraft (airport objective)
- Maximization of effective stand use (airport objective)
- Minimization of aircraft taxi distance (airline objective)

- Minimization of the number of aircraft tows (airline objective)
- Minimization of passenger walking distance (passenger objective)

The first objective, namely, the minimization of non- and remote allocations serves as the objective on top of the hierarchy to guide the allocation process to be as realistic as possible. Namely, it is the primary goal of the allocation to ensure that all turnarounds(consisting of flights) are assigned to a remote or (preferably) a contact stand[3]. The hierarchy of the other 4 objectives is not specifically defined in order to allow for the discovery of different solutions. It means that different hierarchy combinations are going to be examined throughout the research to analyze whether these hierarchies lead to solutions that are appropriate for one or more of the stakeholders.

Creation of new alternatives

As the objectives of the tactical stand allocation were already discovered in the previous step, it is important to create alternatives that can be both evaluated and negotiated on. These alternatives are useful in discovering and presenting a range of opportunities that can be the basis for negotiations for the stakeholders. It then allows decision makers to not only explore alternatives and then evaluate those alternatives, it allows them to explore a wider range of alternatives that they did not or could not think of[4]. It shifts the conventional approach of reactively modifying the initial alternative to proactive action, since a (large) set of alternatives are to be generated.

Within the current research framework, alternatives are created using the Weight Space Search algorithm. In this way, the weights of the objectives in the stand allocation model are iteratively modified and the generated allocations' Key Performance indicators are stored. This creates a multi-dimensional solution space from which the k-means clustering algorithm can create alternatives with different performance trade-offs by grouping allocations with similar performances in all dimensions.

Communication and understanding of final decision

As the alternatives are already determined in the previous step, it is important to translate the decision alternatives to a form that non-technical personnel and all stakeholders understand. It means that while the alternatives can be expressed numerically, it is advised to create a framework in which the hierarchy (and the degree of hierarchy) of the objectives' performance is easily perceivable.

Since the k-means clustering algorithm creates clusters that are visually hard to comprehend due to the high number of dimensions that have complex relationships, it is important that the clusters are represented in a way that is easy to understand for decision makers. In this way, the ranges of KPI values (in each dimension) for each cluster are presented and analyzed. Additionally, the weights that correspond to these KPI values are also not considered explicitly, but the ranges that they take for each cluster are to be looked at.

Interconnecting decisions

It is very well possible that the found alternatives can be taken out of the problem context and can be generalized[6]. It means that the decision maker can make the found trade-offs in the decision alternative widely applicable. In the context of the current research, it means that the weights of the clustered KPIs(trade-offs) are identified and used to clearly characterize the trade-offs. It will be later on investigated whether these trade-offs are indeed general.

Evaluation of alternatives

Alternatives were created previously and these alternatives were translated to be perceivable also by not experts. However, the value of the alternatives has to also be defined. It means that it is not only important to define the value of the different objectives separately, but the overall value of the alternative has to be defined[4]. In this way, the user can identify which alternatives are acceptable to certain individuals and which ones are favorable for all of the stakeholders.

For the current stand allocation problem, it is not only important to identify the trade-offs of certain alternatives, it is also essential to recognize the strengths and weaknesses of them. It means that the KPIs of the alternatives have to be quantified on a scale that allows the decision maker to evaluate if the KPIs of the alternative are acceptable or not. Additionally, the total value of the alternatives must also be presented to identify whether value is brought to all stakeholders or not.

Identifying decision opportunities

Identifying decision opportunities is vital for decision makers to proactively control the performance(value) of their decisions on a certain process or system[6]. Decision makers can also be aware of the degree to which these objectives are achieved. It means that in case the decision maker wishes to obtain a better performance for an individual stakeholder or for the collective, he or she can decide proactively on that performance change. It also means that the benefit-to-effort ratio of this proactive thinking is higher than for the conventionally used reactive alternative-focused thinking[5].

As far as the stand allocation problem is concerned, it firstly has to be assessed that the previously determined decision alternatives are reproducible for a different scenario (different flight schedule or even a different terminal). Then, it also has to be researched whether the reproduced trade-offs are indeed realized and if they bring value to both the decision maker and the other stakeholders.

3.3.2 Research structure

The previous section presented the methodology that governs this research. The steps to be taken in value-focused thinking was also introduced and elaborated on. However, these steps have to be converted into steps that are more general and that both the modeling and assessment procedures of this research are clearly defined. Therefore, this section presents the structure of this research. Firstly, the research hypothesis will be defined that serves as a starting point from which the investigation can begin.

- **Hypothesis 1:** The objective weight combinations of the many-objective tactical stand allocation model should provide an exact trade-off in the standardized KPI design space irrespective of the used flight schedule.

As far as the research hypothesis is concerned, it is expected that the clusters(trade-offs) created using the k-means clustering algorithm will still hold when a different flight scheduleis under consideration. In case the hypothesis is proven to be valid, one would be able to choose between standardized trade-offs (between the objective KPIs) a priori to carrying out the actual stand allocation optimization. This would give the possibility to use the selected relative significance of the objectives as the basis of the overall performance of the tactical stand allocation.

In order to test the above listed hypothesis, the a step-by-step procedure is developed for the current research. The high-level overview of this 5 step procedure is presented in Figure 3.1 below. It also has to be pointed out that the 5 steps are described in detail below the figure.

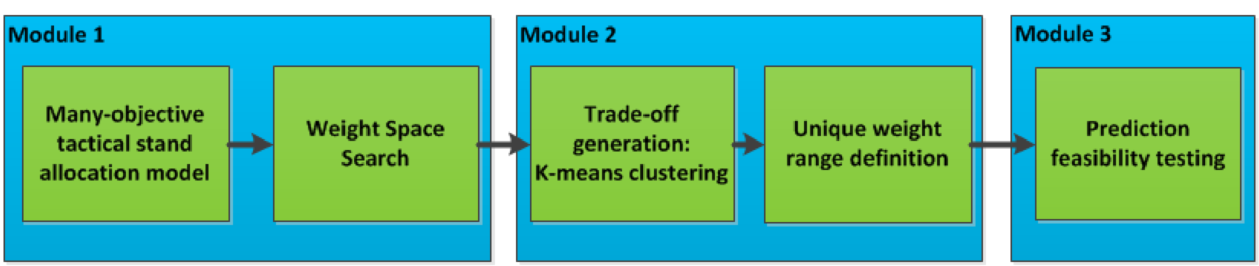


Figure 3.1: High-level overview of the components of the performance planning framework of a many-objective tactical stand allocation

Step 1: the development of the many-objective tactical stand allocation model with the necessary allocation objectives and allocation constraints

The first step comprises of the establishment of the SAP model with at least one objective that represents the interests of each stakeholder. A total of 5 allocation objectives will be present, namely, the minimization of non- and remote allocation of flights, the minimization of aircraft taxi distances, the minimization of the number of towing operations and the minimization of passenger walking distances. the non- and remote allocation objective will be a top priority objective which will be expressed with a higher priority. The other objectives are on the same hierarchical level and trade-offs between their performances will be made. It will be seen later on that the introduction of this hierarchy will affect the trade-offs between the objectives. Furthermore, it is essential to include allocation constraints that accurately model the stand allocation problem. These constraints include constraints on the allocation conflict avoidance at each stand, the single allocation of one flight to one stand and constraints on the working principles of MARS stands.

Step 2: the generation of a multitude of allocations using the weight space search algorithm

As the many-objective tactical stand allocation model is developed in Step 1, it is essential to generate a large set of allocations. This is done by employing the weighted sum method on the stand allocation model. By varying the weights (significance) of the objectives, one can create a large set of allocations. This is done by the Weight Space Search algorithm. As a result of this algorithm, the alternative solutions of a large number of MIPs (with different objective weight combinations) will be obtained that will be sent for creating trade-offs.

Step 3: the clustering of the solutions using the k-means clustering algorithm

As the algorithm in Step 2 created a large set of allocations (and related KPI values), these solutions will be related to each other through the k-means clustering algorithm. This algorithm groups multi-dimensional KPI values together that are similar. In this way, stable trade-offs between the objectives will be established. These trade-offs are realized through the clusters (of KPI values) that are created in the process.

Step 4: the definition of unique (continuous) weight ranges for the set of clusters

Since the clusters of KPI values are created by different MIPs using different weight combinations for the objectives, the clusters do not only have KPI values included, but they also have the corresponding allocation weight values of the objectives. It is very well possible, that the weight ranges of some clusters overlap in one or more dimensions. This is not a problem in general, but if one would like to use the clusters for forecasting the performance of the stand allocation, each cluster (in terms of weight ranges) have to be unique. As a consequence, the objective weight ranges of each cluster are reduced to a level where they are unique.

Step 5: the projection of each observed cluster onto an allocation with different characteristics

As the clusters are made unique in Step 4, it is possible to project these weight ranges onto a future stand allocation. This is done in Step 5. Namely, it is investigated whether the pre-defined clusters (trade-offs) can be projected onto a future stand allocation using the weight ranges associated with the KPIs contained in the clusters.

3.4 Research setup

This section presents the conceptual setup of this research presented in Section 3.3 above on tactical stand allocation in more detail. This is visualized in Figure 3.2 below. One can see that the initial step in the process is to collect the necessary input information. This information is divided up into three different sources. These sources include information on the airport's geometry, such as the amount of aircraft stands, their sizes, taxi distances from the stands to the runways, terminal areas and passenger pathways. The other source is the flight schedule which includes information on the arrival and departure times of the aircraft, its size, the amount of passengers among others. Furthermore, detailed information is necessary on the stand allocation planning procedures. Since this research uses London Heathrow Airport(LHR) for proving the feasibility of this research as a case study, the allocation planning procedures will be collected through consultations with LHR. It must be noted that the information presented in this thesis is partially obtained upon consultation with capacity planners at Heathrow Airport Limited, however, the analysis and opinions drawn from this information are done by the author solely and do not necessarily represent those of Heathrow Airport Limited.

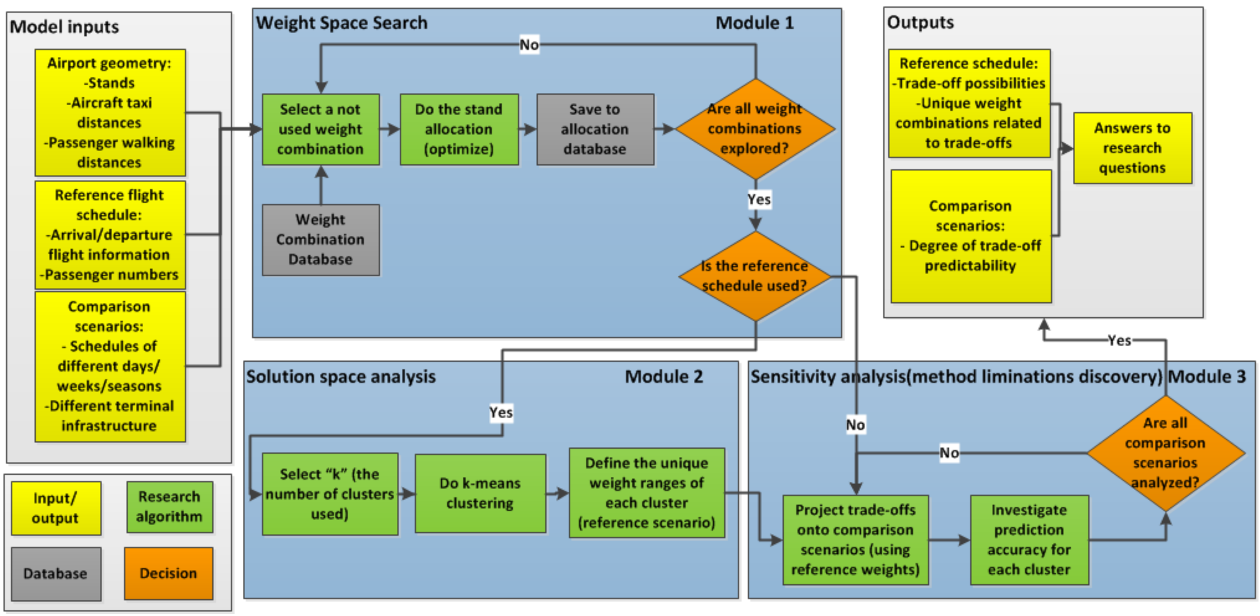


Figure 3.2: Conceptual research setup for the identification of relationships between objectives

When all these information are fed into the system, the many-objective optimization model is set up. A more detailed information on the setup can be seen in Chapter 4. Then, the model is ready for optimization, therefore, it is sent to the Weight Space Search process. In this process, the weights of the objectives are defined for each separate MIP and an optimization is done on each one of them. Then, the resulting allocation is stored which is followed by the progressive modification of the objective weights which is again followed by the optimization. This process is executed until a pre-defined cutoff point. The result of all of this is a certain set of feasible non-dominated solutions for each MIP generated by the pre-defined weight combinations. These solutions are then sent for solution space analysis(Module 2).

Module 2 first divides the multi-dimensional solution space generated by the Weight Space Search algorithm into a k number of trade-offs (clusters) through the k-means clustering algorithm. These clusters are defined as the stable regions in the multi-dimensional solution space that have the results of the allocations that are similar to each other in the multi-dimensional KPI solution space.

Although, the clusters define trade-offs in for the allocation, it is also important that one makes sure that the clusters are unique before any analysis on their forecastability can be done. Therefore, one has to reduce the clusters in size so that only solutions that can be uniquely defined by that cluster can be present. These unique solutions will be the input for forecasting the performance of the stand allocation. The forecasting is done by projecting the unique weights of the clusters onto a future allocation and measuring the accuracy and error (and the sensitivity) of the projections.

Module 3 of this research focuses on analyzing the accuracy of the performance prediction proposed. It is done by measuring the accuracy of overlap between the expected performance values and the predicted performance values. As soon as the projections are analyzed, conclusions on the feasibility and the degree of applicability of the presented methods for the performance planning of a many-objective tactical stand allocation can be drawn.

It is also important to mention that the research and the corresponding many-objective optimization will be carried out in a Python-Gurobi interface with Python 2.7.12 version and the Gurobi 6.5.2 version. For the purpose of optimization, a Windows 10 64-bit operating system environment with a 2.8 GHz processor and 8 GB RAM will be utilized.

3.5 Expected research results

It is expected that the above outlined research model serve as a basis for airport decision makers to plan the performance of their stand allocation a priori. It means that the resulting model should be able to provide feedback on planning options that are visualized through trade-offs between the allocation objectives. In this way, decision makers at airports would be able to select the weight settings (significance) of the objectives in the many-objective tactical stand allocation model. This would allow them with high certainty to decide on their allocation's performance a priori. Furthermore, this a priori knowledge would be a strong negotiating advantage for airports when consulting with the other stakeholders of the tactical stand allocation in the form of empathetic negotiation. It most be noted that in case the methods prove to be feasible, research could be done on other allocation problems that make use of multiple conflicting objectives, such as the check-in allocation problem or the baggage reclaim belt allocation problem.

Conclusions

This research project intends to find a suitable way to aid airport decision makers to plan the absolute performance of their tactical stand allocation a priori to the allocation itself. The model developed in the research would suggest the necessary inputs to airport decision makers based on projected Key Performance Indicators from a past reference allocation. As it was shown in this chapter, this reference would be created by applying Weight Space Search on a many-objective tactical stand allocation model and projecting the uniquely defined trade-off regions of its KPIs to a future allocation. The practicability of this concept will be tested on a London Heathrow Airport case study.

4 The many-objective tactical stand allocation model

This chapter presents the tactical stand allocation model that is built for this present research. Firstly, general definitions and the used nomenclature will be introduced in Sections 4.1 and 4.2. This will be followed by description of the objectives and constraints of many-objective tactical stand allocation model in Section 4.3.2. Furthermore, the complete many-objective tactical stand allocation model and its enhancements are presented in Section 4.3. Then, the Weight Space Search method for the exploration of the solution space is detailed in Section 4.5.3. Finally, Section 4.4 gives a description on the solver algorithm that is used to carry out the optimization.

4.1 General definitions of the airport stand allocation problem

Passenger gate vs. aircraft stand

Passenger gate and aircraft stand allocations are usually considered in combination at airports. This is called the stand and gate allocation problem (SGA). It is important to make a distinction between the two used terms. An aircraft gate is located inside the airport terminal and allows passengers to gain access to the airport bridge that is either connected to the parked aircraft or a passenger bus that drives to the aircraft[1]. On the other hand, an aircraft stand is a location on the airside of the airport where an aircraft parks. There are two types of stands, namely, a contact and a remote stand. A contact stand is a stand where an aircraft parks and it is also directly connected to a passenger bridge that is hence connected to a passenger gate. It has to be noted that a distinction is made between the passenger gate and the aircraft stand, because not all passenger gates are connected to an aircraft stand. It means that remote aircraft stands are not directly connected to any gate, but can be connected to any of them. In this research, it is assumed that for each contact stand the passenger gate used the one that is is directly connected to it. Also, the remote stands are grouped and connected to a common terminal entrance point to which buses transport the passengers. It means that the stand and gate allocation problem can be reduced to be a SAP.

Turnaround vs. operation

An aircraft that arrives at an airport has a turnaround at the airport where it unloads (disembark) the arriving passengers, waits at the airport at one or multiple stands (idle time) and loads (embark) its departing passengers. In light of this, the turnaround of the aircraft can be divided into 3 operations. These operations are arrival flight (disembarkation), (remote) idle operation, and departure flight (embarkation)[10]. This is also visualized in Figure 4.1 below.

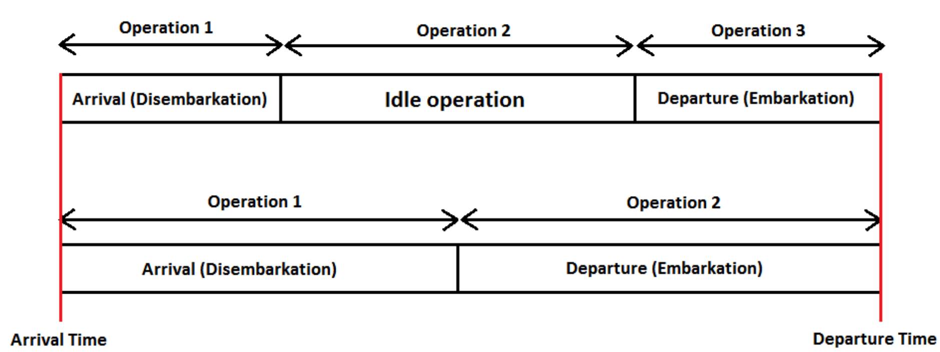


Figure 4.1: The breakdown of a turnaround: arrival flight (disembarkation), (remote) parking and departure flight (embarkation)

As it can be seen above, two types of splits can be made for the turnarounds. One of them splits the turnaround into 3 and the other one splits the turnarounds into 2 operations. The main reason for the difference between these splits is that some operations can be subject to tows (to occupy another stand). This will be explained in detain in Sections 4.3.1 and 6.1.

Successor of an operation

As it was mentioned in the previous subsection, the turnarounds are split into either two or three operations. Since these operations are now considered separate and independent, they can be assigned to any stand (within the set of constraints). In order to keep track of the aircraft that serves all 2 or 3 operations, the operation that uses the same aircraft within the same turnaround has to be specified. This is called the successor of an operation. As it will be seen later on, it also serves as an aid keep the same aircraft at the same stand (if it is required and operationally feasible). This is done by assigning a successor to each operation that is not the departure operation. This forces the operations within the same turnaround to stay at the same stand if there is no reason for a towing. An example for the definition of the successor is given in Table 4.1 below.

Table 4.1: The definition of a successor for each operation when the turnaround is split into 3

Operation	Successor
Arrival (Operation 1)	Idle operation (Operation 2)
Idle operation (Operation 2)	Departure (Operation 3)
Departure (Operation 3)	-

It has to be mentioned that the same rules apply to the case when the turnaround that is split into 2 operations. However, due to the lack of an idle operation, the successor of the arrival operation is the departure operation. Also, the departure operation does not have a successor similarly to the 3 operation case presented in Figure 4.1 above.

Time overlap of two operations

Since hundreds of flights can arrive and depart from a certain airport during an operational day, it is unavoidable to have aircraft (operations) with overlapping turnaround times. It means that certain operations cannot be assigned to the same stand in order to avoid a stand conflict. A time overlap for two operations can be visualized in Figure 4.2 below.

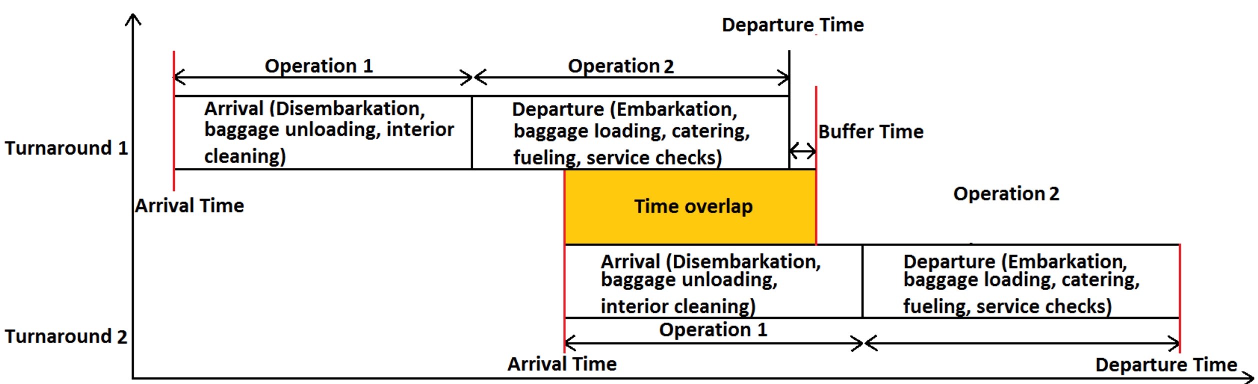


Figure 4.2: The breakdown of a turnaround: arrival flight (disembarkation), (remote) parking and departure flight (embarkation)[48]

It is visible that a buffer time is introduced for the departure operation of Turnaround 1. This buffer time serves as a robustness measure to account for operational variances of the arrival and departure time. It has to be mentioned that a buffer time is only added after the departure time of the departure operation, since the constraint that models this phenomenon ensures that there is a buffer time between two operations (whether it is an arrival or departure operation). This buffer time is explained in great detail in the paragraph below and also in Section 4.3.1. Also, a time overlap can be determined if the statement in Equation 4.1 below holds.

$$t_{arr_{i'}} \leq t_{dep_i} + t_{rob} \tag{4.1}$$

where $t_{arr_{i'}}$ is the arrival time of turnaround 2 and $t_{dep_i} + t_{rob}$ is the departure time of turnaround 1 along with some buffer time. This buffer time is explained in the subsection below.

Buffer time (Stand allocation robustness)

It is crucial for a tactical stand allocation plan to be insensitive to minor deviations that can occur on the day of operation. In an ideal situation, flights arrive and leave the stands precisely at their prescribed arrival and departure times. Unfortunately, real life stand operations are often disrupted by severe weather conditions, flight earliness or delay, airport or airline personnel induced errors, aircraft or stand malfunction and maintenance and emergency flights[27]. These events can result in a chain effect of delays at the airport, since some flights might have to be allocated to another stands that might also have operations already allocated there. In consequence, a buffer time (safety interval) has to be introduced at the end of each operation to account for apparent delays. In this way, one can decrease the chance of creating a domino effect and avoid the accumulation of more delay. The buffer time will be implemented as part of the stand allocation constraints as it can be seen in Section 4.3.1.

4.2 Nomenclature of the modelled objectives and constraints

This section presents the nomenclature that is used for the many-objective tactical stand allocation model. The used scalars, lists and variables are listed in alphabetical order with the necessary description to define the problem.

- s_k: The k^{th} stand in the group of all stands.
- s_{dummy}: Dummy stand that accommodates all operations that could not be assigned to an actual stand. Also, it has unlimited capacity.
- S: The group of all stands, namely, $S = (s_1, s_2, ..., s_k)$.
- $S_{contact}$: The group of contact stands, namely, $S_{contact} = (s_1, s_2, ..., s_k)$ in case stand s_k is a contact stand. Also, the group of contact stands is the part of the group of all stands, namely, $S_{contact} \epsilon S$.
- S_{remote}: The group of remote stands, namely, $S_{remote} = (s_1, s_2, ..., s_k)$ in case stand s_k is a remote stand. Also, the group of remote stands is the part of the group of all stands, namely, $S_{remote} \epsilon S$.
- S_{dummy}: The group of dummy(fictitious) stands, namely, $S_{dummy} = (s_1, s_2, ..., s_k)$ in case stand s_k is a dummy stand. Also, the group of dummy stands is the part of the group of all stands, namely, $S_{dummy} \epsilon S$.
- $S_{o_i,comp}$: The group of stands that are compatible with operation o_i, namely, all stands that operation o_i can be allocated to.
- o_i: The i^{th} operation in the group of all operations.
- O: The group of all operations, namely, $O = (o_1, o_2, ..., o_i)$
- $O_{towable}$: The group of operations that are towable, namely, $O_{towable} = (o_1, o_2, ..., o_i)$ if the operation is towable.
- $O_{non-towable}$: The group of operations that are not towable, namely, $O_{towable} = (o_1, o_2, ..., o_i)$ if the operation is not towable.

- o_i^j: The j^th operation that is in conflict with operation i.
- $O_{i_{conflicts}}$: The group that contains all operations that are time conflicting with operation i, namely, $O_{i_{conflicts}} = (o_1, o_2, ..., o_j)$ of operation j is in time conflict with operation i. Furthermore, the time conflict that an operation o_i^j has with operation o_i can be stated as $t_{arr_{o_i}} \leq t_{arr_{o_i^j}} \leq t_{dep_{o_i}} + t_{rob}$. Namely, if the arrival time of operation o_i^j is later than that of o_i while the arrival time of o_i^j is prior the departure time plus the robustness measure of operation o_i.
- O_a: The group of arrival operations, namely, $O_a = (o_1, o_2, ..., o_i)$ in case operation o_i is an arrival operation. Also, O_a is in the group of all operations, namely, $O_a \epsilon O$.
- O_d: The group of departure operations, namely, $O_d = (o_1, o_2, ..., o_i)$ in case operation o_i is a departure operation. Also, O_d is in the group of all operations, namely, $O_d \epsilon O$.
- O_{idle}: The group of idle operations, namely, $O_{idle} = (o_1, o_2, ..., o_i)$ in case operation o_i is an idle operation. Also, O_{idle} is in the group of all operations, namely, $O_{idle} \epsilon O$.
- $O_{s_{k_{comp}}}$: The group of all operations that are compatible with stand s_k, namely, all those operations that can be allocated to stand s_k.
- $U(o_i)$: The successor of operation o_i. This can both be an idle operation or a departure operation, depending on the nature of operation o_i.
- $size_{s_k}$: The ICAO aircraft design group size of stand s_k.
- $size_{o_i}$: The ICAO aircraft design group size of operation o_i.
- se_{o_i,s_k}: The stand effectiveness coefficient for the decision variable that corresponds with the allocation of operation o_i to stand s_k.
- $t_{arr_{o_i}}, t_{dep_{o_i}}$: Arrival and departure times of operation i. In case operation i is an arrival operation, its departure time is the time after which its successor operation is considered. The arrival time of departure operations is equal to departure time of the operation of which it is a successor of.
- t_{rob}: The time measure of robustness that is to be introduced into the allocation model.
- $MARS^m$: MARS stand group that has stand s_m as the large stand, where each group contains the large (with stand ID m) and the two small MARS stands.
- $MARS_k^m$: The k^th stand within the m^th MARS stand group, namely, $MARS_k^m = (s_1, s_2, ..., s_k)$.
- $d_{arrwalk,s_k}, d_{depwalk,s_k}$: The arrival/departure walking distances to/from stand(gate) s_k.
- d_{arr,s_k}, d_{dep,s_k}: The arrival/departure taxi distances (of aircraft) to/from stand s_k.
- pax_{o_i}: The number of O&D passengers of operation o_i.
- p_{remote}: The penalty factor used in the objective function of Objective 1 (Obj1) for allocating operations to remote stands.
- p_{dummy}: The penalty factor used in the objective function of Objective 1 (Obj1) for allocating operations to dummy stands(non-allocation of the operation).

It is not only important to define the scalars and lists that are included in the tactical SAP, one also has to define the decision variables that are present. The first type of decision variable is presented in Equation 4.2 below. It can be seen that a decision variable is created for each operation-stand combination[11]. If a flight is assigned to a certain stand, then the decision variable takes on a value of 1, otherwise, a 0. It means that this decision variable is a binary decision variable.

$$x_{o_i,s_k} = \begin{cases} 1, & in\ case\ operation\ o_i\ is\ assigned\ to\ stand\ s_k \\ 0, & otherwise \end{cases} \tag{4.2}$$

Although the decision variables in Equation 4.2 were created for each operation-stand configuration, the second type of decision variable does not consider stands. This decision variable determines whether an operation is being towed from one stand to another one. Also, this decision variable can be seen in Equation 4.3 below[10].

$$y_{o_i} = \begin{cases} 1 & \textit{in case operation } o_i \textit{ is being towed} \\ 0 & \textit{otherwise} \end{cases} \tag{4.3}$$

It has to be mentioned that this decision variable differs from the one allocating the operations to stands in Equation 4.2. The decision variable in Equation 4.3 is a continuous decision variable that can take on any values that are bigger than or equal to zero. However, Equation 4.3 shows that it either takes on a 0 or 1. The reasons behind such a quality is explained in detail in Section 4.3.1 below.

4.3 The many-objective stand allocation model

This section presents the many-objective tactical stand allocation model. Firstly, the complete model is presented which is followed by the detailed description of the model constraints in Subsection 4.3.1 and the description of the allocation objectives in Subsection 4.3.2. The tactical SAP model includes Equations 4.4 to 4.12.

$$min \sum_{j=1}^{4} w_j \frac{F_j(x_{o_i,s_k})}{\theta_j} + w_5 \frac{F_5(y_{o_i})}{\theta_5} \tag{4.4}$$

Subject to:

$$\sum_{s_k \; \varepsilon \; S} x_{o_i,s_k} = 1 \quad \forall \; o_i \; \epsilon \; O \tag{4.5}$$

$$x_{o_i,s_k} = 0 \quad \forall o_i \; \epsilon \; O, \; \forall \; s_k \not\epsilon \; S_{o_i,comp} \tag{4.6}$$

$$x_{o_i,s_k} + x_{o_i^j,s_k} \leq 1 \; \forall o_i \; \epsilon \; O, \; \forall \; o_i^j \; \epsilon \; O_{i_{conflicts}}, \; \forall \; s_k \; \epsilon \; S_{o_{i_{comp}}} \tag{4.7}$$

$$2x_{o_i,s_m} + 2x_{o_i^j,s_m} + \sum_{s_n \; \epsilon \; MARS_n^m} x_{o_i,s_n} + \sum_{o_i^j \; \epsilon \; O_{i_{conflicts}}} \sum_{s_n \; \epsilon \; MARS_n^m} x_{o_i^j,s_n} \leq 2$$
$$\forall \; MARS^m \epsilon \; O, \; \forall \; o_i \epsilon \; O_{s_{k_{comp}}}, \; \forall \; o_i^j \; \epsilon \; O_{i_{conflict}} \tag{4.8}$$

$$x_{o_i,s_k} - x_{U(o_i),s_k} \leq y_{o_i} \quad \forall \; o_i \; \epsilon \; O_{towable}, \; U(o_i) \neq 0, \; \forall \; s_k \; \epsilon \; S_{o_i,comp} \tag{4.9}$$

$$x_{o_i,s_k} - x_{U(o_i),s_k} = 0 \quad \forall \; o_i \; \epsilon \; O_{non-towable}, \; U(o_i) \neq 0, \; \forall \; s_k \; \epsilon \; S_{o_i,comp} \tag{4.10}$$

$$x_{o_i,s_k} \; \epsilon \; \{0,1\} \quad \forall \; o_i \; \epsilon \; O, \quad \forall \; s_k \; \epsilon \; S \tag{4.11}$$

$$y_{o_i} \geq 0 \quad \forall o_i \; \epsilon \; O_{towables} \tag{4.12}$$

It is visible that in equation 4.4 the objectives included the objective function are both normalized and equipped with weights to express the ranking between them. The reason for using these enhancements will be explained later on in this chapter. It can also be seen that the above presented model contains both binary and continuous variables. Consequently, it means that the model uses Mixed Integer Programming(MIP) decision variables. Furthermore, both the objective function and the constraints are linear, namely, no quadratic terms are used. Accordingly, the many-objective tactical stand allocation model is a Mixed Integer Linear Programming(MILP) model.

4.3.1 Stand allocation constraints

This section presents the various constraints that are applied on the tactical stand allocation problem. Most of these constraints are absolutely necessary for the establishment of the SAP, but other constraints serve the purpose of introducing a more detailed and controlled stand allocation.

Correct stand use (Cstr1)

It is an essential requirement for any sort of stand allocation to ensure that an operation is only assigned to one stand, therefore the correct stand usage constraint has to be applied. This is visualized in Equation 4.13 below[10].

$$\sum_{s_k \, \varepsilon \, S} x_{o_i,s_k} = 1 \quad \forall \; o_i \; \epsilon \; O \tag{4.13}$$

One can see that a constraint is applied for each operation separately, where the sum of the operation-stand variable combinations has to be equal to one. It can also result in the operation being assigned to a remote or a dummy stand, since non-assignment is modelled through the dummy stands. Interestingly, this constraint can be used for employing similar, custom-made constraints such as the availability of certain stands for only Schengen or International flights(operations)[1]. However, these customized constraints are not included for the present research to be able to obtain generalized solutions.

Operation assignment to compatible stands (Cstr2)

It is not only important to ensure that an operation is assigned to one stand only, it also has to be ensured that the operations are assigned to compatible stands. It means that aircraft that is in a larger ICAO ADG that a certain stand, then that stand is deemed not compatible to that operation. It means that the operation cannot be assigned to that stand. This constraint is formulated in Equation 4.14[10].

$$x_{o_i,s_k} = 0 \quad \forall o_i \; \epsilon \; O, \; \forall \; s_k \not\epsilon \; S_{o_i,comp} \tag{4.14}$$

It is visible that the decision variables that consider the operation-stand combination that is not feasible have to be set to zero. That means that the operation cannot be assigned to that stand.

Overlapping operations and robustness (Cstr3)

One of the most important constraints in the tactical stand allocation problem is the overlapping operations constraint. Its main purpose is to prevent two flights which have overlapping ground times to be assigned to the same aircraft stand[11]. In this way, stand conflicts can be avoided. Furthermore, it is also in the interest of the stakeholders of the SAP to apply some robustness to the schedule to avoid disruptions due to flight delays or early arrivals. Other reasons for applying robustness of the schedule include uncertainty introduced by the inherent variability of arrival and departure times of the flights, stand or gate breakdown, emergency flights and severe weather conditions[27]. Accounting for this consideration is possible by introducing buffer times at the end of each operation that has no successor. Operations with successors do not get a buffer time, since the two operations use the same aircraft which is already on the ground. The implementation of these ideas is done in the most efficient way if they are grouped together into a common constraint. This constraint can be seen in Figure 4.15 below.

$$x_{o_i,s_k} + x_{o_i^j,s_k} \leq 1 \; \forall o_i \; \epsilon \; O, \; \forall \; o_i^j \; \epsilon \; O_{i_{conflicts}}, \; \forall \; s_k \; \epsilon \; S_{o_{i_{comp}}} \tag{4.15}$$

In Equation 4.15, one can see that a constraint is created for every single conflicting pair of operations. This is used to ensure that no two conflicting operations are assigned to the same stand. Furthermore, the criteria for creating the constraints include a buffer time of 10 minutes in the form of the t_{rob} parameter after each operation.

Stand adjacency: MARS stands (Cstr4)

Almost all large hub airports utilize Multiple-Aircraft Receiving System(MARS). These MARS stands can either accommodate a large aircraft (category D,E or F) or two medium size aircraft (category C or smaller). The reason for using such an infrastructure is to reduce the space used for the stands. The MARS stands are depicted in Figure 4.3 below.

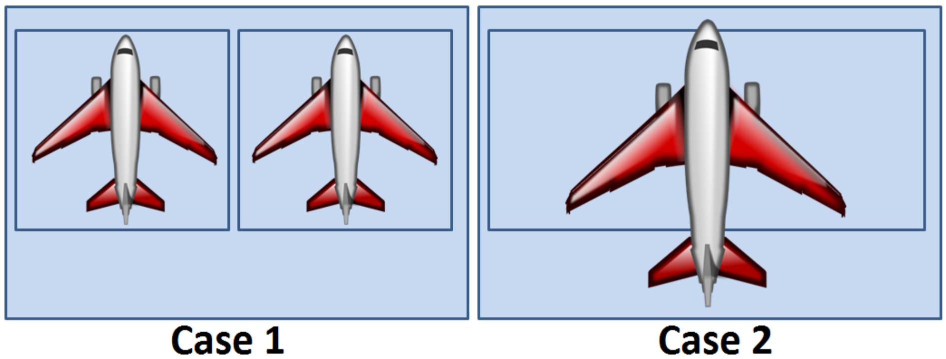


Figure 4.3: Multiple Aircraft Receiving Stands (MARS) representation showing two medium aircraft operations versus one large aircraft operation

Stand adjacency is also known as shadow restrictions and can have many different forms[11]. However, for the current research, a new representation of this constraint is used and verified. It can be seen in Equation 4.16 below.

$$2x_{o_i,s_m} + 2x_{o_i^j,s_m} + \sum_{s_n \ \epsilon \ MARS_n^m} x_{o_i,s_n} + \sum_{o_i^j \ \epsilon \ O_{i_{conflicts}}} \ \sum_{s_n \ \epsilon \ MARS_n^m} x_{o_i^j,s_n} \leq 2$$
$$\forall \ MARS^m \epsilon \ O, \ \forall \ o_i \epsilon \ O_{s_{k_{comp}}}, \ \forall \ o_i^j \ \epsilon \ O_{i_{conflict}} \tag{4.16}$$

It is visible that large MARS stands are penalized with a factor of 2 and small MARS stands are penalized with a factor of 1. The right-hand side of the equation is also equal to two which means that only one large MARS occupancy or two small MARS occupancies are allowed at the same time for a MARS stand.

Towing constraints (Cstr5)

At most airports, towing of certain aircraft from one stand to another due to various reasons is a regular task, therefore, it is important that the allocation is modelled accurately. For that, one has to employ a set of towing constraints. Firstly, it will be seen later on, that not all aircraft can be towed in this mathematical model, therefore, one has to ensure that the operations of this type of turnaround are kept at the same stand. The corresponding constraint is visible in Equation 4.17 below.

$$x_{o_i,s_k} - x_{U(o_i),s_k} = 0 \quad \forall \ o_i \ \epsilon \ O_{non-towable}, \ U(o_i) \neq 0, \ \forall \ s_k \ \epsilon \ S_{o_i,comp} \tag{4.17}$$

It can be noticed, that in case the arrival (or idle) operation is assigned to a certain stand, then its successor also has to be assigned to the same stand making the equation equal zero. In the other case, none of the operations of the turnaround are assigned to the stand. On the other hand, some operations can be subject to towing. For these operations, a different set of towing constraints have to be employed. In this way, a new set of towing constraints are presented in Equation 4.18 below[10].

$$x_{o_i,s_k} - x_{U(o_i),s_k} \leq y_{o_i} \quad \forall \ o_i \ \epsilon \ O_{towable}, \ U(o_i) \neq 0, \ \forall \ s_k \ \epsilon \ S_{o_i,comp} \tag{4.18}$$

The left hand side of this equation is identical to that of Equation 4.17. However, the right hand side of the equation contains the decision variables that represent the towing of individual operations. It means that if a successor of an operation is not assigned to the same stand, then the towing decision variable gets activated in the constraint. It will be seen later on that the objective function contains the decision variables on the right hand side of Equation 4.18, however, this will be explained in the subsequent subsection. In this way, these variables will have to be zero (in case no towing occurs) or one (in case a towing is present) to minimize the relevant part of the objective function[10].

Binary variable constraints (Cstr6)

As it was suggested earlier, it is important to ensure that the imported operation-stand variables are binary. In this way, an operation can either be assigned to a stand or it is not assigned to that stand. Thus, the binary variable constraints are presented for each operation-stand decision variable in Equation 4.19 below[9].

$$x_{o_i,s_k} \in \{0,1\} \quad \forall\ o_i \in O, \quad \forall\ s_k \in S \tag{4.19}$$

Continuous variable constraints (Cstr7)

As the operation-stand decision variables had to be constrained to be binary values, it is also important to constrain the towing decision variables to be continuous, namely, to take on numbers that are either zero or larger. This constraint is depicted in Equation 4.20 below[10].

$$y_{o_i} \geq 0 \quad \forall o_i \in O_{towables} \tag{4.20}$$

4.3.2 Stand allocation objectives

This section presents the objectives that are included in the tactical stand allocation problem. Furthermore, a mathematical description of these objectives is also given which will be included in the many-objective optimization setup.

Non- and remote allocations (Obj1)

Although, it is the goal of all airports to assign all (or as many as possible) turnarounds to contact stands to provide a high service level, it is possible that for peak hours or short periods of time, all contact stands are occupied. In that case, aircraft have still to be assigned to a stand. To serve this purpose, remote stands are also present at the airport from which passengers are bused to the terminal area. These stands are not preferred by legacy carriers, since their service level is lowered by the additional inconvenience towards the passengers, however, low cost carriers might opt for these stands due to their lower costs. For this reason, the remote stands are also modelled in the stand allocation problem as it is depicted in the first term in Equation 4.21[3, 22]. In the worst possible case, the amount of aircraft on the ground is higher than the total amount of stands including remote stands. Then, some aircraft cannot be assigned to any of the stands. It would mean that an infeasible solution is obtained for the allocation. This is undesirable, since the allocation of the majority of the aircraft would be possible. As a result, a dummy decision variable (dummy stand) is created as it is seen as the second term in Equation 4.21. It can be seen that the operations that cannot be allocated to any actual stand, they are allocated to the dummy stand that has unlimited capacity.

$$F_1(x_{o_i,s_k}) = \sum_{o_i \in O} \sum_{s_k \in S_{remote}} (p_{remote} + \frac{1}{pax_{o_i}}) x_{o_i,s_k} + \sum_{o_i \in O} \sum_{s_k \in S_{dummy}} (p_{dummy} + \frac{1}{pax_{o_i}}) x_{o_i,s_{dummy}} \tag{4.21}$$

It can be seen that a penalty factor p_r is applied for assigning an aircraft to a remote stand. Also, a penalty factor p_d is applied for not being able to assign an aircraft to any existing and operational stand. Additionally, the penalty factors of the dummy variables have to be at least a magnitude bigger than that of the remote stand variables. It then creates a hierarchy between the stand types. The stands with the largest penalty factor(dummy stand variables) have to be avoided first, since the allocation is minimization-based. Then, remote stands have to be avoided as much as possible, since they have the second largest penalty factors.

While the goal of the optimization problem presented above is to minimize the objective function value of the objective under consideration, a quantifiable measure for the performance of the objective needs to be derived. This measure is called a Key Performance Indicator(KPI). For the current objective and the remainder of the objectives, the KPIs are presented as well.

Objective 1 has two Key Performance Indicators, namely, the number of non-allocated operations and the number of operations allocated to a remote stand. These two KPIs are marked with KPI_{1_n} and KPI_{1_r}. These KPI values are extracted from investigating the active decision variables at the end of the allocation procedure.

Effective stand use (Stand effectiveness) (Obj2)

One of the most important policies of airports is to efficiently use their stand infrastructure. It means that airports aim to allocate aircraft based on their size. It is considered unfavorable if an aircraft is assigned to a stand that is bigger than the aircraft itself based on its ICAO Aircraft Design Group[12]. Not only aircraft are assigned an aircraft design group category, but the airport stands as well. These design categories are presented in detail in Appendix A in Table A.1. Since the goal of this objective is to use the stands as efficiently as possible, aircraft that are assigned to a stand that can accommodate a bigger aircraft are penalized. It is necessary to allow for larger stands to be available for larger aircraft, since most airports have less large stands than medium ones. This policy can be expressed in a mathematical formulation as an objective in Equations 4.22 to 4.24 below.

$$F_2(x_{o_i,s_k}) = \sum_{o_i \ \epsilon \ O} \sum_{s_k \ \epsilon \ S} se_{o_i,s_k} x_{o_i,s_k} \tag{4.22}$$

If $size_{o_i} > size_{s_k}$:

$$se_{o_i,s_k} = 0 \tag{4.23}$$

If $size_{o_i} \leq size_{s_k}$:

$$se_{o_i,s_k} = \frac{size_{s_k} - size_{o_i}}{max(size_{s_k})} \tag{4.24}$$

Equations 4.23 and 4.24 show the rule to set up the penalty factor. Namely, the difference between the sizes of the stand and the aircraft are divided by the size of the biggest stand at the airport[12]. In an ideal case, the size of the aircraft and the stand match, therefore, the penalty factor ends up being zero. It also must be noted that when an aircraft is larger than the stand, a penalty factor of 0 is applied. While this does not correctly represent the actual situation, the penalty factors of these operation-stand combinations are of no concern, since Constraint 2 above ensures that these operations are not assigned to a smaller stand. It means that the penalty factors of these operations can be any value.

The KPI of the stand effectiveness objective is defined in Equation 4.25. It can be seen that the stand effectiveness scalars (se_{o_i,s_k}) of all operations are summed up. That is multiplied by the maximum stand size due to the division in the definition of this constant (Equation 4.24). Then, that is divided by the number of operations. The resulting KPI shows the average size difference between the stand and the aircraft serving the turnaround, hence the unit of this KPI is called Average Size Mismatch [SM].

$$KPI_2 = \frac{(\sum \sum se_{o_i,s_k}) max(size_{s_k})}{i} \quad [SM] \qquad when \ \ x_{o_i,s_k} = 1 \tag{4.25}$$

KPI_2 always has to be more than or equal to zero, since it is forbidden to allocate an aircraft to a stand that is smaller than itself. Furthermore, the smaller the KPI is, the more efficient the stand allocation is (on average).

Aircraft taxi distances (Obj3)

One of the main concerns at large hub airports is the environmental effects[11] of the arrival and departure taxi distances of aircraft. Long taxi distances result in high fuel consumption and possible delays on the ground which are both disadvantageous for the airlines, the passengers and even the airport[13]. This is due to the fact that large airports have multiple runways and a large apron area combined with a significant amount of traffic. Since, it would be mathematically complex(and highly probabilistic) to model taxi times (both impeded and unimpeded taxi times)[49], this research is only restricted to taxi distances both for arrival and departure operations. The mathematical formulation of the taxi distances can be seen in Equation 4.26 below[11].

$$F_3(x_{o_i,s_k}) = \sum_{o_i \ \epsilon \ O_a} \sum_{s_k \ \epsilon \ S} (d_{arr,s_k}) x_{o_i,s_k} \ + \sum_{o_i \ \epsilon \ O_d} \sum_{s_k \ \epsilon \ S} (d_{dep,s_k}) x_{o_i,s_k} \tag{4.26}$$

It is important to note that one must include the arrival and departure operations separately. As Section 4.1 above listed, the turnarounds are sliced into 2 or 3 operations which means that the arrival and departure operation of each turnaround can be assigned to a separate stand. Also, as the model makes use of a decision variable for each operation, the operations within a turnaround are decoupled, hence their taxi distances also have to be modeled separately. In Equation 4.26, the arrival and departure operations(their decision variables) are multiplied by the corresponding arrival or departure taxi distances. Idle operations are not present in this objective, since these operations are not subject to taxiing.

The aircraft taxi distance objective's KPI is described in Equation 4.27. It can be seen that the KPI is the sum of all taxi distances divided by the total number of operations that actually have a taxi process(the cardinalities of the lists containing the arrival and departure operations). It means that idle operations are not taken into account when calculating the taxi distance KPI.

$$KPI_3 = \frac{\sum_{o_i \ \epsilon \ O_a} \sum_{s_k \ \epsilon \ S} d_{arr,s_k} \ + \ \sum_{o_i \ \epsilon \ O_d} \sum_{s_k \ \epsilon \ S} d_{dep,s_k}}{|O_a| + |O_d|} \ [m] \ \ when \ x_{o_i,s_k} = 1 \tag{4.27}$$

The resulting KPI is the average taxi distance per taxiing operation. It is more favorable to obtain an as small as possible taxi distance value. That results in the overall minimization of the taxi distance covered on the specific operational day.

Passenger walking distance (Obj4)

One of the mostly used passenger related objectives in the tactical stand allocation problem is the minimization of the passenger walking distance[11, 35]. Its main purpose is to minimize the distance passengers have to walk from the security control to their defined gate (in case of a departure) or the distance they have to walk from the arrival gate to the baggage reclaim area (in case of an arrival). The passenger walking distance equation can be seen in Equation 4.28 below.

$$F_4(x_{o_i,s_k}) = \sum_{o_i \ \epsilon \ O_a} \sum_{s_k \ \epsilon \ S} (pax_{o_i} * d_{arrawalk,s_k}) x_{o_i,s_k} + \sum_{o_i \ \epsilon \ O_d} \sum_{s_k \ \epsilon \ S} (pax_{o_i} * d_{depawalk,s_k}) x_{o_i,s_k} \tag{4.28}$$

It has to be noted that only origin and destination passengers are considered which means that transfer passengers are not included in this objective. The main reason for omitting transfer passengers is the modeling limitations present which is elaborated on below. Moreover, while passengers have to walk to airport gates, the current stand allocation model makes use of aircraft stands. In this way, the assumption is made that a certain airport gate is linked to a certain stand. It means that one can assume that the passengers are walking (indirectly) to the stands.

The passenger walking distance objective's performance metric is expressed as it is shown in Equation 4.29. It is visible that the KPI measured as the total number of passengers times walking meters are divided by the total number of passengers.

$$KPI_4 = \frac{\sum_{o_i \ \epsilon \ O_a}(pax_{o_i} * d_{arrawalk,s_k}) + \sum_{o_i \ \epsilon \ O_d}(pax_{o_i} * d_{depawalk,s_k})}{\sum_{o_i \ \epsilon \ O_a} pax_{o_i} + \sum_{o_i \ \epsilon \ O_d} pax_{o_i}} \ [m] \ \ when \ x_{o_i,s_k} = 1 \tag{4.29}$$

KPI_2 is favored to be as small as possible to ensure that the average walking distance of the passengers is minimized.

Aircraft towing (Obj5)

The tows of aircraft are considered to be a common operation at an airport. The towing of an aircraft can happen in one of two cases. Firstly, in case the turnaround of the aircraft is longer than a pre-defined time, then it can be towed to a remote or a not used (contact) stand to make valuable (contact) stands available for other operations[10] as it was already described in Section 4.1. Secondly, it might be possible (mostly at large hub airports) that an arrival flight and the departure flight (using the same aircraft) has to be located in separate stands. Then, a towing operation has to be utilized. In the Stand Allocation Problem(SAP), the towing operation can be expressed using both an objective and a constraint part at the same time. As a result, the aircraft towing objective can be seen in Equation 4.30 while the constraints were already shown in Equations 4.17 and 4.18.

$$F_5(x_{o_i,s_k}) = \sum_{o_i \ \epsilon \ O_{towable}} y_{o_i} \tag{4.30}$$

It can be noted that y_{o_i} is a continuous variable that is activated in case a towing operation is done. In that case, a penalty factor is also added to the objective function value that worsens the solution. This penalty factor is equal to 1 when the towing of an operation is done. If one looks at Equation 4.18, one can see that the above mentioned y_{o_i} is present on the right-hand side of the constraints. It means that the objective and the constraint work in symbiosis[10]. Namely, if the specific operation is assigned to stand k and its successor (the departure flight of the same turnaround) is also assigned to the same stand, then the left-hand side of Equation 4.18 is zero. It results in the right-hand side being zero to minimize Equation 4.30.

The KPI of the aircraft tows objective is depicted in Figure 4.31. It can be seen that the active towing decision variables are summed up, since when a towing is carried out, the decision variable is equal to 1.

$$KPI_5 = \sum_{o_i \ \epsilon \ O_{towable}} y_{o_i} \quad when \ y_{o_i} = 1 \tag{4.31}$$

Similarly, as for the other 4 objectives, the goal of the decision maker is to minimize the towing objective's KPIs.

Arguments for omitting transfer passengers

Most airports (and terminals) process transfer passengers that arrive with a certain flight to the airport and use another one to travel to another destination without leaving the territory of the airport. Some airports have a large share of transfer passengers, which means that transfer passengers should be taken into account when the passengers are considered as a stakeholder in the tactical stand allocation problem. As it was seen in Section 4.3.2 above, the current many-objective tactical stand allocation model does not consider transfer passengers. The arguments for omitting these passengers will be discussed in the following paragraphs.

First and foremost, the interests of the local passengers are modelled in terms of walking distance as it was shown above. The walking distances of transfer passengers could also be modelled, however, that model would give overestimated results. In a MILP representation, the walking distance of arrival transfer passengers could only be modelled by calculating the distance between the gate at which a transfer passenger arrives and a common transfer point. Then, the departure transfer passengers would also have to walk from the common transfer point to the departure gate. The main disadvantages of this approach is that at most airport such transfer point does not exist. Hence, if one passenger would like to transfer from one gate to another one that is next to it, then his or her walking distance would be largely overestimated. This would result in inaccurate KPI values in the solution space that would distort the resulting trade-offs.

In light of the previously presented modeling options, highly accurate data is required on the number of transfer passengers between each two sets of flights. Unfortunately, most airports only have data that is realized during an operational day, namely, data is only acquired when the actual operations take place. It means that accurate(forecasted) flight-to-flight transfer data cannot be obtained a priori to the operational day, hence, it cannot be used for planning purposes. This is due to the fact that this is sensitive airline data and airlines are (in most cases) not willing to share such information. Furthermore, transfers also exist between different airlines and this information is considered even more sensitive for them.

Additionally, the transfer time is a more critical measure for transfer passengers than the transfer distance. This is due to the fact that it is a common occasion at most airports that a delayed flight causes passengers to miss their connections. In this way, the transfer times of these passengers would have to be modelled[11]. The main disadvantage of this approach is similar to the first argument, namely, in a MILP representation, transfer times would only be overestimated. It means that one would have to model the transfer of each passenger from one operation to another. It can only be modelled using quadratic decision variable where the objective function contains decision variables that are multiplied with each other. This would result in a Mixed Integer Quadratic Programming(MIQP) model. Since a large number of operation-to-operation transfer cases exist, the problem would become NP-hard that would significantly increase the computational time of that model. Furthermore, as it was mentioned in Section 2.4, it is possible to linearize the MIQP, however, it would be disadvantageous due to the problem complexity and the increased run time.

Lastly, the current research investigates the conflict between the interests of the different stakeholders at airports. Although it is possible to model the interests of local and transfer passengers in separate objectives, one would introduce another source of conflict that is between the different types of passengers. Since the present research does not aim to investigate the conflicting interests of one stakeholder, it is not suitable to model the transfer and local passengers separately.

4.4 Solver algorithm

In order to allocate the operations to stands efficiently and optimally, one has to make use of a solver algorithm. While there are numerous solver algorithms that are developed for such a problem, the one that is employed by the modelling framework will be described below.

As it was mentioned earlier, the present many-objective tactical stand allocation model is a mixed integer linear programming (MILP) problem that contains both binary and continuous variables[9, 10]. This model is solved using a Python-Gurobi interface. The Python interface makes use of its 2.7.12 version and the Gurobi interface is the 6.5.2 version. Gurobi is the software that provides the solver algorithm for the optimization problem. Gurobi uses the branch-and-bound($B\&B$) algorithm[13] for finding feasible and optimal solutions for MILP problems, therefore, it will be described in the followings.

The Branch-and-bound algorithm is commonly used in combinatorial optimization problems, namely, for linear programming problems where some or all of the decision variables are integers[50]. The current problem's MIP representation therefore fits the requirements of the branch-and-bound algorithm. It has to be mentioned that the branch-and-bound algorithm is an exact algorithms, which means that the actual optimal solution is looked for and found at the termination of the algorithm.

Within the Gurobi interface the $B\&B$ algorithm is automatically executed when the optimization is called for. It initially looks for a solution while removing all the integrality restrictions[51]. Namely, the decision variables are not constrained at all to take on a certain value. This results in the linear programming relaxation of the original MIP. Then, a decision variable is selected that is (most of the time) integer and that has a fractional relaxation. Restrictions are imposed on this variable which means that the possible solutions for this decision variable are less and less. The new restrictions on this decision variable create new MIPs (based on the number of restrictions), therefore, this decision variable is called the branching variable. It also means that the initially relaxed MIP is replaced with two more restricted MIPs. The same procedure is carried out for these two relaxed MIPs. In doing so, one creates a search tree which has the generated MIPs as the nodes of this tree. The leaves of this tree represent the nodes that are not yet used for branching. The search procedure continues until one is able to solve or disregard all leaves, since when that happens, the original MIP is solved (a feasible solution is found).

Solving the original MIP does not necessarily mean that an optimal solution is found. As a consequence, one has to make sure that the best objective function value (for minimization, it is the smallest) and the feasible solution attached to it is recorded. This is called the incumbent solution. As the different branches of the search tree are explored, the incumbent solution is updated and at the end of the procedure, the optimal solution is retrieved.

4.5 Solution pool generation

The sections above presented the many-objective tactical stand allocation model. It was also mentioned that a reference set of stand allocations are used for the performance prediction of a future allocation. Therefore, this section presents the techniques that are applied to the many-objective stand allocation model to generate these reference allocations. Firstly, the weighted sum representation of the allocation objectives is shown in Subsection 4.5.1. Since the included objectives have different dimensions, these objectives have to be normalized to acquire proper allocations, so the normalization of the allocation objectives is presented in Subsection 4.5.2. As the many-objective stand allocation model is now in a proper form, the reference set of allocations are created using the Weight Space Search as it will be described in Subsection 4.5.3.

4.5.1 A weighted sum representation

As it was seen in Section 4.3, 5 different objectives are included in the many-objective tactical SAP. Since the purpose of this research is to be able to manipulate the stand allocation problem setup to acquire a desired trade-off between the stand allocation objectives, the objective function of the stand allocation problem has to be set up in such a way that it enables the user to do so. Subsection 2.4.2 revealed that a suitable method for expressing the ranking between objectives (the significance of each objective) is the Weighted Sum Method(WSM). The objective function using this method can be seen in Equation 4.32[52, 53].

$$min \sum_{j=1}^{5} w_j F_j(x, y) \tag{4.32}$$

where $w_j \geq 0$. One can see that a weight w_j is assigned to each objective. This weight illustrates the rankings between the significance of the objectives. In addition, $F_j(x, y)$ represents the sum of the decision variables multiplied by their scalars that are included in objective j.

The investigation of trade-offs between the stand allocation objectives is not the only purpose of the objective function containing 5 objectives. It can be seen that the first objective forces the operations to be allocated to contact stands or in a worst case scenario to remote stands. While this objective could be part of the trade-off, it is an objective that does not take part in the contention between the objectives. It can be explained by the fact that this objective is used to make the allocation as realistic as possible. Namely, it aims to simulate the behavior of capacity planners to allocate as many operations to contact stands as possible. It means that the non- and remote allocations objective has to be treated differently than the remainder of the objectives that are competing. This can be done by assigning this objective to be on top of the allocation hierarchy, while keeping the other 4 competing objectives on the second level of hierarchy. All of the above is realized by the manipulation of the weights each objective within the weighted sum representation.

The hierarchical preference for Objective 1 is expressed by applying a significantly higher objective weight compared to the other 4 objectives. In this way, the objective function weight of Objective 1 is always set to 1000 in all iterations, whereas, the weights of the other 4 objectives have to be between 0 and 1. The value of 1000 is chosen to assign a weight that is several orders higher than the magnitude of the other objective weights. As the other 4 objectives (objectives 2 to 5) compete within the stand allocation, the weights of these objectives will lie between 0 and 1. This is visible in Table 4.2 below. The main reason for not clearly specifying the weights of these objectives is that the stand allocation model will be ran multiple times with different weight combinations to create the solution space. However, that will be explained in the following section.

Table 4.2: Possible weight ranges for each stand allocation objective

Objective	w_{NRA}	w_{SE}	w_{ACTD}	w_{PWD}	w_{TW}
Weight range	$w_{NRA} = 1000$	$0 \leq w_{SE} \leq 1$	$0 \leq w_{ACTD} \leq 1$	$0 \leq w_{PWD} \leq 1$	$0 \leq w_{TW} \leq 1$

It is not only important to constrain the weight values of each objective, it is also important to mention that the sum of weights of Objectives 2 to 5 has to be equal to 1. It is necessary to be able to express the magnitude of significance of each objective (excluding Objective 1) on a fixed scale. In other words, the desired performance differences between the allocation objectives can be indicated relative to each other by the user. This is visualized in Equation 4.33 below.

$$w_{SE} + w_{ACTD} + w_{PWD} + w_{TW} = 1 \tag{4.33}$$

As an example, when the weight of Objective 2 is set to be 1, then the weights of Objective 3 to 5 are set to zero, which means that after it is ensured that each operation is assigned to a stand (Objective 1), then the only allocation objective that remains is Objective 2. Furthermore, if the weights of Objectives 2 to 5 are equal, then these objectives are equally important when the optimization is carried out.

Discussion on the hierarchy of objectives

It was discussed above that a hierarchy is created between Objective 1 and the remainder of the objectives. This hierarchy can be created in two different ways. Firstly, one can employ the hierarchical (or lexicographic) method where a hierarchy is applied between the set of objectives. This is a sequential hierarchy, namely, that the degree importance of an objective can only be set by the sequence of the objectives. In this way, the objective with the highest priority is optimized first, then the second one is optimized, etc[54]. On the other hand, hierarchy can also be created by the approach of blended objectives[11]. It has to be mentioned that this approach is identical to the Weighted Sum Method used for this research. Specifically, the hierarchy (and also the degree of hierarchy) is created by the magnitude of the weight of each objective. When the magnitude of the weight of a certain objective is determined to be high enough (orders higher), the same effect is achieved as in the hierarchical objectives approach. This gives more flexibility to the user to define the importance of each objective while also holding the possibility to break the hierarchy and assign each objective on the same hierarchical level when necessary. For this reason, the approach of blended objectives is used in the current research.

4.5.2 Normalization of the objectives

As it was seen in Section 4.3.2, 5 different allocation objectives are used in the many-objective tactical SAP. It was also seen that the units (and orders) of the scalars of the decision variables are different for each objective. It means that carrying the optimization out with different units would raise the possibility for bias towards one or more objectives[52]. It means that the normalization of objectives has employed to be able to use each objective accurately in the many-objective optimization problem. In this way, one is able to use a common, dimensionless form of each variable where the scalars of the decision variables are directly comparable. When normalization is considered, one has to make sure that all the objectives are dimensionless. This results in an additional scalar multiplier for each and every objective which is called the normalizer multiplier.

There are 3 main techniques that are used for the normalization of objectives in connection with the WSM. The first of these methods normalizes by the objective function value at the initial point. Namely, it sets the normalization constant to be the initial objective function value that the solver algorithm finds for that specific objective. Unfortunately, this gives a poor normalization factor, since the initial point is usually not an accurate representation of the optimization problem[52]. The second method normalizes by setting the normalization factor to the minimum of all of the objectives. It is very well possible that in this case, the best objective has an objective function value of 0, therefore, the normalization factor does not result in a feasible normalization factor[52]. An effective method for the normalization of each of the objectives considers the Nadir and Utopia points of all the objectives. Accordingly, this method will be elaborated on in the preceding paragraphs.

The Utopia point of an objective is defined as the optimal objective function value of an objective when it is considered as the only objective in the optimization problem with the constraints being unchanged. It means that if one has n objectives, then n optimization runs have to be made in order to end up with n optimal solutions (each one corresponds to an objective). These optimizations result in the set of Utopia points for the objectives as it can be seen in Equation 4.34[52].

$$F_j^{Utopia} = [F_j(dv^{j^*})] \tag{4.34}$$

where dv^j is the type decision variable(s) included in the objective function of objective j. It is not enough to only have a Utopia point for each objective, one has to also find the Nadir points the each objective. The Nadir point is defined as the point where a certain objective takes on its worst possible objective function value. In other words, one has to substitute the active decision variables of the other objectives into the one investigated and keep the one that results in the worst objective function value. This is shown in Equation 4.35.

$$F_j^{Nadir} = max[F_j^{dv^1} \ F_j^{dv^2} \ ... \ F_j^{dv^j}] \tag{4.35}$$

The normalization constant can then be calculated by the difference of the Nadir and Utopia point of the objective under consideration. Alternatively, one can say that the range of the objective is received. This normalization constant can be seen in Equation 4.36[29, 52].

$$\theta_j = F_j^{Nadir} - F_j^{Utopia} \tag{4.36}$$

In this way, all objectives become dimensionless which makes them comparable during the optimization procedure. It must be noted that if the Nadir point and the Utopia point of a certain objective is the same, then sc_i is divided by itself which makes u_i 1. It means that all of the decision variable scalars of that specific objective are equal to 1. Furthermore, it also can be concluded that there is only 1 objective function value that the optimization can take, so the objective cannot be further optimized. Also, when both the Nadir and Utopia points of an objective are 0 and all the decision variable scalars of a certain objective are 0, then the normalized scalars are also 0. The main reason for such a representation is to ensure that the normalized objective function values are accurate for each optimization run to be able to deduct a meaningful KPI value from that.

As all of the objectives of the MaOO are normalized, one is able to accurately carry out the many-objective optimization. As a result, the following section presents the Weight Space Search(WSS) algorithm that will generate the necessary amount of feasible solutions.

4.5.3 Weight Space Search

This section presents the Weight Space Search(WSS) framework that is employed to discover the solution space of the many-objective tactical stand allocation problem. The solution space is generated by optimizing the model mentioned in Section 4.3 iteratively. For each iteration, the weight settings of the objectives are changed, therefore, a new optimization problem is generated. This section describes the rule that generates the weight settings of the objectives.

It was mentioned above that a weighted sum framework is applied on the allocation model to ensure that all 5 objectives are included and also that the ranking between the allocation objectives can be quantitatively expressed. To be able to investigate the trade-offs between the 4 competing allocation objectives, one has to explore the solution space of the allocation model. As it was already defined in Section 2.1, the solution space of an allocation problem is the multi-dimensional set of KPI values generated by running (and optimizing) the many-objective tactical stand allocation model iteratively with different weight combinations. The more weight combinations one considers, the clearer the trade-offs can be. Furthermore, the wider the explored range of weights the wider the known part of the solution space is to the user. An effective method for exploring the solution space of a stand allocation model is proposed by [11]. There, the weights of the 3-objective stand allocation model are varied between 0 and 1 with a weight increment change of 0.1 for each iteration while keeping the sum of the objective weights 1. In this way, 66 iterations were conducted with 66 different weight combinations, hence 66 different allocations (and the related KPIs) resulted. Since the weight of all of the objectives were varied between 0 and 1, all borders of the solution space were explored.

As the WSS method in a similar research setup was described above, the algorithm that is linked to the current stand allocation problem is described in detail below. S.H. Kim et al. in [11] used a weight increment of 0.1 for creating new weight combinations. In case one uses the same increment for the current research, a total of 286 weight combinations would be generated (since the weights of 4 objectives can be varied while keeping the sum of the 4 weights equal to 1). The numbers of iterations for different weight increments are introduced in Table 4.3 below.

Table 4.3: The number of allocation iterations as a function of the chosen weight increment

Weight increment	No. of iterations
0.5	10
0.25	35
0.2	56
0.1	286
0.05	1771
0.01	176851

It can be seen that if one chooses a low refinement of the weight space, the number of times the allocation has to be carried out is low. However, if the refinement is high (the weight- and solution space is well explored), then the total number of iterations significantly increase. The main consequence of conducting a high number of iterations is that the computational time significantly increases as well. It was demonstrated by [11] that a weight increment of 0.1 provides sufficient detail for creating trade-offs in a multi-objective optimization setting, due to the lack of information for the many-objective optimization case, it is assumed that this weight increment is to be used for the present research. As a result, the many-objective tactical stand allocation model will be solved a total of 286 times. A different weight combination will be applied for each iteration. As the weight increment for each objective weight is already defined, the Weight Space Search algorithm itself has to be described. The flowchart of this algorithm can be seen in Figure 4.4 below.

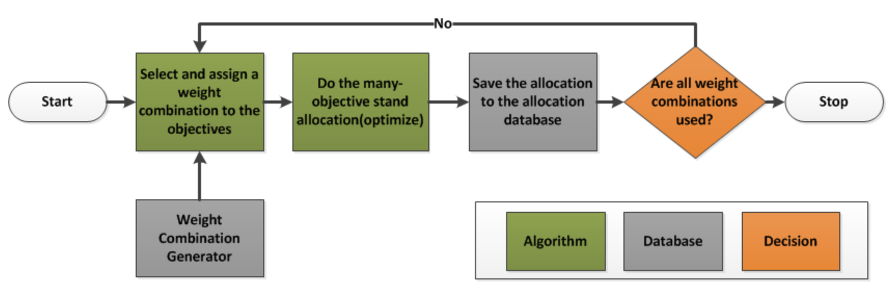


Figure 4.4: The Weight Space Search Algorithm connected to the many-objective tactical SAP model

It can be seen that all 286 weight combinations are first generated in the Weight Combination Generator. These weight combinations can be seen in Appendix B in Table B.1. Then, the weights of the 5 objectives are assigned to respective objectives in the stand allocation model. Since the stand allocation model has both the proper inputs and objective weights, the optimization is executed. Afterwards, the resulting allocation along with the used weights and KPI values are stored in the allocation database. This concludes the first iteration. Afterwards, a different (not yet used) weight combination is selected and assigned to the objectives and the optimization is carried out again. When all 286 weight combinations are used (at most once), the Weight Space Search algorithm stops.

It has to be mentioned that for each iteration, the complete non-dominated solution set is saved. It means that all equally optimal solutions for an iteration are stored and are considered equally valid members of the solution space. This is explained in more detail in Section 6.5.

5 Objective relationship discovery

This chapter presents the methods that are being used for the identification of trade-offs between the different allocation objectives. As it was seen earlier in Section 3.4, several technical modules are being used in this current research and this chapter aims to detail the working principles behind the module that identifies the trade-offs between the objectives. Firstly, the selected cluster analysis technique, namely, the k-means clustering algorithm is detailed in Section 5.1. Afterwards, the methods for further ensuring the uniqueness of the found trade-offs is described as the unique weight range finder algorithm in Section 5.2. Lastly, the testing framework along with the related nomenclature of the predictability of the found trade-offs will be presented in Section 5.3.

5.1 Cluster analysis: k-means clustering

Section 2.4 revealed that it is not feasible to investigate the alternative solutions of different allocations using traditional techniques for finding relationships between allocation objectives. In other words, it is not practical to use regression-based techniques on the present problem structure. The main reason is that in the current framework, the results of not one allocation (not the non-dominates solutions of one optimization run) are investigated, but a large set of allocations' alternative solutions. It means that it is highly anticipated that the resulting solution space will appear highly irregular. As a result, it is important to define trade-offs between the selected objectives by grouping the solutions generated by the WSS. The allocations are grouped by identifying the similarities between each other (through their KPI values) in multiple dimensions. So, a different data mining method has to be employed that is able to relate subsets of data points in multi-dimensional space to each other. This section therefore presents the k-means clustering methodology that is effective in grouping data points within a solution space.

The main goal of k-means clustering is to subdivide n data points into k separate groups or clusters. This is done as an optimization problem with the goal to find the minimum distance of each data point to k cluster centroids in multi-dimensional space[43]. In other words, k groups have to be found with data points in the k clusters that are closest to the fictitious centroids of those clusters[55]. The distance between the fictitious center and the data points is measured as the absolute distance between those points. K-means clustering is aided by heuristic algorithms to quickly and efficiently arrive at a local optimum. The minimization problem of the k-means clustering algorithm is depicted in Equations 5.1 to 5.3[16].

$$min \sum_{l=1}^{k} \sum_{i=1}^{n} w_{i,l} d(X_i, Q_l) \tag{5.1}$$

Subject to:

$$\sum_{l=1}^{k} w_{i,l} = 1, \quad 1 \ \leq i \ \leq n \tag{5.2}$$

$$w_{i,l} \ \epsilon \ \{0, 1\}, \ \ 1 \ \leq \ i \ \leq \ n, \ 1 \ \leq \ l \ \leq \ k \tag{5.3}$$

where n is the total number of data points in the solution space, k is the number of clusters. In this way, w is the variable indicating whether a data point is included in a cluster or not, while Q is the set of clusters(including data points) in the solution space. Also, $d(X_i, Q_l)$ is the squared Euclidean distance between the fictional cluster centroid(X_i) and the data point in the solution space. It must be noted that the number of clusters have to be less than or equal to the number of data points in the set, namely, $k \ \leq \ n$[16]. This is essential, since one cannot create more groups than the number of available data points. For that reason, if k is larger than n, then the optimization algorithm will not give a feasible solution.
As it was mentioned above, the squared Euclidean distance measures the distance between the fictitious centroid and the data points. The squared Euclidean distance is depicted in Equation 5.4 below[16].

$$d(p,q) = (q_1 - p_1)^2 + (q_2 - p_2)^2 + .. + (q_c - p_c)^2 = \sum_{i=1}^{n}(q_i - p_i)^2 \tag{5.4}$$

where p and q are two c-dimensional data points such as $p = (p_1, p_2, ..., p_c)$ and $q = (q_1, q_2, ..., q_c)$. Although, the minimization problem is defined above, it is important to briefly detail the algorithm that ensures that optimum is found, namely, the clusters are created. This is done by the so-called Lloyd's algorithm[56]. The algorithm alternates between two subsequent steps until the pre-set number of iterations are done.

- **Step 1 (assign):** appoint each data point in the data set to a cluster which has a centroid that generates the smallest within-cluster sum of squares(WCSS). This WCSS is represented by the squared Euclidean distance[55].
- **Step 2 (update):** As the data points are assigned into clusters, calculate the centroid (mean) of the data points within each cluster to be the new means.

It has to be noted that these two steps are repeated as many times as the user defines it. In case the algorithm finds the optimal solution before the pre-set number of iterations is reached, then the algorithm stops. The algorithm knows when the optimal solution is found when the means (centroids) of the clusters do not change at the end of the iteration.

Advantages of k-means clustering

A main advantage of the k-means clustering algorithm is that one is able to relate a set of data points in a multi-dimensional solution space. This would be very hard using conventional regression techniques, since the accuracy of these measures decreases as the number of considered dimensions increase as it was discussed in Section 2.4.

Furthermore, one is able to define a priori the amount of clusters (or data sub-sets) that are to be used. This is beneficial, since as it will be seen later on, the number of generated clusters greatly influences the sizes of these clusters. It means that the unambiguity and precision of these clusters can be directly influenced.

Disadvantages of k-means clustering

While it was deemed an advantage, one of the main disadvantage of the k-means cluster algorithm is also that one has to define the number of clusters to be found a priori to carrying out the optimization. Since k clusters will be developed, the sizes of these clusters will be determined by the overall minimization of the distances of all data points to the cluster centers. It can result in clusters of (significantly) different sizes. In other words, if one chooses a k of 3 and an n of 200, it is possible that two clusters will have one data point each in them and the third cluster might end up with the remaining 198 data points. Furthermore, by introducing more clusters, one cannot ensure that the initially large clusters break up into smaller ones.

As the k-means clustering algorithm was described in this section, it is important to define its role in the current research. In consequence, the following section will give a detailed description on how the k-means clustering algorithm breaks up the multi-dimensional solution space generated by the WSS.

K-means clustering in the research scope

The working principles of k-means clustering were presented above. In order for one to effectively make use of this algorithm, the application of the k-means clustering to this research is outlined here. The k-means clustering algorithm will be used on the multi-dimension KPI solution space generated by the WSS algorithm. The main goal is to ensure that KPI values that are similar in multiple dimensions are grouped together. This would enable the user to differentiate between certain parts of the solution space. Having to work with a certain part of the solution space would open up the possibility to figure out if similar weight combinations created those results. If so, then suggestions can be made to airport decision makers to on which weight combinations to use in order to end up at the selected sub-set of the solution space.

As it was mentioned in Chapter 4, a total of 5 allocation objectives are used in the many-objective tactical stand allocation framework. It was also mentioned that Objective 1(minimization of non- and remote allocations) is on the top of the hierarchy(with an objective weight of 1000) which means that optimization on this objective is done first and while optimality is found on this one, then the other objectives can be investigated and compared. It means that the KPI value of Objective 1 will not change even when the weights of the other 4 objectives change. Accordingly, the k-means clustering algorithm will only make use of the KPI values (making up the 4-dimensional solution space) of Objectives 2 to 5.

Furthermore, the number of iterations have to be set high enough for the algorithm to find the optimal allotment of data points into the clusters. Accordingly, the number of iterations is set to be 15, which is deemed to be more than sufficient during the test runs.

5.2 Unique cluster weight range definition

In this section, the algorithm uniquely defining the clusters based on their objective weights is described in detail. It was mentioned in Chapter 3 that one of the main goals of this project is to identify regions of the solution space that contain similar KPI values of the created allocations. It is also important to investigate whether the similarities between the allocations can also be linked to weight combinations that are similar to each other. This would enable one not only to identify the combined effect of the objectives on the overall allocation, but it would also reveal whether there is any pattern (or link) between the objective weights and the resulting KPIs which would allow for mapping the weights (and the standardized KPIs) of a reference allocation to a different scenario.

The flow chart of the developed algorithm for finding unique weight ranges for the clusters is depicted in Figure 5.1 below. The algorithm makes use of the weight combinations and the corresponding cluster membership of the data points saved after the WSS and the clustering algorithms. This algorithm is also present in Module 3 of the complete research flow chart in Figure 3.2.

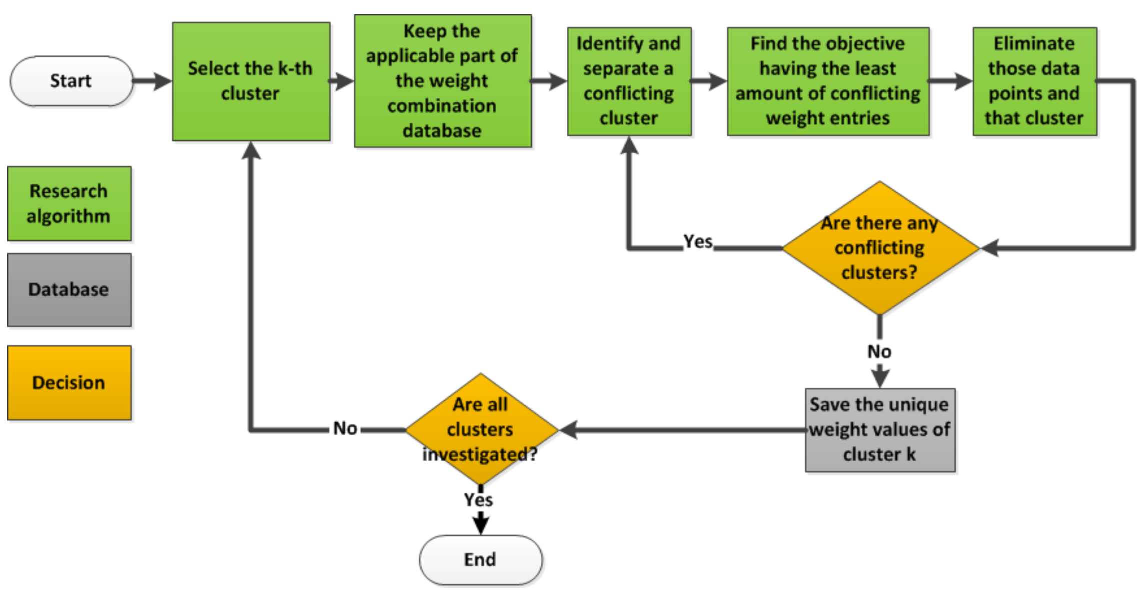


Figure 5.1: The flow diagram of the unique weight range finder algorithm

The algorithm begins by selecting the first cluster and all the allocations that have weight entries(for one or more objectives) within the range of weights that the selected cluster has. Unfortunately, by selecting some of the weight combinations from that list, one would have the possibility of ending up with an undesired cluster.

Consequently, the conflicting clusters that are in the selected range have to also be sorted out. However, it has to be done in a way that the number of data points within the originally investigated cluster decreases as marginally as possible.

Accordingly, the next step in the algorithm is to select a conflicting cluster and identify the objective (out of the four) that has the least amount of weight entries that are conflicting with the original cluster. Once these weight entries are identified, they can be eliminated from the data base. It means that both the selected conflicting cluster is deleted from the data base and the cluster under consideration is reduced in size. This part of the algorithm is repeated until no more conflicting clusters are present for the selected one. When the cluster is deemed to be unique (in weight range values), then the remaining weight combinations are stored.

For one to better understand the work flow presented in Figure 5.1, an example is given below on finding the unique weight range of a certain cluster. The weight combination entries that is applicable to a randomly selected cluster (Cluster 4) is presented in Figure 5.2 below. Furthermore, the range of the weights of Cluster 4 is visible in Figure 5.3 below.

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
1	1000	0.8	0.1	0.1	0
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.1	0.8	0.1	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.7	0.1	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0
4	1000	0.9	0.1	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.3	0.6	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.4	0.5	0.1	0
8	1000	0.6	0.3	0.1	0
8	1000	0.7	0.2	0.1	0

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.1	0.8	0.1	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.7	0.1	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.3	0.6	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.4	0.5	0.1	0
8	1000	0.6	0.3	0.1	0
8	1000	0.7	0.2	0.1	0

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0

Figure 5.2: Demonstration on the working principle of the unique weight range finder algorithm

Cluster ID	W_{NRA} range	W_{SE} range	W_{ACTD} range	W_{PWD} range	W_{TW} range
4	1000	0.1-0.9	0.1-0.9	0-0.1	0

Cluster ID	W_{NRA} range	W_{SE} range	W_{ACTD} range	W_{PWD} range	W_{TW} range
4	1000	0.1-0.8	0.2-0.9	0-0.1	0

Cluster ID	W_{NRA} range	W_{SE} range	W_{ACTD} range	W_{PWD} range	W_{TW} range
4	1000	0.1-0.8	0.2-0.9	0-0.1	0

Figure 5.3: Changes in the weight ranges of the cluster in the unique weight range finder demonstration

It can be seen that there are two conflicting clusters present which are Clusters 1 and 8. Namely, these allocations have weight entries(for one or more objectives) within the weight ranges of Cluster 4. Therefore, Cluster 4 cannot be unambiguously defined based on its weight ranges, so these ranges have to be reduced. The first cluster that is conflicting is Cluster 1. When one compares the four weight ranges in Cluster 4 that can take on Cluster 1's weights, one can see that Objective 3's weight of 0.1 appears only once in Cluster 4. It means that by eliminating the weight entry of 0.1 in Objective 3, the least amount of data points would be erased from Cluster 4. Therefore, this value is erased from Cluster 4 as the workflow presented above in Figure 5.1 proposes.

As Cluster 1 is erased from the data base, Cluster 8 is still conflicting. Hence, one has to investigate which weights of Cluster 8 are present the least amount in Cluster 4's weight ranges. One can see that the maximization of stand effectiveness and minimization of passenger walking distance objectives are present with

5 data points each. In this way, one of the two has to be eliminated. The algorithm randomly selects one of the two to be deleted. In the current case, the weight value of 0.1 is eliminated from the minimization of passenger walking distance objective. In this way, the rows marked with yellow(in the second iteration) are eliminated from the data base of Cluster 4. The remaining data points (weights) make up the unique weight range of Cluster 4. It is also important to note that when two or more objectives could be used for elimination at the same time, it is not essential that one chooses one of the objectives based on a rule, since either selection will result in a unique weight range.

While the workflow of eliminating some of the weights from the weight ranges of a certain selected cluster was demonstrated in Figure 5.2, one can see the effect of these weight range reduction procedures in Figure 5.3. As the size of Cluster 4 decreased, the weights from the edges of the ranges also were eliminated which reduced the size of the weight ranges of this cluster. The rightmost table in Figure 5.3 shows the unique weight range of Cluster 4, since this cluster has no more conflicting clusters within its weight ranges.

While the unique weight range finder algorithm was presented in this section, it has to be noted that the sample list used in Figure 5.2 contains weight combinations that are present twice in the list. This is due to the fact that it is a sample taken from a case study that is detailed in the next chapter, namely, Chapter 6. For that case study, the optimization run creating the allocations was able to find allocations that are equally good in overall allocation performance, namely, non-dominated Pareto optimal solutions. It means that both of these allocations are saved to the database. However, this phenomenon is explained in detail in Chapter 6.

5.3 Feasibility testing of tactical stand allocation performance planning

This section presents the nomenclature and work flow of using the found unique weight ranges for the clusters to test whether these unique weight ranges can predict the performance of a future tactical stand allocation. Furthermore, it is also the goal of feasibility testing to see if the unique weight ranges have weight combinations that can be proactively applied on a future stand allocation that will produce the desired allocation performance. However, it is firstly important to describe the nomenclature that will be used while analyzing the research results, therefore, this nomenclature is presented below.

- **Forecaster weight range:** the multi-dimensional unique weight range of a certain cluster that is used as a reference, and it is projected onto a comparison test case for the investigation of standardized KPI overlap.
- **Projection of unique cluster weights:** the employment of unique (forecaster) cluster weights of a reference test case on a comparison test case (having different inputs).
- **Forecasted (Captured) KPI values:** the (standardized) KPI values of a certain test case obtained by applying the unique cluster weights of a reference test case (the projected cluster weights).
- **Captured KPI range:** the range of (multi-dimensional) KPI values(of a comparison test case) coming from projecting the unique cluster weights of a reference test case.
- **Prediction error:** the absolute difference between the medians of the reference and the projected standard KPI values of a certain cluster.

It can be seen that both the KPI values and the error with which one can predict the performance of a certain allocation are defined and will be used. It is not only important to define the nomenclature for feasibility testing, it is also important to define the flow of the feasibility test. Consequently, the feasibility test setup is presented in Figure 5.4 below.

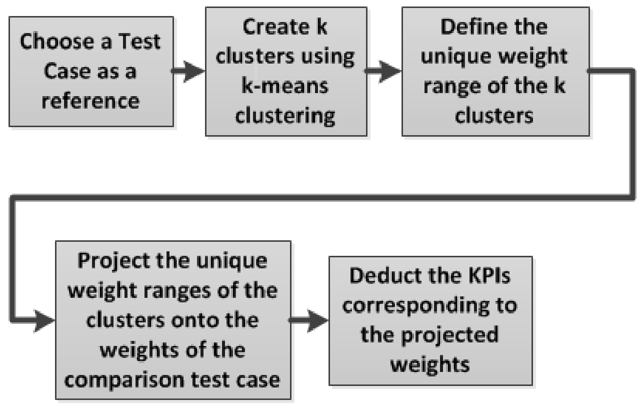


Figure 5.4: Work flow of testing the feasibility of performance prediction

It was seen in Figure 3.2 that the Weight Space Search will be done on multiple different test cases. These test cases will be created using different flight schedules (of different operational days) at different terminals. These will be elaborated on in Chapter 6. Accordingly, the k-means clustering is initially done on a chosen Test Case (introduced in Section 6.2 below). Then, one has to reduce the 4-dimensional weight range of each cluster using the technique presented in Section 5.2 for one to end up with weight ranges that uniquely define the clusters. Then these unique weight ranges of this reference Test Case are projected onto a comparison Test Case. The weight values within these weight ranges produce allocations(and their KPI values). These standardized KPI values then are investigated whether they lie within the specified standardized KPI ranges of the clusters from which their weights were used for creating the allocations. If so, then the weights of a certain cluster can be re-used for the allocation performance planning of future allocations. However, the degree to which the standardized KPIs can be predicted is explained in detail in Chapter 8.

Conclusions

This chapter revealed that in order to end up with meaningful trade-offs between the stand allocation objectives for a future allocation, it is important to use a clustering algorithm that is able to relate the KPI solutions of the large number of different allocations generated by the Weight Space Search. Although, 4 different clustering methods are available, the k-means clustering algorithm (Centroid-based clustering) is found to be the most suitable one for the present research due to the fact that it relates similar KPI values in a multi-dimensional space the best. Furthermore, it was seen that it is essential for one to reduce the weight range of each cluster, since uniqueness is not ensured naturally. That enables the users to later on predict the performance of future allocations. Lastly, the feasibility testing framework of the performance planning capabilities of the presented methods was elaborated on. The next chapter will introduce the London Heathrow Airport case study that will demonstrate the practical(and industrial) use of the above presented methods.

6 A case study: London Heathrow Airport (LHR)

This chapter presents the case study that is employed on the research models presented in Chapters 4 and 5. Namely, the practical validity and correctness of the models will be tested on an actual airport. This airport is London Heathrow Airport. Firstly, general information on London Heathrow Airport, its stand allocation practices and characteristics will be presented in Section 6.1. Secondly, a detailed discussion is given on the terminals that are selected for the current research in Section 6.3. As the used terminals are set, schedules of these terminals with different characteristics have to be selected and investigated. This is done in Section 6.4. As the terminals and the corresponding schedules are determined, these are fed into the research models that will produce the required results. The resulting allocations and the related trade-offs are investigated in Section 6.5. It must be noted that the information presented in this chapter is partially obtained upon consultation with capacity planners at Heathrow Airport Limited, however, the analysis and opinions drawn from this information are done by the author solely and do not necessarily represent those of Heathrow Airport Limited.

6.1 General information on London Heathrow Airport

London Heathrow Airport is considered to be among the busiest airports in the world with its 75.7 million passengers and 1.54 million metric tonnes of cargo annually[1]. It is the hub airport of British Airways and it is also a destination for 80 other airlines to serve 194 destinations in 82 countries. It also has 2 runways in the 09/27 direction (09L/27R and 09R/27L). Furthermore, it has 4 currently functioning terminals.

As far as the present case study is concerned, several important stand planning operations practices need to be defined to provide appropriate and accurate input to the stand allocation model presented in Chapter 4. In light of that, a consultation procedure was conducted with the capacity planning department of London Heathrow Airport. It has to be mentioned that the following operations practices are used on an every day basis for the tactical planning of the aircraft stands at all 4 open terminals.

Rule on the possibility of aircraft tows

Section 4.3.2 introduced the towing operations objective and Section 4.3.1 introduced the related constraints. London Heathrow Airport reserves the right to tow any aircraft that is scheduled to be on the ground for at least 4.5 hours. It means that the towing operations objective only comprises of decision variables of operations that are associated with a turnaround that is at least 4.5 hours long. Additionally, as it was seen in Section 4.3.1, 2 types of towing constraints were introduced. The ones shown in Equation 4.18 allow for the towing of the operations of the long turnarounds. However, the towing constraints shown in Equation 4.17 ensure that turnarounds with a turnaround time less than 4.5 hours are not towed, hence, these are kept at the same stand.

The reason for such a distinction is that towing operations are costly[2] as well as time consuming. Furthermore, it increases the congestion of the aprons and taxiway systems, therefore, only turnarounds that are scheduled to occupy an aircraft stand for an extended period of time are subject to the possibility of towing.

Embarkation and disembarkation times

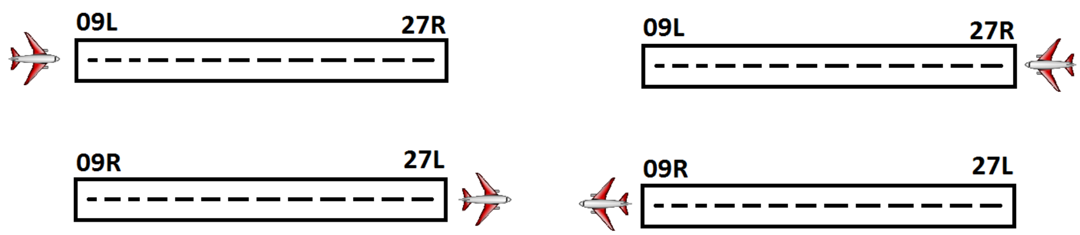
The turnarounds that can be subject to towing have to be appropriately divided into 3 distinct operations as it was mentioned in Section 4.1. Namely, the time duration of each operation has to be correctly defined. London Heathrow airport allows long turnarounds to have a maximum of 60 minute disembarkation and a 60 minute embarkation time. These times should be adequate enough for the loading and unloading of

[1] http://www.heathrow.com/company/company-news-and-information/company-information/facts-and-figures
[2] https://www.munich-airport.de/media/download/bereiche/efm/preisliste.pdf

passengers and goods, the re-fueling and catering plus the safety checks of the aircraft. The remainder of the turnaround time is called the idle time where the aircraft is allowed to be towed to another contact or a remote stand to avoid the sub-optimal use of certain stands. Additionally, turnarounds less than 4.5 hours are divided up into two operations with equal embarkation and disembarkation times. It ensures that there is no bias towards one or the other operation during the allocation.

Runway configurations

Furthermore, several additional model settings are set that are not constant for all LHR operations. It means that these settings are set based on scientific references and observed practices. Accordingly, it is essential to choose a runway configuration in order to simulate the aircraft taxiing procedures. For the current research, 2 runway configurations will be used which are the so-called Easterly 1 and Westerly 1 runway configurations. These runway configurations can be seen in Figure 6.1 below. The reason for selecting 2 runway configurations is to simulate the effect of different aircraft taxi distances for the aircraft stands.



(a) The Easterly 1 runway configuration at LHR (b) The Westerly 1 runway configuration at LHR

Figure 6.1: London Heathrow Runway configurations that are used in the research

It is also important to mention that there are 2 other runway configurations at LHR. These 2 runway considerations are similar to the ones presented in Figure 6.1 above. One of these runway configurations is called Easterly 2, which is similar to the one in Figure 6.1a, but the flights are arriving at runway 09R and departing from runway 09L. The 4^{th} runway configuration is called Westerly 2 which is similar in the same fashion to Westerly 1 as the Easterly configurations to each other. Namely, the arriving flights land on runway 27L and the departing flights take off from runway 27R.

While one of two differing runway configurations are selected to be constant for each operational day, it is important to note that in reality there is a runway change at LHR at 15:00 each day[3]. This is due to the necessary noise mitigation measures that are employed to reduce the footprint on certain areas around the airport. In 70 % of the year, Westerly operations apply at LHR [4]. It means that for those days, the operational day begins for example with the Westerly 1 runway configuration and a shift is made towards Westerly 2 at 15:00 until the end of the operational day. However, as it was pointed out earlier, only 1 runway configuration is considered for the current research to be able to keep the problem simple enough to be applied in a general sense.

As Terminals 2,3 and 5 are located between the two active runways at LHR, the effect of runway configuration change on the arrival and taxi distances is balanced. It means that for one of the runway configurations, the arrival taxi distance is short, but the departure taxi distance is long and vice versa. On the other hand, Terminal 4 is located south of the 09R-27L runway which means that lengthy taxi distances can be obtained when the 09L-27R runway runway is used. However, this present research does not consider such an extreme case.

Schedule robustness measure

Section 4.1 and Constraint 3 in Section 4.3.1 mentioned the need for a time gap in order to ensure some flexibility of the stand allocation in case a flight arrives early or departs late from its stand. This time gap

[3]http://www.heathrow.com/noise/heathrow-operations/runway-alternation

[4]http://www.heathrow.com/file_source/HeathrowNoise/Static/Runway_Alternation_Programme_2017.pdf

is called the schedule robustness and it is marked with the variable t_{rob}. This robustness measure is very subjective based on the airport or research under consideration. Additionally, London Heathrow Airport did not provide a specific requirement on the robustness of the allocation. Therefore, a robustness measure of 10 minutes will be set for this research to ensure that each specific stand is left empty for 10 minutes before and after a turnaround that is assigned to it[12]. During the consultation procedure with LHR, this 10 minute robustness value was approved by the capacity planning department.

Flight schedule planning seasons

London Heathrow Airport makes use of two separate planning seasons when it comes to the development of flight schedules. One of the planning seasons is called the summer planning period which runs from the end of March's last weekend until the end of October's last weekend in each year. The second planning period is the winter planning period that begins from the end of October's last weekend and finishes at the end of March's last weekend. It has to be mentioned that the number of arriving and departing flights as well as the ground demand of each aircraft type are significantly different for these two seasons. Furthermore, the flight schedules within the same season either do not differ or differ insignificantly. These statements will be proven in Section 6.4 below.

6.2 Research cases

Chapter 3 introduced 3 main research questions and 3 additional sub-questions. These research questions are investigated through different test cases. Accordingly, it is important to develop test cases that are suitable to properly argue for the answers of each research question. The main purpose of this section is to define and argue for research cases that are suitable to answer the research questions. These test cases are visible in Table 6.1 below. It is visible that days, terminals and runway configurations are selected. Sections 6.3 and 6.4 below give a detailed explanation for the selection of these test cases through the investigation of terminal layouts and flight schedules.

Table 6.1: The test cases used for the analysis of the research results and research questions

Case ID	Date	Terminal	Runway configuration
Case 1	August 12 (Friday)	3	Easterly 1
Case 2	August 12 (Friday)	3	Westerly 1
Case 3	May 12 (Thursday)	3	Easterly 1
Case 4	December 23 (Friday)	3	Easterly 1
Case 5	August 12 (Friday)	2	Easterly 1

For this current research, Terminal 3 will be the baseline terminal, that simulates well the operations at LHR, since it simulates the behavior of a transfer terminal well. This statement and the reasoning for selecting the remainder of the test cases will be justifiend in Sections 6.3 and 6.4 below. Furthermore, August 12 and the Easterly 1 runway configuration will serve as the baseline date and runway configuration. It means that Case 1 is the baseline case (reference case). This case will be compared to other test cases based on the research question under consideration.

As 5 test cases were developed for the investigation of the validity of this research, it is important to link the test cases to the research questions. It is necessary to give the reader a better understanding on the setup of answering each research question. In this way, the problem setups for each research question are presented below.

Test cases for RQ1, RQ1a, RQ2

The analysis of the main Research Question 1 (RQ1) will be done by the analysis of Case 1. The reason for selecting only one case is that the developed objective trade-offs within one case need to be analyzed. As it was mentioned in Chapter 5, the number of clusters used will determine the amount of trade-offs. Hence, the comparison of these clusters will be the core of this analysis.

Furthermore, the investigation of RQ1a will also make use of Case 1. There, the KPI value of the objective will be compared to its weight in the objective function. It will be determined whether the strength of the weight setting of a certain objective represent the KPI value of that objective. This analysis will also give a valid argument for employing the k-means clustering algorithm for the definition of the clusters.

Lastly, RQ2 summarizes the conclusions of RQ1 and RQ1a. Also, the answers to RQ2 will determine whether the remainder of the research questions can be answered.

Test cases for RQ3a

Research Question 3a investigates whether the type of airport (or terminal) has an effect on the established objective trade-offs. This test comprises of the comparison of Case 1 and Case 5. It will be seen below that both the flight schedules and the aircraft stand infrastructures of the two terminals differ significantly. Therefore, the combined effect of these two considerations will determine the similarities and differences between the trade-offs.

The core of this investigation is based on Module 3 of the research setup mentioned in Figure 3.2. Firstly, the weight space search process is employed on both Case 1 and Case 5. Then, Case 1 is chosen to be the reference scenario. For this reference scenario, a unique weight range for each cluster (trade-off) will be established. Then, these unique weight ranges will be projected onto the weight space of Case 5. The motivation behind it is to see whether trade-offs established for 1 terminal also hold for another terminal.

Test cases for RQ3b

Although, the effect of employing the methods developed in this research is already investigated through different airport (terminal) types, it is also essential to investigate the effect of using a differently structured flight schedule for the same terminal. Namely, the effects of dissimilarities between different days at the same airport (terminal) are investigated by looking at flight schedules of different days of the week, different schedule and also the change in runway configuration for the same day.

Firstly, the effect of a different runway configuration will be evaluated by the comparison of Case 1 and Case 2. It was mentioned in Figure 3.2 in Chapter 3 that Module 3 defines a unique weight range for each cluster (trade-offs) for the reference case. Then, these unique weight ranges will be projected onto the comparison cases to investigate how well these comparison cases can be predicted. The resulting projections will be compared to the reference case trade-offs to see whether the predicting capabilities of the method are acceptable.

Secondly, the effect of a different operational day within the week will be evaluated in the same fashion. Case 1 with a Friday flight schedule is compared to Case 3 with a Thursday flight schedule. Section 6.4 will later on reveal that the flight schedules of these two days are very similar.

Finally, Case 1 and Case 4 will be compared to investigate the effects of using a flight schedule of a different allocation season. Section 6.4 will reveal that although the same terminal infrastructure is used for both cases, the ground demand differs significantly.

Test cases for RQ3

Research questions 3a and 3b (RQ3a and RQ3b) already investigate the effect of terminals and flight schedules to see the variability in the trade-offs between the allocation objectives. Research Question 3 summarizes the findings of these two research questions and aims to find one or multiple rules that are applicable to the trade-off prediction capabilities of the developed model. This research question employs Case 1 as the reference case and compares it to cases 2,3,4 and 5 simultaneously. It also creates a hierarchy between the test cases based on the prediction accuracy.

6.3 Terminal information and selection

Section 6.2 above introduced the test cases that are used for finding answers to the research questions. This section aims to explain the reasons behind the development of the test cases mentioned in Table 6.1 through the investigation of the different terminals at LHR.

Research question 3a (RQ3a) investigates whether the type of airport under consideration does have an effect on the trade-offs that are made between the stand allocation objectives. Therefore, it is essential to compare different airport models. In this research, the different airport types will be modelled through some of London Heathrow's terminals. As it was mentioned earlier, Heathrow Airport has 4 currently operational terminals. Additionally, each of these terminals accommodate different sorts of traffic in order to ease the flow of passengers and to simplify airport processes such as the different security checks and transfer procedures. Table 6.2 below summarizes the traffic that goes through each terminal. [5]

Table 6.2: Airline traffic breakdown at London Heathrow Airport

Terminal name	**Operating airlines and airline alliances**
T2	Star Alliance, Icelandair, Eurowings, Aer Lingus
T3	British Airways, Oneworld, Delta, Virgin Atlantic and all Middle East airlines
T4	Skyteam, Qatar Airways and Malaysia Airlines
T5	British Airways and Iberia

It can be seen that LHR separates the traffic of the airline alliances effectively. The main purpose for that is to avoid unnecessarily long and complicated transfer procedures. Unfortunately, this information alone is not sufficient enough to find suitable terminals to be investigated. Therefore, a more detailed investigation is necessary. The analysis of the traffic structure and infrastructure arrangements reveal two candidates for the current research. These two candidates are Terminal 2 and Terminal 3. These terminals and the reasons for their selections will be discussed in detail below.

6.3.1 Terminal 2

Terminal 2 is located on the Eastern side of the LHR apron system and as it was seen earlier, it accommodates Star Alliance traffic. The analysis of the passenger traffic at Terminal 2 proves that it is an *O&D* terminal. This can be proven by the fact that approximately 11.5 % of the passengers are transfer passengers. This can be seen in Table 6.3 below. It means that the majority of the passengers are local passengers.

Table 6.3: The traffic structure of Terminal 2

Date	**Local PAX (A/D)**	**Transfer PAX (A/D)**	**Turnarounds**	**Towable operations**
August 12	23709/23086	3126/3124	171	31/62

Furthermore, it is important to investigate the aircraft stand infrastructure of Terminal 2. Table 6.4 shows the number of stands at Terminal 2. It is visible that two types of capacity are measured. This is due to the presence of MARS stands. In case all the large MARS stands are used, the minimum capacity is applicable to type 3 stands and maximum capacity is considered for type 4,5 and 6 stands and vice versa. It can be seen that the majority of the type 3 (medium) ICAO ADG stands are part of MARS stands, mostly of type 6 stands. Also, it can be seen that most of the stands are medium stands accommodating single isle aircraft. It means that single isle traffic is more common in Terminal 2. This is a common characteristic of *O&D* airports, since these types of airports serve to feed the hubs with traffic.

[5] http://www.heathrow.com/plan-and-book-your-trip/destinations-and-airlines

Table 6.4: The minimum and maximum capacities of the different stand types at Terminal 2 of LHR

ICAO ADG stand size	**3**	**4**	**5**	**6**
Minimum capacity [stands]	8	0	11	3
Maximum capacity [stands]	30	0	13	12

The investigation of the flight schedules for Terminal 2 also provide a strong argument for considering it as an *O&D* airport. For August 12 2016, 72 % of the turnarounds were of single-aisle aircraft. In comparison, only 46 % of the turnarounds in Terminal 3 are served by single-isle aircraft. Furthermore, the share of turnarounds of the largest airline present at the terminal has to be investigated. The largest airline (in terms of turnaround share) is Lufthansa for Terminal 2. They account for 25 % of the turnarounds. On the other hand, the largest carrier for Terminal 3 is British Airways and they own 46 % of the turnarounds. It means that almost half of the turnarounds are operated by one single airline for Terminal 3 compared to the quarter of turnarounds in Terminal 2. It can be used as a strong argument for deeming Terminal 2 an *O&D* terminal, therefore, it will be considered as such in the remainder of this report.

6.3.2 Terminal 3

Previously, it was determined that Terminal 2 serves as an appropriate model for the investigation of an *O&D* terminal. On the other hand, one is also in need of a transfer terminal for this current research. Therefore, Terminal 3 will be investigated. The traffic structure of Terminal 3 initially reveals that the Oneworld alliance, Delta Air Lines and Virgin Atlantic are the majority users. It would also suggest that this is a transfer terminal, however, one also need to investigate the passenger breakdown. This is visible in Table 6.5 below. One can see that roughly 26-27 % of the passengers are transferring. This figure is in alignment with the transfer data provided by London Heathrow Airport. [6] This means that the transfer passenger numbers are a strong indication that this is a transfer terminal.

Table 6.5: The traffic structure of Terminal 3

Date	**Local PAX (A/D)**	**Transfer PAX (A/D)**	**Turnarounds**	**Towable operations**
August 12	19771/18932	7098/7481	136	47/94
May 12	19761/18879	6923/7318	136	47/94
December 23	16663/16342	6260/6653	120	35/70

Furthermore, the aircraft stand infrastructure reveals that Terminal 3 is a transfer terminal. This can be seen in Table 6.6 below. It is clearly visible that there are a significantly more large aircraft stands (types 5 and 6). It means that the majority of the stands are suitable for twin isle aircraft. Since hub airports usually serve long distance destinations (for which twin isle aircraft are used), the aircraft stand infrastructure is a valid argument for deeming Terminal 3 as a transfer terminal.

Table 6.6: The minimum and maximum capacities of the different stand types at Terminal 3 of LHR

ICAO ADG stand size	**3**	**4**	**5**	**6**
Minimum capacity [stands]	5	3	26	7
Maximum capacity [stands]	11	3	26	10

The above mentioned arguments serves as enough proof to make the assumption that Terminal 3 acts as a transfer terminal. It means that the two terminals and the corresponding objective trade-offs can be established. Although, the terminals used for the current research are determined, one also has to make sure that the used flight schedules are also selected based on an educated argument. The following section therefore discusses the schedule selection.

[6] http://www.heathrow.com/company/company-news-and-information/company-information/facts-and-figures

6.4 Schedule analysis and selection

As it was seen previously, flight schedules of different days have to be chosen for the proper evaluation of the predictive capabilities of the developed model. Therefore, this section investigates the schedule structures of different days, seasons and even terminals. Firstly, Terminal 2 will be examined in Subsection 6.4.1, which will be followed by the investigation of Terminal 3 flight schedules in Subsection 6.4.2.

6.4.1 Terminal 2

It was mentioned in Section 6.2 previously that Terminal 2 will serve as a comparison terminal, therefore, only 1 schedule will be examined for this terminal as it is present for Case 5 in Table 6.1. The ground demand graphs for this flight schedule present detailed information on whether the number of stands are enough for the allocation of each turnaround. Firstly, the ground demands for turnarounds with an ICAO ADG aircraft size of 3 are investigated in Figure 6.2 below. It is clearly visible that both the minimum and maximum stand capacities are depicted in the figures. Figure 6.2 shows that mostly in the beginning and at the end of the day, the minimum stand capacity is exceeded for ICAO ADG 3 stands. It means that MARS stands have to be employed to accommodate the excess type 3 turnarounds.

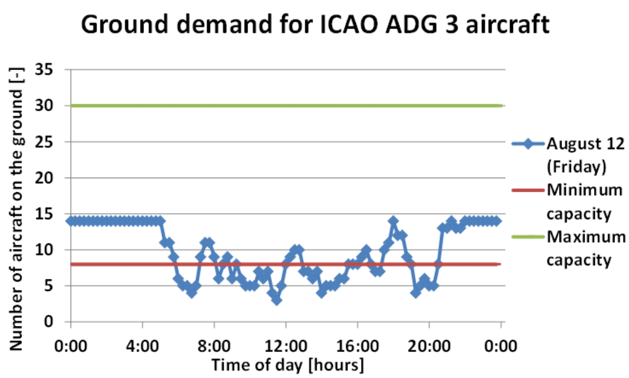
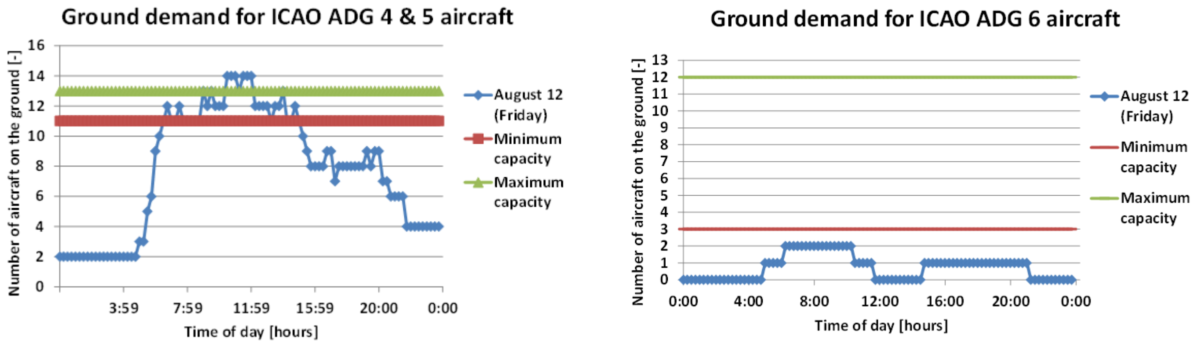


Figure 6.2: ICAO ADG 3 ground demand and stand capacity for Terminal 2 on the 12^{th} of August 2016

Interestingly, there are no dedicated type 4 stands at Terminal 2 which means that each type 4 aircraft (turnaround) has to be allocated to either type 5 or type 6 stands. In this way, the type 4 turnarounds are considered together with the type 5 turnarounds to investigate the gound demand. Figures 6.3a and 6.3b reveal that the excess turnarounds mentioned previously can be allocated to either type 5 or type 6 stands. This is due to the fact that the ground demand for type 6 stands never reach the maximum capacity limit. Since Figure 6.2 revealed that some small MARS stands have to be used, it means that some of the type 5 and type 6 MARS stands cannot be employed. However, since the ground demand does not reach the maximum capacity limit for these two categories, the apron can still deal with the ground demand at all times throughout the day.



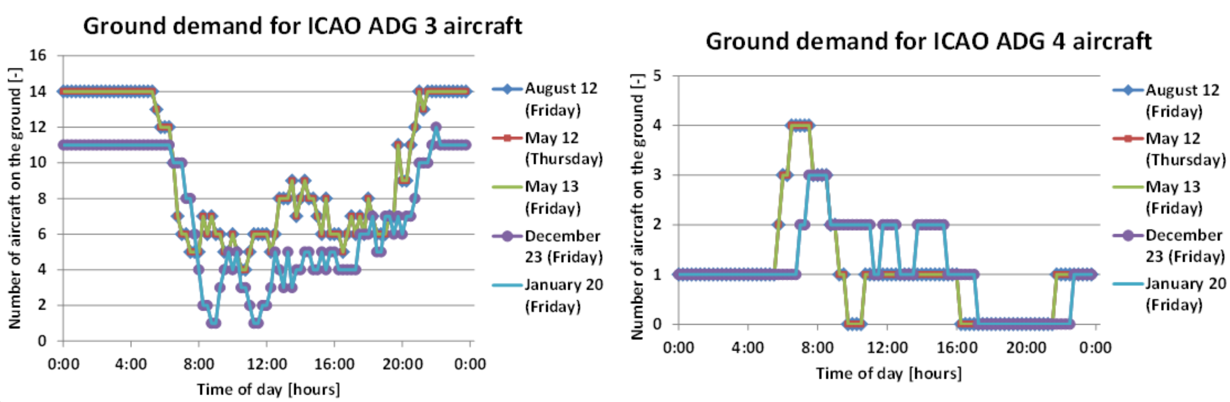
(a) ICAO ADG 4 and 5 ground demand and stand capacity (b) ICAO ADG 6 ground demand and stand capacity

Figure 6.3: Ground demand and stand capacity for ICAO ADG 5 and 6 stands for Terminal 2 on the 12^{th} of August 2016

Figures 6.2 and 6.3 revealed that using the combination of MARS and non-MARS stands, one make sure that all turnarounds can be allocated to either a remote or a contact stand. Therefore, the allocation of operations (of the turnarounds) will be determined based on the allocation objectives.

6.4.2 Terminal 3

The previous subsection investigated the ground demand of Terminal 2 for one day. However, Section 6.2 outlined that the test cases considering Terminal 3 will make use of multiple days. Accordingly, this subsection aims to assess the choices made when selecting the flight schedule days that are used for the test cases. Figures 6.4a and 6.4b depict the ground demands for ICAO ADG type 3 and 4 turnarounds for various days (both for the summer and winter season) at LHR. It has to be mentioned that the stand capacities are not plotted on these figures in order not to over-saturate the graphs. The capacities can be found in Table 6.6 above.

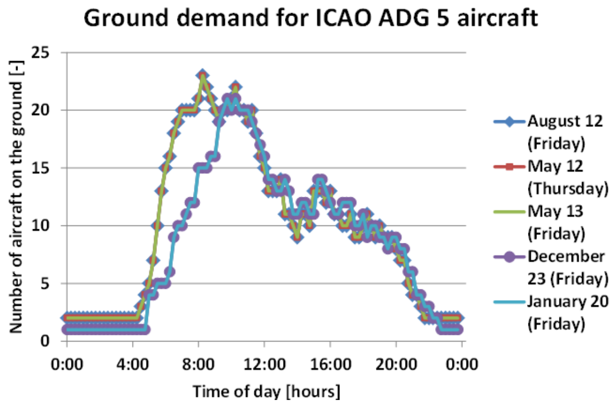


(a) ICAO ADG 3 ground demand and stand capacity (b) ICAO ADG 4 ground demand and stand capacity

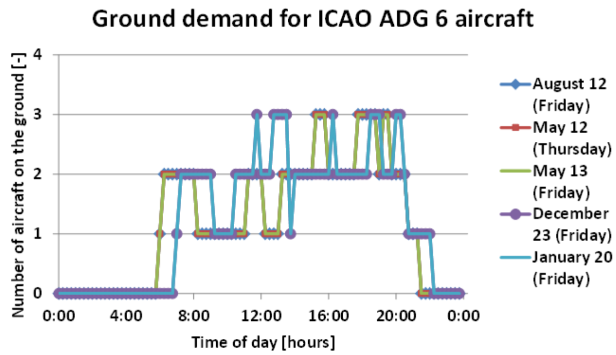
Figure 6.4: Ground demand and stand capacity for ICAO ADG 3 and 4 stands for Terminal 3 on various days

It is clearly visible that the ground demands for days in the same season (May 12, May 13 and August 12) are the same for type 3 and type 4 aircraft. It can also be seen that the ground demands for the winter season days (December 23 and January 20) are also the same. It means that for the winter season, it is sufficient to choose one of the two operational days. This acts as a proof for selecting December 23^{rd} for the investigation of the winter season as it was already mentioned in Section 6.2 above.

The ground demands for type 5 and 6 stands are also visible in Figures 6.5a and 6.5b below. It is visible that the same trends are present as for the type 3 and 4 aircraft. It means that the overall ground demands for the summer days are identical which is the consequence of a flight schedule with no variability. The same statement can be made on the winter schedules, hence it is justified that for the winter season, it is sufficient to investigate one flight schedule only.



(a) ICAO ADG 5 ground demand and stand capacity



(b) ICAO ADG 6 ground demand and stand capacity

Figure 6.5: Ground demand and stand capacity for ICAO ADG 5 and 6 stands for Terminal 3 on various days

It was also examined whether the ground demands are within the capacity limitations of the airport such as for Terminal 2. For that, the capacity limits of each stand type presented in Table 6.6 are compared to the ground demand. It can be concluded that with the right combination of MARS and single stands, it is able to accommodate all turnarounds within the operational day. Therefore, it is also expected that no non-allocatied operations will result in the test cases considering Terminal 3.

It is important to note, that the reason for selecting both the 12^{th} of May and the 12^{th} of August (regardless of having the same ground demand) is that the number of passengers differ for the two operational days (as seen in Table 6.5). Accordingly, the effect of the changes in the passenger numbers have to be investigated.

6.5 Resulting allocations and comparison

This section assesses the resulting allocations that are generated using the inputs that were analyzed in the earlier sections of this chapter. The weight space search was conducted for each of the 5 test cases introduced in Section 6.2. Namely, a total of 286 iterations were conducted for each of these test cases. It has to be mentioned that some of the iterations resulted in multiple non-dominated solutions, which means that the solution space for these cases will be larger than 286. The total number of solutions (allocations) along with the run times for these test cases are summarized in Table 6.7 below.

Table 6.7: The number of non-dominated allocations and the computational run time for each test case

Case name	No. of non-dominated allocations	Run time [hh:mm]
Case 1	337	19:47
Case 2	345	24:25
Case 3	324	22:41
Case 4	298	13:39
Case 5	293	11:08

It can be seen that for each test case, more than 286 solutions exist which means that for a certain objective weight combination, multiple equally optimal (non-dominated) solutions exist. It is important to mention that all of these non-dominated solutions have to both be retrieved and be used later on in this research. This is due to the fact that for a given objective weight combination, any of these non-dominated solutions can be accepted, which means that in case one re-uses this objective weight combination, any of these solutions can result. It means that excluding one or another could morph the solution space and the clustering that will be employed on it which would result in inaccurate clusters.

It is not only important to investigate the solution sizes and run times of the test cases, one also has to look at the characteristics of all of the objectives for each test case. These characteristics can be seen in Table 6.8 below. The KPI ranges for all 5 allocation objectives are presented for each test case. Furthermore, an example allocation for Test Case 1 is presented in Figure D.1 along with Tables D.1 to D.4 in Appendix D. The allocation was created with objective weights of: $w_{NRA} = 1000$, $w_{SE} = 0.2$, $w_{ACTD} = 0.2$, $w_{PWD} = 0.2$ and $w_{SE} = 0.2$.

Table 6.8: KPI value ranges of the different allocation objectives for each test case

Name	**Remote allocations**	**Stand effectiveness [SM]**	**Avg. A/C taxi distance [m]**	**No. of tows [-]**	**Avg. PWD [m]**
Case 1	4	0.26-0.84	1640-1981	7-80	417-596
Case 2	4	0.26-0.8	1355-1691	6-77	417-585
Case 3	4	0.26-0.79	1640-1978	6-81	414-592
Case 4	0	0.17-0.8	1604-1975	0-69	410-594
Case 5	0	0.12-0.44	2298-2518	0-61	356-495

It can be concluded that each of the operations could be allocated to either a remote or a contact stand. This means that all allocations are considered feasible. Furthermore, for the first 3 cases, a total of 4 operations could only be allocated to a remote stand, while the remaining operations are allocated to contact stands. All operations could be allocated to contact stands for cases 4 and 5. As far as the remaining objectives are concerned, one has to see that the KPIs do not assume a singular value, however, a range of KPI values are listed. This is due to the fact that both the weights of each objective were varied between 0 and 1 and that the weights of the other objectives had a effect on the KPI values. Unfortunately, the KPI ranges for each of the test cases differ, which means that the test cases cannot be explicitly compared. The ability to compare different test cases is important in order to be able to assess Research Question 3 and its sub-questions.

In order for one to be able to compare the above listed test scenarios, a straightforward approach to convert the resulting KPIs and the KPI ranges is introduced. The KPIs will be standardized for each test case which means that all test cases will have the same units in all dimensions (for all objectives). In the new standardized KPI range, for each test case, the smallest KPI value (the best, since the model sense is minimization) assumes the value of 0, while the largest KPI value (the worst) takes the value of 1. This is done for each of the objectives (dimensions). It means that each objective of each test case will have all of its KPI ranges between 0 and 1. The standardization is done using the rule presented in Equation 6.1 below.

$$KPI_{i_j}^{std} = \frac{KPI_{i_j} - KPI_{min_i}}{KPI_{max_i} - KPI_{min_i}} \tag{6.1}$$

The standardized KPI value is obtained by taking the difference between the KPI value and the smallest KPI value for the same objective and dividing this difference by the complete KPI range. In this way, one obtains the location of the KPI within the complete KPI range.

Effect of objectives on runtime

The previous sections revealed the allocation performance of the used test cases, however, it is also important to assess the computational performance of the many-objective tactical stand allocation model. Accordingly, the model is ran excluding one objective at a time to investigate the effect of not having that objective on the runtime. It also has to be mentioned that the minimization of non- and remote allocations objective is still kept at the top of the hierarchy(with an objective weight of 1000) and that the competing objectives that are still part of the problem have equal objective weights, namely, a weight of 0.33. The resulting runtimes for these test runs are visible in Table 6.9 below.

Table 6.9: The runtime of the many-objective tactical stand allocation model when excluding one objective

w_{NRA}	w_{SE}	w_{ACTD}	w_{PWD}	w_{TW}	**Runtime [sec]**
1000	0	0.33	0.33	0.33	350
1000	0.33	0	0.33	0.33	215
1000	0.33	0.33	0	0.33	200
1000	0.33	0.33	0.33	0	48
0	0.25	0.25	0.25	0.25	55

It can be seen that the runtimes are relatively high when the maximization of stand effectiveness, minimization of aircraft taxi distance and minimization of passenger walking distance objectives are excluded from the problem. However, when the minimization of non- and remote allocations and the minimization of tows objectives are excluded from the problem, the runtime quickly drops. Regarding the minimization of non- and remote allocations objective, the relatively low computational time can be explained by the fact that when this objective is excluded, the penalty of assigning operations to dummy stands(with unlimited capacity) is also eliminated. Additionally, these dummy stands are not penalized in the other objective functions, therefore, the solver algorithm can swiftly find a feasible and optimal solution to the allocation problem.

Although, being aware of the fact that the exclusion of the objective on top of the hierarchy decreases computational time, this result is not representative, since this objective is always included in the case study test cases. However, when looking at the exclusion of the minimization of tows objective, one can clearly see that the runtime is the lowest. It means that (compared to the other included competing objectives), the minimization of tows objective is the hardest to solve, hence the computational time of the problem greatly increases when this objective is actively present in the problem. It also means that while the runtime of the model is primarily driven by the Weight Space Search(see Table 6.7), there is a difference between the computational times of the different allocations based on which objectives are present in the objective function.

Conclusions

This chapter described the case study setup with London Heathrow as the modelled airport. Firstly, general aircraft and passenger handling processes at LHR were presented and are implemented. This was followed by the description of the test cases that will help to investigate the validity of the used methods and to also answer the research questions of this project. Afterwards, the reasoning behind the selection of such test cases was detailed both regarding the terminal and flight schedule selection. These selections were based on the types of passengers visiting the airport, their total numbers, the ground demand of the turnarounds at the terminal aprons and also the runway configurations to be used. Then, the Weight Space Search on all 5 selected test cases was carried out in Section 6.5. Also, the main characteristics of these test cases were also presented in this section. Lastly, the standardized KPI solution space was demonstrated in the same section. As the test cases are created, it is already possible to analyze these results and to draw conclusions on the research questions. This is done in the following chapter.

7 Verification and validation

It is inevitable for every mathematical model to be properly verified and validated. Namely, one has to ensure that the model reads the proper inputs, executes the right processes, calculate the appropriate variables and delivers the desirable outputs. Furthermore, validation of the data is critical to ensure that the obtained results indeed represent actual, real-life processes. Firstly, unit verification tests of the SAP model will be presented through simplified allocations that are tailored for the specific unit test in Section 7.1. Then, the complete many-objective tactical stand allocation model is verified through a system test in Section 7.1.2. It is followed by the verification of the weight space search algorithm in Section 7.2. Afterwards, Section 7.3 presents the verification of the k-means clustering algorithm and the cluster weight range identifier algorithm. Finally, the validation of the combination of the SAP and clustering models is provided in Section 7.4 by comparing the resulting allocations and the arising objective relationships with user experience of the case study airport.

7.1 Verification of the SAP model

The stand allocation problem model is used to generate the necessary allocations for the analysis of stakeholder trade-offs. As it was seen in Chapter 4, the many-objective SAP model is built up of 5 objectives and 7 constraints. Therefore, it is important to verify each and every objective and constraint to ensure that the model conducts the required tasks. This will be explained in detail in the form of unit tests in Subsection 7.1.1 below. Furthermore, it is important to investigate the combined effect of the objectives and constraints verify that the model gives the correct solution. Therefore, the complete SAP will be verified in the form of a system test in Subsection 7.1.2.

7.1.1 Code verification: unit tests

This subsection presents the unit tests that are conducted on both the separate parts of the stand allocation model and also the weight space search model. Each objective and each constraint will be unit tested. It has to be mentioned that some constraints are essential to be present in the test for each of the objectives (to make it a stand allocation problem), therefore, these constraints will be tested first with a dummy objective (each objective function scalar will be one). Then, when these constraints are proven to be verified, then the remainder of the constraints and the objectives will be tested one-by-one including only the necessary constraints. It has to be noted that the input data (flight schedule and apron information) will differ significantly for certain tests due to the nature of the objective or constraint under consideration. Therefore, the input data for each unit test will be carefully presented.

Unit test 1: Correct stand use (Cstr1)

The first unit test intends to verify one of the essential constraints that make the optimization problem a stand allocation problem, namely, the correct stand use constraint. The main goal of this test is to verify that the flight(s) in the schedule are assigned to one stand only in the airport infrastructure. Furthermore, the correct input of the flight and stand data will be verified as well. Also, the division of the turnarounds into the required amount of operations will be verified.

Firstly, the test schedule will be presented. The schedule consists of two turnarounds, one short turnaround (less than 4.5 hours) and a long one (longer than 4.5 hours). This schedule can be seen in Table 7.1 below.

Table 7.1: The test schedule for unit test 1

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	6:44	240	3	AB 0229	14:42	233	3	478
CD 0048	16:00	256	3	CD 0049	19:00	236	3	180

The above presented schedule will be used to allocate the operations to the stands listed in Table 7.2. It can be seen that there are two stands available for allocation.

Table 7.2: The test apron for unit test 1

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 2_1	2	3		1687	1777	130	130
Stand 2_2	2	3		1687	1777	130	130

The optimization problem makes use of a blank objective that has a decision variable coefficient of 1 for each operation-stand combination. It means that any of the two turnarounds can be assigned to any of the two stands. The resulting allocation is visualized in Figure 7.1.

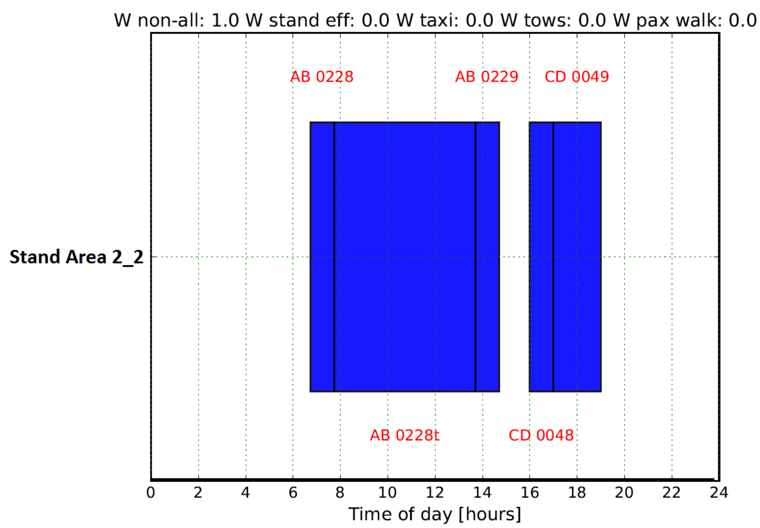


Figure 7.1: The resulting allocation of unit test 1

It can be seen that both turnarounds and their corresponding operations are assigned to the same stand (Stand Area 2_2). Also, each operation is assigned to one stand only which means that unit test 1 was successful and Constraint 1 (Cstr1) is verified.

Unit test 2: Operation assignment to compatible stands (Cstr2)

The aim of unit test 2 is to force all operations to be assigned only to stands that can accommodate those operations. It means that operations that are larger in size than a certain stand, then that operation cannot be assigned to that specific stand. The test schedule used for this unit test contains two turnarounds that are of different sizes. This schedule can be seen in Table 7.3. Furthermore, the test apron for unit test 2 can be seen in Table 7.4 below. it is visible that one of the stands is only of size 3, whereas, the smallest turnaround is of size 4. Therefore, it is expected that the small stand (Stand Area 2_1) will not be used.

Table 7.3: The test schedule for unit test 2

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	6:44	240	4	AB 0229	14:42	233	4	478
CD 0048	10:58	256	5	CD 0049	14:41	236	5	223

Table 7.4: The test apron for unit test 2

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 2_1	2	3		1687	1777	130	130
Stand 2_2	2	6		1687	1777	130	130

The resulting allocation of unit test 2 can be seen in Figure 7.2 below. It is indeed confirmed that none of the operations are assigned to Stand Area 2_1. The operations are assigned to only stands that are of the same size or larger. Accordingly, it can be concluded that constraint 2 (Cstr 2) is verified.

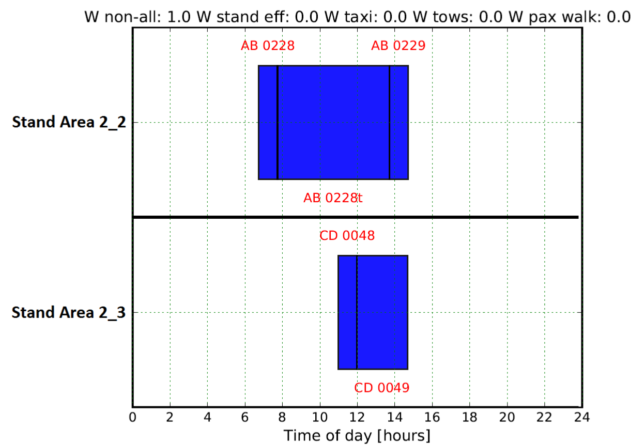


Figure 7.2: The resulting allocation of unit test 2

Unit test 3: Overlapping operations and robustness (Cstr3)

The third constraint that is essential to be included in the optimization problem concerns the allocation of the operations to separate stands in case these are on the ground at the same time. For this unit test, the test schedule is presented in Table 7.5. It can be seen that the two turnarounds that are employed are on the ground at the same time(the "AB" and "CD" turnarounds) which means that these will have to be allocated to different stands. Furthermore, this constraint includes the buffer time that is introduced behind any turnaround. For this reason, a third turnaround is added (the "EF" turnaround). It can be seen that this turnaround arrives 4 minutes after the other two turnarounds depart, therefore, the "EF" turnaround cannot be assigned to the same stand as the other two.

Table 7.5: The test schedule for unit test 3

Arr. Fl. No.	Arr. Time	No. of pax.	ICAO ADG	Dep. Fl. no.	Dep. Time	No. of pax.	ICAO AGD	Blocktime [mins]
AB 0228	10:58	240	4	AB 0229	14:41	233	4	223
CD 0048	10:58	256	4	CD 0049	14:41	236	4	223
EF 0068	14:45	256	4	EF 0069	16:41	236	4	116

Table 7.6 presents three stands that are available for allocation. These are of size 6, which means that each stand can accommodate each of the three turnarounds.

Table 7.6: The test apron for unit test 3

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 2_1	2	6		1687	1777	130	130
Stand 2_2	2	6		2500	2500	215	215
Stand 2_3	2	6		2500	2500	215	215

The resulting allocation for this unit test is visible in Figure 7.3. The results reveal that the two turnarounds simultaneously on the ground are allocated to different stands due to the fact that they are on the ground at the same time. It means that these allocations cannot be assigned to the same stand. Furthermore, the "EF" turnaround is assigned to a third stand to avoid the conflict introduced by the introduction of the buffer time.

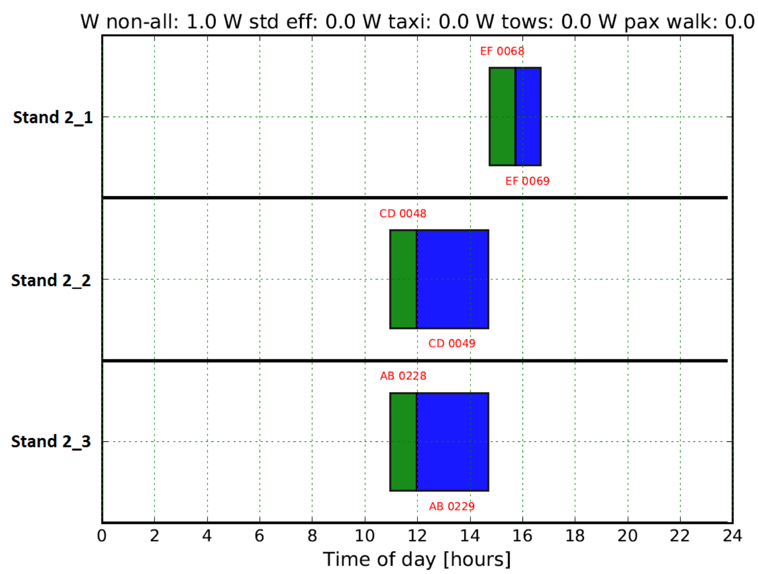


Figure 7.3: The resulting allocation of unit test 3

Since the three turnarounds are not assigned to the same stand, it can be concluded that constraint 3 is verified(both the time overlap and the buffer time). The above mentioned constraints are essential for the accurate functioning of the stand allocation problem, therefore, for the remainder of the objectives and constraints (and the related unit tests), these constraints will always be included.

Unit test 4: Non- and remote allocations (Obj1)

Unit test 4 evaluates the non- and remote allocations objective. Two scenarios are evaluated simultaneously for which a total of 5 turnarounds are used as it can be seen in Table 7.7 below. It will also be seen below that three stands are present in this unit test. It is visible that there are two turnarounds present in the afternoon (turnarounds "AB" and "CD"). It means that these two turnarounds should avoid the dummy stand. Moreover, three turnarounds are on the ground simultaneously in the evening(turnarounds "EF", "GH" and "IJ"). It means that one of the turnarounds will be assigned to the dummy stand to comply with the allocation constraints.

Table 7.7: The test schedule for unit test 4

Arr. Flight No.	**Arr. Time**	**No. of pax.**	**ICAO group**	**Dep. Flight no.**	**Dep. Time**	**No. of pax.**	**ICAO group**	**Blocktime [mins]**
AB 0228	10:58	240	4	AB 0229	14:41	233	4	223
CD 0048	10:58	256	4	CD 0049	14:41	236	4	223
EF 0068	17:45	256	4	EF 0069	19:41	236	4	116
GH 0068	17:45	256	4	GH 0069	19:41	236	4	116
IJ 0068	17:45	256	4	IJ 0069	19:41	236	4	116

Unit test 4 uses the same apron layout as unit test 3. This apron layout can be seen in Table 7.6 above. It is visible that a total of 3 stands are to be used in the test apron, two stands are contact stands and one stand is a dummy stand. It means that according to the working principle of objective 1, the dummy stand needs to be avoided by both afternoon turnarounds, however, since there are three evening operations simultaneously on the ground, one of them has to be assigned to the dummy stand. It also has to be mentioned that all the above mentioned constraints will be part of this optimization problem, making it a stand allocation problem for which the first objective will be verified.

The resulting allocation visible in Figure 7.4 below proves that the dummy stand is indeed avoided by all of the operations in the afternoon and all these operations are assigned to the contact stands. It means that the objective function is minimized by avoiding the dummy stand. Furthermore, as there are 3 overlapping operations in the evening, one of the turnarounds had to be assigned to the dummy stand. However, since this stand has unlimited capacity(and the overlapping operations constraint does not apply to this stand), all three evening operations could have been assigned to this stand, but the objective function is minimized when the minimum amount of operations are assigned to this stand. It means that the non- and remote allocations objective can be considered verified.

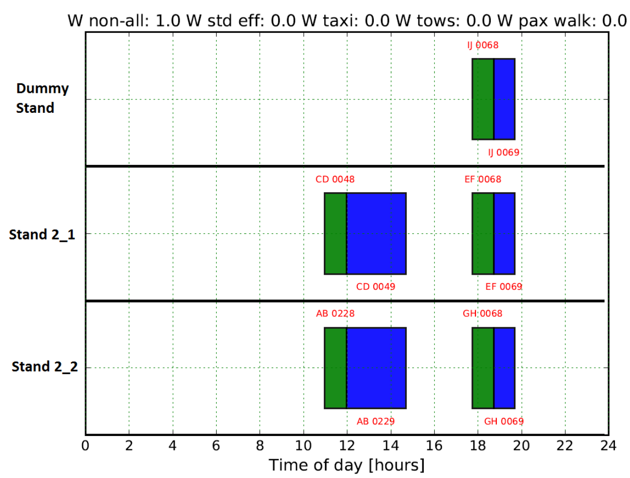


Figure 7.4: The resulting allocation of unit test 4

Unit test 5: Effective stand use (Obj2)

Unit test intends to verify the effective stand use objective. Namely, the unit test should ensure that all the allocations are assigned to a stand that is either its own size, or if that is not possible, to a stand that is larger by the smallest amount. The test schedule used for unit test 5 is identical to that of unit test 2. This test schedule can be seen in Table 7.3 above. Additionally, the used test apron consists of 3 stands of different sizes. This test apron is visible in Table 7.8 below.

Table 7.8: The test apron for unit test 5

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 2_1	2	4		1687	1777	130	130
Stand 5_1	2	5		1687	1777	130	130
Stand 5_2	2	6		1687	1777	215	215

Since the two turnarounds are of sizes 4 and 5, the objective should force these flights to the stands with the same size. Also, Stand Area 5_2 should completely be avoided, since it is larger than any of the operations. The resulting allocation can be seen in Figure 7.5 below.

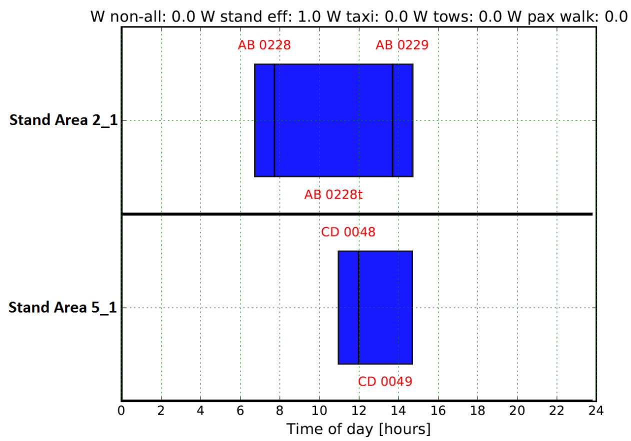


Figure 7.5: The resulting allocation of unit test 5

It is clearly visible that Stand Area 5_2 is avoided and the "AB" operations (with size 4) are assigned to Stand Area 2_1 and the "CD" operations are assigned to Stand Area 5_1. it means that each operation is assigned to a stand that is of its size. Therefore, the effective stand use objective is minimized which also means that the objective is verified.

Unit test 6: Arrival and departure taxi distances (Obj3)

The arrival and departure taxi distances objective aims to minimize the taxi distance covered by all flights during their ground roll to and from the stands. The test schedule for this objective includes one turnaround that consists of two operations. This is visible in Table 7.9. The test apron in Table 7.10 reveals that there are two available stands for this turnaround to take. However, one of the stands is better in terms of arrival taxi distance, whereas the other stand is more beneficial regarding departure taxi distance. Therefore, it is expected that both stands will be used by one operation each.

Table 7.9: The test schedule for unit test 6

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	13:00	240	4	AB 0229	16:00	233	4	180

Table 7.10: The test apron for unit test 6

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 5_1	2	4		1500	1800	130	215
Stand 5_2	2	4		1800	1500	215	130

The results of unit test 6 in Figure 7.6 reveal that the turnaround is separated, namely, the two operations are assigned to separate stands. It means that the arrival operation is assigned to the stand with the smaller arrival taxi distance and the departure operation is assigned to the stand with the smaller departure taxi distance. It means that unit test 6 verifies the arrival and departure taxi distances objective.

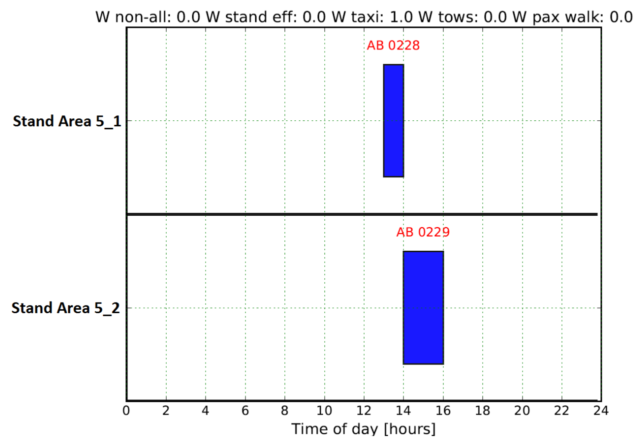


Figure 7.6: The resulting allocation of unit test 6

While it was mentioned in Chapter 4 that the turnarounds that are on the ground for more than 4.5 hours can be split into 3 operations (arrival, idle and departure), it is important to note that two operations were assigned to a different stand above that are on the ground for less than 4.5 hours. This can be explained by the fact that the model does not yet include the towing constraints, therefore, the operations of these turnarounds can be assigned to different stands.

Unit test 7: Towing constraints (Cstr5)

Unit test 7 intends to verify the two types of towing constraints that are present in the stand allocation problem. For this test, two turnarounds are used, one which is a short turnaround (less than 4.5 hours) and long turnaround (more than 4.5 hours) as it is visible in Table 7.11 below. Furthermore, two stands are used for this problem that are shown in Table 7.12. Since the two turnarounds are on the ground at the same time, one would expect that each turnaround will take one of the stands for all of their own operations to avoid the conflict between each other. However, the towing constraints enable the "AB" operations to be towed. This means that multiple different allocations can result. Also, the "CD" operations are not allowed to be towed due to the short turnaround time they possess. It has to be noted that objective 1 (non- and remote allocations) were used as an objective function for this optimization problem.

Table 7.11: The test schedule for unit test 7

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	6:44	240	4	AB 0229	14:42	233	4	478
CD 0048	10:58	256	4	CD 0049	14:41	236	4	223

Table 7.12: The test apron for unit test 7

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 2_1	2	4		1687	1777	130	130
Stand 2_2	2	4		1687	1777	200	200

The resulting test allocation reveals that it is indeed possible to tow the "AB" operations, whereas it is not allowed to tow the "CD" operations. This is visible in Figure 7.7 below. It can be seen that operation "AB0228" is assigned to Stand Area 2_2 and that its successor operations are towed to Stand Area 2_1. This is necessary, since the "CD" operations also occupy this stand at the same time the "AB" operations are on the ground. As this constraints produced the predicted behavior, the towing constraints are considered to be verified.

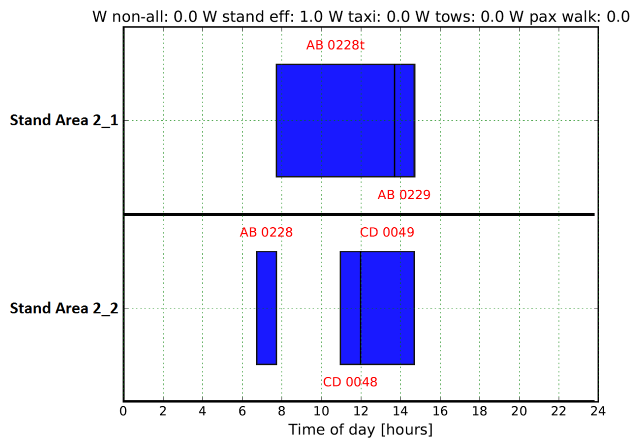


Figure 7.7: The resulting allocation of unit test 7

Unit test 8: Aircraft towing operations (Obj5)

Unit test 8 aims to verify the working behavior of the aircraft towing operations objective. This objective intends to minimize the total number of towing operations that take place. For the verification of this objective, a similar problem setup to unit test 7 is used. The test schedule can be seen in Table 7.13 below. Two separate turnarounds are present that are on the ground at the same time. Additionally, the "AB" operations are towable (these are on the ground for more than 4.5 hours), while the "CD" operations are not towable. Furthermore, the test apron is also similar to that of unit test 7. Namely, two stands are present with stand sizes 4. The rest of the characteristics can be neglected, since the problem does not include objectives or constraints that make use of this information. This is visible in Table 7.14 below. It is expected that no towing operations will be present for this test allocation, since two stands are available for two turnarounds.

Table 7.13: The test schedule for unit test 8

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	7:00	240	4	AB 0229	13:00	233	4	360
CD 0048	11:00	240	4	CD 0049	13:00	233	4	120

Table 7.14: The test apron for unit test 8

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 5_1	2	4		1500	1800	130	215
Stand 5_2	2	4		1800	1500	215	130

The results of unit test 8 are visible in Figure 7.8 below. It is indeed confirmed that the operations of each turnaround are placed at the same stands. It means that compared to unit test 7 (where a tow was present), the number of tows is minimized and is equal to zero. It means that the aircraft towing operations objective is considered verified.

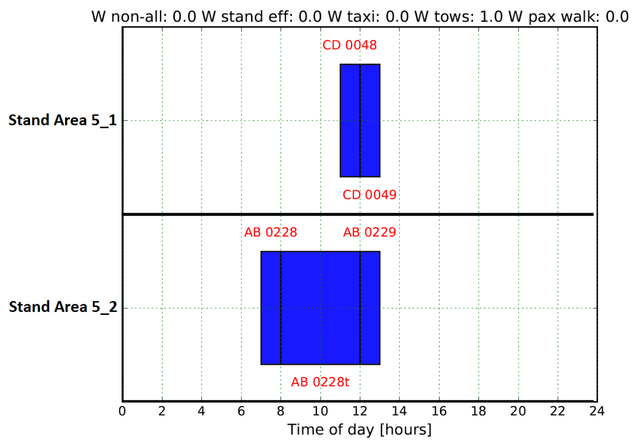


Figure 7.8: The resulting allocation of unit test 8

Unit test 9: Passenger walking distance (Obj4)

The next objective to be verified is the passenger walking distance minimization objective. For this unit test, a test schedule of 1 turnaround will be used that can be broken up into 3 operations. This test schedule is visible in Table 7.15 below. Furthermore, the test apron contains two stands which are both size compatible with the test turnaround. It means that each operation of the turnaround can be assigned to any of the two stands. This test apron is visible in Table 7.16 below. It can also be seen that Stand Area 5_1 is preferable for departure operations, since the departure walking distance is less for this stand, whereas the same is true for Stand Area 5_2 concerning the arrival walking distance. In this way, it is expected that the arrival operation will be assigned to Stand Area 5_2 and the departure operation to Stand Area 5_1. It has to be mentioned that the towing operations constraints are present in this problem, which means that the towing of the turnaround is possible.

Table 7.15: The test schedule for unit test 9

Arr. Flight No.	Arr. Time	No. of pax.	ICAO group	Dep. Flight no.	Dep. Time	No. of pax.	ICAO group	Blocktime [mins]
AB 0228	6:44	240	4	AB 0229	14:42	233	4	478

Table 7.16: The test apron for unit test 9

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
Stand 5_1	2	4		1500	1800	130	215
Stand 5_2	2	4		1800	1500	215	130

The results of unit test 9 are visible in Figure 7.9 below. It is indeed confirmed that the operations are assigned to a stand where the walking distances are minimized. It is important to note that the idle turnaround does not have any passengers, which means that this flight can be assigned to any of the (compatible) stands, because each has the same "value" for the idle turnaround. As the results of unit test 9 are satisfactory, the passenger walking distance objective is considered to be verified.

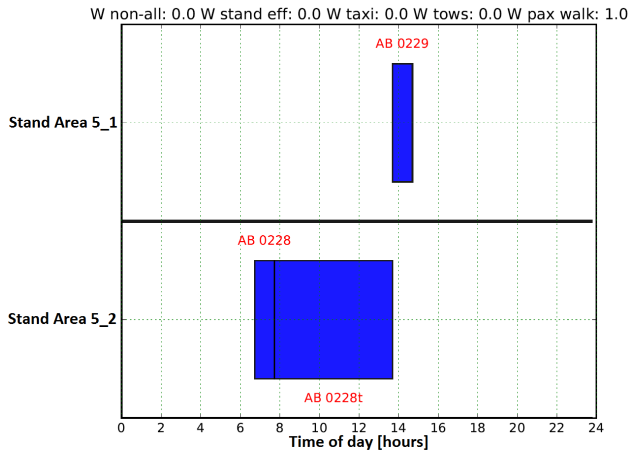


Figure 7.9: The resulting allocation of unit test 9

Unit test 10: Stand adjacency: MARS stands (Cstr4)

Unit test 10 investigates the stand adjacency (MARS stands) constraints. The aim is to prove that the MARS stands are used correctly, namely, either the large MARS stand or the one or two of the small MARS stands are occupied at a given time. Accordingly, the test schedule can be seen in Table 7.17 below. Additionally, the test apron is visible in Table 7.18. It is important to note that the stand effectiveness objective (Obj2) is used as the objective function for this optimization problem.

It can be seen that a total of 5 turnarounds are present in the schedule. The three "KG" turnarounds are on the ground at the same time. Also, the "KG0228-KG0229" turnaround is size 6 while the other two are of size 3. It means that the "KG0228-KG0229" turnaround is only compatible with MARS Area_1, whereas the other "KG" turnarounds are compatible with any of the stands. However, as the stand effectiveness objective is employed, it is favorable to assign the "KG" turnarounds to the small MARS stands (MARS Area_2 and MARS Area_3). The same holds for the "XY" and "PW" turnarounds which are also on the ground at the same, however, these are not in conflict with any of the "KG" turnarounds.

Table 7.17: The test schedule for unit test 10

Arr. Flight No.	**Arr. Time**	**No. of pax.**	**ICAO group**	**Dep. Flight no.**	**Dep. Time**	**No. of pax.**	**ICAO group**	**Blocktime [mins]**
KG 0228	10:58	240	6	KG 0229	14:41	233	6	223
KG 0048	10:58	256	3	KG 0049	14:41	236	3	223
KG 0753	10:58	178	3	KG 0732	14:41	111	3	223
XY 0030	19:06	166	3	XY 0031	20:08	154	3	62
PW 9462	19:06	176	3	PW 9463	20:08	164	3	62

Table 7.18: The test apron for unit test 10

Name	Terminal	ICAO stand size [-]	Blocked Stands	Arr. taxi distance [m]	Dep. taxi distance [m]	Dep. walking [m]	Arr. walking [m]
MARS 1	2	6	MARS 2, MARS 3	1446	2100	495	495
MARS 2	2	3	MARS 1	1446	2100	130	130
MARS 3	2	3	MARS 1	1446	2100	130	130
Stand 2_1	2	4		1687	1777	130	130
Stand 2_2	2	4		1687	1777	130	130

The resulting allocations of unit test 10 can be seen in Figure 7.10 below. It can be seen that the "KG0228-KG0229" turnaround occupies the large MARS stand (since it is the only compatible stand), whereas the other "KG" operations are forced to be on the non-MARS stands. Additionally, the "PW" and "XY" turnarounds are assigned to the small MARS stands due to the fact that the large MARS stand is not occupied and that the stand effectiveness objective is minimized. Therefore, it can be concluded that unit test 10 was successful and that the MARS stand constraint is verified.

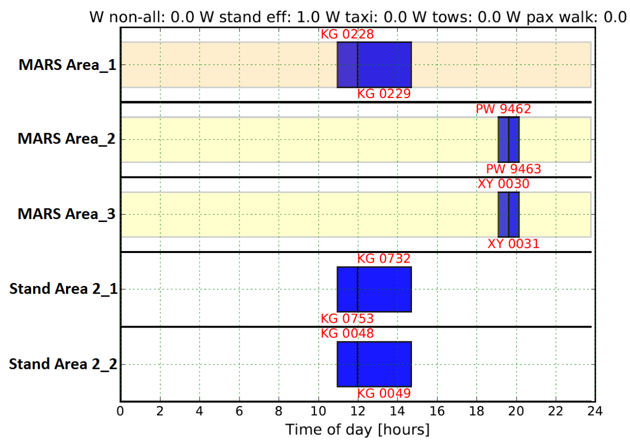


Figure 7.10: The resulting allocation of unit test 10

Unit test 11: the objective normalization algorithm

It is not only important to verify the allocation objectives and constraints, it is also essential to make sure that the objectives are normalized correctly. In this way, the verification of the objective normalizer algorithm is presented below. For the present verification setup, the input values of Unit test 8 (Aircraft towing operations) is used.

The optimization of each objective separately and the consequent process of finding the Utopia and Nadir points of each of these objectives provides the values seen in Table 7.19. The values were checked to see if indeed the Utopia and Nadir points are obtained and as a result of this check, it can be concluded that indeed the Utopia and Nadir points are found. Moreover, the normalization constants (θ_j) are also presented in Table 7.19 as the difference between the Nadir and Utopia points.

Table 7.19: The Utopia and Nadir points along with the normalization coefficient of the different objectives

Objective	Obj1	Obj2	Obj3	Obj4	Obj5
Utopia points	0	0	6300	0	142785
Nadir points	0	0	6900	1	183585
Normalizers (θ_j)	0	0	600	1	40800

The next step in the verification process is to apply the Normalization factors on the scalars of the decision variables of the MIP used for the verification. Table 7.20 shows the dimensional and normalized decision variable scalars of the decision variables of the objectives. It must be noted that each objective except for Objective 5 have 10 decision variables accounting for the 10 operation-stand combinations, while Objective 5 has only 2 decision variables to model the two possible tows.

Table 7.20: The decision variable scalars of the verification test case before and after normalization

	DV 1	**DV 2**	**DV 3**	**DV 4**	**DV 5**	**DV 6**	**DV 7**	**DV 8**	**DV 9**	**DV 10**
Obj1 dimensional	0	0	0	0	0	0	0	0	0	0
Obj1 normalized	0	0	0	0	0	0	0	0	0	0
Obj2 dimensional	0	0	0	0	0	0	0	0	0	0
Obj2 normalized	0	0	0	0	0	0	0	0	0	0
Obj3 dimensional	1500	1800	0	1800	0	1800	1800	1500	1500	1500
Obj3 normalized	2.5	3	0	3	0	3	2.5	2.5	2.5	2.5
Obj4 dimensional	50095	30290	0	31200	0	30290	31200	50095	51600	51600
Obj4 normalized	1.227	0.742	0	0.764	0	0.742	0.764	1.227	1.264	1.264
Obj5 dimensional	1	1	-	-	-	-	-	-	-	-
Obj5 normalized	1	1	-	-	-	-	-	-	-	-

The dimensional decision variable scalars extracted from the model are divided by the correct normalization factors for each decision variable of each objective. It also means that the objective normalization algorithm is considered verified.

7.1.2 Code verification: system test

As each of the objectives and constraints of the many-objective tactical stand allocation were validated separately in the form of unit tests, it is crucial for one to also verify the complete many-objective tactical stand allocation model in the form of a system test. Here, all objectives and all constraints of this model will be included in the verification test and it will be examined whether the received solution is feasible (all operations are allocated to compatible stands and no stand conflict is present).

The flight schedule and apron layout for the system verification will be identical to the unit test of the MARS stands constraints, namely, Unit test 10. The flight schedule input can be found in Table 7.17 while the apron layout is visible in Table 7.18. Furthermore, the weights of the objectives will be balanced for the system verification. It means that while the weight of Objective 1 will be set to 1000, the weights of Objectives 2 to 5 will be equal. This is visible in Table 7.21. The motivation behind selecting balanced weights (importances) is to avoid allocations with extreme importance on one or more objective.

Table 7.21: The weight inputs of the 5 objectives to the system test

W_{obj1}	W_{obj2}	W_{obj3}	W_{obj4}	W_{obj5}
1000	0.25	0.25	0.25	0.25

The allocation created by the complete and balanced many-objective tactical stand allocation model is presented in Figure 7.11. The used weights for the 5 objectives are also visible on the figure as well as the flight IDs of the operations.

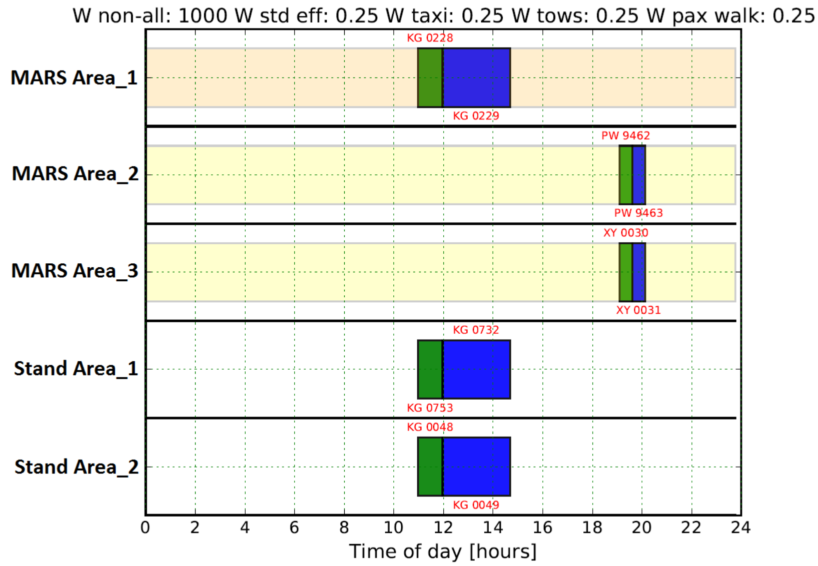


Figure 7.11: The resulting stand allocation for the system test of the many-objective tactical stand allocation model

It is visible that each operation was assigned to one single stand. Also, no stand conflicts are visible which means that those constraints work well. The MARS stands are also utilized well and the linked operations (creating a turnaround) are also assigned after each other which shows the proper working of the towing objective. All in all, it can be concluded that the complete many-objective tactical stand allocation model works according to the expectations, therefore, it can be deemed verified.

7.2 Verification of the Weight Space Search algorithm

The purpose of the weight space search algorithm is to ensure that the weights of the different objectives are varied properly and evenly. Additionally, it is also important to avoid weight space searches that are already present in the set of allocations with the same weights. This is important to avoid inefficient computations and to minimize computational time as much as possible. The weight space search algorithm therefore is verified for a simplified four objective (out of which only three are varied, the weight remote and dummy stand objective is kept constant) problem. There, steps of 0.1 will be applied on the weights of each objective, which has to result in 66 different weight combinations[11]. It must be noted that in the research SAP and the case study, a total of 5 objectives are used. It means that this present verification test is a compact version of the final problem. For 4 of these objectives (Obj2-Obj5), the weights are varied and for Obj1 the weights are kept at a constant value. It means that the case study problem will result in 286 combinations compared to the 66 present here.

As for the resulting verification test, weight combinations can be seen in Table B.1 in Appendix B. It is clearly visible that a total of 66 weight combinations are present. Additionally, it was found that each weight combination is unique which means that the correct weight combinations are generated. It means that the WSS algorithm is considered verified. One can directly see that indeed 66 different weight combinations result. In this way, the weight space search algorithm can be considered verified.

7.3 Verification the clustering and cluster weight range algorithms

This section presents the verification tests that were made on the clustering algorithms presented in Chapter 5. Firstly, the k-means clustering algorithm is verified in Subsection 7.3.1 below. Afterwards, Subsection 7.3.2 discusses the verification of the cluster weight range algorithm.

7.3.1 Verification of the k-means clustering algorithm

The k-means clustering algorithm is used to relate allocations with similar KPI characteristics in multiple-dimensions within the design space of the WSS. As it was mentioned in Section 5.1, it is a many-objective optimization problem, therefore, it needs to be verified. It was also mentioned in Section 5.1 that the SPSS software will be used to carry the k-means clustering algorithm out. Since that software is an already verified, scientifically proven and widely used software in both academics and the industry, the verification of this software and the k-means clustering algorithm is omitted in this thesis.

7.3.2 Verification of the unique cluster weight range finder algorithm

The next module to be verified is the unique weight range finder algorithm that clearly separates each cluster from the remainder of the solution space. The verification of this algorithm will be done using the same example presented in Section 5.2. The original weight values of Cluster 4 of a sample data set is selected and it is shown in Figure 7.12 below. It is visible that there are two clusters that are in conflict with Cluster 4, these are Clusters 1 and 8. Therefore, it is important to eliminate these clusters, however, it must be done in an efficient way so that the least amount of data points are excluded.

The verification will be done on the process of eliminating the conflicting data points. As the conceptual process presented in Section 5.2 showed the elimination procedure, the mathematical implementation of the elimination is verified here. For that, the input and the output cluster weight ranges are compared. The initial and unique cluster weight values within the ranges are visible in Figure 7.12.

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
1	1000	0.8	0.1	0.1	0
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.1	0.8	0.1	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.7	0.1	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0
4	1000	0.9	0.1	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.3	0.6	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.4	0.5	0.1	0
8	1000	0.6	0.3	0.1	0
8	1000	0.7	0.2	0.1	0

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.1	0.8	0.1	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.7	0.1	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0
4	1000	0.3	0.6	0.1	0
4	1000	0.3	0.6	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.5	0.4	0.1	0
8	1000	0.4	0.5	0.1	0
8	1000	0.6	0.3	0.1	0
8	1000	0.7	0.2	0.1	0

Cluster ID	W_{NRA}	W_{SE}	W_{ACTD}	W_{PWD}	W_{TW}
4	1000	0.5	0.5	0	0
4	1000	0.7	0.3	0	0
4	1000	0.1	0.9	0	0
4	1000	0.1	0.9	0	0
4	1000	0.2	0.8	0	0
4	1000	0.2	0.8	0	0
4	1000	0.3	0.7	0	0
4	1000	0.4	0.6	0	0
4	1000	0.6	0.4	0	0
4	1000	0.6	0.4	0	0
4	1000	0.8	0.2	0	0

Figure 7.12: Verification procedure of the unique weight range finder algorithm

It can be seen that the output matches the conceptual demonstrations presented in Section 5.2 which means that the algorithm works correctly. Furthermore, the initial and reduced weight ranges of Cluster 4 as well as the size of the cluster is presented in Table 7.22. It can be seen that the weight ranges per objective either shrank or stayed the same which is in correspondence with the conceptual hand calculations for the modelling of the algorithm. Furthermore, the size of the cluster decreased with the reduction of the data points within the cluster. It means that the algorithm indeed eliminated data points from the cluster data base.

Table 7.22: The weight ranges of the verification cluster for the complete and the unique part of the cluster

	W_{obj2}	W_{obj3}	W_{obj4}	W_{obj5}	**Cluster size**
Initial cluster	(0.1-0.9)	(0.1-0.9)	(0-0.1)	(0)	17
Unique cluster	(0.1-0.8)	(0.2-0.9)	(0)	(0)	11

As the above tests showed positive results regarding the validity of the unique weight range finder algorithm, it can be said that the algorithm is verified. As all the algorithm modules are already verified, the validation of the SAP model will be carried out in the following section.

7.4 Validation of the performance planning framework

This section discusses the validation of the many-objective tactical stand allocation model and the subsequent performance planning modules. This will be done by the comparison of actual (operational) allocations at LHR airport on the 5 used test cases presented in Section 6.2. The KPI metrics of the 5 objectives along with general information on the flight schedules can be seen in Table 7.23 below. The top part of the table lists information on the actual (realized) allocations on the selected days, while the information on the Weight Space Search generated allocations can be seen in the bottom part of the table. It has to also be mentioned that the information on the WSS generated allocations shows the ranges of KPI values in order for one to be able to compare where the actual allocations would lie. The capacity planners at LHR confirmed that the allocations of the operations to stands were done based on past practices and airline preferences, which means that no engineered rule was used for the allocations.

Table 7.23: KPI values and other properties of the flight schedules used for the test cases

Properties	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Actual (realized) allocation					
No. of passengers	39498 (19653/19845)	39498 (19653/19845)	30777 (15423/15354)	37563 (18778/18785)	48364 (23540/24824)
No of operations	237	237	237	216	316
No of remote allocations	7	7	1	13	1
Avg. Taxi distance	1974	1974	1960	1968	2457
Avg. Stand effectiveness	0.363	0.363	0.33	0.343	0.23
Avg. Passenger walking distance	493	493	490	488	426
No. Of tows	-	-	-	-	-
WSS generated (MaOO) allocation					
No. of passengers	38703 (19771/18932)	38703 (19771/18932)	38640 (19761/18879)	33005 (16663/16342)	46795 (23709/23086)
No of operations	274	274	274	242	344
No of remote allocations	4	4	4	0	0
Avg. Taxi distance	1640-1981	1355-1691	1640-1978	1604-1975	2297-2517
Avg. Stand effectiveness	0.257-0.843	0.26-0.8	0.26-0.79	0.175-0.8	0.12-0.437
Avg. Passenger walking distance	417-596	416-585	414-592	410-594	356-495
No. Of tows	7-80	6-77	6-81	0-69	0-61

Although the above presented table provides valuable information on the KPIs of the allocations, it is more valuable to investigate the KPI value locations of the actual allocations within the KPI ranges generated by the WSS. This is visualized in Table 7.24 below. The locations of the actual KPIs could give an indication on the planning strategies (intentional or unintentional) of the capacity planners and also would reveal whether the many-objective tactical stand allocation model would produce allocations with better or similar performance for capacity planners.

Table 7.24: The KPI value locations of the actual allocations in the WSS generated KPI ranges for the 5 test cases

Key Performance Indicator	**Case 1**	**Case 2**	**Case 3**	**Case 4**	**Case 5**
Stand effectiveness (Obj2)	0.18	0.19	0.13	0.27	0.354
Aircraft taxi distance (Obj 3)	0.97	out of range	0.94	0.98	0.73
Passenger walking distance (Obj4)	0.43	0.46	0.43	0.43	0.5
Tows (Obj5)	-	-	-	-	-

It is visible that the KPIs of the actual allocations lie in the ranges discovered by the WSS for 4 of the 5 cases. The taxi distance of Case 2 is out of the modelled range by roughly 300 meters, which can be attributed to the use of a different runway configuration. As for the remainder of the test cases, while the actual allocations were carried out using different objectives, the solutions are still comparable. First and foremost, when one looks at the remote allocations of each case, one can see that the MaOO model was able to allocate slightly less operations to remote stands than in the actual scenario. This does not necessarily mean that the optimization is stronger, but it can also mean that some airlines either requested remote operations, or that a disruption in the flight schedule caused the stand planners to re-allocate some operations to remote stands.

Secondly, the average taxi distances also lie within the KPI ranges generated by the WSS. However, the actual taxi distances lie at the worse end of that range which clearly justifies the fact that the minimization of the average taxi distance is clearly not an objective of the airport. Capacity planners at LHR airport also revealed that the taxi distance is not a determining factor in the progress of allocating the flights.

The generated stand effectiveness KPIs also reveal interesting evidence. It can be seen that the actual stand effectiveness values lie in the 40 % of KPI values for all 5 cases. The main reason for this is that the top priority for capacity planners at LHR is to use the aircraft stands as efficiently as possible. In other words, they would like to avoid using a stand that is larger than the aircraft itself. The two main reasons for this are that larger stands have more and more expensive infrastructure and that since the amount of large stands is marginal, not making them available for large aircraft can cause disruptions.

Furthermore, the actual average passenger walking distance lies mostly in the middle of the WSS generated KPI range. It means that the obtained KPI range is in line with the actual situation. It is important to note that the manipulation of passenger walking distance is not part of the current allocation planning procedure at LHR. This does not necessarily be the reason that the actual average passenger walking distance lies almost in the middle of the KPI ranges.

Unfortunately, a mismatch was found between the flight schedule data for tactical stand allocation and the actual allocation data in terms of the flight numbers. It means that the two lists (that both contain flight numbers) did not contain the same flight numbers for the same allocation day. That prevents one from matching two flight events to compare the allocated stands. It also means that it is impossible to receive information on the number of towing operations at the airport.

It has to be noted that the actual KPI locations in the WSS generated ranges reveal that the same planning rules were used for each operational day at LHR. It will be seen later on that it is possible to use a performance profile that results in a better allocation performance than the actual ones. Therefore, the need for employing a performance planning framework will also be justified.

It has to be pointed out that the validation of the remainder of the algorithms is not possible, since no comparison information is available. Therefore, the validity of those algorithms is assessed through the verification of those algorithms. This can be found in Section 7.3.2.

Conclusions

This section presented the verification tests of the different algorithms that are used for this research project. Firstly, the many-objective tactical stand allocation model's objectives, constraints and normalization algorithm were verified in the form of several unit tests in Section 7.1. Then, the verification of the many-objective tactical stand allocation model was carried out in the form of a system test in Section 7.1.2. Furthermore, the Weight Space Search algorithm and the unique cluster weight finder algorithms are verified in Sections 7.2 and 7.3. It must be mentioned that the verification of the k-means clustering algorithm is omitted due to the fact that a commercially verified and validated software(SPSS) was used for creating the clusters. Finally, the validation of the complete performance planning framework was also carried out in Section 7.4.

8 Research results

The previous chapters presented the research background, framework along with the qualitative and quantitative methods used in this project. Furthermore, Chapter 6 presented the LHR case study to validate the novelty to of the project not only to the academic but also to the industrial world. As the case study on the stand allocation provided a large set of information, it is important to evaluate it in order for one to see the applicability and draw the conclusions of this research (by answering the research questions). In this way, Section 8.1 assesses Research Question 1, namely, the interaction of the allocation objectives through analyzing the created clusters(trade-offs). Secondly, Research Question 1a is investigated in Section 8.2 by scrutinizing the proportionality of the objective weight to the resulting KPI value. Furthermore, Research Questions 3a and 3b are discussed in Section 8.4 by investigating the performance predictability of the presented method. Then, the feasibility of performance planning is assessed in Section 8.5.

8.1 The conflicting nature of the objective KPIs (RQ1)

This section assesses Research Question 1, namely, whether it is possible to find patterns on the relationships between the allocation objectives. More specifically, if there is a set of objectives that are either in synergy or in conflict. For the analysis of the relationship between the allocation objectives, the results of Test Case 1 specified in Section 6.2 will be used. Test Case 1 made use of London Heathrow Airport's Terminal 3 infrastructure with an Easterly 1 runway configuration. Furthermore, the allocations were created for the day of 12^{th} of August(Friday), 2016. As it was outlined in Table 6.7, a total of 337 allocations were created with the Weight Space Search for this Test Case. The KPIs of the created allocations are shown in Figure 8.1 below. It must be mentioned that these data points are already clustered, however, for the initial analysis, this clustering can be disregarded.

Figure 8.1 includes 6 plots to show the reader all the 6 different relationships that are developed between the 4 competing allocation objectives. It is visible that the KPI values of each two set of objectives do not show a clear relationship, in other words, the solution space is irregular. It confirms the assumption made earlier that conventional regression analysis techniques would not provide an accurate relationship between these data points. It is further proven by conducting multiple linear regression(using SPSS version 24) on the obtained solution space[57]. The equation approximating the relationship between the 4 competing objectives is shown in Equation 8.1 while the R^2 value is shown in Equation 8.2.

$$x_{se} = -0.46x_{ACTD} - 0.222x_{PWD} - 0.166x_{TW} \tag{8.1}$$

$$R^2 = 0.107 \tag{8.2}$$

The above presented discussion shows that the relationships should not be defined between the KPIs of the individual allocations, since the R^2 value is low, namely, 0.107. However, trade-offs should be made between groups of (standardized) KPI values that are similar in all 4 dimensions. Therefore, the first step in answering this question is to conduct the k-means clustering algorithm described in Section 5.1 on the allocations. A total of 10 clusters (performance profiles) are created to provide enough variability in the results. The ensuing clusters are represented in Figure 8.1 below. It has to be noted that while a total of 10 clusters were selected, it is possible to draw the same conclusions from the research using a different number of clusters.

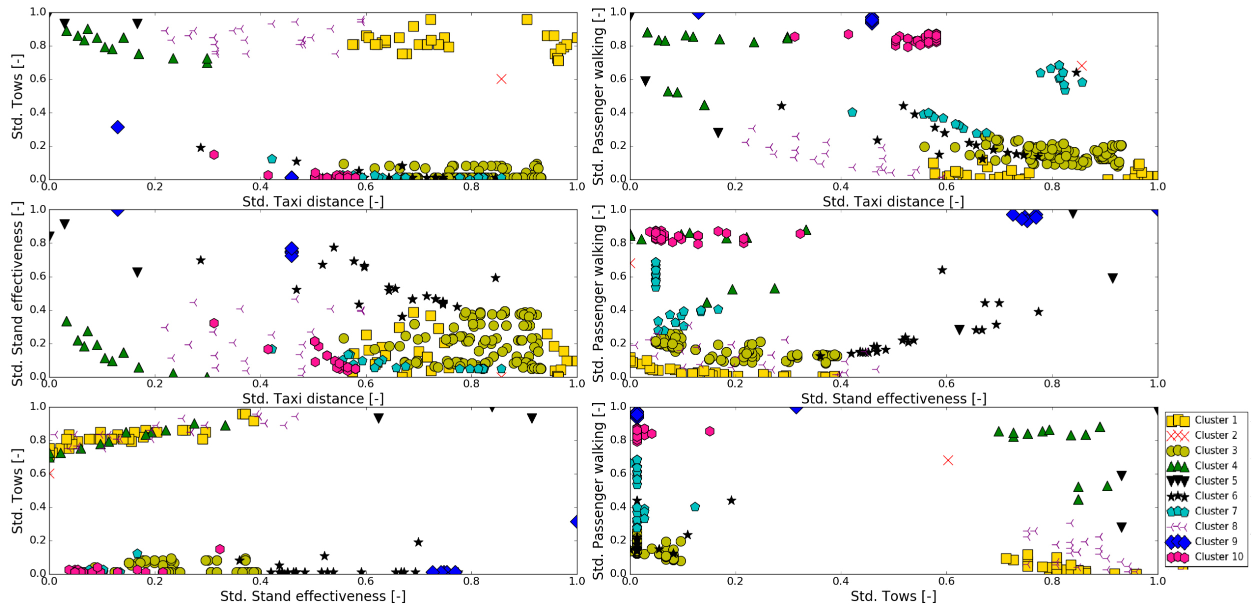


Figure 8.1: The 10 generated clusters of standardized KPI values generated by the k-means clustering algorithm for Test Case 1

Figure 8.1 reveals that the solution space is irregular. It means that no clear identifiable relationship exist between the data points. It can be explained by the complex relationship between the 4 competing objectives that is induced by the combined effect of the different objective weights used. Interestingly, the Pareto front of the solution space is well defined. Namely, it shows a clear and continuous front where a clear trade-off has to be made between the two depicted objectives. Furthermore, Table 8.1 reveals that the Pareto front is obtained(for each sets of two objectives) using only the hierarchical and the two objectives competing in the objective function(only those two competing objectives have weights of larger than zero). This is in alignment with the findings of previous researches mentioned in Chapter 2[11].

It is also visible that the sizes of the clusters (number of data points) are not the same for each cluster. More specifically, there is a large variability in the sizes of the clusters. The variability in the cluster sizes can be seen in Table 8.1 below. It can also be seen in the above figure that the k-means clustering algorithm generated clusters of data points that are similar in multiple dimensions. As an example, when Cluster 9 (marked with blue diamond) is investigated in Figure 8.1, it is visible that the data points are very similar for the stand effectiveness and passenger walking distance KPIs. Furthermore, the degree of similarity is less in the other two dimensions. This can be explained by the fact that the majority of the Cluster 9 data points for the towing operations objective are clustering at a value of 0, however, a single data point is located at roughly 0.3.

Further investigation of the figure reveals that the other clusters have a larger spread of the data points which means that the clusters are less concentrated. However, that still means that the best possible grouping of data points was created. As the spread of the clusters (in each dimension) is significant, it is favorable to investigate the range of the standardized KPI design space they span (in each dimension). It is advantageous, since that representation provides new insights and possibilities for the analysis of the situation.

If one investigates Cluster 9 again in Figure 8.1, one can see that the minimum standardized KPI value for the towing objective is 0 while the maximum is roughly 0.3. It means that the data points (for this objective) lie within this range for this cluster. In case one, determines the range of standardized KPI values for each objective in each dimension, a simpler and more straightforward representation of Figure 8.1 can be created. Accordingly, the standardized KPI ranges(in each dimension) of the defined clusters(trade-offs) can be seen in Figure 8.2 below. These are also called as performance profiles. Moreover, the KPI ranges of the performance profiles are shown numerically in Table D.5 in Appendix D.

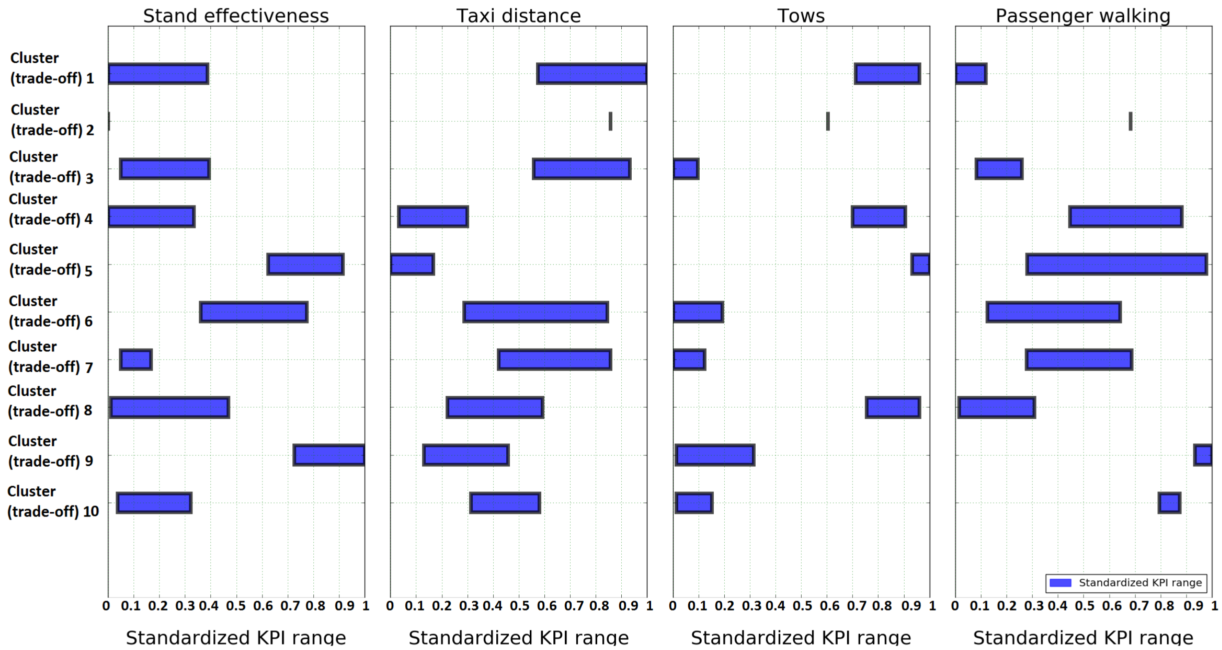


Figure 8.2: The standardized KPI ranges of the 10 clusters (trade-offs) generated for Test Case 1

In order to demonstrate the interpretation of Figure 8.2, Cluster 1 will be chosen. It can be seen that the standardized KPI values in the stand effectiveness dimension span the best 40 % of the design space. It means that in case one would like to select an allocation from Cluster 1, then the KPI value in the stand allocation dimension will always be in the best 40 % for the problem under consideration. Similarly, the taxi distance KPIs lie in the worst 45 % (values worse than 55 %), the tows KPIs are between 70 and 95 % and the passenger walking KPIs are in the best 15 % of the design space. It can also be determined that the ranges of both the clusters and their standardized KPIs vary, however, that variation is not necessarily proportional to the size of the cluster. As an example, Cluster 5 has 3 data points (as seen in Table 8.1) and spans 70 % of the passenger walking distance design space, while Cluster 8 has 28 data points and spans only 30 % of the same design space.

Moreover, it is recognizable that no two clusters provide the same degree of trade-off between the 4 objectives. This can be explained by the systematic grouping (clustering) of the data points in the k-means clustering algorithm. It is also visible that the true nature of the many-objective optimization problem is acquired, namely, it is impossible to optimize all objectives at the same time. This can be explained by the fact that no cluster has all its standardized KPI ranges close to (or at zero). Furthermore, no cluster is created that has the worst standardized KPI values in each of the used objectives which means that indeed a set of optimal solutions were used.

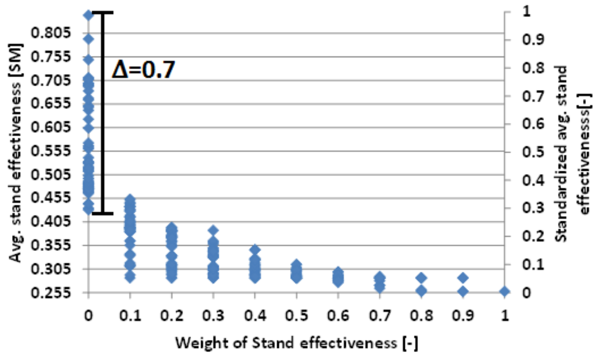
Research Question 1 investigates whether two or more objectives behave the same way for each cluster within the design space. Investigating Figure 8.1 reveals that a large number of combinations are possible when it comes to trade-offs between the objectives. However, it can be concluded that one cannot specify a rule on the absolute symbiosis or the absolute conflict of two or more objectives. It means that the tactical stand allocation model does not have underlying absolute relationships between the objectives.

8.2 Proportionality of objective KPIs to the allocation weights (RQ1a)

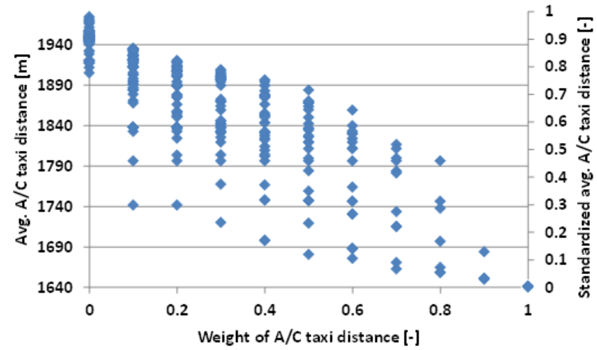
Although, clear trade-offs could be created by the k-means clustering algorithm by grouping the allocations into clusters, one has to investigate the individual allocations before conclusions can be drawn on the validity of these clusters. As a consequence, Research Question 1 studies whether the weight of an objective directly predict KPI value in the design space. Namely, if the weight setting of and objective define the KPI value of that objective or if the weights of the other objectives also have an effect. As an example, does an allocation weight of 0 (worst value) for the Objective 1 result in the worst received KPI value for that allocation? This is demonstrated in Figures 6.5 and 8.4a below.

Figures 8.3 show all the KPI values (both dimensional and standardized) for the maximization of stand effectiveness and minimization of aircraft taxi distance objectives as a function of the weight of the objective that was used for creating the allocation. It can be seen in Figure 8.3a that for low weight values of the stand effectiveness objective, the spread of KPI values is large. Namely, when the weight of the stand effectiveness objective is 0, the KPI value can take on any value within the top 70% of the design space. This is due to the fact that the KPI value does not only depend on the weight of its objective, but it also depends on the weights of the other objectives. As the weight of the objective is increased, the range of KPIs becomes smaller and the KPI values in general also become smaller. This last phenomenon acts as a verification that increasing the weight of an objective indeed decreases its KPI value.

On the other hand, the KPI values of objective 3 show a slightly different behavior. The problem of having a large spread of KPI values at low weights still holds. Unfortunately, this phenomenon is present for the majority of the weight range. It means that the weight of the aircraft taxi distance objective alone cannot determine the actual strength of the KPI in the design space.



(a) Proportionality of the maximization of stand effectiveness objective's KPI values to its weight

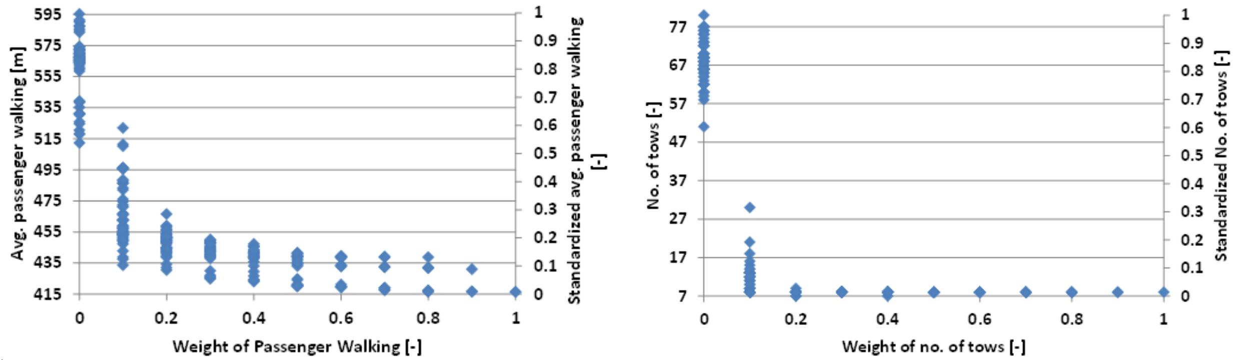


(b) Proportionality of the minimization of aircraft taxi distance objective's KPI values to its weight

Figure 8.3: The proportionalities of the KPI values of Objective 2 and 3 relative to their relative significances

Figures 8.4b and 8.4a can be analyzed similarly. It can be seen that the weights of Objective 5 (minimization of tows) have a different relationship with the KPI values in the design space. In case the weight is set to zero, roughly the worst 35 % of the design space is spanned, but as soon as the weight is equal to and more than 0.2, the KPI values lie in the best 5 % of the design space. It means that a more favorable, but still disproportional relationship lies between the weight and the resulting KPI value of objective 5. It also means, that in case one chooses a weight of at least 0.2 for objective 5, one makes sure that the resulting KPI value will lie in the best 5 % of the design space.

Interestingly, Figure 8.4b can explain the phenomenon seen in Figure 8.1. Namely, a gap in the middle of the solution space for the minimization of aircraft tows objective was identified. This gap can be explained by the fact that even including the minimization of tows objective in the allocation model ensures that the number of tows is greatly reduced(compared to the case when this objective is not present). It also means that there is enough capacity within the stand infrastructure to allow for a large number of tows when its objective weight is zero(it is not part of the objective function).



(a) Proportionality of the minimization of passenger walking distance objective's KPI values to its weight

(b) Proportionality of the minimization of aircraft towd objective's KPI values to its weight

Figure 8.4: The proportionalities of the KPI values of Objectives 4 and 5 relative to their relative significances

The minimization of passenger walking distance objective in Figure 8.4a reveals a similar behavior compared to that of the maximization of stand effectiveness objective. The main difference between the two behaviors is that the range of KPIs covered as a function of the weight is different. While increasing the weight of maximization of stand effectiveness objective provided a minimal decrease in the KPI values (and range), minimization of passenger walking distance does not provide noticeable improvement. Figure 8.4a also proves this, since the KPI range does not change with a weight setting of 0.6 or more. It means that one cannot improve on the performance of the objective by blindly increasing the weight of the objective.

The above presented discussion revealed several important conclusions that set the need for further analysis and also the implementation of the unique weight range finder algorithm. Namely, the weight of an objective alone does not directly determine its KPI value in the design space. Also, the resulting KPI value does not only depend on the weight of the respective objective, but also on the weights of the other objectives. Moreover, increasing the weight of a certain objective does not necessarily result in a better (smaller) KPI value. This can also be attributed to the effect of the presence of the other objectives. All in all, it is impossible for decision makers (capacity planners) to solely rely on the weight settings of the many objective tactical stand allocation to express their preferences for the performance of the allocation.

Despite the fact that the k-means clustering algorithm could create 10 clusters that define 10 completely distinct performance profiles(in the present example), one also has to investigate which weight combinations created the allocations that are included in the clusters. Examining these weight combinations could reveal whether the certain areas of the weight space directly correspond to the (standardized) KPI locations in the design space. For that reason, Table 8.1 below presents the 10 clusters and the corresponding weight ranges that make up those clusters. Furthermore, the sizes of the clusters are also presented, namely, the amount of data points(allocations) contained in the cluster.

Table 8.1: The complete weight ranges of the 10 clusters created for Test Case 1

Cluster ID	No. of data points	SE weight range [-]	ACTD weight range [-]	PWD weight range [-]	TW weight range [-]
1	35	0-0.9	0-0.3	0.1-1	0
2	1	1	0	0	0
3	153	0-0.8	0-0.6	0.1-0.9	0.1-0.9
4	17	0.1-0.9	0.1-0.9	0-0.1	0
5	3	0	0.8-1	0-0.2	0
6	25	0	0-0.8	0-0.4	0.1-1
7	24	0.1-0.9	0;0.3-0.7	0-0.1	0.1-0.9
8	28	0-0.7	0.2-0.7	0.1-0.7	0
9	9	0	0.1-0.9	0	0.1-0.9
10	42	0.1-0.8	0.1-0.8	0	0.1-0.8

It can be seen, that the weight ranges of the clusters are continuous. It suggests that the allocations having similar KPI values in all dimensions also have similar weight settings for all objectives. This is a crucial finding, since this allows for one to use these continuous weight ranges as a reference for ensuring the KPI trade-offs to be made. It is also interesting to note that Cluster 7 has two weight ranges for the minimization of aircraft taxi distance objective. It means that the combination of the weights (within these two ranges) still result in similar KPI values.

Although, the weight ranges of the clusters are defined, the example shown in Section 5.2 indicates that the weight ranges of the clusters are not unique, namely, they overlap, so one might end up in a cluster different from the chosen one. It means that the unique weight range finder algorithm has to be employed which was also detailed in Section 5.2. As this algorithm reduced both the size and the weight ranges of the clusters in this example, the resulting weight ranges can be seen in Table 8.2 below.

Table 8.2: The unique weight ranges of the 10 clusters created for Test Case 1

Cluster ID	No. of data points	SE weight range [-]	ACTD weight range [-]	PWD weight range [-]	TW weight range [-]
1	27	0-0.6	0-0.3	0.4-1	0
2	1	1	0	0	0
3	124	0.1-0.7	0-0.6	0.2-0.8	0.1-0.7
4	11	0.1-0.3;0.9	0.1;0.6-0.9	0-0.1	0
5	3	0	0.8-1	0-0.2	0
6	21	0	0.3-0.8	0.1-0.4	0.1-0.6
7	12	0.1-0.9	0	0	0.1-0.9
8	18	0-0.4	0.4-0.7	0.2-0.6	0
9	9	0	0.1-0.9	0	0.1-0.9
10	42	0.1-0.8	0.1-0.8	0	0.1-0.8

When one compares to the weight ranges shown in Tables 8.1 to the corresponding KPI values of that specific cluster, one can see two distinct behaviors. It is expected that a low standardized KPI value corresponds to a high objective weight. Firstly, when one observes Cluster 2, it can be seen that the KPI values of the allocations are proportional to the objective weights. This is apparent, since the stand effectiveness objective is given all the significance and the other objectives are deemed not important, hence the stand effectiveness KPI is at the best possible value while the other KPIs are worse in their location in the solution space. The other type of behavior is the one where the weight of a certain objective does not proportionally represent the strength of the KPI. As an example, Cluster 1 will be investigated. The aircraft taxi distance objective has a low objective weight range (0-0.3) and the corresponding KPI values are in the worse end of the range which shows proportionally. This phenomenon can be also linked to the towing operations objective, since the low weight corresponds to a high standardized KPI. However, the other two objectives have large weight ranges((0-0.9) and (0.1-1) respectively) that span almost the entire weight range. Regardless of that, the standardized KPI ranges are in the better end of the range. It means that even a very low weight for each of these two objectives puts the KPI is a favorable location. This also means that the combined effect of the objective weights will determine the standardized KPI value of a certain objective. This also means that it is indeed necessary to use the developed Stand Allocation Performance Planning Framework to be able to use objective weights efficiently for the planning of the allocation's performance.

8.3 The effect of k in performance planning

The previous section presented that it is possible to define unique weight ranges for Test case 1 when 10 clusters are used. One can justly ask the question of why would one choose 10 clusters. Is there a certain rule behind it or is the choice of k, the number of clusters is arbitrary? As Section 5.1 already outlined, the number of clusters have to be chosen a priori. It means that the user has to arbitrarily select the number of clusters (performance profiles) that are to be later on investigated. As a result, this section acts as an aid for decision makers for the selection of an appropriate amount of clusters. This is done by the evaluation of several of the cluster parameters.

The analysis begins by selecting an initial number of clusters. For the current analysis, Test Case 1 (as for demonstrating the results previously) is used as an example. Namely, the set of allocations created for LHR Terminal 3 using the Easterly 1 runway configuration on the 12^{th} of August, 2016 are being used. Firstly, the initial number of clusters is set to be 5. The reason for selecting 5 initial clusters was to break the solution space up into enough subset (clusters) so that enough variability is present in the trade-offs. In order to see what happens to the 5 initial clusters, as the number of total clusters is increased, the largest portions of the 5 initial clusters are kept and analyzed compared to their initial state. In this way, the change in size of the initial clusters is investigated in Figure 8.5 below.

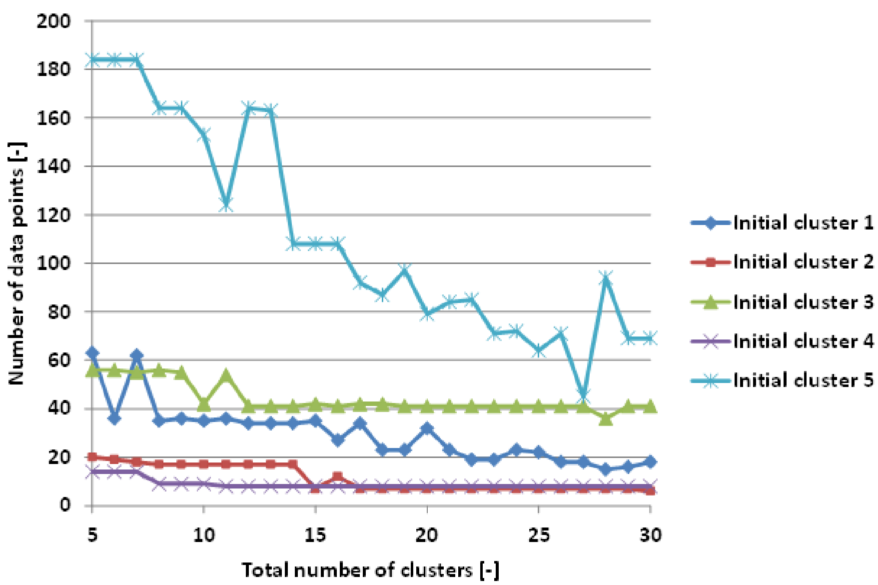


Figure 8.5: The change in the sizes of the initial clusters as the number of clusters is increased

It is visible on the x-axis that the analysis starts with the initial 5 clusters and proceeds until the solution set is broken up into 30 clusters. One can also see the initial sizes of the 5 clusters where Clusters 1 and 3 have approximately 60 data points, Clusters 2 and 4 have roughly 20 while Cluster 5 has around 180 data points. It can be seen that as the number of clusters increase the initial clusters become smaller, since new clusters are created that are fed from the initial clusters. It is also visible that the largest initial cluster is broken up more drastically, which can be explained by the fact that initially smaller clusters are usually more separated from the rest of the solution space (in multiple dimensions) and also that the data points within those clusters are more similar in multiple dimensions.

In light of the above presented discussion, it is important to examine how do the initial clusters change in terms of their KPI ranges. Namely, by braking up a cluster, does the KPI range (in any dimension) of that cluster shrink or expand? This phenomenon is measured by the multi-dimensional centroid location of the 5 initial clusters for the maximization of stand effectiveness objective. This is shown in Figure 8.6 below. The same graphs for the aircraft taxi distance, the towing operations and passenger walking distance objectives can be seen in Figures D.3 to D.5 in Appendix D.

It is visible that the stand effectiveness centroid of Cluster 5 changes significantly which can be explained by the fact that it was dissolved into multiple smaller clusters as the number of clusters is increased. When small clusters are considered such as Cluster 4, one can see that the cluster centroid does not change significantly. That can be explained by the fact that this cluster is not being broken up into other smaller clusters. It means that the cluster centroid does not change.

It is important to note that the aircraft taxi distance and passenger walking distance objectives have a similar behavior, but the towing operations objective is differing. The centroid locations of the initial 5 clusters for the towing operations objective can be seen in Figure D.5. It is visible that the centroids of the 5 initial objectives insignificantly change for this objective. This phenomenon can be explained by investigating Figure 8.1 again. It can be seen that the towing operations KPI range consists of two areas (at both extremes) where the data points accummulate. It means that it is easier for the clustering algorithm to find similar solutions in this dimension, therefore, each cluster will be compact in the towing operations objective. In this way, when one dissolves a cluster, the change in its towing operations KPI centroid is marginal.

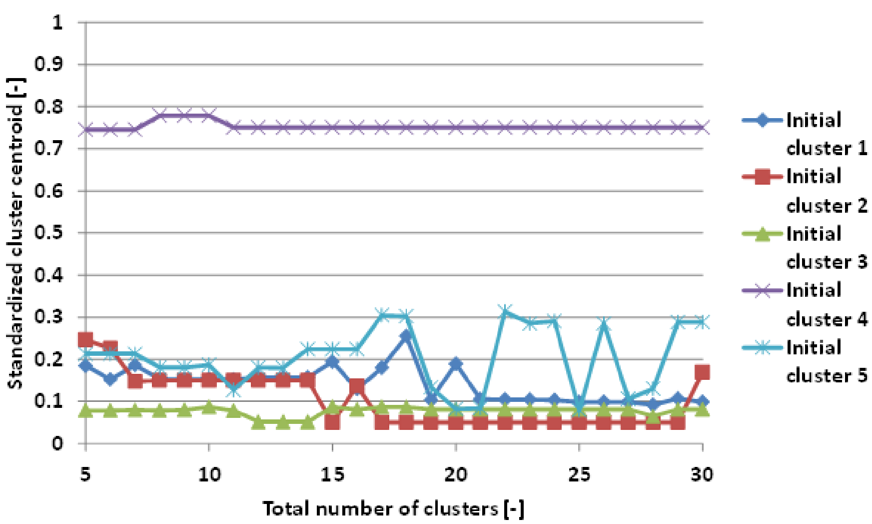


Figure 8.6: The stand effectiveness centroid of the initial clusters as the total number of clusters is varied

It is not only important to investigate the size and location shift of the initial 5 clusters, it is also important to see how their KPI ranges change. The stand effectiveness KPI ranges of the initial 5 clusters can be seen in Figure 8.7 below. The KPI range changes of the other objectives of the 5 initial clusters are also visible in Figures D.6 to D.8 in Appendix D.

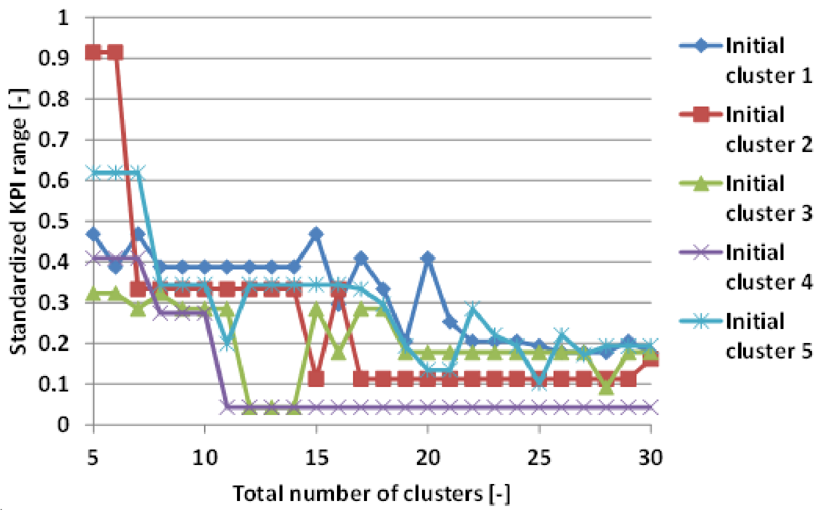


Figure 8.7: The stand effectiveness cKPI range of the initial clusters as the number of clusters is varied

Since the 5 initial clusters are dissolved into smaller clusters, it is expected that the KPI ranges of these clusters decrease. This phenomenon indeed appears for the initial clusters. It can be seen that as the number of clusters is increased, the stand effectiveness KPI range drops significantly. There is also a certain point where certain clusters are not dissolved anymore, therefore, their KPI ranges do not change. The main advantage of using more clusters is that the user will be able to specify the required performance more accurately. As an example, when a user chooses Initial Cluster 2 from Figure 8.7 when the solution space is broken up into 5 clusters, then 90 % of the KPI range is covered. It means that the predicted outcome can be anywhere within that 90 %. On the other hand, when one chooses to have 10 clusters, the same cluster as Initial Cluster 2 will give only a 30 % KPI range. The figures showing similar characteristics for the other competing objectives can be seen in Figures D.3 to D.5 in Appendix D.

The above presented discussion reveals that it is favorable for one to use more clusters in the solution space in order for one to end up with more specific, more precise KPI ranges in the performance profiles. It is important to note that increasing the number of clusters without an educated judgment can result in uncertain performance planning due to the large KPI ranges taken as a reference for forecasting. This will be outlined in the following section.

8.4 KPI predictability: the effects of flight schedules, terminal choice (RQ3a,RQ3b)

Section 8.2 revealed that it is not advised to solely use the weight settings of the objectives in the many-objective stand allocation, since they do not necessarily result in a proportional KPI value. Consequently, it is essential to investigate another approach for the a priori performance planning of the stand allocation. For this purpose, the unique weight ranges of the previously defined performance profiles shown in Table 8.2 are investigated.

The sub-questions of Research Question 3 investigate whether these unique weight ranges (that uniquely define a performance profile for a given case) can predict the performance of a future stand allocation case. In other words, by re-applying the weights of a reference test case (based on the performance of a certain cluster), is it possible to obtain the same performance for a future stand allocation? Accordingly, the method presented in Section 5.2 is applied for demonstration on the unique weight ranges of the performance profiles of Test Case 1 for 10 clusters. In order to test the prediction accuracy of the developed methods, the unique weight ranges defined for the performance profiles in the reference test case (Test Case 1) are projected onto the comparison test case. Then, the expected and the predicted KPI ranges of the performance profiles are compared below to determine the forecasting accuracy of the method.

For the current demonstration, the reference test case is chosen to be Test Case 2(Terminal 3 with Westerly 1 runway configuration on the 12^{th} of August,2016). The resulting performance profile projection is presented in Figure 8.8 below. It can be observed that for most of the performance profiles, there is a certain amount of overlap between the reference case and the predicted case. The overlaps are marked with grey. The more the overlap there is, the more accurate the projection is.

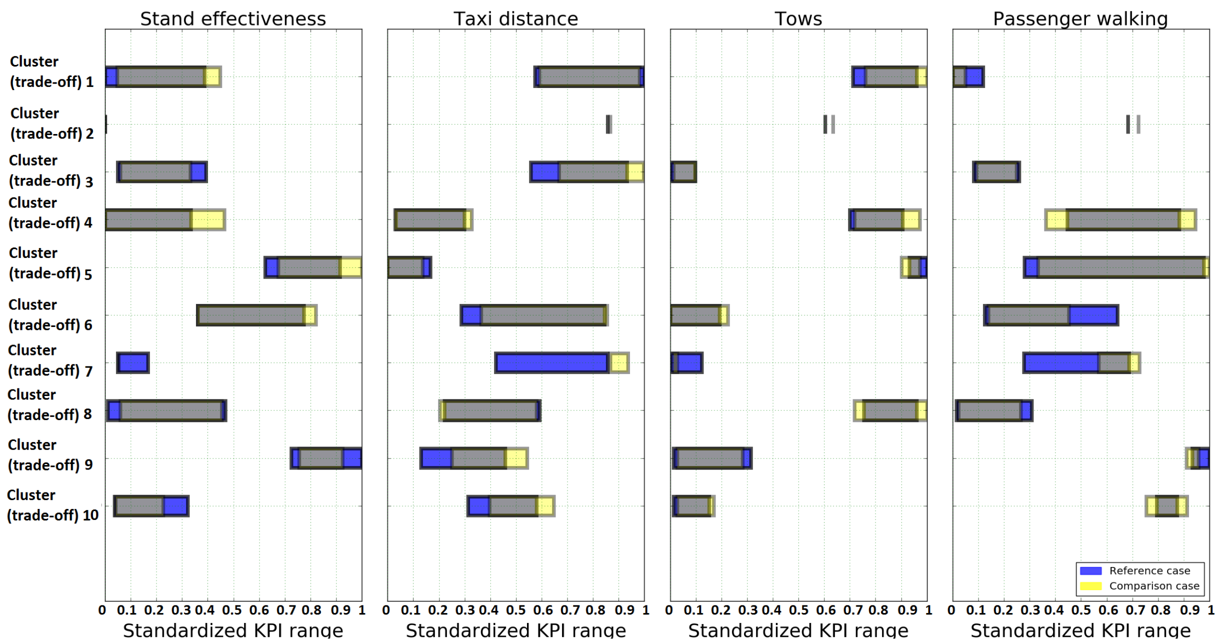


Figure 8.8: Key Performance Indicator prediction from Test Case 1(reference case) to Test Case 2(comparison case)

One could see above that the approximations of the performance profiles seem accurate visually, however, it is important to quantitatively investigate the performance predictability of the employed method. It also has to be noted that the analysis below is created such that the unique weight ranges of the clusters in Test Case 1 are projected onto each of the other test cases. This helps to identify the degree of predictability for different allocation setups.

Furthermore, an analysis of the prediction error of each comparison test case will be carried out. This prediction error analysis will be based on using the median values of both the reference and the comparison range of a performance profile's selected objective and taking the absolute difference between the two. In order for the reader to better understand this concept, Figure 8.8 is transformed into a box plot and it is shown in Figure D.2 in Appendix D.

Objective 2: Stand effectiveness

Figure 8.8 showed the overlap between the reference (Test Case 1) and the predicted (Test Case 2) KPI ranges of the performance profiles. It is also important to see the degree of overlap between these two ranges as a function of the number of clusters the design space is broken up into. For the stand effectiveness objective, this can be seen in Figure 8.9 below. The graph shows the average percentage of overlap that the predicted KPI range has with the reference KPI range. It must be noted that the reference KPI ranges are the standardized KPI ranges of each performance profile in Test Case 1.

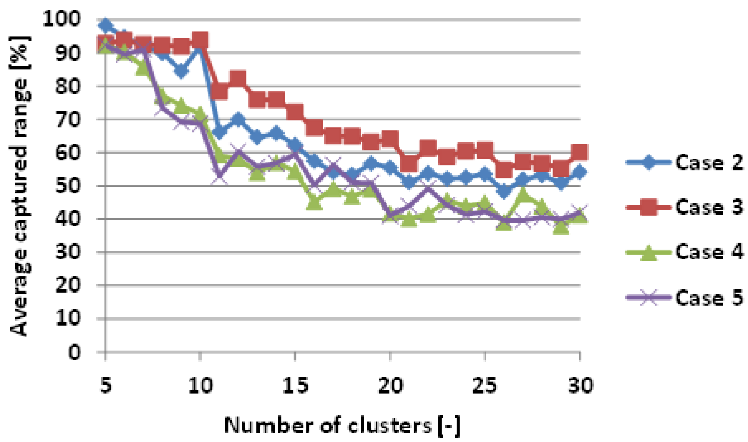
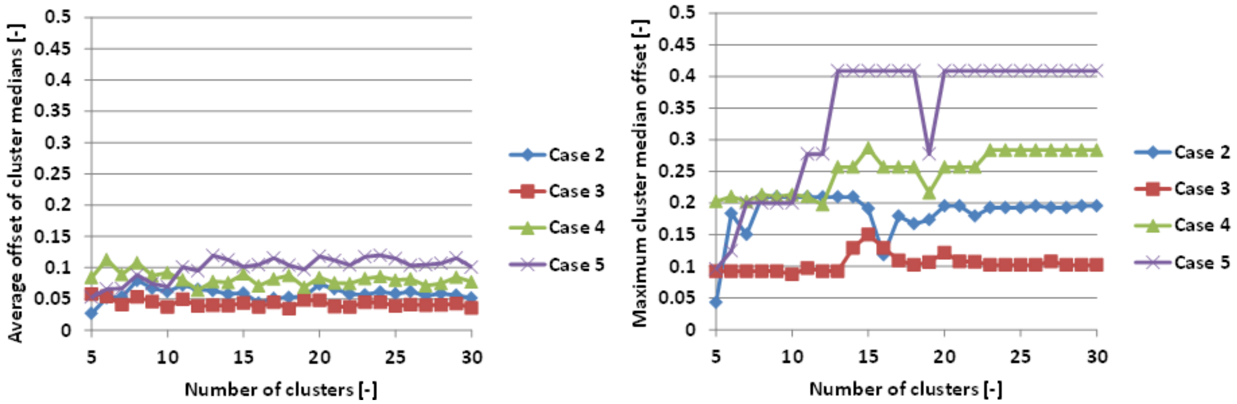


Figure 8.9: Average prediction accuracy of the maximization of stand effectiveness objective as a function of the number of clusters

It can be seen that all 4 of the comparison test cases are depicted on the figure. As it was anticipated, as the number of clusters the solution space is divided up into increases, the overlap(prediction accuracy) between the reference and the predicted KPI ranges decreases. It can be seen that Test Case 3 is predicted the most accurately as the average captured range is always the highest. Then, Test Case 2 is the second most accurate followed by Test Cases 4 and 5 which show particularly similar behavior. The observed patterns reveal that when the stand effectiveness objective is under consideration, Test Case 3 can be predicted with the highest certainty, since only the number of passengers is changed(the ground demand is the same). This can be explained by the fact that the number of passengers only have a (partial) effect on minimization of passenger walking distance objective. Furthermore, the second most predictable case is Test Case 2, where the runway configuration is changed. The drop in predictability can be attributed to the complete influence of the runway configuration on the minimization of aircraft taxi distance objective. In other words, the scalars of the objective function decision variables changed significantly(due to the different taxi distances that the stands have). Interestingly, when a different season is used for the same terminal (Terminal 3) the degree of predictability drops again as it can be seen on the trend of Test Case 4. Furthermore, the predictability of Test Case 5 (Terminal 2) is very similar to that of Test Case 4. One would expect that the predictability of a different terminal will be much lower, however, the similarity can be explained by the fact that the ground demand of Test Case 4 is completely different than the ones of Case 1 to 3. It means that a degree of dissimilarity in the inputs is so high that the problem setup seems as if a different terminal is under consideration.

It can also be seen for the prediction from Test Case 1 to Test Case 3 that as the amount of clusters reaches roughly 20, the average percentage range captured does not continue to decrease. Moreover, the average of captured range is roughly 90 % up until 10 clusters are used, however, as the solution space is broken up into more clusters (but more compact clusters), the predictability decreases significantly. The same phenomenon is observed for the prediction of the other Test Cases. Therefore, it is advised to used 10 clusters maximum for the performance planning of the tactical stand allocation.

Even though, it was seen that the average captured range decreases as the number of clusters is increased, it has to be also examined how much error is introduced when the number of clusters is increased. Hence, the prediction error of the clusters are investigated. This is done by looking at absolute differences in the median values of the reference and the predicted standardized KPI values. The median values are used, since they accurately represent the accumulation of data points within the standardized KPI range. The average(of all clusters) and maximum(the cluster with the biggest deviation) absolute differences between the two median values as a function of the number of clusters can be seen in Figures 8.10a and 8.10a.



(a) Average prediction error for the stand effectiveness objective

(b) Maximum prediction error for the stand effectiveness objective

Figure 8.10: Average and maximum prediction error of the maximization of stand effectiveness objective as a function of the number of clusters

First and foremost, one can see that as the number of clusters is increased, the average error does not increase, which means that the prediction capabilities of the developed method are very stable. Also, the same phenomenon can be observed as for the one seen in Figure 8.9. Specifically, it is most accurate to predict Case 3 and it is the least accurate to predict Case 5.

It is also important to investigate the maximum observed absolute median difference. The main reason for this is to give the reader an accurate perception of the problem, since having low and stable average error still holds the chance of encountering individual discrepancies, namely, there is a possibility of choosing a cluster that has a high deviation. In this way, the maximum perceived error as a function of the number of clusters is presented in Figure 8.10. It can be seen that when the performance of the same terminal and season (Cases 2 and 3) are predicted, the maximum error is stable, but when the other cases are predicted, the maximum error increases as a function of clusters. Accordingly, it is advised either not to predict the performance of a different season or terminal or to predict with a low amount of clusters.

Objective 3: Aircraft taxi distance

The predictability behavior of the minimization of aircraft taxi distance objective is examined the same way as it was done for the maximization of stand effectiveness objective. The average captured KPI range can be seen in Figure 8.11. It can be seen that this objective has a trend similar to the one mentioned above. Namely, the average captured range decreases as the number of clusters is increased. Furthermore, the predictability for Test Case 3 is higher for this objective, but smaller for the other test cases. Also, it is clear that the predictability of Test Case 5 diminishes as the number of clusters is increased which means that it is not advised to use Test Case 1 to predict the taxi distance performance of Test Case 5.

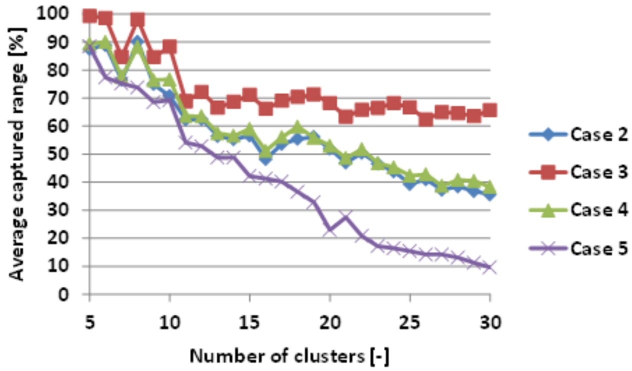
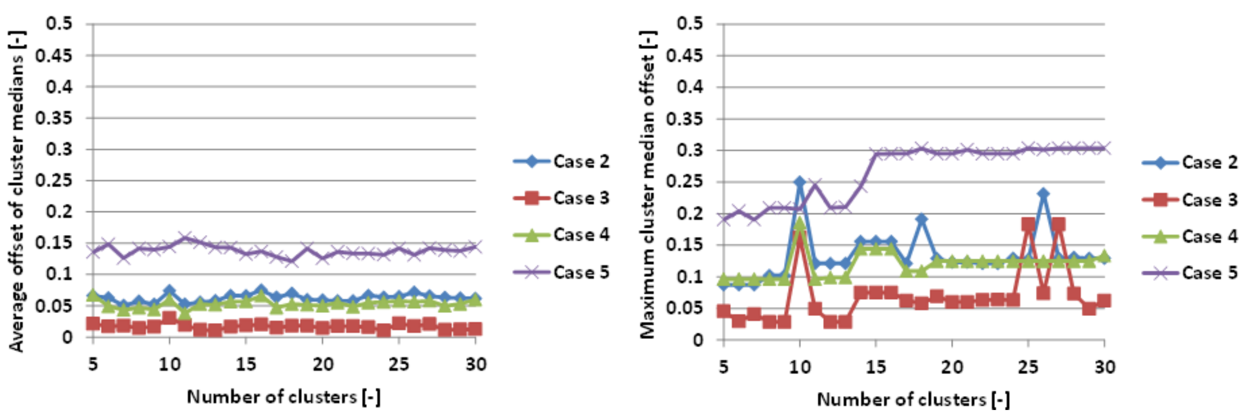


Figure 8.11: Average prediction accuracy of the minimization of aircraft taxi distance objective as a function of the number of clusters

Regarding the applicability of this finding, the above presented figure shows the effect of the choice on k in the k-means clustering algorithm. Namely, if one uses a large k, hence, breaks the solution space up into more clusters, one might receive more trade-off possibilities, however, the reproducibility(prediction accuracy) of these clusters decreases as it is shown in Figure 8.11. Therefore, one should stay away from slicing the solution space up into too many clusters.

Moreover, the average and maximum prediction errors are inspected in Figures 8.12a and 8.12b. It can be seen that Test Cases 2 to 4 show a similar behavior to that of the maximization of stand effectiveness objective, but the average error for Test Case 5 is higher. It means that the aircraft taxi distance objective is harder to predict than the stand effectiveness objective.



(a) Average prediction error for the aircraft taxi distance objective

(b) Maximum prediction error for the aircraft taxi distance objective

Figure 8.12: Average and maximum prediction error of the minimization of aircraft taxi distance objective as a function of the number of clusters

It can also be observed that several spikes are observed in the maximum prediction error in Figure 8.12b. Investigation of the solution spaces revealed that these spikes can be attributed to the formations of completely new clusters (instead of dissolving large clusters).

Objective 4: Passenger walking distance

As 2 of the 4 objectives were already investigated, it is important for one to also investigate the predictability of the passenger walking distance minimization objective. As for the previous two objectives, the average captured range shows a similar trend here and it is shown in Figure 8.13. The ranking between the performance predictability of the test cases is the same, the degree of predictability is similar to that of the stand effectiveness objective.

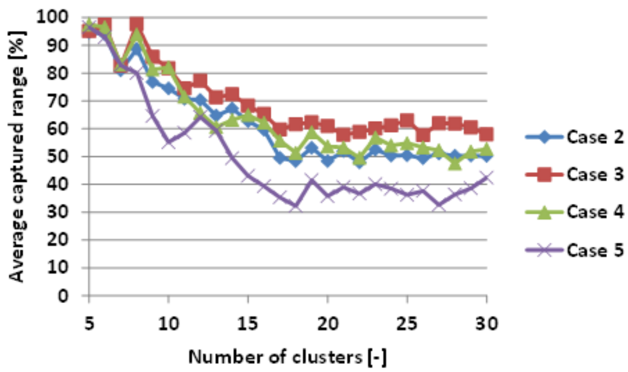
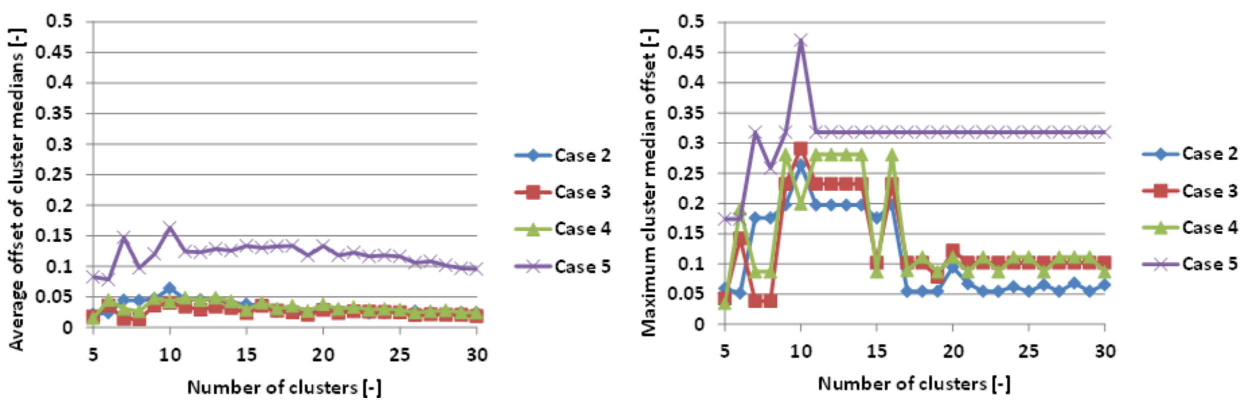


Figure 8.13: Average prediction accuracy of the minimization of passenger walking distance objective as a function of the number of clusters

As far as the average prediction error is concerned, it can be seen that this metric for Test Cases 2 to 4 are very low, below 0.05 and also very similar. It can be seen in Figure 8.14a below. Furthermore, as it was expected, the average error of Case 5 is significantly higher than the rest of the cases. This is due to the fact that a different terminal (hence a different ground demand) is under consideration.



(a) Average prediction error for the passenger walking distance objective

(b) Maximum prediction error for the passenger walking distance objective

Figure 8.14: Average and maximum prediction error of the minimization of passenger walking distance objective as a function of the number of clusters

When it comes to the maximum prediction error, the trends of the comparison cases are significantly different than for the previous two objectives. One can see in Figure 8.14b that the maximum prediction error increases until a certain point, but it starts to decrease after a while making the predictions more accurate. This is due to the k-means clustering algorithm developing clusters that span a large portion of the design space of the passenger walking distance objective. It means that when one would like to predict with large variations in the weights of an objective (in multiple dimensions), it is highly likely that the offset between the reference and the predicted KPI range is large.

Objective 5: Towing operations

Lastly, the degree of predictability of the towing operations objective is investigated the same way as the other 3 objectives. The average captured KPI range is visible in Figure 8.15. A similar ranking between the comparison cases can be observed along with a similar trend in the predictability as a function of the number of clusters. However, one must note that the predictability decreases sharper than for the other objectives, which means that a smaller portion of the KPI range can be captured. This is induced by the difference between the test cases on the number of possible tows(in light of the capacity of the terminal apron). Namely, when the apron can allow for more tows, then the data points standardized KPI range of the towing objective are more spread out, but when not a lot of capacity there is to space, the data points accumulate on the two ends of the standardized KPI range.

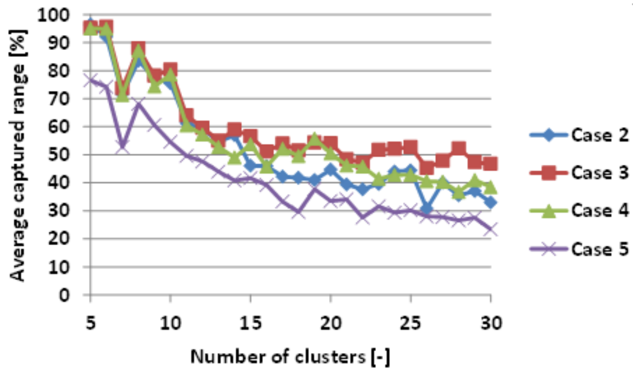
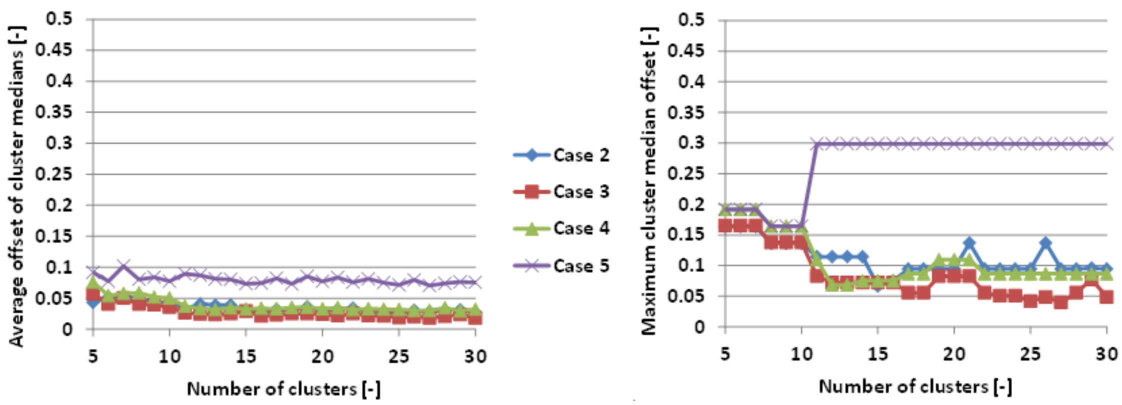


Figure 8.15: Average prediction accuracy of the minimization of aircraft tows objective as a function of the number of clusters

When the average prediction error is investigated in Figure 8.16a below, it can be seen that the situation is not as alarming as Figure 8.15 above suggests. it can be seen that the average prediction error is not only low initially, but it also decreases slightly as the number of clusters is decreased. It means that while the ranges are matched more inaccurately, the predicted KPI values actually lie closer to the forecaster range. It means that if one chooses a compact cluster (performance profile) with a small KPI range for towing, then the forecasted towing performance will actually be better when more clusters are used.



(a) Average prediction error for the aircraft tows

(b) Maximum prediction error for the aircraft tows

Figure 8.16: Average and maximum prediction error of the minimization of aircraft tows objective as a function of the number of clusters

The above presented argument can further be strengthened by the evidence shown in Figure 8.16b. When the same terminal is considered, the maximum predictability error decreases as the number of clusters is increased. This can be explained by the observations of Section 8.3, namely, as the number of clusters is increased, the sizes of the clusters generally (not after each refinement) also decrease. It means that when one approximates closer to a 1-on-1 mapping(using as many clusters as data points), the chance of predicting a data point to lie at the same standardized KPI location is decreasing, but when the prediction range increases, the prediction accuracy also increases.

It must be pointed out that it is not advised to take the predictability behaviors of individual objectives out of context, since the degree of predictability of a certain objective KPI is highly dependent on the multi-dimensional relationships between the objectives. It means that in case a single-, bi-objective or a many-objective optimization problem with one or multiple differing objectives would be employed, it cannot be guaranteed that the above discussed trends hold. This is also pointed out in the recommendations section of this research paper in Section 9.3. Therefore, the created trade-offs should be applied on future stand allocations that have similar apron infrastructure and flight schedule(ground demand, passenger numbers) characteristics.

8.5 Performance planning feasibility (RQ2,RQ3)

As the previous sections revealed, the WSS method enhanced with k-means clustering and unique cluster weight range definition allows for the prediction of the performance of an allocation (with a high accuracy) a priori. This allows airport decision makers to influence the performance of the allocation. In order to understand the applicability of this concept for practical situations, this section presents the performance planning results for the previously mentioned two terminal types, namely, *O&D* and transfer terminals.

8.5.1 Transfer terminal performance planning

The first terminal to be investigated is the transfer terminal which is modelled as London Heathrow Airport's Terminal 3. For the present analysis, Test Case 1 is used as before, namely, Easterly 1 runway configuration on the 12^{th} of August, 2016. In order to begin the exploration, it is important to examine Figure 8.2 again. It is visible that the 10 different clusters or performance profiles are not identical. Also, it is important to investigate which profile can be associated with which airport stakeholder. Firstly, the value of each performance profile will be determined. This is done by calculating the average standardized KPI value of each objective within each performance profile. As the standardized KPI values lie between 0 and 1, the average of these figures(hence the value of the objective) also lies between 0 and 1. This can be used to define the value brought to each stakeholder. Additionally, the overall allocation value can be expressed as the summation of these objective values. This is visible in Figure 8.3 below.

Table 8.3: Overall value assessment of the trade-offs between the defined performance profiles of the transfer terminal

Perf. Profile ID	**Avg. value of SE**	**Avg. value of ACTD**	**Avg. value of PWD**	**Avg. value of TW**	**Overall value**
1	0.15	0.76	0.03	0.83	1.77
2	0.00	0.86	0.68	0.60	2.14
3	0.19	0.82	0.16	0.03	1.20
4	0.15	0.13	0.74	0.82	1.84
5	0.79	0.07	0.62	0.95	2.43
6	0.52	0.65	0.23	0.03	1.44
7	0.07	0.70	0.48	0.02	1.28
8	0.22	0.39	0.13	0.86	1.61
9	0.78	0.42	0.96	0.05	2.21
10	0.09	0.55	0.84	0.02	1.50

The goal of each stakeholder is to select a performance profile that has the minimum value assigned to it. At first, it might sound counter intuitive, however, as the optimization sense is minimization, the smaller the value, the more favorable it is to the stakeholder. Furthermore, it can be seen that the most value brought to all the stakeholders(the best performance profile for the collective) is Performance Profile 7, since its overall value is the lowest, namely, 1.28. It means that the decision makers at the airport(capacity planners) have to evaluate whether their own goals are most important or the performance of the complete stand allocation is significant.

The main characteristics and goals of the stand allocation stakeholders were examined in Section 2.2. Based on that analogy, the performance profiles and the corresponding standardized KPI values can be liked to the stakeholders. The applicable performance profiles per stakeholder can be seen in Table 8.4 below, while the associated unique weight ranges are visible in Table 8.2. It also must be noted that the suitability of these performance profiles of the stakeholders was qualitatively selected using the discussions in Section 2.2.

Table 8.4: The suitable performance profiles for each stakeholder for the transfer terminal model

Perf. Profile ID	**Airport**	**Airline**	**Passengers**	**Not favorable**
1	x		x	
2	x			
3			x	
4	x	x		
5				x
6				x
7	x			
8			x	
9		x		
10	x			

It can be seen that there are a total of 5 performance profiles that are suitable for the interests of the airport. Profiles 2,4 and 10 ensures that the stand effectiveness of the allocation is maximized (the stands are used effectively) while keeping the passenger walking distance high. It means that these allocations neglect the interests of the passengers. Profile 1 is both beneficial for the airport and the passengers, while the interests of the airlines are jeopardized because the aircraft taxi distance and the number of tows are on the worse end of the standardized KPI range. In light of this discussion, it is advised for the airports to select performance profile 4 or 10 in order to achieve the best performance on their interests.

As far as the airlines are concerned, profiles 4 and 10 ensure that both the taxi distance and the number of towing operations are minimized. It has to be noted that in case one of the two objectives is minimized, that already improves on the airlines' performance in the tactical stand allocation compared to the current situation as it could be seen in Section 7.4. Furthermore, it could be valuable for airport decision makers to involve airlines in the allocation planning procedure, since that would enable the airport operators to both help airlines save on their expenditures and to also charge additional or increased fees for airlines in exchange for the performance improvement.

Concerning the passengers, profiles 1, 3 and 8 would ensure that the interest of the passengers is exercised. It would mean that their walking distance would be minimized. Profile 1 appears to be an attractive profile, because it would also be beneficial for the airport. However, if the airport could choose a profile that does not appear beneficial at first to the passengers, they can still ensure that the walking times and distances meet the standards described in the Service Level Agreements. Profiles 3 and 8 also serve the interest of the airport which means that for Test Case 1, when the interests of the passengers are met, (one of) the interests of the airport is also met.

It is also important to investigate which performance profile the current actual allocation strategy of LHR would fall into. The location of the standardized KPIs of the actual allocations can be seen in Table 7.24. Since the performance profiles of Test Case 1 were presented, the actual allocation of this case is investigated here. The standardized KPI locations of this allocation match Performance Profile 7 the most, namely, high quality stand effectiveness with medium quality passenger walking distance and poor quality aircraft taxi distance. This recognition confirms the results of the consultation with LHR airport where the capacity planners revealed that stand effectiveness is the only real interest that is considered when creating the allocations.

It was seen in Section 8.4 that by using the unique weight range finder algorithm, one can accurately predict a priori the performance of the stand allocation when the profiles are applied on the same terminal and the same season. Hence, it can be concluded that it is feasible to use performance profiles of a certain allocation to predict the performance of another similar (future) allocation.

8.5.2 *O&D* terminal performance planning

While suitable performance profiles were discovered for the transfer airport model above, it must also be evaluated whether the performance profiles of the *O&D* terminal are similar or differing. In this way, 10 performance profiles were created (with the k-means clustering algorithm) for Test Case 2 in a similar way as for Terminal 3. These performance profiles are visible in Figure 8.17 below.

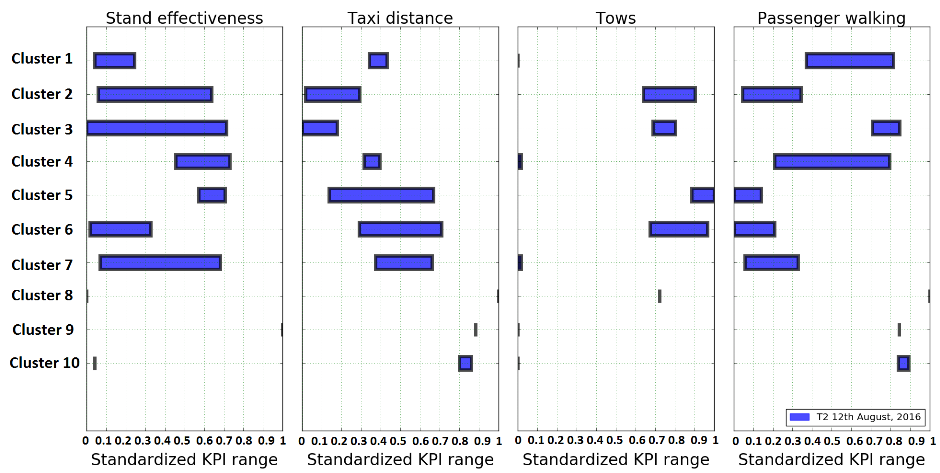


Figure 8.17: The breakdown of a turnaround: arrival flight (disembarkation), (remote) parking and departure flight (embarkation)

Furthermore, the summary on the average value represented in each performance profile can be seen Table 8.5 below. It must be noted that it was created using the same principles as Table 8.3 above.

Table 8.5: Overall value assessment of the trade-offs between the defined performance profiles of the *O&D* terminal

Perf. Profile ID	Avg. value of SE	Avg. value of ACTD	Avg. value of PWD	Avg. value of TW	Overall
1	0.12	0.38	0.68	0.00	1.18
2	0.31	0.14	0.20	0.79	1.45
3	0.16	0.07	0.77	0.73	1.74
4	0.63	0.34	0.61	0.00	1.58
5	0.64	0.36	0.04	0.93	1.97
6	0.15	0.51	0.04	0.76	1.46
7	0.27	0.58	0.11	0.00	0.96
8	0.00	1.00	1.00	0.72	2.72
9	1.00	0.88	0.84	0.00	2.73
10	0.04	0.83	0.87	0.00	1.74

While the performance profiles give a visual representation to the reader, one can also draw some conclusions from this figure and table. This is done in the same way as for the transfer terminal model. The summary of the suitable performance profiles of each stakeholder are also visible in Table 8.6 below. Interestingly, several differences can be observed. Firstly, performance profile 2 shows performance characteristics that are suitable for each stakeholder. While taxi distance is in the lower 30 % of the solution space, the passenger walking distance is also within the best 35 % and the stand effectiveness also shows a balanced performance. It means that none of the stakeholders have to compromise fully. On the other hand, the towing operations performance is very poor which means that the airlines both benefit from the allocation and also have to account for more tows.

Table 8.6: The suitable performance profiles for each stakeholder for the $O\&D$ terminal model

Profile number	Airport	Airline	Passengers	Not favorable
1	x	x		
2	x	x	x	
3		x		
4		x		
5			x	
6	x		x	
7		x	x	
8	x			
9		x		
10	x	x		

It can be seen that compared to the transfer terminal, there are more performance profiles that are favorable for only one of the stakeholders. This can be seen for performance profiles 3,4,7 and 9. These are profiles that are favorable for the airlines, however, it is noteworthy to mention that even in these cases, one cannot minimize the aircraft taxi distance and the number of towing operations at the same time. Furthermore, significantly more suitable profiles are present between the airport and the airlines(performance profiles 1,2 and 10) compared to the transfer terminal. It is favorable for the airport operator, since the airlines are in a direct financial connection with the airports. This is important, since more stand allocation performance options can be subject to negotiations with airlines(empathetic negotiation).

It is also visible that there are 3 performance profiles (performance profiles 8 to 10) which have very small spans in the standardized KPI range. A detailed investigation of the data revealed that this is due to the fact that these profiles represent the extremes of the solution space that are associated with the case when only 1 objective is present in the optimization (the weight of it is 1 and the other weights are 0). It also means that the other part of the solution space is more dense which is also visible through the span of KPI ranges the other clusters have(in Figure 8.6).

While the above shown discussion identified several differences between the generated profiles of the two terminals, it has to be concluded that the differences in the performance profiles do not have characteristics that are a result of using a different terminal type. In other words, the performance profiles of the two terminal types only differ in the span of KPI values, but the trade-off combinations do not show significantly different behavior. It suggests that the two terminal types do not have different characteristics or trade-off options in the performance planning framework.

Conclusions

This chapter presented the detailed answers to the research questions. Firstly, it was proved that it is not possible to find two or more objectives that are in absolute synergy or in absolute conflict in the complete solution space of the many-objective tactical stand allocation problem. Secondly, it was demonstrated that the weights of the objectives do not directly represent the location of the (standardized) KPI values, however, the combination of the weights of all objectives do. Therefore, it is necessary to enhance the decision making process. This decision making process was enhanced by k-means clustering and unique weight range definition which proved to be accurate for allocations within the same terminal and within the same allocation season for London Heathrow Airport. Lastly, it was observed that while the performance profiles of the transfer and $O\%D$ terminal models are similar, the $O\%D$ can produce less balanced allocations(not favorable for any particular stakeholder), but can produce more profiles that favor either one or two of the stakeholders. Also, it was observed that at least one interest of each stakeholder can be met for the $O\%D$ terminal model.

9 Conclusions

This chapter summarizes the conclusions that are drawn from this research project. Firstly, the answers to the research questions are summarized in Section 9.1. Then, Section 9.2 assesses the aspects of this research that contribute to literature. Furthermore, the limitations of the presented methods along with recommendations on how to apply enhancements will be outlined in Section 9.3. Afterwards, recommendations are given on the applicability of the presented methods in other airport operations research fields. Lastly, the research hypotheses and the objectives of the research in general will be revised in Section 9.5.

9.1 Research Results

The analysis of the behavior of the many-objective tactical stand allocation aided by Weight Space Search revealed that it is not feasible to relate the weight of a certain objective to a resulting KPI value, since the combination of objective weights determine the multi-dimensional performance of the stand allocation. It was demonstrated by the fact that the KPI values can span 35 % of the design space in for certain objectives' specific weights as it was shown in Figures 8.3 and 8.4. Accordingly, a more sophisticated approach was developed to cope with the ambiguity of the link between the objective weights and the corresponding KPI values. The use of k-means clustering on the multi-dimensional solution space enabled grouping allocations with similar performance characteristics (in all KPI dimensions). While the weight ranges of the objectives in each cluster (performance profile) proved to be continuous, these weight ranges did not unambiguously describe each performance, which means that these performance profiles had to be reduced in size. This helped one to define the performance profile with a weight range that is unique to it. This allows decision makers to select a performance profile (trade-offs on the different performance metrics of the stand allocation) from a reference stand allocation and map this performance onto a future stand allocation using the unique weight combinations of that profile.

It was found that the number of performance profiles created (from the complete solution space) has a great influence on the accuracy of the expected allocation performance. As the number of performance profiles is increased, the expected KPI accuracy increases, since the performance profiles are both more compact in span and smaller in size. Furthermore, as the number of performance profiles is increased, the number of choices also increases for airport decision makers. For practical purposes, one has to ensure that airport decision makers are not bombarded with a large set of options in order to avoid the paradox of choice.

However, the testing of the prediction accuracy of projecting the unique weight ranges of the performance profiles onto various test cases proved that with a low number of chosen performance profiles (maximum 10), one can predict the performance with an average accuracy of 90 %(see Figure 8.9) when one applies the performance profiles to the same terminal and similar ground demand profiles. When the number of performance profiles increases, the accuracy decreases significantly to an accuracy range of 40-60 %. In case the desired KPI is not captured correctly, the average perceived error in the prediction is stable, but stays below 10 % for predictions for the same terminal. As the average prediction error is stable(it does not significantly change as a function of clusters used), the maximum perceived error increases as a function of the number of performance profiles created. It signals that the airport decision makers need to make a trade-off between the exactness of the required performance and the prediction error. Based on consultation with airport capacity planners, a suggested trade-off is to aim for dividing the solution space into roughly 10 performance profiles. This gives a balanced trade-off between the accuracy of the expected and the predicted stand allocation performance.

The London Heathrow Airport case study caught stakeholder trade-offs that can ensure that at least two stakeholders can operate at optimized performance. Namely, while the airport can operate at excellent stand allocation performance, either the airlines or the passengers can draw benefits from the stand allocation in the form of lower taxi distances or lower walking distances. Furthermore, it could not be ensured that none of the stakeholders compromise their interests, which means that performance optimality for all stakeholders is not achievable. It was also proven that the stand allocation performance planning framework is suitable for airport decision makers for implementing the needs or policies of their different stakeholders efficiently into the planning of their stand allocation. This enables them to improve on the operational efficiency of their airport in the framework of Collaborative Decision Making.

9.2 Scientific contributions

As the previous section summarized the discoveries of the research project, it is important to specify the scientific contributions that result. This is detailed below.

Unique performance profiles(trade-offs)

While previous researches identified the nature of the trade-offs between sets of 2 or 3 stand allocation objectives, the present research was able to relate the ambiguous objective weight combinations to the resulting performance metrics. The significance of this finding lies in the fact that when using more than 3 allocation objectives, one cannot rely on the magnitudes of the single objective weights to influence the performance of the allocation. This is due to the complex relationships that are created between the many objectives that have different relationships with each other. Therefore, the k-means clustering algorithm enhanced with the unique weight range finder algorithm was able to identify unique areas in the solution space that can be used to unambiguously relate the objective weights to the resulting performance metrics.

Stand allocation performance planning

The other important scientific contribution of this research is the ability to re-use the above mentioned unique performance profiles (with a high accuracy) for the planning the performance of future stand allocations. It means that the absolute multi-dimensional performance of the allocation can be manipulated by using the solid knowledge of the objective weight input of the many-objective tactical stand allocation problem. Unfortunately, the performance profiles cannot predict the desired performance with a 100% certainty. Although, the weights of the objectives drive their performances, the solution space of different allocation scenarios(different allocation days) are different in general, hence, a degree of uncertainty is introduced into the prediction.

Furthermore, the previous discussion also reveals that by decreasing the accuracy of the performance one aims for (looking at KPI ranges instead of exact KPIs), one is able to increase the accuracy of actually obtaining the desired performance. This accuracy can be directly controlled by the amount of clusters the solution space is broken up to. Therefore, by carefully selecting the proper "k" in k-means clustering, the prediction accuracy can be managed.

9.3 Method limitations and recommendations

While the research project provided valuable and novel information on the stand allocation problem, it has to be mentioned that there are limitations involved. These limitations are detailed below. Additionally, some recommendations are also listed to further improve on the scientific validity of the findings and to open up new research branches.

Limitation 1: used allocation objectives

Chapter 4 outlined that a total of 5 allocation objectives are used for the current research. These 5 objectives make the problem a many-objective optimization problem. These objectives were also sufficient for the comparison of stakeholder interests and the compromises that have to be made between the stakeholders. However, it has to be mentioned that several other stakeholder interests (objectives) are expressed through an MIP formulation. Such objectives include the maximization of maximization of stand preferences of airlines[3], maximization of passenger walking fairness between airlines[9] and minimization of deviations from a reference schedule[27] amongst others. In summary, the collective use of the researched objectives and the above mentioned ones would provide a stand allocation framework where more interests and more stakeholders would be included.

Limitation 2: granularity of the weight space search

The weight space search algorithm described in Subsection 4.5.3 created a total of 286 complete stand allocations with a weight increment of 0.1 for each allocation objective. It means that 11 different allocation weights are used for each objective. Although, this refinement can be considered sufficient, it is advised to decrease this increment to obtain a more refined solution. This would enable the researcher to justify that the solution space is not discontinuous in between the already researched allocation weights.

Unfortunately, by decreasing the weight increments, the computational time exponentially grows due to the exponential growth of the number of optimization runs that have to be carried out. This can also be seen in Table 4.3. It must also be mentioned that the computational times of independent allocations does not change, but as the number of iterations necessary increases, the overall computational time increases.

Limitation 3: the lack of transfer passengers

As it was argued in Chapter 4, the transfer passengers are not taken into consideration for the stand allocation problem. However, it is advised to include an objective considering the minimization of walking distances or transfer times of transfer passengers. This would also mean that an additional trade-off conflict could potentially be introduced between the objectives of the passengers. In this way, the relationship of the two passenger interests could be investigated.

Recommendation 1: the use of monetary units for the allocation objectives

It was mentioned in Section 4.5.2 that the allocation objectives need to be normalized in order to ensure that their respective units do not introduce bias towards one or another allocation objective. Additionally, the allocation objectives were expressed in units that represent their technical performances. For practical applications, it is more favorable to employ monetary units to measure the performance of each objective. It would not only give an "easier to interpret" solution, but it would also eliminate the use of normalization from the process, since each objective would have the same unit. Consequently, it is recommended to explore the applicability of monetary units in a related future research.

Recommendation 2: the use of more allocation constraints

Although this research presented the most widely used allocation constraints, airports have unique and customized stand allocation algorithms. It means that several different allocation constraints might be used depending on the airport under consideration. Examples of such would be the constraining the maximum number of busing or towing operations per time frame (hour, day)[12], constraining the number of flights allocated to stands that might have a pushback conflict[12] or constraining the ratio of passengers being assigned to a contact or remote stand. Furthermore, Service Level Agreements(SLAs) on the walking distances of passengers, the connection times of transfer passengers, the amount of passengers served on a remote stand and the allocation of flights to only a certain set of stands(e.g. Schengen/Non-Schengen flights) amongst others could be implemented as allocation constraints. As a result, it is recommended to investigate the effect of these additional constraints on the relationships (and trade-offs) between the allocation objectives.

Recommendation 3: predictability trends with one or more differing objectives

Section 8.4 investigated the degree of predictability of each objective in the researched many-objective tactical stand allocation model. Although these trends were proven for this problem setup, it is yet to be investigated whether these predictability trends hold when one or multiple of these objectives are replaced with other stand allocation objectives. In consequence, it is advised to only consider these trends in the current problem setup and it is also advised to investigate the trends of a different setup separately. In this way, one would be able to avoid unnecessarily high predictability errors.

Recommendation 4: run time

The run time of the Weight Space Search method governs the run time of the complete model. This is due to the fact that the allocation has to be carried out as many times as the amount of weight combinations of the problem. Table 6.7 revealed that the run time of the WSS can range between 11 to 24 hours depending on the problem size. This run time only increases when the weight increments used are further reduced(for a more detailed design space). Therefore, it is recommended to carefully evaluate whether the weight increments are to be reduced.

Additionally, the run time of the stand allocation model highly depends on the presence of the towing operations objective as it was presented in Table 6.9. When this objective is in the problem(its weight is not zero), it is harder for the algorithm to find a feasible solution, therefore, the run time is increased. Consequently, it is recommended to either exclude the minimization of tows objective or to carefully monitor the amount of possible tows(to be kept as low as possible) in case one aims to reduce computational time.

Recommendation 5: investigation of the operational disruption mitigating effects of performance planning

As it was mentioned earlier, the interests of the different stakeholders can be planned for using the performance planning framework. As this methodology allows for the improvement of the performance of the different stakeholders, it is expected that the proactive planning on the tactical level also has an influence on the degree of disruption on the operational level. This is suspected, since the operational disruptions are mostly caused by the sub-optimal procedures of one or more stakeholders that are propagated onto the remainder of the stakeholders. Namely, it is recommended to investigate whether the implementation of tactical performance planning in creating the stand allocation decreases the operational disruption levels for the different stakeholders and the overall system.

9.4 Practical applications and future research

Although the clustering-based performance planning framework was developed for the tactical stand allocation problem, it is advised to investigate the possible exploitation of the method's strengths in other research areas. As a consequence, this section provides some suggestions on prospective (appealing) research areas.

Tactical stand and gate allocation

The present research excluded the links between aircraft stands and airport gates for the allocation of operations. However, the allocation of stands and gates are carried out simultaneously applying rules on which gate is connected to which stand at which point in time. It means that the structure of the allocation problem can be different. As a result, it is advised to investigate the applicability of the clustering-based performance planning framework on a tactical stand and gate allocation problem. Some additional objectives and constraints that could be added to the stand (and gate) allocation problem[11, 3].
Objectives:

- Maximization of airline preferences[3]
- Maximization of non-aeronautical revenues
- Minimization of passenger transfer times[13]
- Minimization of passenger busing operations[3]

Constraints:

- Compliance with passenger processing SLAs
- Limits on aircraft taxiing within clu-de-sacs[12]

Airport check-in desk allocation

Rule-based check-in desk allocation at airports is becoming an increasingly common phenomenon where airport capacity planners take several considerations into account such as the allocation of a cluster of check-in desks to a single airline, minimization of crew utilization and minimization of queue length. Since these allocations can be based on multiple conflicting objectives, it is advised to conduct research on the applicability of the presented methods. Commonly used objectives and constraints for this problem are also listed below[58].

Objectives:

- Maximization of airline preferences
- Balancing the workload between the check-in desks
- Minimizing the maximum number of check-in desks used per flight (while complying with SLAs)

Constraints:

- Infrastructure constraints: the capacities of the counters should be respected

Baggage reclaim belt and sorting station allocation

Baggage reclaim belts are scarce and expensive resources that serve multiple flights simultaneously. In this way, capacity planners have to carefully monitor the flow of baggage to each baggage reclaim belt an airport has. Employing the clustering-based performance planning framework could improve on the flexibility capacity planners have when allocating reclaim belts to flights. Hence, it is also advised to explore the possibilities of this research area. Some regularly used objectives and constraints that are used for baggage reclaim belt allocation are also listed below[59].

Objectives:

- Minimization of walking distance to the reclaim belt
- Maximization of buffer times between two flight allocations to the same belt
- Maximization of fair workload between the reclaim belts (aiming for similar usage times for each belt)
- Maximization of airline preferences
- Clustering of the flights of the same airline to the same reclaim belt
- Minimization of used baggage sorting stations

Constraints:

- Assigning one flight to one sorting station and baggage reclaim belt
- Ensuring that a sorting station processes one flight at a time

Airside bus scheduling

Most airports provide remote parking possibilities to the airlines. It means that stands are not directly connected to the airport gates which means that the passengers must be bused to/from the aircraft. Since the airport provides the busing operations most of the time, it would be interesting to investigate whether the presented framework would provide more robustness for the scheduling department at airports. A few commonly used objectives and constraints are also listed below[22, 60].

Objectives:

- Maximization of robustness between two busing operations
- Minimization of busing distance
- Maximization of passengers processed per bus

Constraints:

- Assignment of a certain bus to a single flight at a time
- Compliance with the capacity of each type of bus

Airport financial budget allocation(e.g. passenger security screening)

The researched tactical stand allocation model and the above presented suggestions use objectives that measure the technical performance of their respective allocations. In case one would convert these technical KPIs to financial KPIs, one would be able to affect the costs and revenues associated to the allocation objectives. It would mean that the airports would be able to decide on the financial consequences of an allocation a priori. That would give airports a negotiating advantage over the stakeholders at the airport which would facilitate a stronger Collaborative Decision Making (CDM). Accordingly, it is advised to investigate the use of the clustering-based performance planning method in a financial framework. Some regularly used objectives and constraints that are used for airport financial budget planning through the example of passenger security sreening facility development are also listed below[61].

Objectives:

- Minimization of total installation costs
- Minimization of operating costs per hour per device
- Minimization of fixed costs

Constraints:

- Resource capacity constraints
- Resource availability constraints
- SLAs on service level

9.5 Review of hypotheses and research objectives

The research hypothesis was presented in Section 3.3. It is also shown again below:

- **Hypothesis 1:** The objective weight combinations of the many-objective tactical stand allocation model should provide an exact trade-off in the standardized KPI design space irrespective of the used flight schedule.

As the detailed analysis of the results have shown in Chapter 8, the weights of a certain many-objective tactical stand allocation MIP do not provide an exact location (in all dimensions) in the standardized KPI design space. It means that the hypothesis does not hold and that the user (airport decision maker) cannot blindly re-use the input weight combinations of the many-objective tactical stand allocation to allocate based on his or her preferences. However, the fact that the research hypothesis does not hold does not prevent one from planning the performance of the tactical stand allocation. The use of the proposed k-means clustering and unique cluster weight range finder algorithms provide an approximation of the performance profile of future allocations. In light of this discussion, it is worthwhile to reflect on the research objectives which are listed below:

- **Research objective 1:** Develop a many-objective tactical stand allocation model that both incorporates at least one interest of the airport stakeholders and also allows for the manipulation of the orders of these interests.
- **Research objective 2:** Develop a framework that provides a priori performance planning options to airport capacity planners on the many-objective tactical aircraft stand allocation.
- **Research objective 3:** Display the industrial applicability of the a priori performance planning framework in a London Heathrow Airport case study.

As the results of this research revealed, the many-objective tactical stand allocation model was developed, verified and used as a basis for answering the research questions and disproving the research hypothesis. This model effectively incorporates the interests of the airport stakeholders while also providing a many-objective framework that is yet to be investigated in literature. For these reasons, Research Objective 1 is deemed to be achieved.

Research Objective 2 concentrates on finding regions of the solution space generated by the multitude of stand allocation MIPs through the Weight Space Search method. As the results of the research revealed that it is indeed possible to break the design space up into stable regions where the multi-dimensional KPI values are similar. Furthermore, it was also discovered that these regions are corresponding to stable objective weight ranges. Also, by reducing the size of each found cluster (trade-off), one is able to project the chosen performance profile with high accuracy to a future allocation. It means that Research Objective 2 is also met.

Last but not least, translation of the achievements of Research Objectives 1 and 2 is the main goal of Research Objective 3. Namely, making the research findings applicable for industrial use. It was demonstrated that with a value-focused thinking approach, it is possible to plan the performance of the tactical stand allocation at LHR Airport with high certainty prior to actually creating the allocation. It means that it is also proven that a negotiating advantage can be provided to airport decision makers to shape the Collaborative Decision Making process through empathetic negotiation.

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A ICAO Aircraft Design Groups

Table A.1: ICAO and FAA aircraft design group categorization [19]

ICAO code	**FAA code**	**Aircraft wingspan [m]**	Example aircraft
A	I	<15 m	Cessna 172
B	II	15-24 m	CRJ-900
C	III	24-36 m	B737, A319, A320
D	IV	36-52 m	B757, B767
E	V	52-65 m	A330, A340, B747
F	VI	65-80 m	A380

B The Weight Space Search algorithm

Table B.1: The weight combinations generated by the Weight Space Search algorithm

Iteration	W_{Obj1}	W_{Obj2}	W_{Obj3}	W_{Obj4}	W_{Obj5}
1	1000	0	0	0	1
2	1000	0	0	0.1	0.9
3	1000	0	0	0.2	0.8
4	1000	0	0	0.3	0.7
5	1000	0	0	0.4	0.6
6	1000	0	0	0.5	0.5
7	1000	0	0	0.6	0.4
8	1000	0	0	0.7	0.3
9	1000	0	0	0.8	0.2
10	1000	0	0	0.9	0.1
11	1000	0	0	1	0
12	1000	0	0.1	0	0.9
13	1000	0	0.1	0.1	0.8
...	...	...	...	...	...
278	1000	0.8	0	0.1	0.1
279	1000	0.8	0	0.2	0
280	1000	0.8	0.1	0	0.1
281	1000	0.8	0.1	0.1	0
282	1000	0.8	0.2	0	0
283	1000	0.9	0	0	0.1
284	1000	0.9	0	0.1	0
285	1000	0.9	0.1	0	0
286	1000	1	0	0	0

C LHR terminal information

Table C.1: Terminal 2 model input information with the Easterly 1 runway configuration (1/2)

Name	Size	Blocked	ATD [m]	DTD [m]	AWD [m]	DWD [m]
141	5		2200	3500	495	495
216	3		500	4350	130	130
217	3		505	4350	133	131
218	6	218L, 218R	510	4370	132	132
218L	3	218	515	4365	131	133
218R	3	218	520	4360	130	130
219	3		500	4355	215	215
220	3		500	4350	218	216
221	6	221L, 221R	600	3850	217	217
221L	3	221	600	3850	216	215
221R	3	221	600	3850	215	215
223	3		600	3850	415	415
224	3		600	3850	415	415
225	3		600	3850	415	415
226	3		600	3850	415	415
241	5		1000	4200	705	705
242	6		1005	4220	705	705
243	6	243L, 243R	1010	4215	705	705
243L	3	243	1015	4210	705	705
243R	3	243	1020	4205	705	705
244	6		1000	4200	578	575
246	6	246L, 246R	1400	3900	577	576
246L	3	246	1400	3900	576	577
246R	3	246	1400	3900	575	578
247	6	247L, 247R	1400	3900	705	705
247L	3	247	1400	3900	705	706
247R	3	247	1400	3900	705	707
248	5		1400	3900	705	708

Table C.2: Terminal 2 model input information with the Easterly 1 runway configuration (2/2)

Name	**Size**	**Blocked**	**ATD [m]**	**DTD [m]**	**AWD [m]**	**DWD [m]**
249	5		1400	3900	705	709
231	5		2200	3500	713	710
232	5		2200	3500	712	711
233	5	233L, 233R	2200	3500	711	712
233L	3	233	2200	3500	710	705
233R	3	233	2200	3500	709	705
236	5	236L, 236R	500	4350	708	705
236L	3	236	500	4350	707	705
236R	3	236	500	4350	706	705
238	6		500	4350	705	705
239	5		500	4350	704	705
251 Rem	5		1000	4200	215	215
252 Rem	5		1005	4200	215	215
253 Rem	6	253L Rem, 253R Rem	1010	4205	215	216
253L Rem	3	253 Rem	1015	4200	215	217
253R Rem	3	253 Rem	1000	4210	215	218
254 Rem	6	254L Rem, 254R Rem	1000	4215	224	219
254L Rem	3	254 Rem	1020	4200	223	220
254R Rem	3	254 Rem	1000	4220	222	221
255 Rem	6	255L Rem, 255R Rem	1400	3900	221	222
255L Rem	3	255 Rem	1400	3900	220	223
255R Rem	3	255 Rem	1415	3900	219	224
256 Rem	5		1400	3905	218	215
257 Rem	5		1405	3900	217	215
258 Rem	6	258L Rem, 258R Rem	1400	3910	216	215
258L Rem	3	258 Rem	1410	3915	215	215
258R Rem	3	258 Rem	1400	3900	215	215
Dummy Stand	10		5000	5000	1000	1000

Table C.3: Terminal 3 model input information with the Easterly 1 runway configuration

Name	Size	Blocked	ATD [m]	DTD [m]	AWD [m]	DWD [m]
301	6		350	3300	500	500
303R	3	303	350	3300	500	500
303	6	303L, 303R	350	3300	500	500
303L	3	303	350	3300	500	500
305R	3	305	350	3300	400	400
305	6	305L, 305R	350	3300	400	400
305L	3	305	350	3300	400	400
307	6		500	3150	300	300
309	3		750	3200	200	200
311	3		750	3200	200	200
313	5		750	3200	515	515
316	5		1050	2400	490	490
317	5		1050	2400	490	490
319	5		1050	2400	640	640
321	5		1350	2100	640	640
363	5		1350	2100	700	700
365	5		1350	2100	700	700
364	5		1750	2150	700	700
322	5		1950	2150	640	640
320	5		1950	2350	640	640
318	5		1950	2350	490	490
325	4		1950	2350	350	350
327	5		1950	2350	350	350
329	4		1750	2150	530	530
331	5		1750	2150	530	530
335	5		1750	2150	630	630
342	6		1650	1800	730	730
340	6		1650	1800	730	730
336	5		1950	1850	730	730
334	5		1950	1850	630	630
332	5		2150	1850	630	630
330	5		2150	2200	630	630
328	5		2300	2200	530	530
326	5		2300	2200	530	530
351_Rem	3		2300	2200	350	350
352_Rem	3		2300	2200	350	350
353_Rem	5		2300	2200	350	350
354_Rem	3		2150	2200	350	350
355_Rem	4		2150	2200	350	350
357R_Rem	3	357_Rem	2400	2300	350	350
357_Rem	6	357L_Rem, 357R_Rem	2400	2300	350	350
357L_Rem	3	357_Rem	2400	2300	350	350
582_Rem	5		1350	2350	350	350
583_Rem	5		1350	2350	350	350
590_Rem	5		1500	2100	350	350
591_Rem	5		1500	2100	350	350
592_Rem	5		1500	2100	350	350
594_Rem	6		1900	1700	350	350
595_Rem	6		1900	1700	350	350
596_Rem	6		1900	1700	350	350
Dummy Stand	10		5000	5000	1000	1000

Table C.4: Terminal 3 model input information with the Westerly 1 runway configuration

Name	ATD [m]	DTD [m]
301	1700	1350
303R	1700	1350
303	1700	1350
303L	1700	1350
305R	1550	1500
305	1550	1500
305L	1550	1500
307	1550	1500
309	1560	1750
311	1560	1750
313	1560	1750
316	1000	2100
317	1000	2100
319	810	2100
321	810	2200
363	650	2200
365	650	2250
364	700	2680
322	780	2790
320	900	2920
318	900	2920
325	900	2920
327	780	2790
329	780	2790
331	700	2680
335	700	2680
342	350	2500
340	350	2750
336	400	2970
334	400	2970
332	660	3200
330	660	3200
328	780	3300
326	780	3300
351_Rem	780	3300
352_Rem	780	3300
353_Rem	780	3300
354_Rem	780	3300
355_Rem	660	3200
357R_Rem	850	3380
357_Rem	850	3380
357L_Rem	850	3380
582_Rem	1050	2380
583_Rem	1050	2380
590_Rem	650	2540
591_Rem	650	2540
592_Rem	650	2540
594_Rem	350	2870
595_Rem	350	2870
596_Rem	350	2870
Dummy Stand	5000	5000

D Example stand allocation

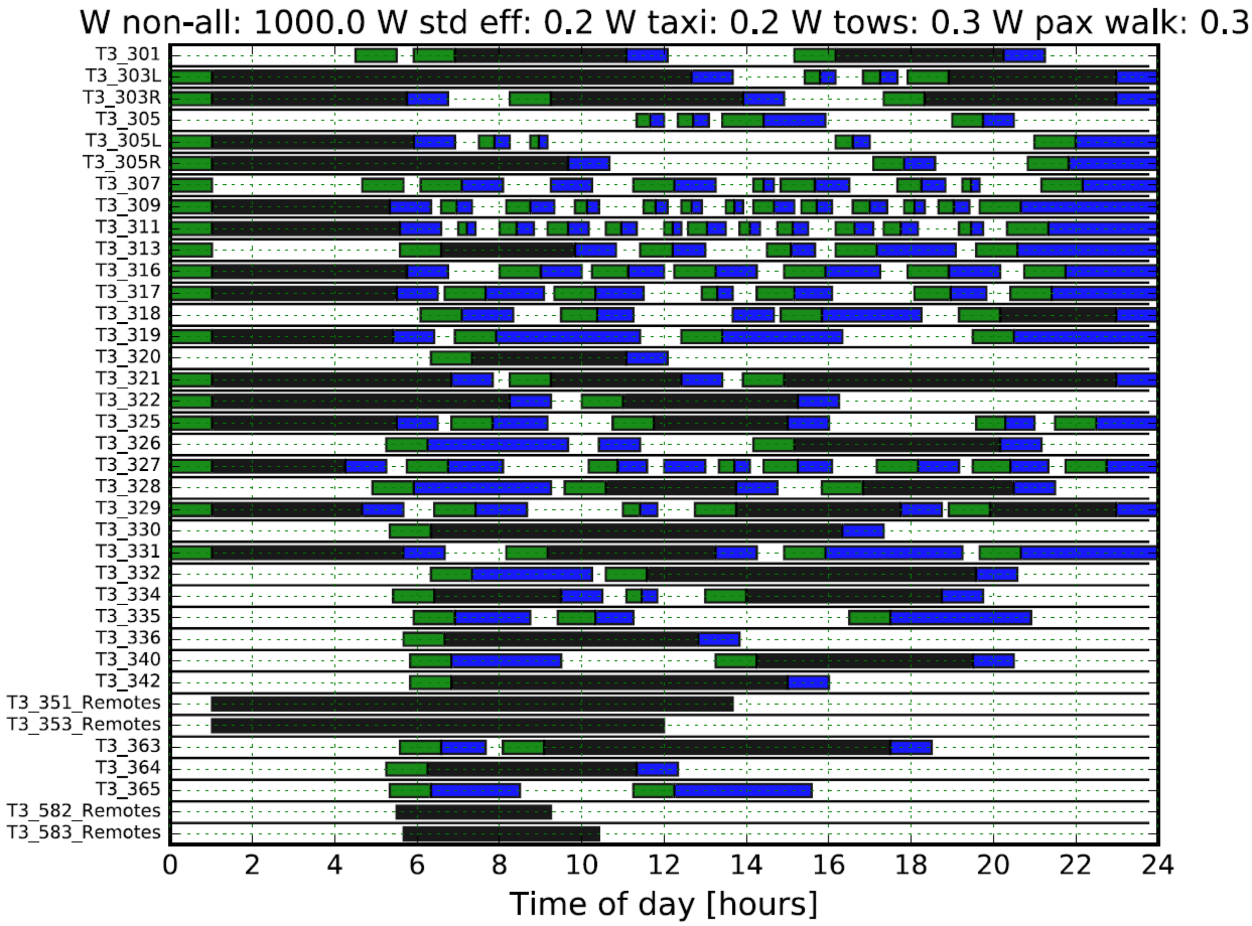

Figure D.1: Allocation timeline for the stands of Terminal 3 on the 12^{th} of August, 2016 with Easterly runway configuration

Table D.1: Many-objective stand allocation operation-stand list for the 12^{th} of August, 2016 with Easterly runway configuration for Terminal 3 (1/4)

Flight no.	Start time	End time	Stand	Flight no.	Start time	End time	Stand
BA 0661p	0:01	1:01	329	BA 0078	5:15	6:15	364
BA 0799p	0:01	1:01	309	CX 0255	5:20	6:20	330
BA 0491p	0:01	1:01	319	AA 0100	5:20	6:55	365
BA 0851p	0:01	1:01	317	BA 0492	5:20	6:20	309
VS 0026p	0:01	1:01	307	VS 0108	5:25	6:25	334
BA 0469p	0:01	1:01	327	BA 0366	5:25	6:25	319
BA 0705p	0:01	1:01	311	VS 0207t	5:30	9:15	582_Rem
BA 0869p	0:01	1:01	331	BA 0500	5:30	6:30	317
AY 3125p	0:01	1:01	325	AY 3126	5:30	6:30	325
BA 0857p	0:01	1:01	303R	VS 0602	5:35	6:35	313
BA 0503p	0:01	1:01	305L	AA 0086	5:35	6:37	363
BA 0419p	0:01	1:01	321	BA 0854	5:35	6:35	311
BA 0487p	0:01	1:01	305R	CX 0251t	5:40	10:25	583_Rem
BA 0371p	0:01	1:01	303L	BA 0206	5:40	6:40	336
AA 0142p	0:01	1:01	322	BA 0846	5:40	6:40	331
BA 0471p	0:01	1:01	313	VS 0004	5:45	6:55	327
AA 0090p	0:01	1:01	316	BA 0478	5:45	6:45	303R
BA 0661pt	1:01	4:40	329	AA 0099	5:45	6:45	316
BA 0799pt	1:01	5:20	309	AA 0174	5:50	7:40	340
BA 0491pt	1:01	5:25	319	AA 0106	5:50	6:50	342
BA 0851pt	1:01	5:30	317	QF 0001	5:55	6:55	301
VS 0026pt	1:01	12:00	353_Rem	AA 0050	5:55	7:20	335
BA 0469pt	1:01	4:15	327	BA 0696	5:55	6:55	305L
BA 0705pt	1:01	5:35	311	EK 0007	6:05	7:05	307
BA 0869pt	1:01	5:40	331	DL 8104	6:05	7:12	318
AY 3125pt	1:01	5:30	325	BA 0078t	6:15	11:20	364
BA 0857pt	1:01	5:45	303R	VS 0046	6:20	7:20	320
BA 0503pt	1:01	5:55	305L	VS 0022	6:20	8:17	332
BA 0419pt	1:01	6:50	321	CX 0255t	6:20	16:20	330
BA 0487pt	1:01	9:40	305R	DL 0058	6:25	7:32	329
BA 0371pt	1:01	12:40	303L	VS 0108t	6:25	9:30	334
AA 0142pt	1:01	8:15	322	BA 0365	6:35	6:57	309
BA 0471pt	1:01	13:40	351_Rem	VS 0602t	6:35	9:50	313
AA 0090pt	1:01	5:45	316	AA 0047	6:37	7:40	363
BA 0472	4:15	5:15	327	AA 0730	6:40	7:52	317
VS 0207	4:30	5:30	301	BA 0206t	6:40	12:50	336
CX 0251	4:40	5:40	307	DL 0401	6:50	8:00	325
BA 0360	4:40	5:40	329	AA 0106t	6:50	15:00	342
BA 0064	4:55	7:05	328	BA 0866	6:50	7:50	321
BA 0058	5:15	7:27	326	AA 0051	6:55	8:30	365

Table D.2: Many-objective stand allocation operation-stand list for the 12^{th} of August, 2016 with Easterly runway configuration for Terminal 3 (2/4)

Flight no.	Start time	End time	Stand	Flight no.	Start time	End time	Stand
AA 0056	6:55	7:55	319	VS 0111	9:30	10:30	334
QF 0001t	6:55	11:05	301	VS 0002	9:35	10:35	328
VS 0003	6:55	8:05	327	BA 0702	9:40	10:40	305R
BA 0416	6:57	7:20	309	BA 0474	9:40	10:10	311
BA 0853	7:00	7:12	311	VS 0019	9:50	10:50	313
BA 0065	7:05	9:15	328	BA 0361	9:50	10:07	309
EK 0008	7:05	8:05	307	AA 0038	10:00	11:00	322
DL 8039	7:12	8:20	318	BA 0794	10:07	10:25	309
BA 0466	7:12	7:25	311	DL 0806	10:10	10:52	327
VS 0046t	7:20	11:05	320	ME 0201	10:15	11:07	316
AA 0057	7:20	8:45	335	AA 0039	10:20	11:15	335
BA 0207	7:27	9:40	326	AA 0087	10:22	11:15	318
BA 0477	7:30	7:52	305L	CX 0252	10:25	11:25	326
DL 0059	7:32	8:40	329	AA 0109	10:25	11:25	319
AA 0173	7:40	9:30	340	BA 0271	10:25	11:30	317
AA 0729	7:52	9:05	317	BA 0218	10:35	11:35	332
BA 0484	7:52	8:15	305L	BA 0473	10:35	10:57	311
AA 0728	8:00	9:00	316	VS 0002t	10:35	13:45	328
BA 0795	8:00	8:25	311	IR 0711	10:45	11:45	325
DL 0001	8:00	9:10	325	DL 8021	10:52	11:35	327
AA 0046	8:05	9:05	363	BA 0490	10:57	11:20	311
AY 0831	8:10	8:45	309	BA 0417	11:00	11:25	329
VS 0012	8:10	9:10	331	AA 0038t	11:00	15:15	322
BA 0699	8:15	9:15	303R	QF 0010	11:05	12:05	301
AA 0732	8:15	9:15	321	VS 0011	11:05	12:05	320
AA 0101	8:15	9:15	322	AA 0098	11:05	11:27	334
VS 0021	8:17	10:15	332	ME 0202	11:07	12:00	316
BA 0862	8:25	8:50	311	EK 0001	11:15	12:15	307
BA 0865	8:45	8:57	305L	BA 0367	11:15	13:25	365
AY 0832	8:45	9:20	309	VS 0008	11:20	11:40	305
BA 0700	8:57	9:10	305L	BA 0081	11:20	12:20	364
AA 0731	9:00	10:00	316	AA 0108	11:25	12:12	313
AA 0046t	9:05	17:30	363	BA 0874	11:25	11:50	329
BA 0499	9:10	9:40	311	AA 0081	11:27	11:50	334
VS 0012t	9:10	13:15	331	BA 0855	11:30	11:47	309
VS 0007	9:15	10:15	307	BA 0218t	11:35	19:35	332
BA 0699t	9:15	13:55	303R	VS 0005	11:40	12:00	305
AA 0732t	9:15	12:25	321	IR 0711t	11:45	15:00	325
BA 0208	9:20	10:25	317	BA 0368	11:47	12:05	309
AA 0078	9:25	10:20	335	VS 0045	12:00	13:00	327
AA 0104	9:30	10:22	318	BA 0479	12:00	12:12	311

Table D.3: Many-objective stand allocation operation-stand list for the 12^{th} of August, 2016 with Easterly runway configuration for Terminal 3 (3/4)

Flight no.	**Start time**	**End time**	**Stand**	**Flight no.**	**Start time**	**End time**	**Stand**
AA 0135	12:12	13:00	313	RJ 0111	14:25	15:15	327
BA 0860	12:12	12:25	311	VS 0041	14:25	14:40	307
AA 0080	12:15	13:15	316	BA 0274	14:30	15:05	313
EK 0002	12:15	13:15	307	EK 0030	14:40	15:55	305
BA 0288	12:20	12:42	305	AY 0840	14:40	15:10	309
BA 0467	12:25	12:40	309	BA 0701	14:45	15:07	311
BA 0697	12:25	14:22	319	VS 0042	14:50	15:40	307
AA 0733	12:25	13:25	321	JL 0043	14:50	16:32	318
BA 0847	12:35	13:02	311	BA 0867t	14:55	22:59	321
BA 0850	12:40	12:55	309	VS 0401	14:55	17:05	331
BA 0868	12:40	13:40	303L	PK 0757	14:55	16:05	316
BA 0209	12:42	13:05	305	AA 0091	15:00	16:00	342
BA 0501	12:45	13:45	329	IR 0710	15:00	16:00	325
BA 0219	12:50	13:50	336	BA 0275	15:05	15:40	313
BA 0084	12:55	13:17	317	BA 0486	15:07	15:30	311
BA 0493	13:00	14:00	334	EK 0031	15:10	16:10	301
BA 0480	13:02	13:30	311	JJ 8084t	15:10	20:10	326
AA 0105	13:15	14:15	316	CX 0238	15:10	16:05	317
QF 0009	13:15	14:15	340	RJ 0112	15:15	16:05	327
VS 0250	13:15	14:15	331	AA 0107	15:15	16:15	322
BA 0289	13:17	13:40	317	VY 7100	15:20	15:42	309
AA 0136	13:20	13:42	327	BA 0475	15:25	15:47	303L
EK 0029	13:25	14:40	305	VS 8003	15:40	16:30	307
BA 0856	13:25	15:35	365	VY 7101	15:42	16:05	309
BA 0485	13:30	13:42	309	BA 0370	15:47	16:10	303L
BA 0468	13:40	14:40	318	VS 0652	15:50	16:50	328
AA 0079	13:42	14:05	327	PK 0758	16:05	17:15	316
BA 0704	13:42	13:55	309	EK 0031t	16:10	20:15	301
BA 0501t	13:45	17:45	329	VS 0251	16:10	17:37	313
VS 0023	13:45	14:45	328	BA 0703	16:10	16:35	305L
BA 0863	13:50	14:05	311	AY 0833	16:10	16:37	311
BA 0867	13:55	14:55	321	CX 0250	16:20	17:20	330
BA 0362	13:55	14:55	303R	VS 0301	16:30	18:42	335
BA 0493t	14:00	18:45	334	JL 0044	16:32	18:15	318
BA 0502	14:05	14:20	311	VY 7842	16:35	17:00	309
VS 0024	14:10	14:25	307	BA 0418	16:35	17:00	305L
JJ 8084	14:10	15:10	326	AY 0834	16:37	17:05	311
AY 0839	14:10	14:40	309	BA 0369	16:50	17:15	303L
CX 0257	14:15	15:10	317	VS 0652t	16:50	20:30	328
QF 0009t	14:15	19:30	340	VY 7843	17:00	17:25	309
BA 0470	14:22	16:20	319	AY 0995	17:05	17:50	305R

Table D.4: Many-objective stand allocation operation-stand list for the 12^{th} of August, 2016 with Easterly runway configuration for Terminal 3 (4/4)

Flight no.	**Start time**	**End time**	**Stand**	**Flight no.**	**Start time**	**End time**	**Stand**
VS 0025	17:05	19:15	331	UL 0504	19:45	20:30	305
CX 0239	17:10	18:10	327	BA 0851t	19:55	22:59	329
BA 0798	17:15	17:40	303L	VS 0026t	20:10	22:59	318
BA 0799	17:20	17:45	311	JJ 8085	20:10	21:10	326
BA 0861	17:20	18:20	303R	BA 0059	19:35	20:35	332
AA 0141	17:30	18:30	363	BA 0705	19:35	21:47	313
VS 0601	17:37	19:05	313	BA 0869	19:40	21:49	331
EK 0003	17:40	18:15	307	AY 3125	19:40	21:49	309
BA 0858	17:45	18:45	329	EK 0006	20:15	21:15	301
BA 0482	17:45	18:10	311	ME 0204	20:17	21:00	325
BA 0875	17:50	18:05	309	BA 0857	20:20	22:09	311
AY 0996	17:50	18:35	305R	CX 0254	20:25	21:20	327
GA 0086	17:55	19:02	316	BA 0503	20:25	22:12	317
BA 0491	17:55	18:55	303L	VS 0651	20:30	21:30	328
BA 0706	18:05	18:20	309	BA 0419	20:45	22:22	316
WY 0101	18:05	18:57	317	BA 0487	20:50	22:24	305R
CX 0256	18:10	19:10	327	BA 0371	21:00	22:29	305L
EK 0032	18:15	18:50	307	AA 0142	21:10	22:34	307
BA 0861t	18:20	22:59	303R	BA 0471	21:30	22:44	325
BA 0481	18:40	19:02	309	BA 0472n	21:44	23:59	319
VS 0300	18:42	20:55	335	AA 0090	21:45	22:52	327
BA 0364	18:45	19:45	334	BA 0854n	21:47	23:59	313
BA 0491t	18:55	22:59	303L	BA 0846n	21:49	23:59	331
BA 0851	18:55	19:55	329	AY 3126n	21:49	23:59	309
WY 0102	18:57	19:50	317	BA 0478n	22:09	23:59	311
UL 0503	19:00	19:45	305	BA 0416n	22:12	23:59	317
GA 0087	19:02	20:10	316	BA 0866n	22:22	23:59	316
BA 0504	19:02	19:25	309	BA 0702n	22:24	23:59	305R
BA 0363	19:10	19:27	311	BA 0868n	22:29	23:59	305L
VS 0026	19:10	20:10	318	AA 0101n	22:34	23:59	307
EK 0005	19:15	19:27	307	BA 0468n	22:44	23:59	325
BA 0870	19:27	19:45	311	AA 0099n	22:52	23:59	327
EK 0004	19:27	19:40	307	BA 0360n	22:59	23:59	321
CX 0253	19:30	20:25	327	BA 0492n	22:59	23:59	303R
BA 0469	19:30	21:44	319	BA 0366n	22:59	23:59	303L
QF 0002	19:30	20:30	340	BA 0500n	22:59	23:59	329
ME 0203	19:35	20:17	325	VS 0045n	22:59	23:59	318

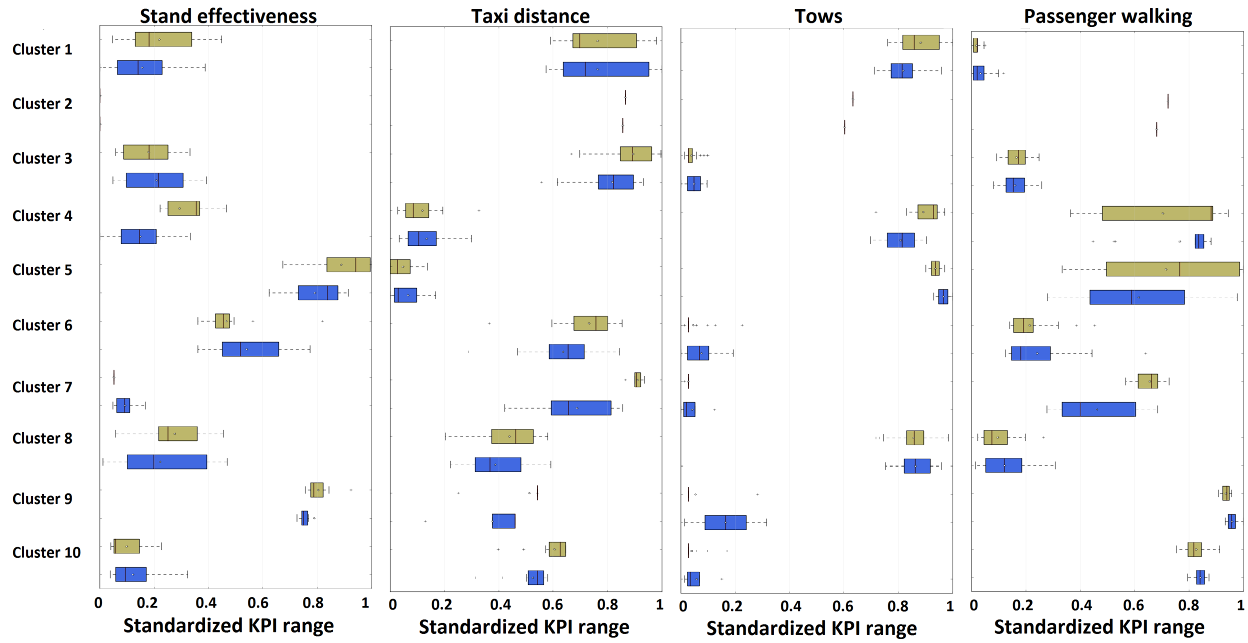

Figure D.2: Box plot of the 10 clusters of the reference test case(Test Case 1) and to the projected test case(Test Case 2), (blue = Test Case 1, yellow = Test Case 2)

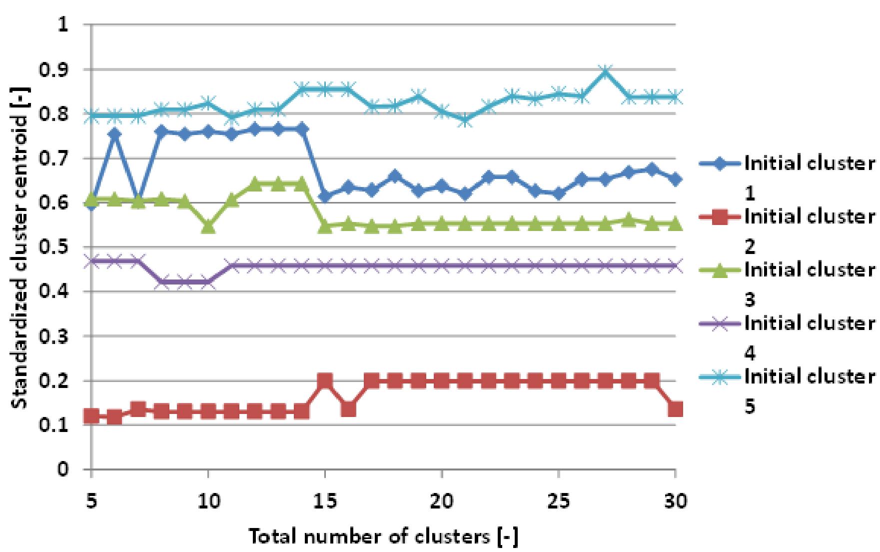

Figure D.3: The aircraft taxi distance centroid of the initial clusters as the total number of clusters is varied

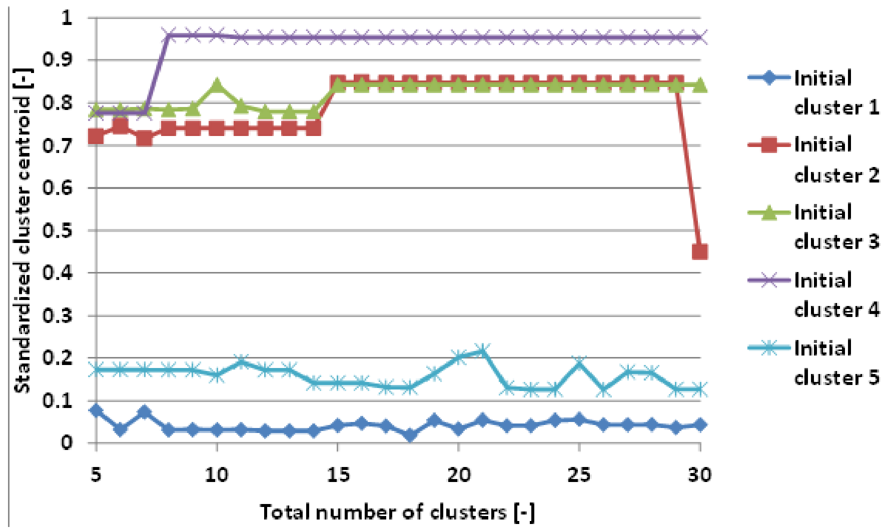

Figure D.4: The passenger walking distance centroid of the initial clusters as the total number of clusters is varied

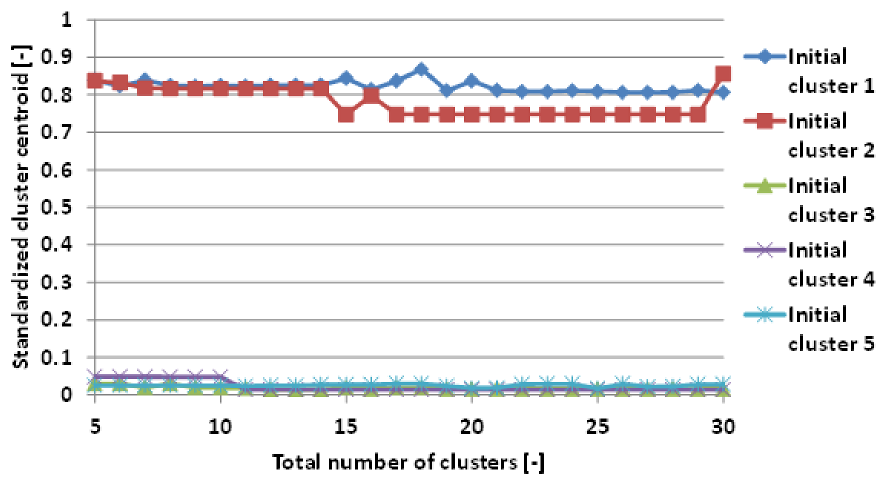

Figure D.5: The towing operations centroid of the initial clusters as the total number of clusters is varied

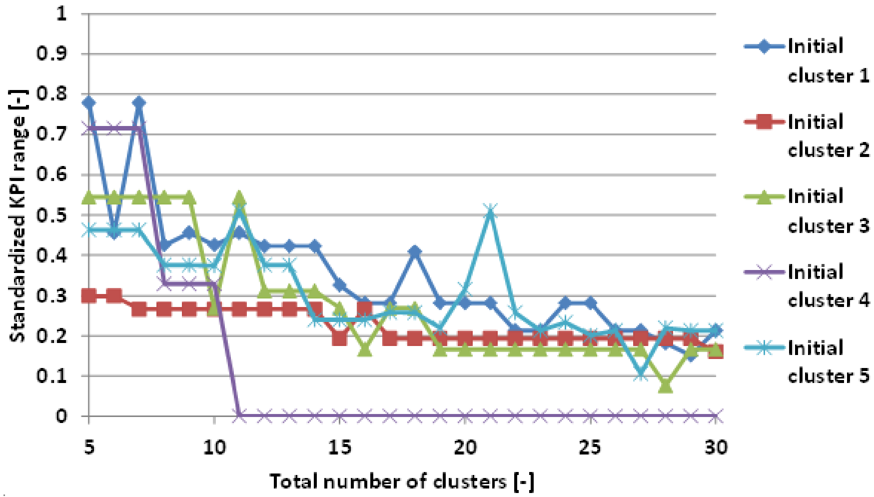

Figure D.6: The aircraft taxi distance objective KPI range of the initial 5 clusters as the number of clusters is varied

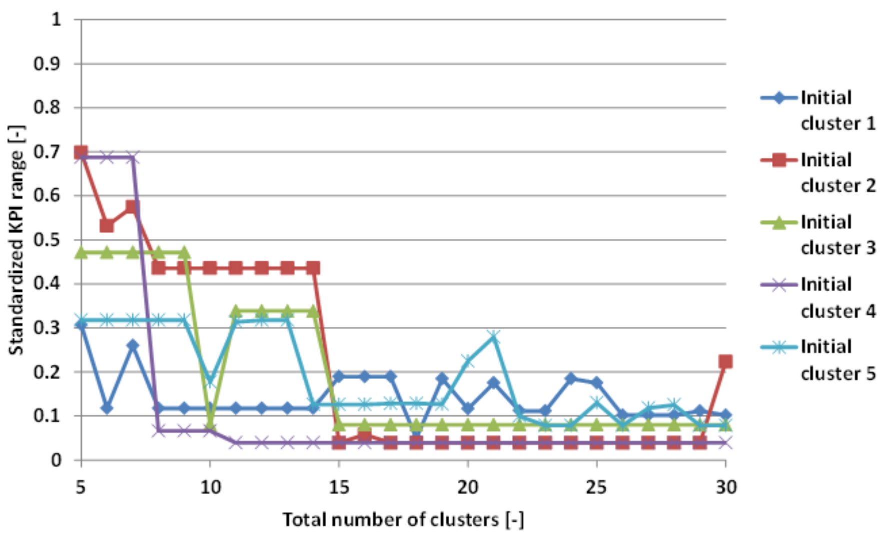

Figure D.7: The passenger walking distance objective KPI range of the initial 5 clusters as the number of clusters is varied

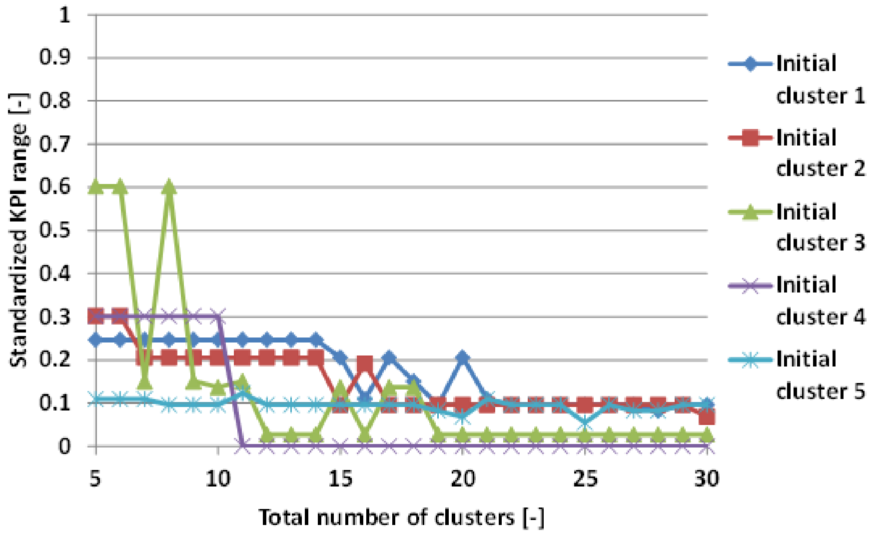

Figure D.8: The aircraft tows objective objective KPI range of the initial 5 clusters as the number of clusters is varied

Table D.5: Numerical representation of the standardized KPI ranges of the 10 clusters for Test Case 1(LHR Terminal 3 with Easterly 1 runway configuration for the flight schedule of 12^{th} August, 2016)

Cluster	Obj2	Obj3	Obj4	Obj5
1	(0-0.387)	(0.57-1)	(0-0.117)	(0.71-0.959)
2	(0)	(0.856)	(0.682)	(0.6)
3	(0.048-0.392)	(0.557-0.93)	(0.08-0.258)	(0-0.095)
4	(0-0.33)	(0.033-0.298)	(0.446-0.88)	(0.698-0.9)
5	(0.62-0.913)	(0-0.166)	(0.28-0.978)	(0.93-1)
6	(0.36-0.774)	(0.286-0.845)	(0.124-0.64)	(0-0.19)
7	(0.048-0.166)	(0.42-0.856)	(0.277-0.685)	(0-0.123)
8	(0.01-0.467)	(0.221-0.592)	(0.014-0.3)	(0.753-0.958)
9	(0.72-1)	(0.129-0.458)	(0.933-1)	(0.014-0.315)
10	(0.037-0.322)	(0.31-0.58)	(0.794-0.874)	(0.014-0.15)