Dedicated to innovation in aerospace

NLR-TR-2016-461 |

A multi-agent operational planning model for airport stakeholders

using capacity forecasts in winter scenarios

CUSTOMER: Netherlands Aerospace Centre

NLR – Netherlands Aerospace Centre

Netherlands Aerospace Centre

NLR is a leading international research centre for aerospace. Bolstered by its multidisciplinary expertise and unrivalled research facilities, NLR provides innovative and integral solutions for the complex challenges in the aerospace sector.

NLR's activities span the full spectrum of Research Development Test & Evaluation (RDT & E). Given NLR's specialist knowledge and facilities, companies turn to NLR for validation, verification, qualification, simulation and evaluation. NLR thereby bridges the gap between research and practical applications, while working for both government and industry at home and abroad.

NLR stands for practical and innovative solutions, technical expertise and a long-term design vision. This allows NLR's cutting edge technology to find its way into successful aerospace programs of OEMs, including Airbus, Embraer and Pilatus. NLR contributes to (military) programs, such as ESA's IXV re-entry vehicle, the F-35, the Apache helicopter, and European programs, including SESAR and Clean Sky 2.

Founded in 1919, and employing some 650 people, NLR achieved a turnover of 73 million euros in 2014, of which three-quarters derived from contract research, and the

EXECUTIVE SUMMARY

UNCLASSIFIED

Dedicated to innovation in aerospace

A multi-agent operational planning model for airport stakeholders

using capacity forecasts in winter scenarios

REPORT NUMBER
NLR-TR-2016-461

AUTHOR
J.A.P. Borst

REPORT CLASSIFICATION
UNCLASSIFIED

DATE

KNOWLEDGE AREAS
Luchtverkeersmanagement (ATM)- en luchthavenoperaties
Planning, geavanceerde (sensor)informatieverwerking en -regeling

DESCRIPTORS
Airport Capacity
Runway Allocation
Snow Removal
Multi-Agent Systems

Problem area

Airports have a hard time keeping up with the air traffic growth rate. Apart from the expansion of airport infrastructure to increase capacity, airports aim to higher the efficiency of operations. All stakeholders (ATC, airlines, and service providers) require capacity figures in order to plan their operations and thus rely on airports to provide these. Capacity underestimation lead to unnecessary cancellation costs, customer dissatisfaction, and inefficient use of the system, whilst overestimations lead to long delays and congestion. These are problems that are introduced in (pre-)tactical planning; a few days before the planning execution. Accurate capacity forecasting is one means of increasing predictability and therefore the use of resources. How to integrate accurate capacity forecasts in the planning process of multiple stakeholders?

Description of work

This document is the thesis research project of Jelmer Borst. The research entails the development of capacity forecasting models and integrating these as part of a negotiation model for distributed operational planning. The content focusses on the forecasting of runway operations, snow removal operations, and de-icing operations, based on winter weather forecasts.

Results and conclusions

This document presents heuristic models as alternative to computationally expensive planning algorithms. Additionally, decision flows for air traffic control, snow removal, de-ice operator and airlines are presented as basis for distributed planning simulation using principled negotiation. The simulation is the basis for a decision support system for predictive operations. Additionally, the impact of overestimating and underestimating of capacity shows a 1.5% increase in delay and cancellation costs for each deviation percentage with respect to the realization.

Applicability

The focus of this research is planning under winter scenarios. The underlying predictive models are extended to include winter capabilities and therefore remain valid for other weather scenarios.

The capacity models are input for an airport collaboration toolset. The stakeholders included are the airport, air traffic control, snow removal, and de-icing operator. The same methodology can be applied to other stakeholders whom are involved in the airport operations or in different areas that includes operational planning processes.

Lastly, this work is applicable to any major airport and does not confine itself to a specific airport.

NLR
Anthony Fokkerweg 2
1059 CM Amsterdam
p) +31 88 511 3113 f) +31 88 511 3210

Dedicated to innovation in aerospace

NLR-TR-2016-461 |

A multi-agent operational planning model for airport stakeholders

using capacity forecasts in winter scenarios

CUSTOMER: Netherlands Aerospace Centre

AUTHOR:

J.A.P. Borst Netherlands Aerospace Centre

NLR - Netherlands Aerospace Centre

CUSTOMER	**Netherlands Aerospace Centre**
CONTRACT NUMBER	
OWNER	**Netherlands Aerospace Centre**
DIVISION NLR	**Aerospace Operations**
DISTRIBUTION	**Limited**
CLASSIFICATION OF TITLE	**UNCLASSIFIED**

APPROVED BY :		
AUTHOR	**REVIEWER**	**MANAGING DEPARTMENT**
J.A.P. Borst	H.H. Hesselink	R.W.A. Vercammen
DATE	DATE	DATE

Abstract

Airports have a hard time keeping up with the air traffic growth rate. Apart from the expansion of airport infrastructure to increase capacity, airports aim to higher the efficiency of operations. All stakeholders (ATC, airlines, and service providers) require capacity figures in order to plan their operations and thus rely on airports to provide these. Capacity underestimation lead to unnecessary cancellation costs, customer dissatisfaction, and inefficient use of the system, whilst overestimations lead to long delays and congestion. These are problems that are introduced in (pre-)tactical planning; a few days before the planning execution. Accurate capacity forecasting is one means of increasing predictability and therefore the use of resources.

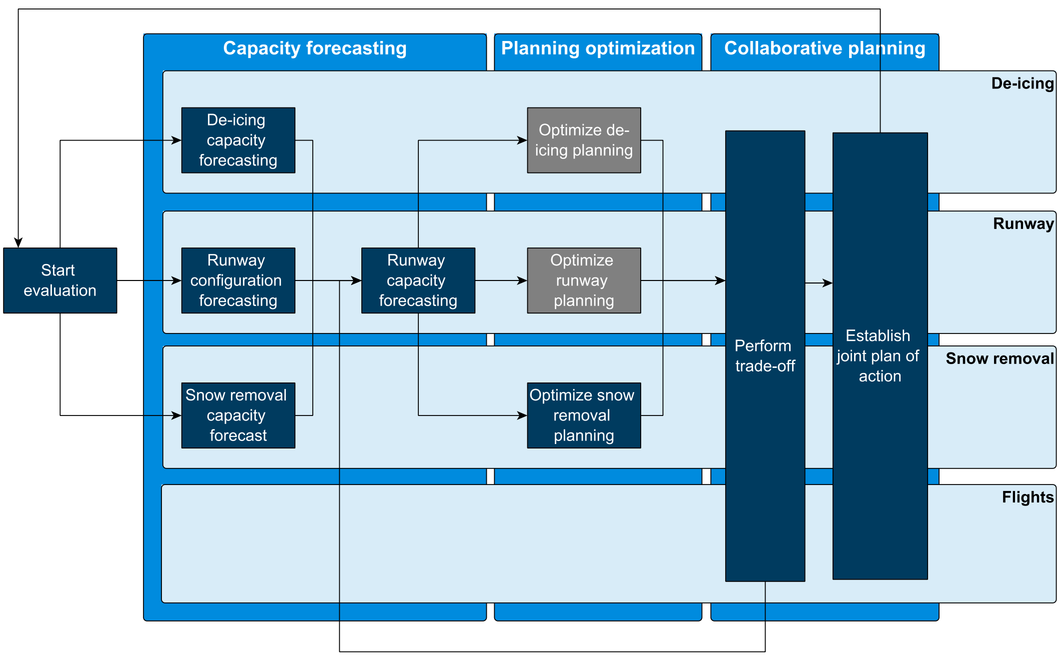
The above lead to the following research objective:

Research objective
"To increase predictability in the (pre-)tactical airport airside operational processes through integrating capacity forecasting and decision support for air traffic control, the airport and service providers under winter conditions."

At the core of the objective of the research objective, are the 2 main goals:

1. To extend current capacity forecasting models to include winter conditions, thus allowing for all-weather capacity forecasting.
2. To develop a decision support facility that evaluates the effect of capacity forecasting and integrates the collaborative planning of runway management, de-icing, and snow-removal operations.

The above objective and goals require forecasting for the runway configuration and forecasting for de-icing, snow removal, and runway capacity. This is used in planning algorithms for de-icing, snow removal, and runway flight planning. Lastly, the stakeholders need to establish a joint plan of action through collaborative planning with the aforementioned planning algorithms based on the capacity forecasts.



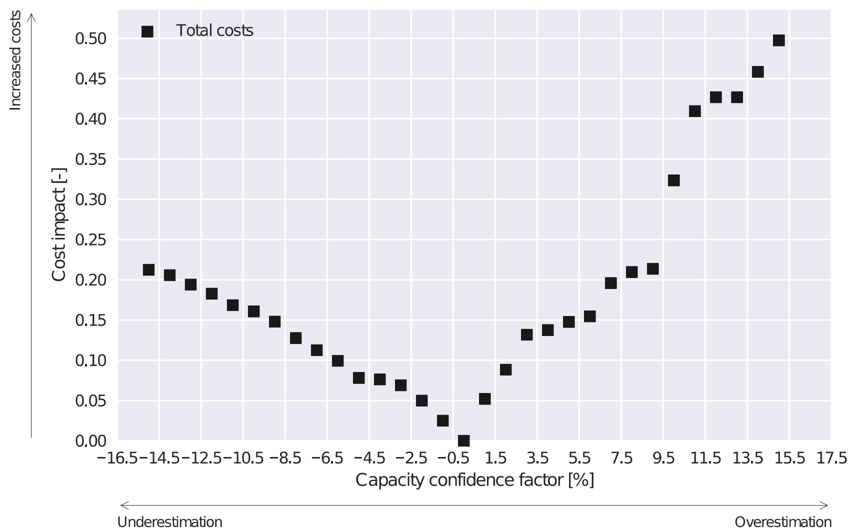
Runway, de-icing, and snow removal capacity is mostly determined by meteorological influences such as precipitation, temperature and wind conditions as well as available staff and equipment. Therefore, KNMI model output statistics (MOS) forecast data has been used to determine aircraft wind and visibility conditions and snow accumulation. These are then used as input to ensure values do not exceed safety limitations, such as maximum cross or tailwind or snow depth at the runway.

The joint plan of action is established through a multi-agent negotiation model using the principled negotiation protocol. Each stakeholder (air traffic control, snow removal team, de-icing service provider, and airlines) is modelled as a self-motivated agent, aiming to maximize their goals. For each agent an option generation algorithm is introduced that resembles the agent its decision making.

- Runway management: Ensure safe operations and deliver best capacity / demand fit
- Runway flight planning: Minimize arrival and departure delays
- Snow removal management: Satisfy runway availability during snowfall
- De-icing planning: Minimize departure delays
- Airlines: Minimize (disruption) costs through possible flight cancellations

Simulating the negotiation process shows an average of 13.8 proposals required per agent to reach an agreement. This is acceptable with a fairly large amount of agents (121, consisting of mostly airlines) and relatively ‘dumb’ agents compared to sophisticated planning algorithms and long-term experts. Estimated is that in reality the negotiation process would require an average of 0.5 proposals per agent to reach the agreement. Both are very favourable compared to the current situation in which all stakeholders are meeting for hours in similar winter scenarios.

Lastly, the costs of over- or underestimating runway capacity are analysed. In both cases costs are impacted significantly. Underestimations lead to unnecessary cancellations and cancellations costs increase, whilst overestimations lead to unnecessary delays and delay costs increasing. Underestimating with 10% lead to a 15% increase in total costs and 10% overestimating lead to 20% increased costs. Whilst both lead to extra costs, underestimating capacity remains a better option than overestimating it.



Contents

List of figures

List of tables

Abbreviations

Acronym	Description
AAS, AMS	Amsterdam Airport Schiphol
A-CDM	Airport Collaborative Decision Making
AEA	Association for European Airlines
ANSP	Air Navigation Service Provider
AOP	Airport Operations Plan
ARR	Arrival
ATC	Air Traffic Control
ATFCM	Air Traffic Flow and Capacity Management
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
CAT	ILS Category
CDPS	Cooperative Distributed Problem Solving
DAI	Distributed Artificial Intelligence
DCB	Demand and Capacity Balancing
DEP	Departure
DPS	Distributed Problem Solving
EUROCONTROL	European Organisation for the Safety of Air Navigation
FAA	Federal Aviation Administration
FIFO	First in, First out
GSS	Ground Support System
ICAO	International Civil Aviation Organization
IFR	Instrument Flight Rules
ILS	Instrument Landing System
KPA	Key Performance Area

KPI	Key Performance Indicator
LP	Linear Programming
MAS	Multi-Agent System
MILP	Mixed-Integer Linear Programming
MOS	Model Output Statistics
NLR	Netherlands Aerospace Centre
NWP	Numerical Weather Prediction
PIREP	Pilot Report
RCCE	Runway Capacity Curve Envelope
ROT	Runway Occupancy Time
RVR	Runway Visual Range
RWY	Runway
SLDT	Scheduled Landing Time
SMA	Self-Motivated Agent
STOT	Scheduled Take-Off Time
TALPA	Take-off And Landing Performance Assessment
TLDT	Target Landing Time
TTOT	Target Take-Off Time
VFR	Visual Flight Rules

Nomenclature

Symbol	Description
α_r	Heading of runway r
α_w	Wind direction
ϵ	Visual contrast threshold
Δt	Time step
η_p, η_R	Displacement or rotary plough efficiency
ρ	Ratio of water density over snow density, typical values range from 1:11 to 1:20 depending on the type of snow and compaction
ρ_s	Snow density
b_e, b_a	Effective or actual displacement plough blade width
$c_{t,r}$	Variable indicating the clearing of runway r at time t
d_{max}	Maximum allowable snow depth
$d_{t,r}$	Snow depth on runway r at time t
$n_{t,r}$	Number of runways available at time t
$n_{t,r}^{max}$	Number of runways available at time t, only considering wind direction and cross/tailwind limits.
r_t	Whether runway r can be used at time t s.t. $r_t \in R_t$
t	Time, where $t \in T$
t_{sr}	Required runway snow clearing time
q_p, q_R	Displacement or rotary plough capacity
x_t	Decision variable indicating if another runway can be cleared, without reaching d_{max} on the current used runway
C	Set of runway configurations
C_F^D	Forecasted de-icing capacity
C_F^R	Forecasted runway capacity
C_F^S	Forecasted snow removal capacity
C_3	Constant, relating snow density to snowflake diameter; dependent on snow type (dry or wet/rimed)

C_t	Tuple consisting of inbound and outbound runway capacity
C_{DB}	Constant of proportionality
I_o	Luminous intensity, measured in candles
I_t	Rate or intensity of water equivalent of snow, usually in mm/h
M_t	Water melt intensity, usually in mm/h
R	Set of usable runways s.t. $R \subset S$
S	Set of all airport's runways
S_a	Surface area of snow removal priority area a
T	Set of time series
T_t	Temperature at time t
V	Velocity
V_d	Daytime visibility
V_c	Crosswind
$V_{c,max}$	Crosswind limit
V_n	Night-time visibility
V_t	Snow terminal velocity
V_t	Tailwind
$V_{t,max}$	Tailwind limit
V_w	Wind speed
Vis	Visibility

1 Introduction

Airports have a hard time keeping up with the air traffic growth rate. Apart from the expansion of airport infrastructure to increase capacity, airports aim to higher the efficiency of operations. All stakeholders (air traffic control, airlines, and service providers) require capacity figures in order to plan their operations and thus rely on airports to provide these. Capacity underestimation lead to unnecessary cancellation costs, customer dissatisfaction, and inefficient use of the system, whilst overestimations lead to long delays and congestion. These are problems that are introduced in (pre-)tactical planning; a few days before the planning execution. Accurate capacity forecasting is one means of increasing predictability and therefore the use of resources.

1.1 Problem formulation

Airlines have little influence in the expansion of airport capacity, but require capacity figures in order to plan their operations and thus rely on airports to provide these. Currently, declared capacity values are used in long-term planning, but these values are not representative at all scenarios. Factors such as weather affect the capacity such that it affects flight planning.

Underestimations of capacity may lead to unnecessary cancellation costs, customer dissatisfaction, and inefficient use of the system, whilst overestimations lead to long delays and congestion. This is an issue that arises due to the uncertainty (unpredictability) of the operations. This uncertainty can be limited through receiving up-to-date information and forecasting.

Additionally, most current planning systems include advanced algorithms that run in batches (few times a day) but fail to provide real-time planning support. Most real-time planners are done manually, through the use of experts. Additionally, planning systems are at place to support one organization (intra-enterprise). However, with a lot of dependencies in airport operations, there is a need to shift towards inter-enterprise planning [1]. This shift offers the possibilities to spot issues earlier on and help synchronizing supply and demand [2]. Both trends are visualized in Figure 1, where trajectory (1) is desired and can be achieved through firstly move to real-time planning (2) and then move to inter-enterprise planning (3).

In short, two main gaps are identified:

1. Uncertainty in operations: Little capacity forecasting done by all stakeholders
2. Lack of coordination: Little capacity information shared between stakeholders

Based on these two major gaps: how to integrate accurate capacity forecasts in the planning process of multiple stakeholders? And: how to effectively collaborate on the complete airport planning, combining each stakeholder’s wishes?

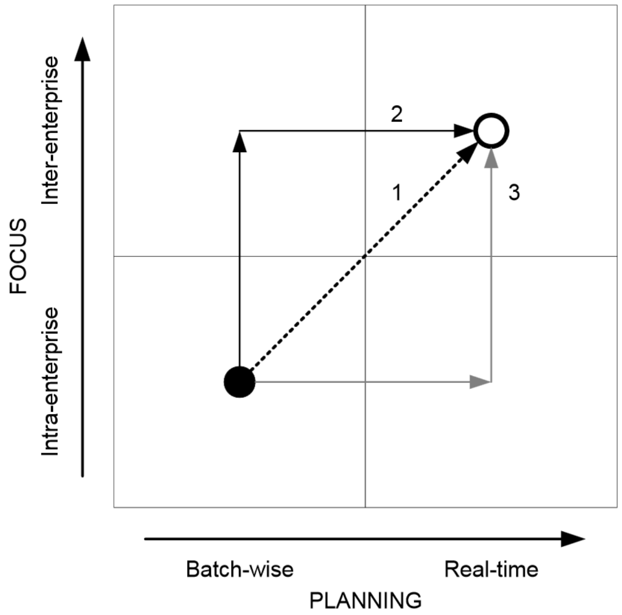


Figure 1: Change in enterprise systems [1]

1.2 Research objective and goals

Through delineation and taking into account scientific relevance, as well as time constraints, the following research objective is derived.

- **What**: Capacity forecasting
- **Who**: Airport, Air Traffic Control, de-icing service providers, and airlines
- **Where**: Airport runway operational processes
- **When**: Winter conditions
- **Why**: To increase operational efficiency and predictability
- **How**: Decision support facility for collaborative operational planning

The delineation is formalized into a research objective, which is defined as:

Research objective
"To increase predictability in the (pre-)tactical airport airside operational processes through integrating capacity forecasting and decision support for air traffic control, the airport and service providers under winter conditions."

At the core of the objective of the proposed research, are the 2 main objectives:

1. To extend current capacity forecasting models to include winter conditions, thus allowing for all-weather capacity forecasting.
2. To develop a decision support facility that evaluates the effect of capacity forecasting and integrates the collaborative planning of runway management, de-icing, and snow-removal operations.

In order to reach the above goals, the following sub-questions are defined that are required to provide a satisfactory answer to the objective. The methodologies that support in answering the questions are discussed in section 1.3.

1. How can the capacity forecast models be extended to include winter conditions?
   a. How to model runway capacity under winter conditions?
   b. How to model the relationship between de-icing capacity and runway capacity in winter conditions?
   c. How to model the relationship between snow removal capacity and runway capacity in winter conditions?
2. How to model a collaborative planning decision support facility?
   a. How to model the stakeholder decisions?
   b. How to include stakeholder interests?
   c. How to integrate forecast uncertainty?
   d. What is and how to choose the best decision w.r.t. the forecasted capacity?
   e. How to incorporate decision deviations (i.e. human factors)?
3. What advantages can be gained through planning with forecasted capacity?
   a. What are the effects for different stakeholders?
   b. What are impacts on the planning through capacity forecasting on efficiency?
   c. What are impacts on the planning through capacity forecasting on predictability?

1.3 Research scope and methodology approach

As the objective includes the extension of current runway capacity forecast models with the inclusion of winter conditions, this leads to scoping the research to airside capacity, snow removal capacity, and de-icing capacity. The reason to include all three is that each influences the other in winter conditions. That is to say, more collaboration is required. With respect to the stakeholders, this means that the main actors whom are responsible for the runway, snow removal, and de-icing processes are taken into account.

Summarized, it means that the scope of this research is limited to:

- The airport airside operational processes
- Airport runway, de-icing and snow-removal capacity
- The stakeholders:
  - Air Traffic Control, performing runway management at an airport
  - Airport, performing the snow-removal operations at an airport
  - Service provider, performing the de-icing operations at an airport
  - Airlines, performing flight operations between airports

The 2 main goals that were defined in the previous section result in 3 major elements for developing the model to evaluate the research objective, namely:

1. Capacity forecasting
2. Planning optimization
3. Collaborative planning

The process that links the forecasting of capacity and the decision support, whilst taking into account the four aforementioned stakeholders is shown in Figure 2. The grey processes, planning optimizers, are assumed external; assuming existing models that can be used and integrated and do not need to be developed within the research project. Snow removal planning models were not found in literature and developing one is therefore in scope for this thesis.

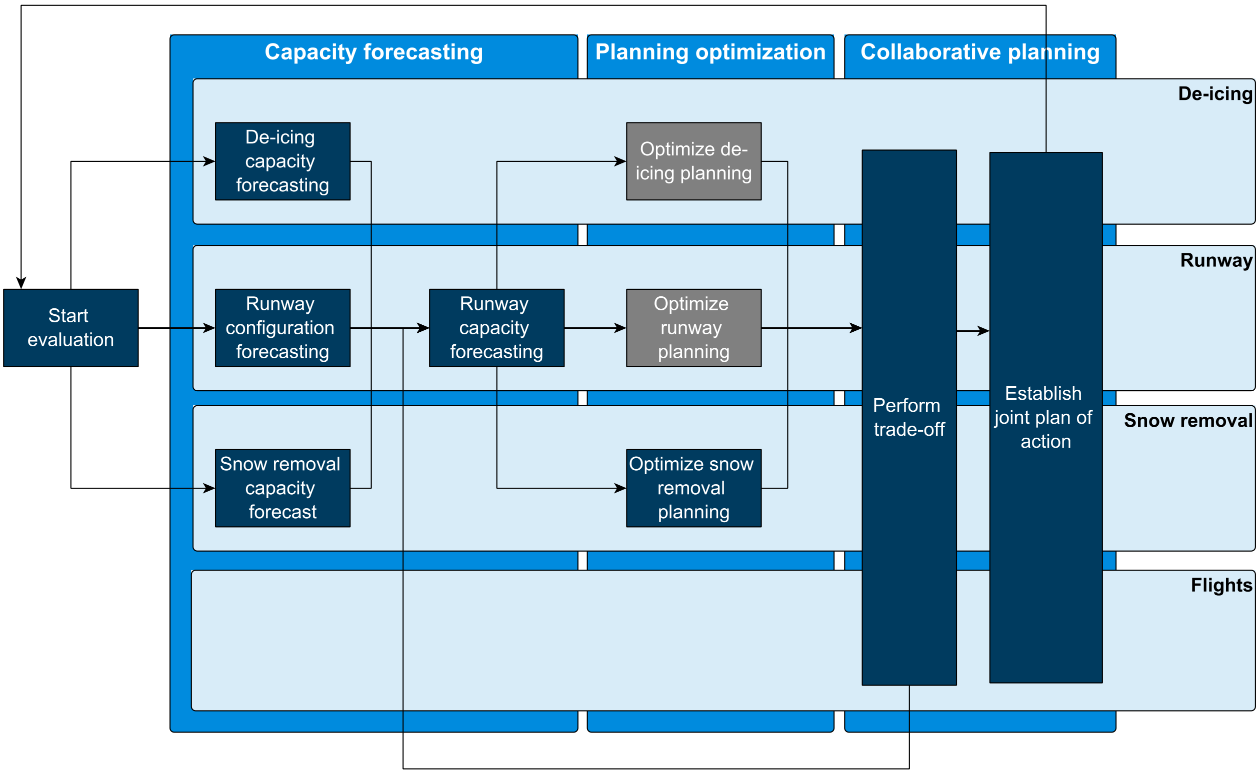


Figure 2: Research process flow indicating to-be-developed (dark blue) and of-the-shelf (grey) processes

The structure of Figure 2 is used as a basis for this document. The capacity forecasting is elaborated upon in chapter 2, planning modelling and optimization in chapter 3, and the collaborative planning is addressed in chapter 4. The integration of all three components can be found in chapter 5.

2 Airport capacity forecasting

The efficiency of an airport is a trade-off between demand and used or available capacity. There have been a multitude of efforts that work on the forecasting of demand, yet to make this trade-off accurately and increase the airport its efficiency, proper forecasting of capacity is vital. The purpose of capacity forecasting can be summarized as follows [3]:

- Major improvement in predictability of airport operations
- Provide input to planning systems through automatic airport capacity forecasts

In Figure 3, a general overview is shown with respect to the integration and goals of forecasting capacity. The dependencies in the models on many aspects of the airport's components, integration of flight plans, ATC systems, meteorological forecasts, planning and other airport systems are necessary in order to deliver useful capacity forecasts to the respective stakeholders.

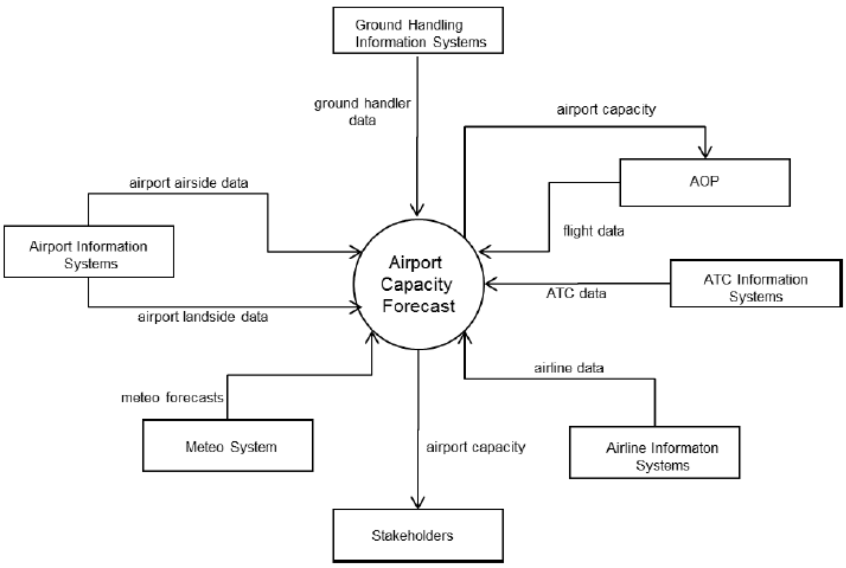


Figure 3: Airport capacity forecasting context [4]

One can provide forecasts for 3 particular phases: strategic, pre-tactical and tactical phase. The strategic phase is up to a week before execution, the pre-tactical phase up to a day before execution, and the tactical phase includes the day before and the day of execution. The scope here is the tactical and pre-tactical phase. In these phases, meteorological forecasts still have acceptable uncertainty ranges and are most useful in the airport operations. Additionally, it is scoped to runway capacity, de-icing capacity, and snow removal capacity as highlighted in Figure 4. The figure provides a comprehensive overview of all airport capacity components.

The first research question deals with the problem of extending forecast models to include winter conditions for the near-term. Firstly, the modelling of capacity is elaborated upon in section 2.1 as a basis. In order to extend forecasting models to include winter conditions, a deeper dive into weather forecast models and weather forecast model outputs is required to comprehend the input of the new model. This is done in section 2.1.3. Individually forecasting the capacity based on the weather information is then done in 2.2 thru 2.4, dealing with runway capacity, snow removal capacity and de-icing capacity, respectively.

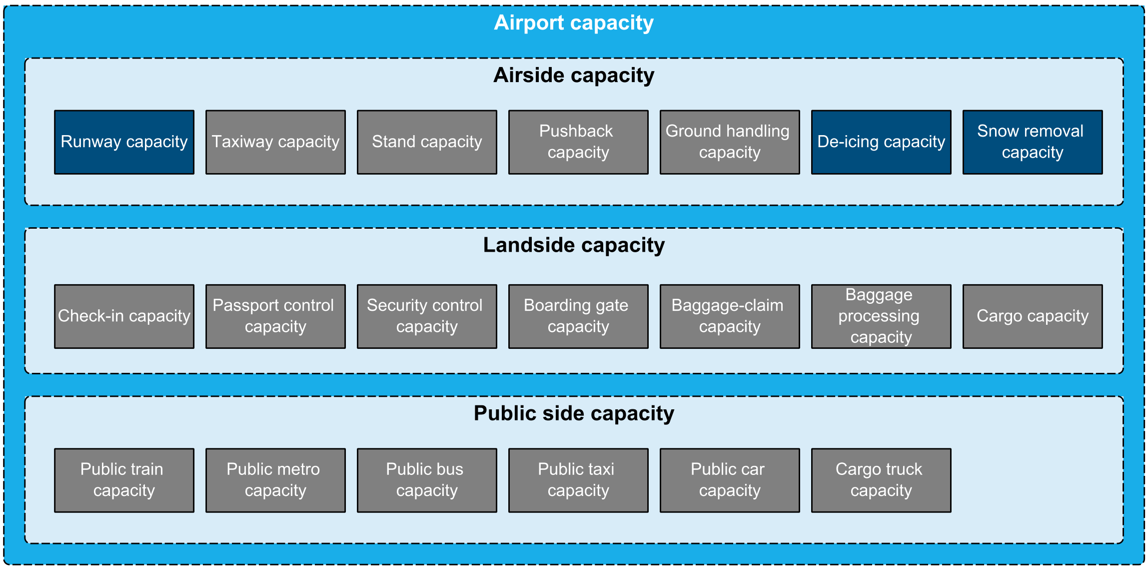


Figure 4: Airport capacity breakdown, based on [3]; in scope (dark blue), out of scope (grey)

2.1 Capacity modelling

Before diving into the forecasting of capacity, it is important to understand what capacity exactly is. This section therefore provides the baseline definitions of capacity in the first subsection, 2.1.1. Following, the main influencing factors on capacity are described, from which the ones that apply to this research are highlighted.

2.1.1 Capacity definitions

Capacity refers to the throughput of a facility, being the maximum number of entities that can be handled in a period of time. When referring to airport capacity, one usually refers to the runway capacity and the associated amount of aircraft that can be handled as this is constraining factor for the majority of airports. However, there is a lot more to airport capacity than just runway capacity as is shown in Figure 4. Generally, when talking of '(airport) capacity' one refers to the `Declared capacity'. Yet, there are 4 types of capacity that can be distinguished in process facilities [3] [5] [6]. Using runway capacity as an example, 'entities' refer to the aircraft that take-off or land (are processed).

- **Intrinsic Capacity**
  Availability of capacity (supply) directly related to infrastructure element or resource; theoretical capacity, does not include external limitations.

- **Operational Capacity**
  Also referred to as **Unconstrained Capacity**: Actual capacity (supply) provided by the infrastructure element or resource; recognizes infrastructural complexity.
- **Saturation Capacity**
  Also referred to as **Ultimate Capacity**: The maximum number of entities that can be served without violating any rules or regulations, assuming continuous demand.
- **Declared Capacity**
  Also referred to as **Practical Capacity**: Number of slots available for schedule coordination purposes, taking into account infrastructure, typical operating conditions, accepted delay and political issues. With declared capacity usually referring to average values that can be used for long-term planning, practical capacity can vary throughout the day, accounting for peaks and other influences.

The above definitions can be visualized as in Figure 5, where the practical capacity is matched to an acceptable amount of delay X. The saturation delay indicates the maximum throughput of the configuration but shows larger amounts of delay occurring. Lastly the unconstraint capacity is shown, which follows the same curve as the saturation capacity, however due to no additional constraints then safety it shows a higher capacity level for the same delay values. Clearly, it can be noted for each demand/delay curve in Figure 5 that steady-state delays growths towards infinity as movements/hour increase due to the nature of the problem: a 10 second delay for the first landing aircraft, introduces at least the same delay in the directly following aircraft.

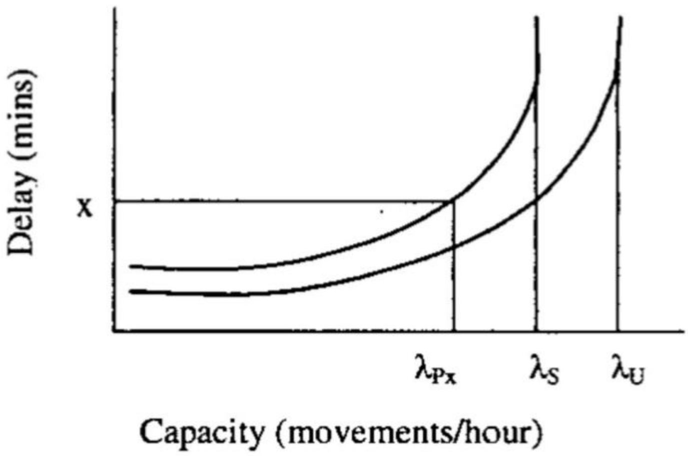


Figure 5: Capacity versus delay indicating practical (λ_{P_x}), saturation (λ_S) and unconstrained (λ_U) capacity [7]

Note: The capacity definitions along with Figure 5 are for general process facilities. In the case of runway capacity, the behaviour is slightly different. After the integration of flow management meant the process cannot be modelled stochastically anymore, which has led to decreased delay at high levels of capacity.

2.1.2 Capacity influencers

Depending on which capacity component one is looking at, there are different sources that impact the capacity level. Landside operations are primary dependent on resource availability and planning. Desks such as passport or security control are subject to the servicing rate of employees and the number of booths that are available, with employees working at a fairly steady rate.

In addition to resources and planning, airside operations also need to take into account the impacts of weather. When weather such as snow arrives, airside capacity is significantly impacted and may only leave a fraction of capacity remaining. But also wind direction and speeds impact capacity through the limitations in cross and tail winds, limiting runway configuration choices.

Lastly, on all aspects of airport operations and planning, rules and regulations are in effect. In the Netherlands, for example, noise abatement is defined by law to which airports simply must adhere to. These regulations are in place to minimize the annoyance amongst citizen of passing aircraft, but in place automatically limits the airport its operations.

Summarized, the list below is a comprehensive list of major influencers on the airport its capacity [8, pp. 238-245] [9]. The influencers highlighted in **bold** are deemed in scope and related to this research. Others are shown here for completeness.

- Airport characteristics
  - Geographic layout
  - Equipment
  - **Runway configuration**
  - **Runway size**
  - Runway exits and taxiways
- Meteorological conditions
  - **Wind speed & wind direction**
  - **Visibility conditions (RVR) & cloud base**
  - **Precipitation, snowfall and ice formation**
- Planning
  - **Staff availability**
  - **Equipment availability**
  - (Un)Scheduled maintenance
  - **Flight schedules and aircraft mixes**
  - Flight trajectories
  - **Aircraft arrival and departure ratios**
- External constraints
  - Noise limits
  - Runway restrictions
  - Safety regulations
  - EU regulations
  - **Human / social factors**
  - ATC workload

Most of the above influencing factors are mapped in Table 1 with respect to the impact per planning phase, partly on basis of [10]. It shows that influences such as human factors have considerable impact in the near-term, but is negligible in the long-term. With ATC guiding aircraft from, to, and around airports, the efficiency of an individual controller directly impacts capacity, yet when measured over a longer term the individual ATC performance evens out. Weather largely impacts the tactical phase as well and has very little influence on the long-term.

For strategic planning, the airport cannot use reliable weather forecasting and thus relies on general capacity figures. Regulations, for example, primarily impacts capacity on a strategic level. The rules at which the processes abide to do not change overnight, but do have substantial impact. Consider noise regulations as an example of a major impacting regulation. These lead to decreasing capacity at night and different runway use distribution over time.

Table 1: Capacity influencing factor impacts per planning phase

Impact	Tactical	Pre-tactical	Strategic
Considerable	• Meteorological conditions • Human factors • ATC workload	• Forecasted meteorological conditions	• Staff / equipment availability • Regulations and limits
Negligible		• Flight trajectories	• Human factors • Meteorological conditions

2.1.3 Meteorological conditions and forecasts

There are various meteorological models that aim to forecast the weather and are usually referred to as NWP models, numerical weather prediction models. In this research, forecasting data format that is used is Model Output Statistics (MOS). MOS aims to provide sensible weather parameters and is usually the output of a transformation of NWP output data. The weather parameters are a set of predictands that are the result of the forecasted physics of the NWP model.

Whilst other techniques usually deliver an ensemble forecast as the result of NWP model output, MOS enhances the NWP output with probabilities of events occurring. Events that are related to our research and are included in MOS data are snow or visibility levels. For example it forecasts the probability of visibility being larger than 5km, instead of merely providing with an (average) forecasted visibility range. Reliability of MOS is usually better than the probabilities that are the result of ensemble post-processing [11]. More information regarding MOS can be found in Appendix B for Dutch KNMI data and Appendix C for US data.

This research is scoped to winter conditions and thus requires snowfall forecasting data. The availability of forecast can be of 3 possible ways: no snow forecast is made, snow intensity category is given, or snow is already forecasted. In Appendix D US snowfall data is explored along with possible methods that can derive snowfall based on other forecast features, in the case where forecast data contain no snow features.

2.2 Runway forecasting

Within the forecasting of runway operations, two major components arise. These two components are the runway configuration and the runway capacity. Here, capacity is driven by the configuration but includes additional criteria and forecast data. In other words, the knowledge of the configuration does not de facto lead to a forecasted runway capacity. The coming two subsections will deal with each of the two components, respectively.

2.2.1 Runway configuration forecasting

During take-off or landing at a particular runway, the manoeuvres of an aircraft are affected by the wind. For aircraft, a headwind is favourable in both take-offs and landings. Namely, more lift is generated and allows for safer operations. Additionally, low crosswinds are favoured, as a high crosswind make it harder to manoeuvre and decreases the safety. Apart from safety, tailwind and crosswind decrease the ground speed at take-off. A lower ground speed leads to a longer required runway length, which might not be available. Therefore, tailwind and crosswind should be below the maximum allowable values.

The result of forecasted wind direction α_w and wind speed V_w on each runway s is different due to its geographic orientation α_s. It is important to know the components of the wind speed in terms of crosswind and tailwind ($V_{c,s}$ and $V_{t,s}$) due to the safety precautions that are defined using these components. Both can be found through simple trigonometry and the relations are shown in eq. (1) and eq. (2).

$$V_{t,s} = V_w \cos(\alpha_w - \alpha_s) \qquad \textit{eq. (1)}$$

$$V_{c,s} = V_w \sin(\alpha_w - \alpha_s) \qquad \textit{eq. (2)}$$

Apart from wind conditions impacting lift, the limits are also established with respect to the runway friction. Especially during crosswind operations a high friction runway is desired, as it prevents the aircraft from slipping sideways. But also during landings the friction is necessary to allow the aircraft to brake within the runway its length or during take-off when braking is required in case of a rejected take-off.

In wet or ice scenarios, the friction is reduced. To assess the impact, the runway is categorized using friction measurements and pilot reports (PIREPs) into a runway condition category (RCC). Or, if both are not available, the category may be determined by the (estimated) amount of liquid present on the runway. This may be done by using the Take-off and Landing Performance Assessment (TALPA) matrix (see Appendix D).

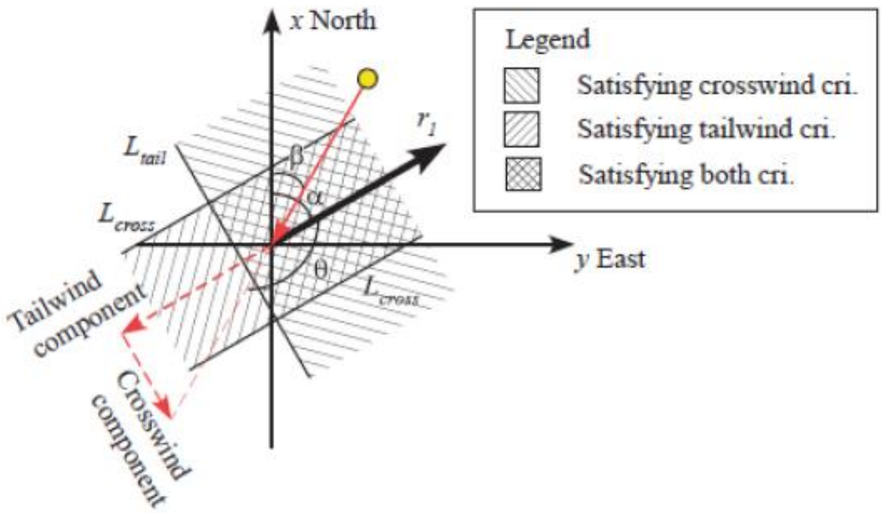


Figure 6: Feasible wind directions for a given runway r_1 [12]

For each given runway condition category, there exists a maximum tail and crosswind coefficient. Checking the cross- and tailwind component that exist for each runway s as done in eq. (3), results in the 'feasibility' of a runway. Figure 6 shows how runway can be checked for feasibility based on the wind direction and speeds. Namely, the hashed areas show the crosswind and tailwind limitations for a given runway, which the forecasted wind conditions can be compared against. Additionally, the snow depth of each runway should be below the maximum allowable depth (more information see section 2.3). This then leads to the set of feasible runways R and defined in eq. (4).

$$s = \begin{cases} 1, & if\, V_{t,s} \leq V_{t,max} \wedge V_{c,s} \leq V_{c,max} \wedge d_s < d_{max} \\ 0, & elsewhere \end{cases}, \qquad \forall s \in S \qquad \textit{eq. (3)}$$

$$R \in \{s | s \in S, s = 1\} \qquad \textit{eq. (4)}$$

With the feasible runways R, a set of feasible configurations C can be found that consist of all possible configurations that consist of runways r that exist in R, as shown in eq. (5). As elaborated in [13], air traffic control at many airports use the concept of runway configuration preference lists. This list consist of possible configurations that is already sorted, where a trade-off between capacity, noise, and other external factors have been made. Combining the set of feasible configurations and the preference list then leads to a sorted list that incorporates cross- and tailwind limitations.

$$C \in \{c | r \in c : r \in R\} \qquad \textit{eq. (5)}$$

For now, the availability of the runway in terms of snow is not accounted for in the set of feasible runway configurations. That is to say, the runway might be *feasible* (safe to use), but not available due to possible snow removal operations. Snow removal might occur before the snow depth reaches its maximum allowed depth. This is due to the fact that the runway condition is dependent on the snow removal operations. More can be found in section 2.3.

2.2.2 Runway capacity forecasting

Visibility is the main driver that determines runway capacity during operations. The visibility refers to seeing the runway over a distance and from a certain height. When a pilot lands an aircraft, it needs to be able to see that a runway is clear of any obstacles and what its altitude is with respect to the runway. If the pilot is not able to do that, instruments are required and for safety reasons more time is reserved per aircraft.

Because of safety regulations, runway configurations have decreased capacity under lower visibility conditions. The levels of capacity are the declared capacity values associated with a certain visibility condition. The conditions are a factor of cloud base height and runway visibility; an example is shown in Figure 7.

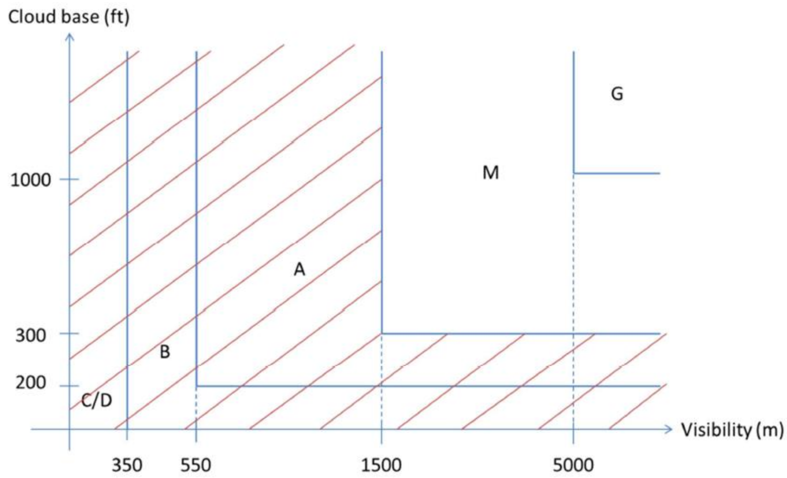


Figure 7: Visibility categories [14]

Combining the forecasted condition with this capacity as done by Hesselink et al. [15], see eq. (6), provides the forecasted reference capacity. Hereby, the weighted average capacity C_F^R is calculated by multiplying the probability $P(M)$ for each visibility condition M, times the capacity $C_M(X,Y)$ of a configuration X in peak category Y under that condition. It is referred to as reference capacity, as snow removal procedures are not yet taken into account that disturb the capacity levels (see 'clearance interval' in Figure 8).

$$C_F^R = \sum P(M) C_M(X, \mathrm{Y}) \qquad \textit{eq. (6)}$$

The maximum theoretical runway capacity decreases over time under winter conditions due to the snow accumulation, as can be seen in Figure 8. However, due to large safety margins that are applied, this effect is not included in the computation of capacity as the practical runway capacity already takes this into account.

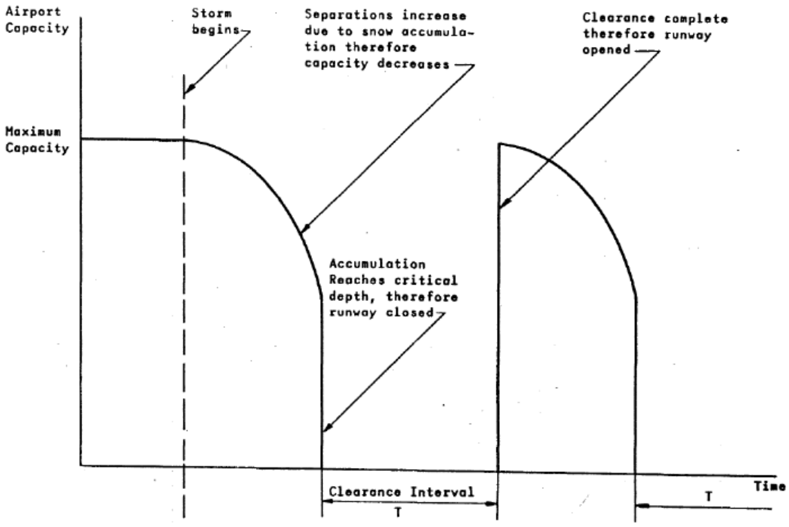


Figure 8: Airport runway capacity under snow conditions [16]

2.3 Snow removal capacity forecasting

During snow removal procedures there are three types of equipment that are being used [17]:

1. Rotary plough, also known as blower
2. Displacement plough
3. Sweeper

In many cases, the sweeper and displacement plough are combined, but the procedure remains the same. The displacement plough will move the snow from the runway to the side of the runways and uses the sweeper to remove the remaining snow. This is done at a relatively high speed: 30-40kph, depending on the equipment. With the width of a runway being around 45m, multiple ploughs need to clear next to the other or multiple passes are required.

At the runway banks, the slower rotary plough will gather the heaps of snow and blow either field inwards or into a truck when the former is not possible. Lastly, a de-icing truck follows provide anti-icing liquid that aims to minimize the snow build-up and ice formation. The ice formation is important to minimize, as its very low friction results in bad braking action and has a major impact on safety.

Based on the previous, the capacity of rotary ploughs is determined through the speed of processing snow, usually in tonne/hr, and the capacity of a displacement plough and sweeper is determined by its blade width i.e. the area it can cover whilst clearing under a certain velocity.

Clearing an area S_a of priority a, velocity of clearing V with a blade of width b_e and n_p number of ploughs, the time to clear the area $t_a$can be computed as in eq. (7). This relation also includes the efficiency factor η_p, which can be assumed constant at 70% as per the Airport Snow and Ice Control Equipment advisory of the FAA [17].

$$t_{p,a} = \frac{S_a d_s \rho_s}{\eta V \sum_p^P q_p} = \frac{S_a}{n_p \eta_p V b_e} \qquad \text{eq. (7)}$$

$$b_e = \frac{q_r \eta_R}{d_s V \rho_s \eta_p} \times 4.545 = b_\alpha \cos\theta \qquad \text{eq. (8)}$$

The capacity of rotary ploughs, q_R, is the amount of snow it can process per time unit. The time required to clear can be easily computed as in eq. (9), using the same notation as in eq. (7).

$$t_{R,a} = \frac{d_s \rho_s}{\eta_R \sum_r^R q_r} = \frac{d_s \rho_s}{n_R \eta_R q_R} \qquad \text{eq. (9)}$$

$$t_a = max\left(t_{R,a}\,, t_{p,a}\right) \qquad \text{eq. (10)}$$

Concluding, the capacity of snow removal is largely dependent on the availability of equipment and staff. Both can be extracted from either planning tools and are not related to the weather forecasts. However, in many cases the staff availability is scheduled using weather forecasts as input.

- t_a = time to clear area a [s]
- S_a = surface area of priority area a [m^2]
- ρ_s = snow density [kg/m^3]
- d_s = snow depth [m]
- V =speed of snow displacement [m/s] (plough: V_p, blower: V_R)
- q_r = snow clear rate of resource r [kg/s]
- η =snow clear efficiency [-] (plough: η_p, blower: η_R)
- n_p = number of ploughs
- b_r = plough blade width (effective: b_e, actual: b_α)

When computing snow removal performance, it can be assumed to clear the maximum allowable depth $d_s = 1$ inch (25.4mm) of snow, with a snow density $\rho_s = 50kg/m^3$ (new snow), and snow removal efficiency $\eta_p = \eta_R = 70\%$. If equipment is not yet specified, a velocity of $V = 40km/h$ can be assumed.

The time to clear an area is – naturally – dependent on the size of that area. Time is therefore not a useful unit to use when forecasting snow removal. A unit that is irrespective of the size of the area is the performance of snow removal operations, which can be described by the area that can be cleared in 1 hour, or m^2/hr.

Rewriting eq. (7) to express the snow removal capacity forecast $C_F^S(t)$, leads to eq. (52). It assumes N ploughs that work and can be staffed at time t. Each plough n has their respective velocity $V(n)$ and the blade width $b_c(n)$.

$$C_F^S(t) = \sum_N \eta_p V(n) b_c(n) \qquad \text{eq. (11)}$$

2.4 De-icing capacity forecasting

Ice formations on the lift surfaces of an aircraft change the aerodynamic performance of aircraft such that it negatively impacts the lift. Not only is this less efficient, it is dangerous as well as stall behaviour is heavily impact. To prevent ice on these surfaces, anti-icing or de-icing fluid is applied to reduce or prevent ice formation. Aircraft de-icing is required when frost, snow, or ice accumulates on the wing of an aircraft. At airports de-icing is done in two possible ways: either an aircraft taxies to a de-icing location for a de-icing truck to apply the fluid, or the truck will drive to the aircraft at the gate. Both have their benefits and an airport might even offer both varieties, depending on the de-icing service provider.

The problem managing de-icing operations is that many airports do not do this very often. When de-icing is less common, fewer de-icing stations are present. Therefore, the de-icing facilities are usually the limiting factor in the departure throughput. With de-icing facilities being limited to a couple of stations, the de-icing capacity is limited as well. The limiting capacity often leads to a capacity-demand imbalance and delays are quickly accumulated.

The de-icing time for an aircraft is determined based on the de-ice category of the aircraft. The categories are defined in the Association of European Airlines de-icing recommendations [18]. Herein, it provides an overview for the majority of aircraft with the associated de-ice category and categorises each aircraft between category A and F, where A takes the least amount of time to de-ice and F the most. As the de-icing is the application of fluids on the wing and tail surfaces, the categories are mostly determined through the surface areas of each aircraft.

The service rate, and thus the capacity, of a de-icing facility can be expressed in the number of aircraft serviceable per hour. However, the service rate then depends on the demand, namely the type of aircraft that need to be serviced. As the time to de-ice an aircraft determined by the amount of de-icing fluid required, which in turn is a function of the surface areas and the fluid rates, the alternative is to express the service rate in the amount of area that can be de-iced per time. The fluid spray rate can be assumed to be constant.

According to the de-icing guidelines [18] it takes 1L per 1m^2 to remove 1mm of ice. With the fluid being constant in the amount of litres per hour, this leads to the cleanable surface area through the aforementioned relationship and is shown in eq. (12). The surface area that can be cleaned per hour by de-icing station m is denoted by $S_d(m)$. Equating the surface area to the fluid required (as 1L = 1m^2) leads that $S_d(m) = \mu(m)$, with $\mu(m)$ denoting the fluid rate by de-icing station m. An efficiency factor is required as application of the fluid is never perfect. Correlating the fluid required and the surface area per aircraft from [18], leads to the estimated de-icing efficiency factor of $\eta_d = 0.25$. This is compensated for in eq. (12), which expresses the forecasted de-icing capacity C_F^D with the aforementioned variables.

$$C_F^D(t) = \sum_M \frac{S_d(m)}{1+\eta_d} = \sum_M \frac{\mu(m)}{1+\eta_d} \qquad \textit{eq. (12)}$$

3 Airport operational planning using capacity forecasts

Each stakeholder involved in the operation of the airport has its own goal and desires; hence, each stakeholder aims for efficient use of its resources. This aim also applies to the planned pre-tactical operations, which is the focus of this research. The evaluation of resource efficiency is done through a comparison between (forecasted) demand and (forecasted) capacity. There is thus no escape in involving some form of planning as it will provide the required output to make the comparison.

Preferably, a heuristic will be used to plan the operations instead of a full-blown optimization technique. This allows for computation speed, which will provide advantages when combining the algorithms during collaboration simulations. Additionally, heuristics also provide more flexibility in modelling and therefore allows more complex decision flows to be integrated in the collaboration model. Also, keep in mind that most stakeholders will always use their own (planning) tools for generation new solutions. The latter will elaborated upon at a later stage, namely in chapter 4. This chapter will also evaluate the heuristic with respect to the optimization to provide a sense of accuracy.

3.1 Runway planning

In order to determine the capacity fit of a runway configuration, it is deemed important to evaluate this measure against the traffic demand. As such, it can be determined if the particular runway configuration provides undercapacity or overcapacity. With additional computation, the delays with respect to the planned arrival and departure times can be determined.

With a given demand, the flights are scheduled and lead to an initial plan. The assumption is made that this initial plan is computed by current planning systems and thus already exists, consisting of the scheduled departure and arrival times. This assumption also means that no sophisticated flight sequencing or planning algorithm is required. Based on the forecasted capacity, a forecasted delay can be computed as a result of the discrepancy between capacity and demand.

The flight planning can be divided up into n slots, where 20min per slot is a generally accepted timeframe by ATC. In such a timeframe (slot k) there exists a forecasted service rate μ_k and a given demand λ_k. Combining both rates lead to the expected (average) delay d_i for flight i in slot k. The distinction between arrival and departure demand, service rate, and delay has to be made. The relationship is shown in eq. (13).

The plan can then be updated by adding the expected delay to the scheduled arrival time T_{SAT} and scheduled departure time T_{SDT}, which is shown in eq. (14).

$$d_i = \max\left(0, d_{i-1} + \frac{\lambda_k}{\mu_k} - 1\right) \quad \textit{eq. (13)}$$

$$\begin{cases} T_{LDT,i}^{new} = T_{SAT,i} + d_i \\ T_{TOT,i}^{new} = T_{SDT,i} + d_i \end{cases} \quad \textit{eq. (14)}$$

3.2 Snow removal scheduling

The snow removal operations have a large impact on the capacity of an airport during winter conditions. Clearing an area of snow implies no flight operations are possible in the vicinity. In many cases it means that an entire runway is not operable and implies that no aircraft can arrive or depart during these procedures. Efficient planning of snow removal operations is therefore key.

Together with the forecasted snow intensity, a model of snow accumulation is required as input for the planning of snow removal operations. This is addressed in the first subsection. No snow removal planning algorithm could be found in literature. Therefore, a linear programming model is developed along with two additional heuristics for snow removal planning procedures. Lastly, the results of both are compared to verify the heuristic.

3.2.1 Snow depth modelling

The simplest method of modelling the snow depth is by adding the snowfall intensity I_t for a specified time interval Δt to the current depth. Snowfall intensity is usually expressed in mm/h with a water-equivalent density. This is done in such a manner to allow for easy comparison between rain and snowfall. However, it does complicate things a little more, as snowfall density is not constant. This varies with temperature, snowflake diameter and water contents.

Additionally, snow melts with temperatures above zero. Whilst this does not eliminate the need for snow removal, it slows the accumulation and thus prolongs the availability of a runway. In the paper of Meyers, et al. [19] a simplistic relationship between temperature and melt rates $M_t$is found and validated. In eq. (15), a derived version of the relationship is shown, where the formula is converted to SI units.

$$M_t = 0.014\, max(T_t, 0) \quad \textit{eq. (15)}$$

In eq. (16) the accumulation of snow is shown for each runway r at each time step t. The depth $d_{t,r}$ at time t and runway r is the simple summation of the snow intensity I and compensating for the melting of snow. As the snowfall intensity is measured in water equivalent rates, for e.g. comparison with rain, a multiplication with the ratio of snow to water ρ is done. Generally, this ratio may vary between wet and dry snow, as well as old and new snow. Values generally range between 1:10 to 1:20. New snow generally has a density with a 1:20 ratio.

$$d_{t,r} = \rho \sum_{h=0}^{t} (I_h - M_h)\, , \forall t \in \boldsymbol{T}, r \in \boldsymbol{R} \qquad \textit{eq. (16)}$$

The depth of snow is reality lower than the previous approach of eq. (16). Simply adding all snow intensities lead to an overestimation of the snow depth. This is because the snow compacts and increases in density over time. To include the concept of snow compaction, eq. (16) is updated and leads to eq. (17). Here, the intensity is multiplied with a negative exponential that is dependent on the time since it the snow fell [20] [21]. The compression constant a is determined to be 0.008.

$$d_{t,r} = \rho \sum_{h=0}^{t} (I_h - M_h)\, exp\left(-a\sqrt{t-h}\right), \forall t \in \boldsymbol{T}, r \in \boldsymbol{R} \qquad \textit{eq. (17)}$$

The impact of compaction is shown in Figure 9. Here, a simulated snowfall of 2.5mm/h during a 120min period is simulated. The snow removal is performed when the maximum allowable snow depth is reached. Temperature is assumed to be below 0 and therefore no melting occurs.

The accumulated snow depth in Figure 9b shows that snow removal is required 10 minutes later when compaction is taken into account, compared to no compaction. This means that snow removal is required about 1.33 times less. It can therefore be concluded that it has a major impact on snow removal operations and thus need to be taken into account.

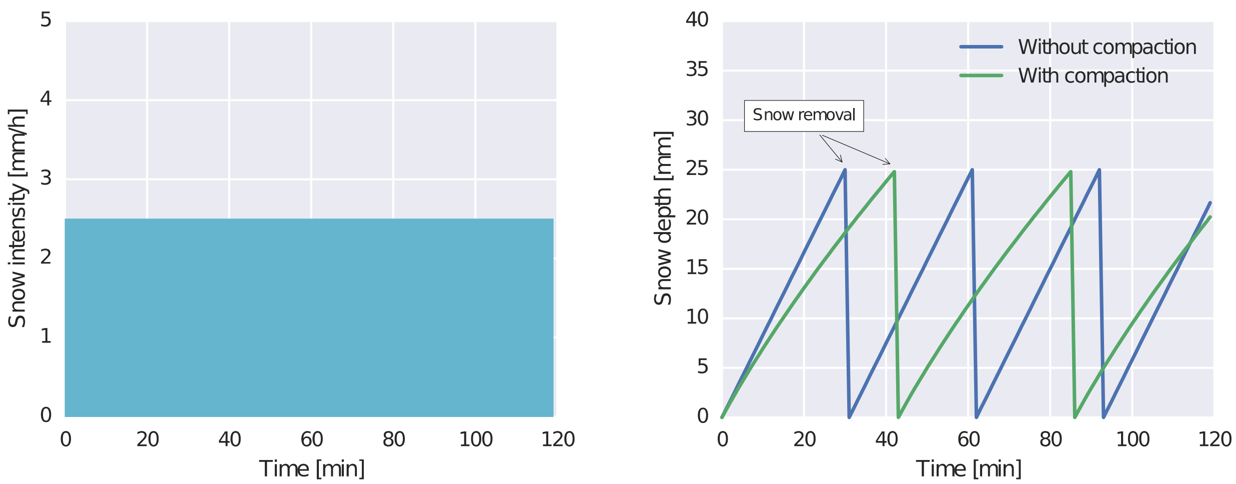


Figure 9a: Snow intensity input

Figure 9b: Snow depth

Figure 9: Snow compaction over time

A side effect from compaction is that the snow density increases. For the purchasing or evaluating of snow removal equipment, this needs to be taken into account. Performance of snow removal equipment is usually expressed in tonnes/hr. As density increases, the same volume needs more heavy equipment. This could form a constraint for snow removal operations or lead to longer snow removal clear times. For the simulated snowfall, the density over time is shown in Figure 10.

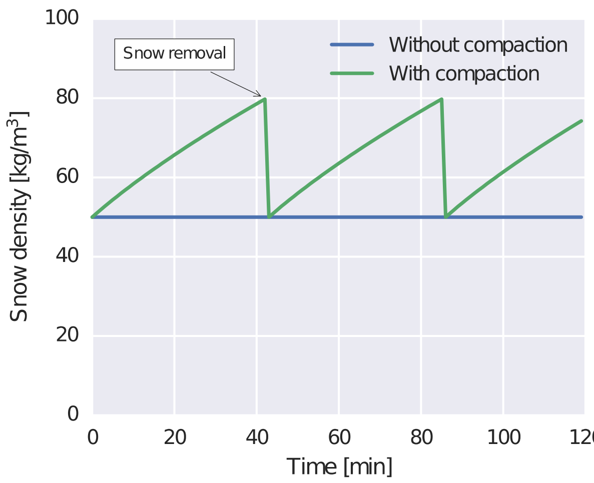


Figure 10a: Snow density over time

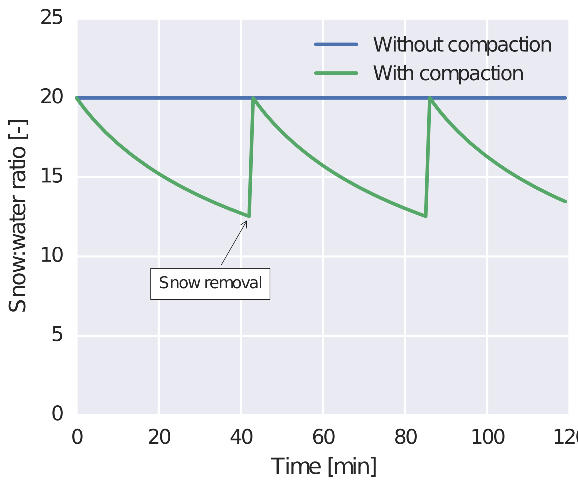


Figure 10b: Snow:water ratio over time

Figure 10: Snow density impact due to compaction

3.2.2 Snow removal planning optimization using MILP

One method of scheduling the snow removal is through an optimization algorithm. A Mixed Integer Linear Programming (MILP) model has been formed that maximizes the availability of runways and therefore schedules the removal of snow at a particular runway optimally, whilst still maintaining safe runway operating procedures. The latter has been achieved through limiting the allowable snow depth on a runway, d_{max}.

With the set of feasible runways $R \in [0, \dots, r_{max}]$ within a time horizon $T \in [0, \dots, t_{max}]$, the runway availability $A_{t,r}$ is maximized in the objective in eq. (18). Additionally, the objective includes a slight preference to minimize the snow depth using the small constant μ.

Objective

$$max\ Z = \sum_{t}^{T}\sum_{r}^{R} A_{t,r} - \mu \sum_{t}^{T}\sum_{r}^{R} d_{t,r} \qquad \textit{eq. (18)}$$

The start of snow clearing is defined by the Boolean $c_{t,r}$. With a time to clean a runway (t_{sr}), the snow removal procedure could have started at $t - t_{sr} + 1$ for any given time t. This defines the interval Q_t, as shown in eq. (27). It is very well possible to have a runway dependent clearance time.

$$A_{t,r} = \begin{cases} 1, & \textit{if } d_{t,r} \leq d_{max} \wedge \sum_{t_s}^{Q_t} c_{t_s,r} = 0 \\ 0, & \textit{elsewhere} \end{cases} \quad \forall t \in T, r \in R \qquad \textit{eq. (19)}$$

$$A_{t,r} = \begin{cases} 1, & \textit{if } d_{t,r} \leq d_{max} \\ 1, & \textit{else if } \sum_{t_s}^{Q_t} c_{t_s,r} = 0 \\ 0, & \textit{elsewhere} \end{cases} \qquad \textit{eq. (20)}$$

The availability of a runway can be expressed two-fold. Firstly, the depth of the accumulated snow has to be below the allowable level d_{max}. Secondly, the runway is not available when any snow removal procedures are in progress for that particular runway. These conditions are shown in eq. (19). In an effort to rewrite these conditions to a constraint for the LP model, both conditions are split as shown in eq. (20). The first condition described is bounded through eq. (23) and the second through eq. (21). Additionally, only one runway can be cleared at any given time, which is constraint by eq. (22).

Using the relation of eq. (16), the snow is accumulated using constraint eq. (24) and eq. (25) using familiar notation.

Subject to

$$A_{t,r} + \sum_{t_s}^{Q_t} c_{t_s,r} \leq 1, \qquad \forall\, t \in T, r \in R \qquad \textit{eq. (21)}$$

$$\sum_{t_s}^{Q_t} \sum_{r}^{R} c_{t_s,r} \leq 1, \qquad \forall\, t \in T \qquad \textit{eq. (22)}$$

$$d_{t,r} - d_{max} \leq \left(1 - \mathrm{A_{t,r}}\right)\mathrm{K} \qquad \textit{eq. (23)}$$

$$d_{0,r} + K c_{0,r} = \rho(I_0 - M_0), \qquad \forall r \in R \qquad \textit{eq. (24)}$$

$$d_{t,r} - d_{t-1,r} + K \sum_{t_s}^{Q} c_{t_s,r} \geq \rho(I_t - M_t), \qquad \forall t \in \{t | t \in T, t > 0\}, r \in R \qquad \textit{eq. (25)}$$

$$A_{t,r} \in \{0,1\}, \qquad c_{t,r} \in \{0,1\}, \qquad d_{t,r} \geq 0 \qquad \textit{eq. (26)}$$

$$\begin{gathered} T = [0, 1, 2, \dots, t_{max}] \\ \mathrm{R} = [0, 1, 2, \dots, \mathrm{r_{max}}] \\ \mathrm{Q_t} = [\max(0, t - t_{sr} + 1) \quad \dots \quad \min(t, t_{max})] \end{gathered} \qquad \textit{eq. (27)}$$

Additionally, K is an arbitrary large number which is assumed to be $K = 9999$. Also, μ is a small number such that $\mu \ll 1$ and is assumed to be $\mu = 0.01$.

3.2.3 Snow removal scheduling using heuristics

Alternatively to optimize the runway scheduling, one can use a heuristic to speed up the process that does not require an implementation of the LP. The advantage is that the heuristic allows for more flexibility and computation speed. This is shown in Heuristic 1 by eq. (28). Interestingly, this relation is very analogous to eq. (19). The difference is that the former relation defines the availability of the runway as a result of the snow clearing procedures, whilst the heuristic prescribes the snow removal times.

Heuristic 1

$$c_{t,r} = \begin{cases} 1, & if d_{t,r} > d_{max} \wedge \sum_{t_s}^{Q_t} c_{t_s,r} = 0 \\ 0, & elsewhere \end{cases} \quad \forall t \in, \in T, r \in R \qquad \text{eq. (28)}$$

It can be noted that the heuristic of eq. (28) is very ad-hoc: the snow clearing will only start when the boundary is reached. This might result in inefficient clearing. To partly improve this, eq. (29) introduces a form of look-ahead to start clearing earlier and thus allows to spot issues earlier on.

Heuristic 2

$$c_{t,r} = \begin{cases} 1, & if d_{t,r} > d_{max} \wedge \sum_{t_s}^{Q_t} c_{t_s,r} = 0 \\ 1, & else\ if \sum_{t'=t}^{t+t_{sr}} d_{t',r} > d_{max} \wedge \sum_{t_s}^{Q_t} c_{t_s,r} = 0 \\ 0, & elsewhere \end{cases} \quad \forall t \in T, r \in R \qquad \text{eq. (29)}$$

3.2.4 Results and verification

This section contains the results of applying the linear programming model and the two heuristics that were developed previously. The behaviour of the heuristics are analysed with comparison to the exact model.

3.2.4.1 Snow removal heuristic verification

A scenario of moderate snow fall was simulated. The given snow intensity over time can be seen in Figure 11a, which is a water-equivalent 0.5 mm/h snowfall over the course of 90min, which corresponds to ‘Moderate Snowfall’ as defined by ICAO. The snow-water ratio ρ is assumed constant at 1:11. The temperature T is assumed to be below zero, therefore eliminating the snow melting rate M_t.

The scenario assumes an airport with 2 independent runways with equal snow clearing times of 20min. It is expected that at most one runway can be operable during the period of snow. It may occur that a period of no availability results.

Using the MILP formulation as described in 3.2.2 and the above input, optimal snow clearing time is determined (see Figure 12a) with the resulting availability (see Figure 12b).

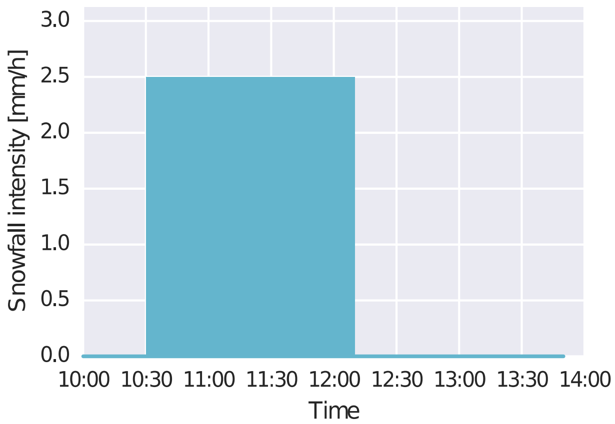


Figure 11a: Given water-equivalent snow intensity over time

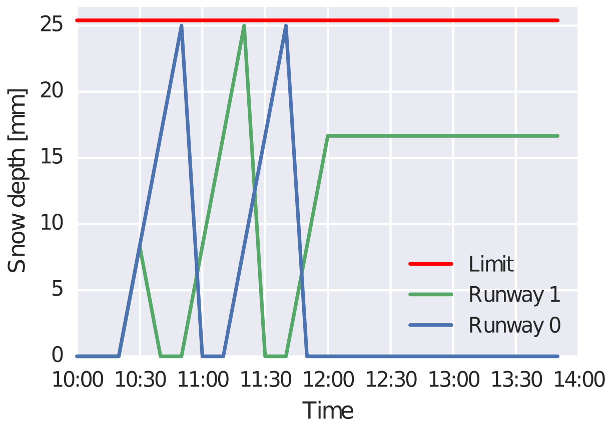


Figure 11b: Runway snow accumulation in actual depth i.e. not water-equivalent

Figure 11: Scenario snow accumulation under given snow intensity

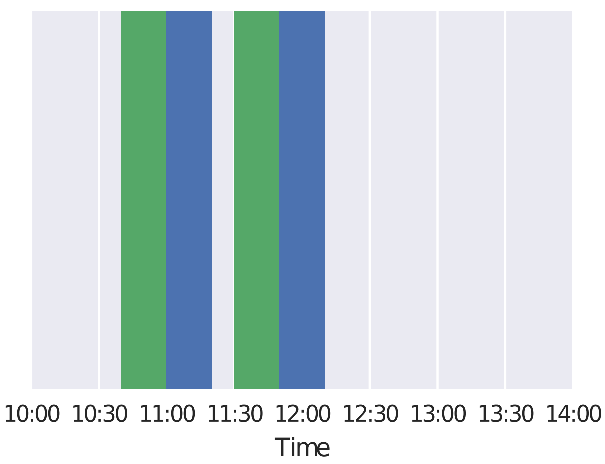


Figure 12a: Snow clearing times

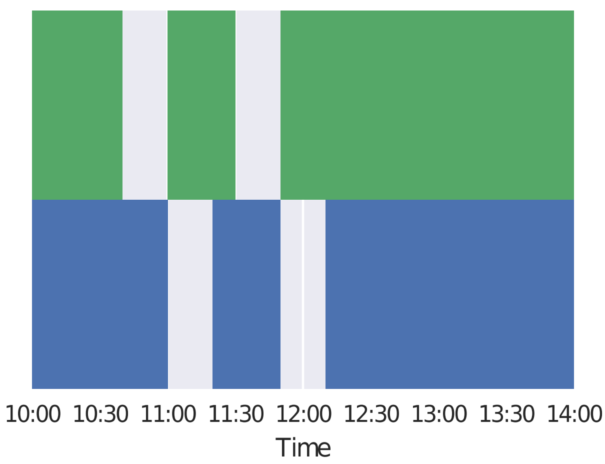


Figure 12b: Runway availability

Figure 12: Scenario results of optimal snow removal planning using a MILP solver

Using the first heuristic as described in 3.2.3 (see eq. (28)), the clearing times are found as shown in Figure 13a and leads to runway availability as shown in Figure 13b. The colours correspond to the same runways as in the MILP results. It can be seen that the sum of the availability of the heuristic (40) equals that of the MILP, the runway usage of the MILP is more efficient i.e. there is no moment where no runways are available. To be precise, 92% of times at least one runway is available using the first heuristic. The MILP does, however, spend more snow removal resources by clearing 4 times instead of 3, which leads to a 100% uptime (at least one runway available).

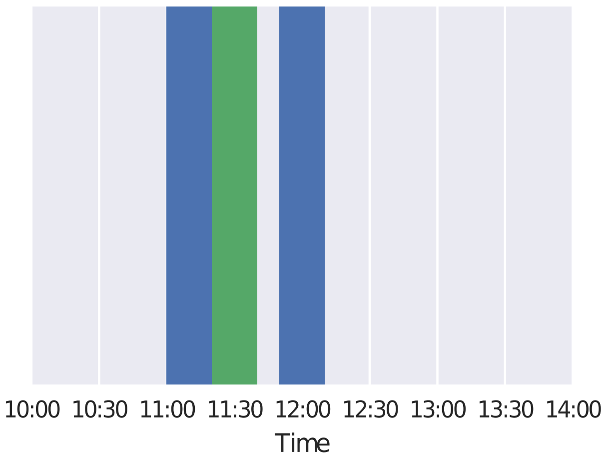


Figure 13a: Snow clearing times

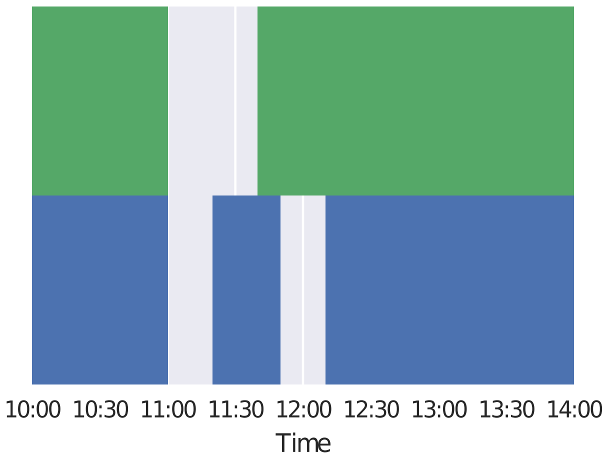


Figure 13b: Runway availability

Figure 13: Scenario results of optimal snow removal planning using heuristic 1

A second heuristic was also introduced (see eq. (29)) to better look ahead and integrate a very simplistic form of preventive snow removal. This increases the times with at least one runway operable as can be seen in Figure 14. Namely, 96% of times at least one runway is available. Comparing these results to that of the first heuristic, it can be concluded that heuristic 2 performs better.

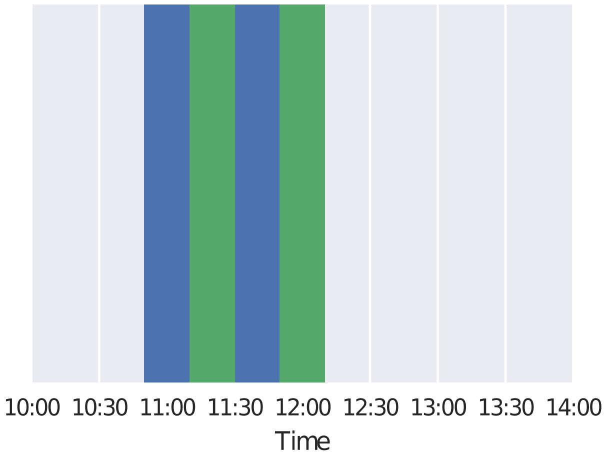


Figure 14a: Snow clearing times

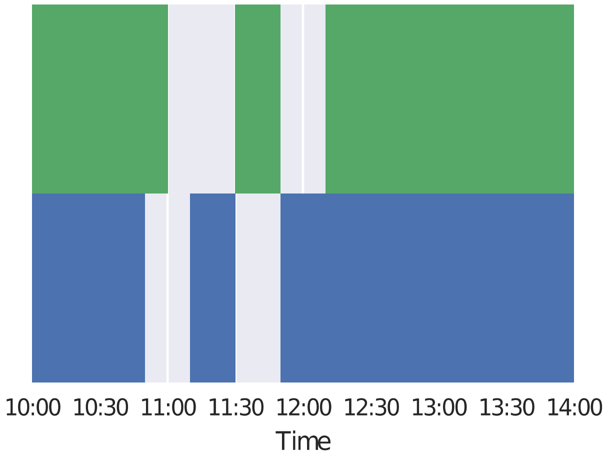


Figure 14b: Runway availability

Figure 14: Scenario results of optimal snow removal planning using heuristic 2

N.B.: for convenience, the naming refers to runway clearing and runway availability, but could be very well substituted for *area* clearing and availability. Both the MILP and the heuristics remain equally valid in that case with the use of area clearing times instead of runway clear times.

4 Airport collaborative operational planning

This research aims to model and evaluate the collaboration between various parties in the airport environment. Stakeholders are the airport, air traffic control, snow removal operator, and airlines. The question will be to investigate whether the multiple stakeholders can operate and collaborate more efficiently by forecasting their operations.

Before any answer can be given to whether and to what extent forecasting increases efficiency, the interaction flows between the stakeholders need to be modelled. By creating this model, one can simulate the behaviour. The resulting behaviour can then be compared with the behaviour if no forecasting would have been done. The models introduced in chapter 2 and 3 are required as underlying models as input to the simulation of decision making in stakeholder collaboration.

More specifically, this section addresses the research question #2, which was defined as:

- How to model a collaborative planning decision support facility?
  - How to model the stakeholder decisions?
  - How to include stakeholder interests?
  - How to integrate forecast uncertainty?
  - What is and how to choose the best decision w.r.t. the forecasted capacity?
  - How to incorporate decision deviations (i.e. human factors)?

Firstly, an appropriate technique to model stakeholder decision making is selected in section 4.1. Using this technique, each stakeholder's decision flow is modelled in 4.2, in which the stakeholder interests are integrated. Both section 4.1 and 4.2 are focussing on choosing the best possible decision, based on the information available. Combining all flows and simulating the response can be found in 5.

4.1 Modelling stakeholder decisions: negotiation techniques

The operational processes at an airport consist of many stakeholders and many people playing their part in the larger process. Airlines schedule flights, but it is the air traffic control that determines when a flight can depart. The crew fly the aircraft and operate the flight, but if the airport ground personnel has not loaded baggage, cleaned the aircraft, or fuelled the aircraft, it cannot take-off. These are all examples of how different parties are involved in the process and may limit the performance of each party, because they are simply dependent on each other.

The best way to cope with the problem of dependency is collaboration. The challenge of collaborating between multiple stakeholders, however, is reaching common agreement. In the case of runway configuration management, stakeholders have completely orthogonal goals: airlines desire as little delay as possible, whilst air traffic control would wish as much separation as possible to ensure safe operations. Types of problems such as planning across multiple stakeholders are referred to as Distributed Problem Solving (DPS) or referred to its research area Distributed Artificial Intelligence (DAI).

This section provides an overview of the current techniques as can be found in section 4.1.1 along with their pros and cons. From these, a selection will be made for the most appropriate technique, which is elaborated upon in section 4.1.2 and is combined with examples in section 4.1.4.

4.1.1 Overview of techniques in distributed artificial intelligence

When multiple stakeholders interact and their actions depend on the actions of the other, reaching common plans is usually required if some form of collaboration exists. Negotiation is this process that aims to reach agreement through exchanging relevant knowledge; however, it may very well be that different stakeholders aim for different goals. An example is the case of airlines that aim for as little delay as possible, whilst air traffic control is interested in safe operations. Negotiation helps in forming a joint decision.

Modelling the negotiation as a multi agent system, follows the general process as can be seen in Figure 15. Namely, the world / environment is in a certain ‘State’, the agent processes the information that is available in that state and then perform an ‘Action’ to alter the state and so forth. The actions of one agent also impact the state of other agents and therefore impact their actions as well.

A multi agent system is decentralized, local, and relies on autonomous agents. More specifically each agent has the following characteristics [22] [23]:

- **Autonomous:** exercises control over its own actions
- **Reactive**: responds in a timely fashion to changes in the environment
- **Goal-oriented**: does not simply act in response to the environment
- **Continuous**: a continuous running process

Additionally an agent may be:

- **Communicative**: communicates with other agents or people
- **Learning**: behaviour changes based on experienced on the past
- **Mobile**: able to transport itself from one machine to another
- **Flexible**: actions are not scripted

In order to perform the negotiation, a protocol and some form of strategy is required to enable the agents to interact and form a joint decision. The protocol shared between agents and is the method that governs the interactions between the participants, whilst the strategy may be different per agent and consists of the model that support the agent’s decision making to achieve the desired goal [24].

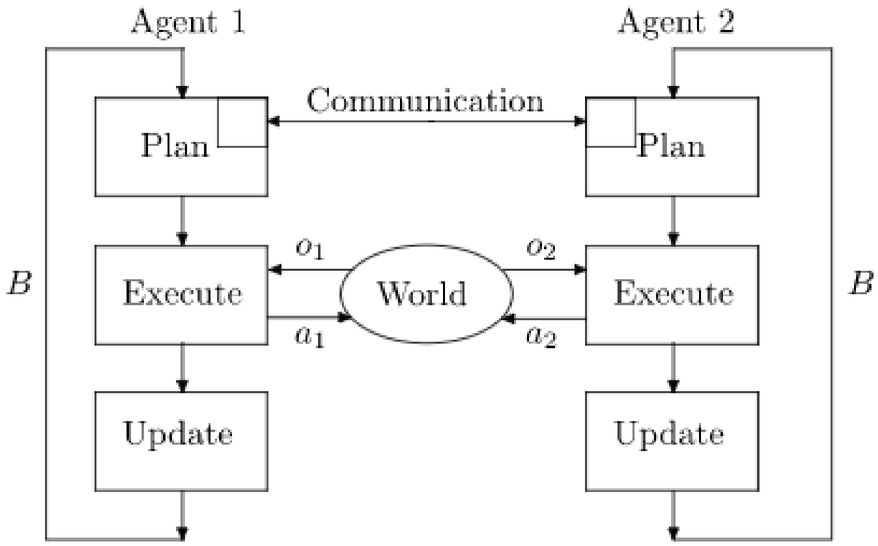


Figure 15: Planning framework with 2 agents [25]

The protocol and strategy to be employed by the agents are the decision factors that determine the most appropriate negotiation technique. Parameters influencing the decision for appropriate negotiation techniques as summarized by Kraus [26]:

1. Level of cooperation
2. Regulations and protocols
3. Number of agents
4. Type of agents
5. Communication and computation costs

In literature, various negotiation techniques are described. Each include pros and cons and are usually tied to a specific research area. Not only are negotiation techniques researched in the environment of multi-agent systems, but also within economics and political sciences to study conflict resolution [24].

In Table 2, a summary and categorization is shown of various multi-agent negotiation techniques. Here, SMA and CA refer to 'self-motivated agents' and 'cooperative agents', respectively. This determines their strategy when defining possible actions in the planning phase. The size refers to the small (S, handful), medium (M, few dozen), or large (L, hundreds) number of agents involved. Additionally, a differentiation has been made whether the negotiation technique can handle mixed automated and human agents in the category 'People' and lastly the table indicates whether or not a technique requires communication between agents. For the latter: the modelling of particles in a physics simulation, for example, does not require communication but each particle its kinetics can be modelled as one individual agent.

Table 2: Characterization of multi-agent negotiation techniques across multiple research fields by collaboration, agent cluster size, mixing of human agents and communication abilities [26]

Technique type	Multi-entity technique	Distributed Artificial Intelligence	SMA/CA	Size	People	Communication
Game theory	Strategic bargaining models	Negotiation for task distribution & Resource allocation in MA	SMA	S	no	yes
	Coalition formation	Coalition formation in MA	SMA	M	no	yes
	Principle-agent models	Contracting tasks in MA	SMA	S	no	yes
Physics	Classical mechanics	Goal satisfaction in very large DPS environments	CA	L	no	no
Operations Research	SPP & SCP	Coalition formation in DPS	CA	M	no	yes
	Queueing networks	Task allocation in DPS	CA	M	no	yes
Behavioural sciences	Negotiation guides	Diplomatic negotiation	SMA	M	yes	yes
	Persuasion models	Argumentation	SMA	S	yes	yes
	Focal points	Cooperation without communication	CA	M	yes	yes
Philosophy	Logic	Collaborative plans	CA & SMA	M	yes	yes

4.1.2 Selecting an appropriate negotiation technique

For our problem, we are looking for a technique that is suited for a small number of agents. Namely, the stakeholders involved are only ATC, snow removal operator, de-ice service provider and airlines operating at the airport in question. Additionally, the agents are able to communicate with each other.

The agents are self-motivated (SMA) and coalitions that are found amongst cooperative agents can be assumed to not be present. That is, whilst the stakeholders combine their efforts to operate in a joint plan and are relatively willing to help each other, they prioritize their own goals higher than other's goals.

Considering the possibilities of Table 2, we require models that deal with SMA and a small number of agents. People are not mixed with automated agents and communication is required. That results in either strategic bargaining models or principle-agent models.

The principle of working towards a shared goal, but operating in self-interest, can be very well modelled using "Principled negotiation" as it embodies this very idea [27] [28] . Principled negotiation is a form of principle-agent model (see "Game theory", Table 2). It was developed as a method to reach better agreements by proposing options that will benefit both parties, which therefore increases the probability of a successful agreement between parties. A general flow of this process can be seen in Figure 16.

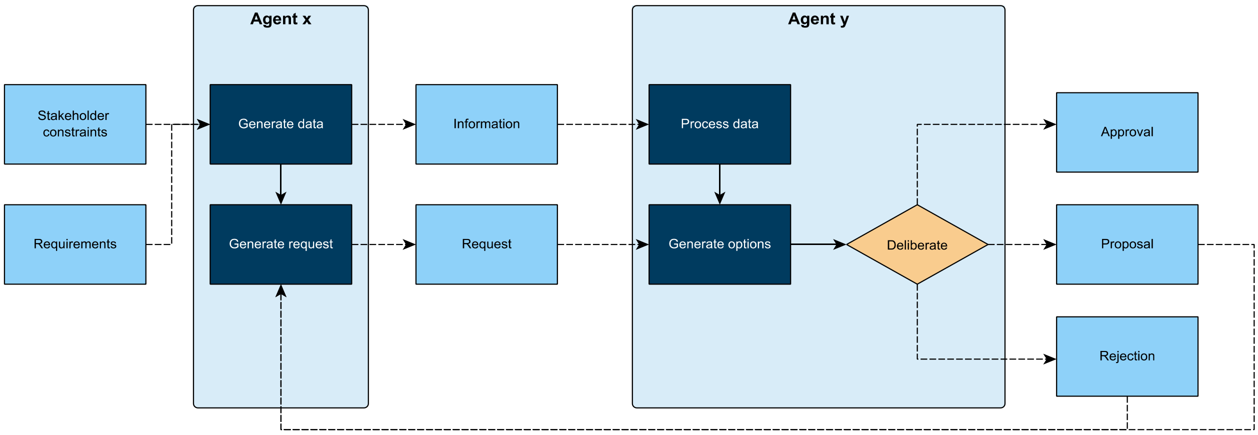


Figure 16: General interaction and communication flow between agents including feedback loops; based on Principled Negotiation

When evaluating the feasibility of proposed options, two different strategies can be employed and define the agent's behaviour. Within principled negotiation, an agent can be either maximizing or satisficing. The former only accepts new plans when it is as good, or better, than the current plan. The latter only seeks to satisfy certain criteria and therefore accepts anything as long as that is achieved.

The general flow, as is also depicted in Figure 16, follows the following concept:

- First agent starts:
  - Proposes best solution (option)
- Second agent:
  - Calculate best solution
  - Calculate overlap between best solution and proposed option of first agent
  - Then either:
    - Reject option if not in bounds i.e. not possible to execute
    - Accept option if it exist in the overlap
    - Propose best solution if in bounds, but no overlap found

    - If reject or propose: exclude option from further proposals
- First agent receives either acceptance, proposal or rejection
    - If acceptance, request next solution to next agent
    - If proposal, deliberate and send acceptance, proposal or rejection
    - If rejection, exclude from further proposals and start over

It is important to realize that no exact same option can be proposed multiple times, to prevent endless negotiation iterations regarding the same options.

The criteria mentioned are assumed to be objective when using the principled negotiation technique. The objectivity allows for benchmarking decisions against factual pieces of information, independent on the parties in the negotiation. It means that arguments such as “a pilot wanting to be home early to be with his kid” when negotiating aircraft arrival times, is irrelevant. However, the fact that further delaying the flight costs x amount of money is an objective criteria to measure against. The advantage is that such objective criteria are well suited for modelling purposes and allows for costs functions to be formalized that measure the wishes of an agent.

Figure 16 details the agent interactions on a high level. In order to properly model the decision making process (referred to as ‘Deliberate’ in Figure 16) a more detailed version is shown in Figure 17. It is important to realize that when modelling multi-agent systems, there is no start and no end; the agent is evaluating and communicating in a continuous process where agreements can be made.

4.1.3 Incorporating human factors

The previous section (4.1.2) selected a most appropriate technique for simulating stakeholder behaviour. But as might be evident, both focussed purely on the simulation of decisions. When employing this simulation as input for a decision support system human input is required. Namely, having a decision support system means that the system facilitates efficiency and computation simplicity. The system ought to aid the human stakeholders. It is therefore important that the model should be able to incorporate this.

Human input means that stakeholders need to be able to override the simulated agent’s decision, when desired. This may be the case due to the discrepancy between the real world and the modelled representation. For some reason that is unknown to the agent model, a different decision for a set time period is selected. Alternatively, stakeholders can alter limitation that the model needs to respect. This process is included in Figure 16 and Figure 17, through incorporating “Stakeholder constraints” in the request generation of the simulated agent that limit the search space.

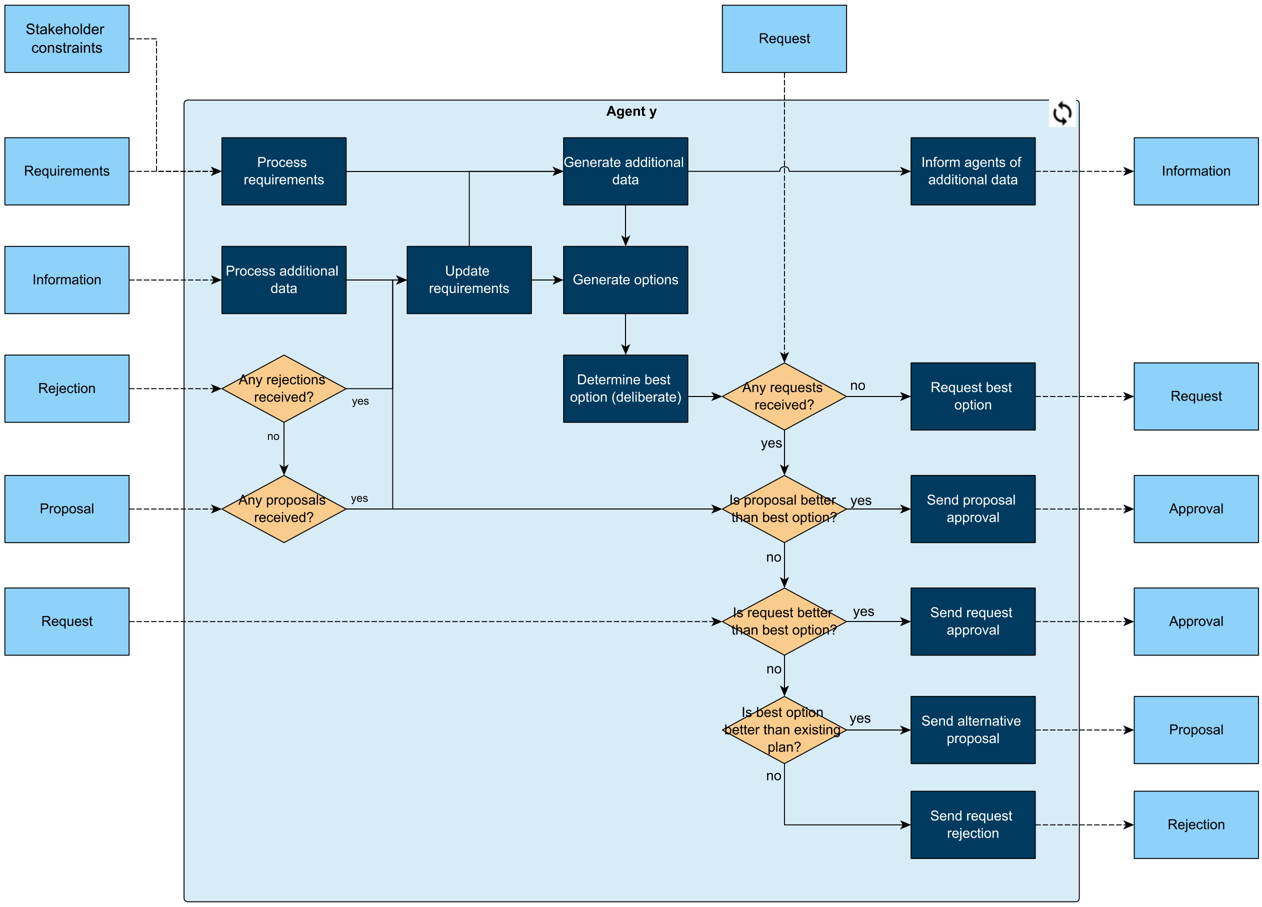


Figure 17: Detailed flow indicating general agent communication and decision flow indicating data exchange, requests, proposals and rejections; based on Principled Negotiation

4.1.4 General principled negotiation system description

The process of negotiation is proposing and assessing options of other agents. There exist *disturbances* (inputs) that affect the decision making that impact the actions or *control parameters*, which lead to the resulting *states* of the agent in its environment. Based on the decision making and states of other agents, the actions of the agent are influenced.

One can think of the disturbances as changes in the environment, such as the position of another agent. The control parameters then translate the disturbances into actions. For example, if the other agent is to the right of the agent, move left. The results of the actions are then the new states of the agent. In this case, the new state is the new position of the agent.

The following definitions will be used, when referring to principled negotiation [28].

General dynamics

The general dynamics of the system with a set of agent $\boldsymbol{A}$ based on all agents' states $x(t)$, the control parameters $u(t)$ and disturbances $w(t)$ for each time t in the time horizon $t \in \boldsymbol{T}$ can be described through eq. (30).

$$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}(t), \boldsymbol{u}(t), \boldsymbol{w}(t), t) \qquad \textit{eq. (30)}$$

Agents

An agent is assumed to behave rationally and has self-interest in mind. The set of agents $\boldsymbol{A}$ consists of N entities; see eq. (31).

$$\boldsymbol{A} = \{a_i : i = 1, \dots, N\} \qquad \textit{eq. (31)}$$

Plan

Sequences of actions are defined as plans, that are executed by the set of agents $\boldsymbol{A_M}$ as part of all agents in $\boldsymbol{A}$.

$$\begin{gathered} \boldsymbol{u}_{\boldsymbol{A_M}}(t_1, t_2) = \left\{\boldsymbol{u}_{a_m}(t_1, t_2) : m = 1, \dots, M\right\} \\ \boldsymbol{A_M} \subseteq \boldsymbol{A} \end{gathered} \qquad \textit{eq. (32)}$$

Action plan

A single agent's action plan is part of the overall plan by the agent set $\boldsymbol{A_M}$.

$$\boldsymbol{u}_{a_j}(t_1, t_2) \in \boldsymbol{u}_{\boldsymbol{A_M}} \qquad \textit{eq. (33)}$$

Option

Options are alternatives to the existing plan, which are proposed by a set of agents $\boldsymbol{A_K}$. When an option is found by an agent, this may also be referred to as '**solution**'.

$$\begin{gathered} \tilde{\boldsymbol{u}}_{\boldsymbol{A_K}}(t_1, t_2) = \left\{\tilde{\boldsymbol{u}}_{a_k}(t_1, t_2) : k = 1, \dots K\right\} \\ \boldsymbol{A_K} \subseteq \boldsymbol{A} \end{gathered} \qquad \textit{eq. (34)}$$

Utility

For each agent there exists an utility function, with respect to the state $\boldsymbol{x}$, control $\boldsymbol{u}$, and disturbances $\boldsymbol{w}$ as a function of time t. A maximizing agent will try and optimize the utility function.

$$\max\ \boldsymbol{U}_{a_i}(\tilde{\boldsymbol{x}}, \tilde{\boldsymbol{u}}, \boldsymbol{w}, t) \qquad \textit{eq. (35)}$$

The utility function is subject to a set of constraints that may be based on the states, control and disturbances. Satisficing agents only need to satisfy the constraints and lack a utility function.

$$\boldsymbol{c}_{a_i}(\tilde{\boldsymbol{x}}, \tilde{\boldsymbol{u}}, \boldsymbol{w}, t) \leq 0 \qquad \textit{eq. (36)}$$

Option generation

There exist multiple methods for option generation techniques. For simple problems, one could compute the entire sample space and select the best option. However, usually this is not efficient enough and results in too long computation times. In that case one could provide a heuristic that specifies a recipe of steps, which consists of statements in the form of "if-this-than-that". More advanced techniques consist of branch-and-bound searching, neural networks, or evolutionary algorithms [29].

4.1.5 Examples of principled negotiation

In order to better understand the process of principled negotiation, two examples are provided. One is a very trivial example of two maximizing agents in a very limited sample space, which is elaborated upon in the first section. Secondly, an example is given that relates to this thesis' use-case, namely winter conditions with air traffic control, snow removal, and airline agents.

4.1.5.1 Simple principled negotiation example

Consider the following scenario described below and depicted in Figure 18. There are two maximizing agents ($N = 2; A = \{a_1, a_2\}$) in a sample space of $\Omega = \{x, y\} = \{-2, \ldots, 2;\ 0, \ldots, 2\}$. The agents have the following utility functions:

- $U_{a_1} = y - x$
- $U_{a_2} = y + x$

In Figure 18, the utility gradients (lines) are shown for both agents, where white is lowest utility and black is highest utility; For clarity, gradients for agent 1 is shown only on the positive x axis and corresponds with the blue area, and for agent 2 this is the negative x axis and the green area, respectively. The bar next to the figure indicates the value of the gradients, based on its colour; from white representing 0 utility, to black representing a utility of 4.

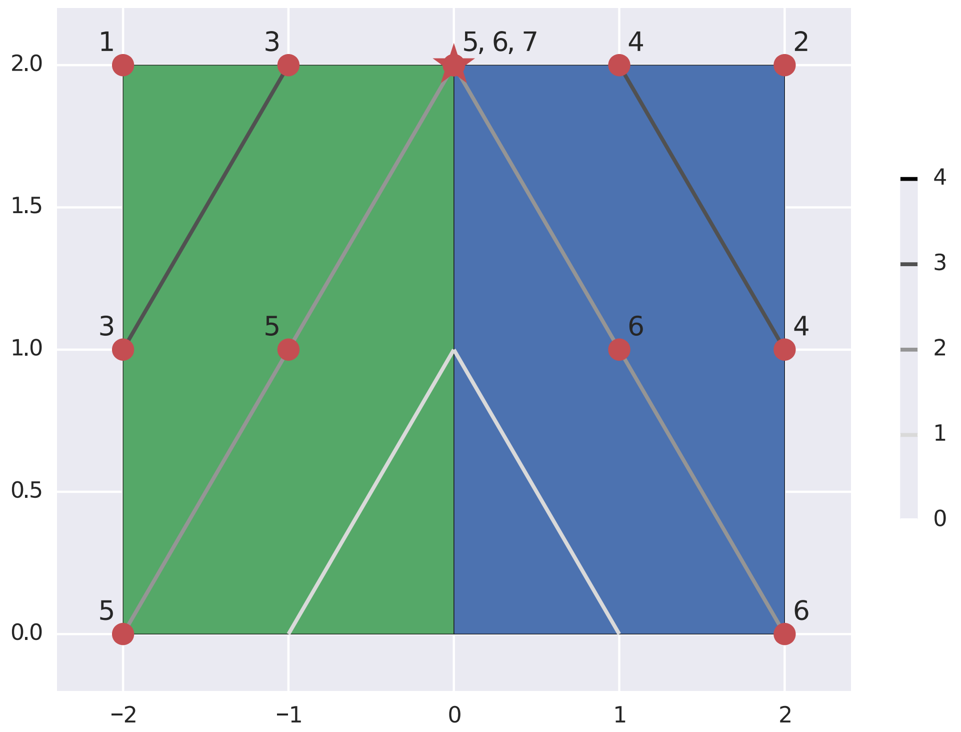


Figure 18: Example principled negotiation case with two maximizing agents and their utility gradients

Following the points as shown in Figure 18, the negotiation that occurs is described below. Agent 1 starts, to which Agent 2 responds, and so on. The agent to start may be chosen at random. At the 6th step in the negotiation, an overlap in options is found. The overlap (joint) found in both proposed solutions, namely $(0,2)$, and thus agreement is reached. In this case the agreement is reached after 6 steps.

1. $\tilde{u}_{a_1} = [(-2,2)]$
   $U_{a_1}(\tilde{u}_{a_1}) = 4$
2. $\tilde{u}_{a_2} = [(2,2)]$
   $U_{a_2}(\tilde{u}_{a_2}) = 4$
3. $\tilde{u}_{a_1} = [(-1,2),(-2,1)]$
   $U_{a_1}(\tilde{u}_{a_1}) = 3$
4. $\tilde{u}_{a_2} = [(1,2),(2,1)]$
   $U_{a_2}(\tilde{u}_{a_2}) = 3$
5. $\tilde{u}_{a_1} = [(0,2),(-1,1),(-2,0)]$
   $U_{a_1}(\tilde{u}_{a_1}) = 2$
6. $\tilde{u}_{a_2} = [(0,2),(1,1),(2,0)]$
   $U_{a_2}(\tilde{u}_{a_2}) = 2$
7. $u = u_{a_1} = u_{a_2} = [(0,2)]$
   $U_{a_1}(u) = U_{a_2}(u) = 2$

4.1.5.2 Principled negotiation applied to a winter scenario

Following the schemes of Figure 16 and Figure 17 using 5 agents, namely agents for runway configuration, runway planning, snow removal operator, and two airlines, the following scenario can take place. Assume we have an airport under constant snow conditions on an airport with 3 runways that can be used in 5 possible runway combinations, referred to ‘Config 1’ to ‘Config 5’. Additionally, the agents negotiate for the runway flight planning, consisting of arrival and departure times.

Here, the runway configuration agent wishes to provide the best runway configuration under the current weather conditions, based on the demand that is scheduled. The scheduling is done by the runway scheduling agent, which aims to minimize delay as much as possible. Contrary to the previous two maximizing agents, the snow removal agent is a satisfactory agent that simply checks if a runway configuration can be cleaned of snow. Lastly, the airline agents are maximizing agents as well, that aim to minimize costs and cancel flights if necessary.

Table 3: Runway configuration and flight planning negotiation example

Actor	Input/output	Process

ATC runway configuration	*Input*
	-
	Output
	Config 1
		1. Exclude runways
		    1. No maintenance; excluded 0 runways
		    2. No snow status available
		2. Determine runway feasibility due to wind conditions
		3. Loop through preferences
		    1. Is 'Config 1' available and feasible? → Yes
		    2. Select 'Config 1'
		4. Request 'Config 1'

ATC runway schedule	*Input* Config 1 *Output* Config 1 Schedule A	1. Generate schedule: "forecasted demand" based on capacity of 'Config 1' 2. Propose 'Config 1' with 'Schedule A'
ATC runway configuration	*Input* Config 1 Schedule A *Output* Config 2	1. 'Config 1' is still feasible 2. Check demand-capacity fit of 'Config 1' and 'Schedule A' 1. Not enough capacity 3. Any alternative with better demand-capacity fit? → Yes, 'Config 2' 4. Is 'Config 2' available and feasible? → Yes 5. Propose 'Config 2'
Airport snow removal	*Input* *Config 2* *Output* *Config 4*	1. Forecast snow build-up 2. Forecast snow removal capacity 3. Is 'Config 2' feasible to clear? → No 4. Is 'Config 3' feasible to clear? → No 5. Is 'Config 4' feasible to clear? → Yes 6. Is 'Config 5' feasible to clear? → Yes 7. Propose 'Config 4' or 'Config 5'
ATC runway configuration	*Input* Config 4 *Output* Config 4	1. Is 'Config 4' available and feasible? → Yes 2. Any alternative with better demand-capacity fit? → No 3. Accept 'Config 4'
ATC runway schedule	*Input* Config 4 *Output* Config 4 Schedule B	1. Re-generate schedule: new "forecasted demand" based on capacity of 'Config 4' 2. Propose 'Config 4' with 'Schedule B'
ATC runway configuration	*Input* Config 4 Schedule B *Output* Config 4 Schedule B	1. 'Config 4' is still feasible 2. Check demand-capacity fit of 'Config 4' and 'Schedule B' 3. Any alternative with better demand-capacity fit? → No 4. Accept 'Config 4' with 'Schedule B'

Airline A	*Input*
	Config 4
	Schedule B
	Output
	Config 4
	Schedule C
		1. For each flight
		    1. Determine cancellation costs:
		    2. Determine delay costs
		    3. Flights with delay costs > cancel costs?
		    Yes, cancel those flights
		2. Alter 'Schedule B' with cancellations, which leads to 'Schedule C'
		3. Propose 'Config 4' with 'Schedule C'

ATC runway schedule	*Input* Config 4 Schedule C *Output* Config 4 Schedule D	1. Re-generate schedule: new "forecasted demand" 2. Propose 'Schedule D'

Airline A	*Input*
	Config 4
	Schedule D
	Output
	Config 4
	Schedule D
		1. For each flight
		    a. Determine cancellation costs
		    b. Determine delay costs
		    c. Delay costs > cancel costs?
		    No
		2. Accept 'Schedule D'

Airline B	*Input*
	Config 4
	Schedule D
	Output
	Config 4
	Schedule D
		1. For each flight
		    a. Determine cancellation costs
		    b. Determine delay costs
		    c. Delay costs > cancel costs?
		    No
		2. Accept 'Schedule D'

This is a simplified negotiation from a high level. In order to generalize the negotiation process such that this can be modelled and simulated, the following section will introduce decision processes for each agent.

4.2 Modelling stakeholder decisions: applying principled negotiation

In the previous section, the choice for using principled negotiation was made as an enabler for distributed decision making within airport collaboration. Using this protocol, the decision flow for each of the stakeholder needs to be established. In the following four subsections, the protocol will be applied to air traffic control for runway configuration and capacity management, as well as for snow removal, de-ice service provider, and airlines. Each will vary in depth with regards to the decision making process. The main goals for each of the stakeholder are:

- Runway management: Ensure safe operations and deliver best capacity / demand fit
- Runway flight planning: Minimize arrival and departure delays
- Snow removal management: Satisfy runway availability during snowfall
- De-icing planning: Minimize departure delays
- Airlines: Minimize (disruption) costs

In order to find common ground between agents, each agent will making use of utility functions that expresses the difference with respect to their most preferred scenario. One can imagine that each minute of delay costs an airline a certain amount of money. The higher the sum of these costs, the more the airline deviates from their ideal scenario, namely: no delay. In the same process, these costs are established for each agent.

4.2.1 Applied principled negotiation system description

Based on the general system description and the decision processes of the previous sections, a system description can be given. Here we consider a time horizon of $t \in \boldsymbol{T}$ that applies to the decision variables for runway configuration and inbound and outbound flight planning. The time horizon is modelled as a discrete variable using a time step of Δt.

Actions / Control variables

Possible actions that will be used in the negotiation between the stakeholders are the runway configuration and inbound and outbound flight plan. The runway configuration is denoted by $\boldsymbol{x_t}$**,** the inbound flight plan by $\boldsymbol{y}^I_{a,f}$ and the outbound flight plan by $\boldsymbol{y}^O_{a,f}$.

$$\boldsymbol{u_a} = \{\boldsymbol{x_t} \quad \boldsymbol{y}^I_{a,f} \quad \boldsymbol{y}^O_{a,f}\} \qquad \textit{eq. (37)}$$

The values for the decision variables are bounded by the configurations that are possible and flights in question by the time horizon. Additionally, f denotes a specific flight of airline a in the total set of flights $\boldsymbol{F}$ that have the intention to fly within the time horizon $\boldsymbol{T}$.

Runways

Per mode (arrival/departure) per time interval indicate whether a runway configuration will be used, which inherently implies the use of the runway itself. The set of configurations are denoted by $\boldsymbol{C}$.

$$\begin{aligned} \boldsymbol{x}_t &= [x_0 \quad \dots \quad x_t] \\ x_t &\in \boldsymbol{C}, t \in \boldsymbol{T} \end{aligned} \qquad \textit{eq. (38)}$$

Flight plan

The flight plan will be based on the scheduled flight times of arrival and departure, SLDT and STOT. The proposed plans between agents represent the targeted arrival and departure times, TLDT and TTOT. With the time horizon as $\boldsymbol{T} \in \{1,2, \dots\}$. The time horizon is 1-indexed, such that it is possible to use $y_{a,f} = 0$ as to denote a flight is not operated or is cancelled by the airline. We thus have a airlines and a maximum of f flights per airline for both the inbound and outbound flights.

$$\begin{aligned} \boldsymbol{y}^{I}_{a,f} &= [y_{0,0} \quad \cdots \quad y_{a,f}] \\ \boldsymbol{y}^{O}_{a,f} &= [y_{0,0} \quad \cdots \quad y_{a,f}] \\ y_{a,f} &\in \{0; \boldsymbol{T}\} \end{aligned} \qquad eq.\ (39)$$

4.2.2 Runway configuration management by air traffic control based on weather forecasts

In our case, the decision flow for the air traffic control consists of runway configuration planning and runway flight planning. Whilst those may seem similar, it has to be noted that it is a feedback loop. Over or under capacity is the result of runway scheduling, which may be adjusted for using a different runway configuration. Therefore, these two are modelled as two separate agents and thus lead to 2 separate decision flows.

The goal of the configuration planner agent is to determine the most appropriate runway configuration with respect to the capacity-demand fit. Whilst, of course, taking safety measures into account, accommodating for variables such as wind conditions or accumulated snow. The goal of the flight planner is to schedule aircraft as efficient as possible, with the current capacity limitations in mind.

4.2.2.1 Runway configuration management decision process

When considering the most appropriate runway configuration to operate, ATC must take into account wind conditions, runway conditions, runway maintenance schedules, etc. Too high cross- or tailwinds and the aircraft cannot safely take-off or land. Additionally, and this especially holds in European airports near densely populated areas, ATC is strongly advised (or even obliged) to use the most noise-preferred runway.

With the possible runway configurations, some are simply not feasible due to constraints such as wind conditions. Additionally, snow removal may indicate it is not possible to clear certain runways and therefore deem those infeasible for a set period of time (see section 4.2.3.2). In Figure 19, a decision flow is shown that indicates the method to find the most preferred configuration by excluding configurations that contain non-feasible runways. Lastly, the selected configuration is communicated to the other agents. Most importantly, this configuration is used as the major input for the runway scheduling.

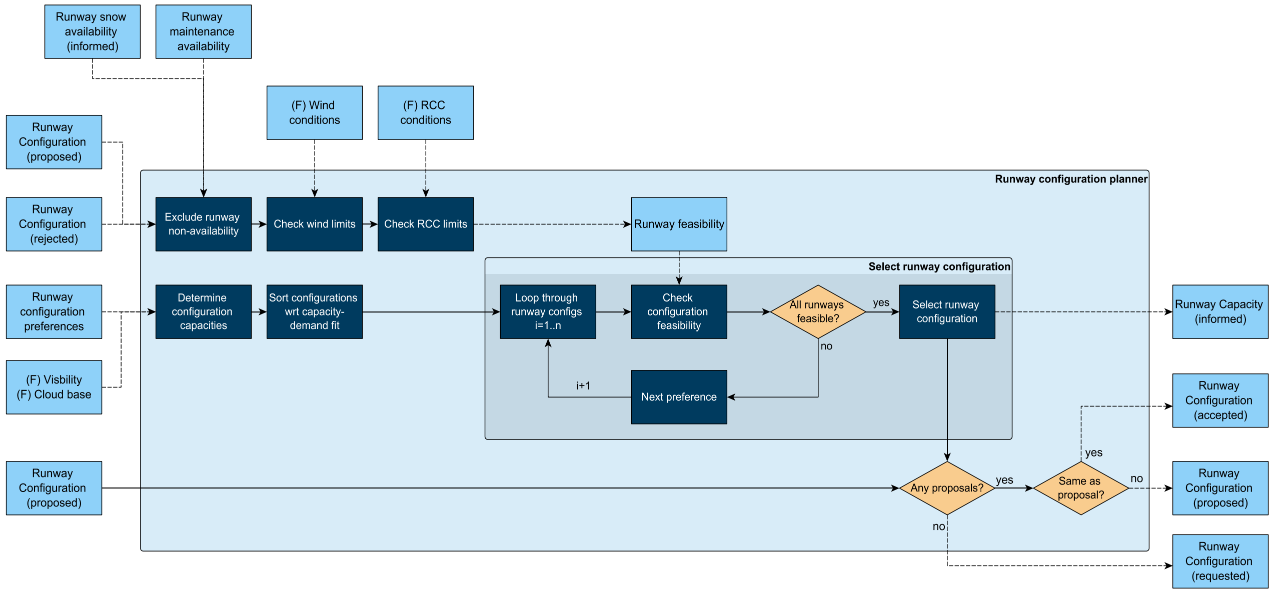


Figure 19: ATC runway configuration decision flow

4.2.2.2 Runway configuration option generation

Transforming the decision flow of Figure 19 this into a heuristic of finding all possible matching options, Algorithm 1 is introduced. It resembles an A* option searching algorithm that goes through all demand-capacity fit based sorted configurations across the time horizon, makes an estimate at each time step if the option is worth pursuing and finally appends the option to the solution set. Additionally, due to feasibility limitations a configuration might not be pursued as well. As is valid for all agents, a solution is only proposed if it is not proposed earlier. This prevents agents from ending up in an infinite flow of proposing the same solutions to each other.

Let us take an example and walk through the option generation process. Suppose there are 3 possible runway configurations an airport operates in and the goal is to find the best configuration selection for the next 3 hours. The configuration options are labelled #1, #2, and #3. Taking, for this example, a time step of 1 hour means that 3 values are required for the selection: one configuration for each hour.

At each time step (each hour in the selection), the three configuration options are possible. In total there are 3^3possible permutations, or more general c^t with c as the number of configuration options and t denoting the time horizon. For each time step the configuration options will be sorted with respect to the demand-capacity fit that is associated with the configuration and the meteorological forecasts. In our example, which is illustrated in Figure 20, the best configuration option for $t = 0$ is configuration #1, then #2 and then #3. For $t = 1$ and $t = 2$, the best option is #2, followed by #1 and #3.

At each time step, the algorithm starts by sorting the configuration options based on demand-capacity fit and add these to the queue. Then, it picks the first option off the queue and generates the set of configuration options for the next time step. It validates which options are feasible and repeats this process until the final time step is reached. In the example, at the second time step, configuration option #2 is unfortunately not feasible and thus is not pursued in generating new options. It will take the next-best option, namely configuration option #1, and continues the process. In this case the solution is [1, 1, 2], which is also highlighted in blue.

When a solution is found, it does not stop here, as there may be other solutions that are equally good or even better. Solutions might be better, as sorting is an estimation method. The algorithm will only pursue the next possible options, if it estimates the utility to be higher. In our example of Figure 20, the solution [1, 1, 1] will be checked next. If the utility is higher or equal to that of [1, 1, 2] , it will be added to our set of solutions. Next, [1, 1, 3] will be tested. Afterwards, no options for time step 3 are possible, so it will check a new option for time step 2 and thus [1, 3, 2] will be checked for feasibility and its utility tested.

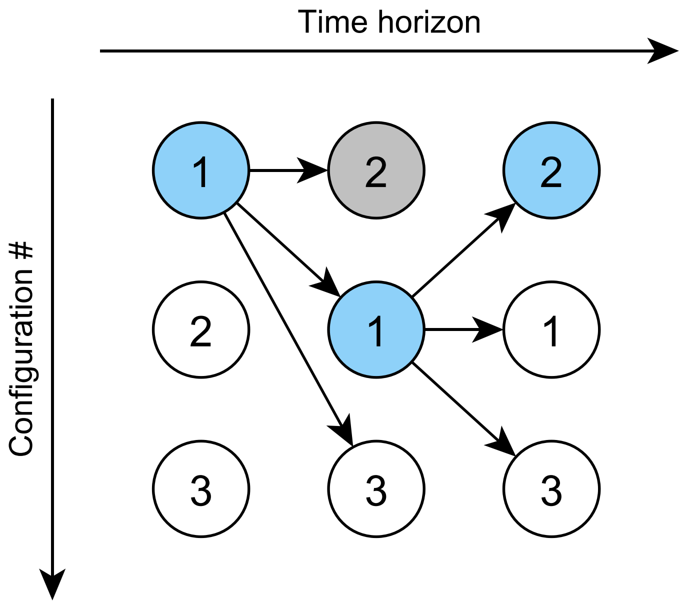


Figure 20: Runway configuration path finding example

On may notice that this is a depth-first search algorithm instead of breadth-first searching. The reason we can model this as a depth-first algorithm, is because the path length is fixed. Therefore, the performance of bread-first searching is equal if not lower.

This method is applied in Algorithm 1. The solution set is denoted by S' and resembles the variable $\boldsymbol{x}_t$ from section 4.2.1. The option O acts as a temporary set to store possible solutions. The sorted configurations at time t, similar to the previous example, are denoted by $C(t)$, which are added to the option O and produces the associated utility $U(O)$.

To make sure the negotiation does progresses over time, it is not possible to propose the same solution twice. Therefore, an option is checked if it occurs in the previous proposed option set S before it is added to the new option set S.

$t \leftarrow$ time step
$t_{max} \leftarrow$ maximum time step
$S \leftarrow$ previously proposed options
$S' \leftarrow$ new options
$M \leftarrow$ minimum threshold
$O \leftarrow \emptyset$
function generate(t, O) **do**
    $C(t) \leftarrow$ sorted configurations at time step t
    for all $c \in C(t)$ **do**
        $O \leftarrow O + \{c\}$
        $U(O) \leftarrow$ computed option utility
        $P(O) \leftarrow$ estimated utility potential between now and t_{max}
        $f(c, t) \leftarrow$ feasibility of configuration c at time step t
        if $\boldsymbol{t < t_{max}}$ **then**
            if $\boldsymbol{f(c, t)}$ **and** $\boldsymbol{U(O) + P(O) \geq M}$ **then**
                next $\boldsymbol{t}$
                generate(t, O)
            end if
        else if not $\boldsymbol{O \subseteq S}$ **then**
            $S' \leftarrow S' + O$
            $M = U(O)$
        end if
    end if
    end for
end function

Algorithm 1: Runway configuration search heuristic

4.2.3 Runway flight planning based on runway configurations

Flights are scheduled as a result of pre-tactical planning. Based on the runway configuration with the associated forecasted capacity, an imbalance between capacity and demand may result. In the previous section, the runway configuration is already proposed, but the impact still needs to be evaluated. This is done through updating the runway flight planning under the newly proposed configuration.

4.2.3.1 Runway flight planning decision process

Figure 21 provides an overview for the decision flow of scheduling flights. Here, runway capacity and configuration choice is the main driver for the flight arrival and departure times. In Figure 19, one can see that the capacity data object is formed and communicated (informed) and will be used as an input for the runway flight planning. Additionally, if airlines decide to cancel flights (see 4.2.5.3), the plan need to be updated.

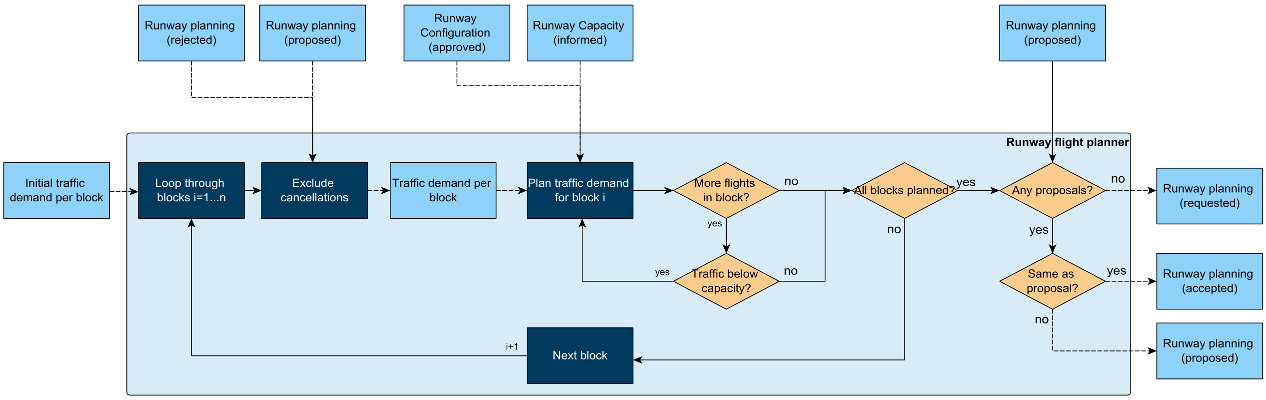


Figure 21: ATC runway flight planner decision flow

4.2.3.2 Runway flight planning option generation

The runway planning is made based on the runway configuration and its associated capacity. For the inbound and the outbound flights, the heuristic of Algorithm 2 is used. The heuristic is largely resembled in the decision flow in Figure 21.

Flights are planned at their scheduled slot (time step) t as long as the demand is below the forecasted capacity. If not, flights are pushed to the next time slot, or $t + 1$. Flights are always handled chronologically, which means that flights are processes in the order of their original schedule. The option-set O resembles the inbound and outbound schedules, $\boldsymbol{y}^I_{a,f}$ and $\boldsymbol{y}^O_{a,f}$, respectively. More information regarding both variables can be found in section 4.2.1.

```
T ← time horizon
O ← ∅

for all t ∈ T do
        C(t) ← capacity at time step t
        F(t) ← flights scheduled at time step t
        D(t) ← planned demand for time step t
        for all f ∈ F(t) do
                D(t) ← ∑(O = t)
                c ← true if f is cancelled
                if not c then
                        if D(t) < C(t) then
                                O ← O + {t}
                        else
                                F(t + 1) ← F(t + 1) + {f}
                        end if
                end if
        end for
end for
```

Algorithm 2: Inbound and outbound runway scheduling heuristic

4.2.4 Snow removal management based on weather forecasts and runway configurations

This section highlights the decision process for snow removal operations. Firstly, the general procedure as advised by the FAA is introduced and used as the input for the decision process modelling. Additionally, the cost function to compare options is introduced.

4.2.4.1 Snow removal decision process

The majority of large airports have the common approach to make use of priority areas. In the advisory report 150/5200-30D of the FAA concerning “Airport field condition assessment and winter operations safety” [30], these areas are defined using the following guidelines:

1. Priority 1 areas include:
    - Directly contribute to safety
    - Re-establishment of aircraft operations at acceptable Level of Service
    - Primary runways, turnoffs and taxiways to terminal, etc.
    - Portion of apron areas immediately necessary at acceptable Level of Service
2. Priority 2 areas include:
    - Not in Priority 1
    - Not essential to re-establishment of aircraft operations at acceptable Level of Service
    - Secondary runways, turnoffs and taxiways
    - Access roads to secondary facilities
3. Priority 3 areas include:
    - Not in Priority 1 and 2
    - Service roads

In Figure 22, these guidelines are applied to a sample airport. It can be seen that priority 1 areas are defined for the major runway, with the secondary, perpendicular, runway indicated with a level 2 priority.

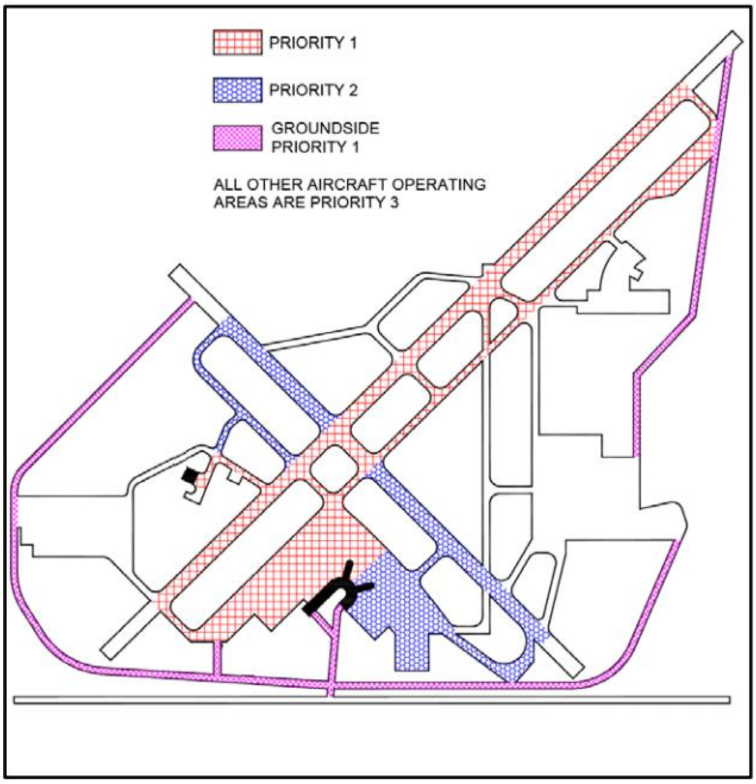


Figure 22: Snow removal priority areas defined for an example airport [30]

The decision strategy of the snow removal operator reflects the prioritization of areas. Herein, the priority areas are checked one by one in ascending order to determine if it requires snow clearing. This is based on the capacity (and thus the speed) of snow clearing. There is no use in clearing a priority 2 area if in the meantime the priority 1 area is contaminated with snow above the allowable depth limit. In Figure 23 the decision flow of the snow removal operator is visualized. The option generation algorithm which determines the runway snow availability is found in section 4.2.4.3.

Nevertheless, within the same priority area, there are various options possible. Larger airports usually have multiple runways in a priority 1 area, but scenarios occur where only 1 can be kept clean. In this case, a trade-off has to be made which runway (subarea) to clear. This can be done using a utility function, expressing the costs of clearing the subarea. Using this approach leads to the favourability of clearing smaller subareas, which is valid from the snow removal point of view. Negotiations between the snow removal and ATC will then be used to balance the runway capacity and demand of airlines.

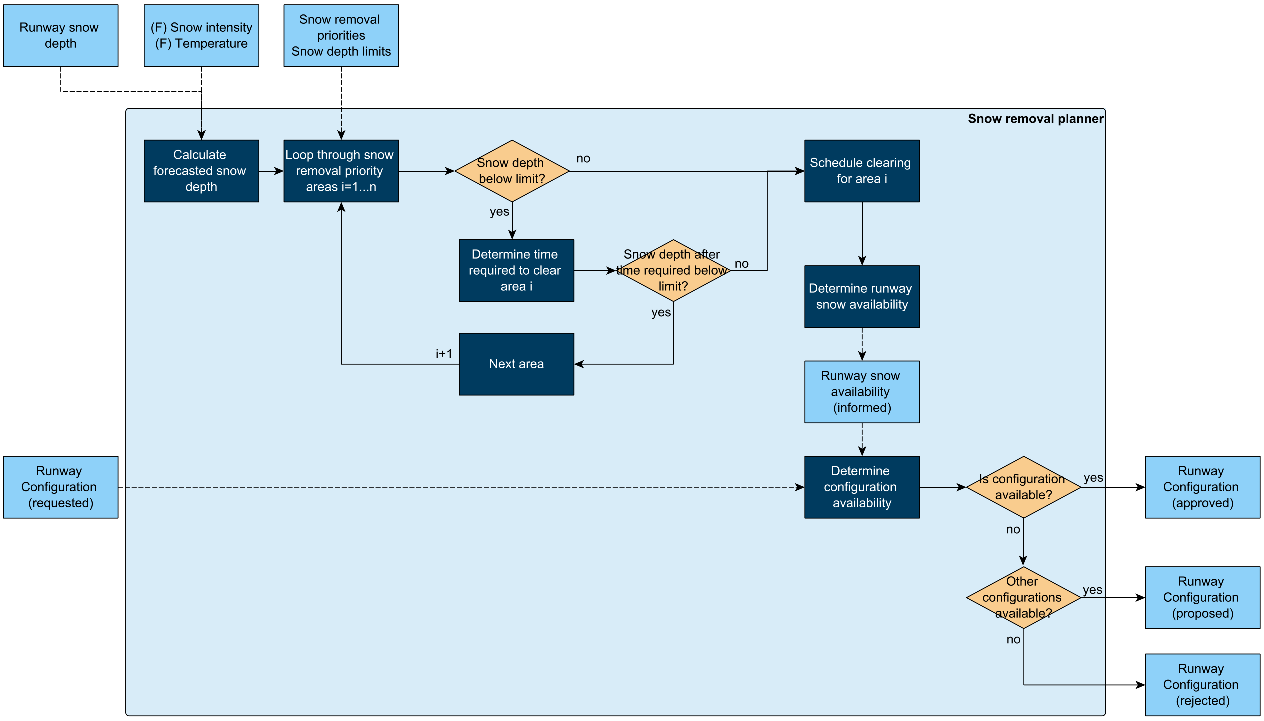


Figure 23: Snow removal operator decision flow

4.2.4.2 Cost of snow removal

Like all other stakeholders, the snow removal team wishes to minimize costs for the area availability that they achieve. The assumption can be made that the snow removal operations only impact the variable costs, as fixed cost such as equipment purchasing cost will have negligible effect on the tactical snow removal planning. The main contributor that determines the variable costs is the operating costs, consisting of fuel and labour costs, and the time spent on removing snow. This is resembled in eq. (40).

$$C_{sr} = \sum_{a}^{A} \sum_{r}^{R} (f_r c_f + c_r) t_a \qquad \textit{eq. (40)}$$

In eq. (41), the variables are defined as follows:

- C_s = snow removal cost [€]
- A = set of (priority) areas to be cleared
- R = set of resources used (ploughs, blowers, etc.)
- f_r = fuel consumption rate of resource r per unit of time [L/hr]
- c_f = cost per unit of fuel [€]
- c_r = labour costs of operating resource r per unit of time [€/hr]
- t_a = time to clear area a [s]

4.2.4.3 Snow removal option generation

Where the runway configuration and runway planning agents are maximizing agents is the snow removal agent a satisficing agent. Based on the proposed Heuristic 2 of section 3.2, a proposed runway configuration plan can be tested if snow removal operations can be planned such that the snow depth limitations are not reached.

It is assumed that only one runway can be cleaned at the same time. Additionally, a configuration can also exist with no runways as no feasible configuration can be found that is below the depth limit.

```
T ← time horizon
P ← proposed options
O ← ∅
for all t ∈ T do
    C ←proposed configuration at P(t)
    d(t,r) ← snow depth of runway r at time t
    c(t,r) ← whether snow removal operations are scheduled for runway r at time t
    for all r ∈ R do
        t_sr ← required clear time of runway r based on forecasted capacity
        update d(t,r)
        estimate d(t + t_sr, r)
    end for
    for all r ∉ C do
        if d(t,r) > d_max and c(t,r) = 0 ∀ r ∈ R then
            schedule clearing runway r
        else if d(t + t_sr, r) > d_max and c(t,r) = 0 ∀ r ∈ R then
            schedule clearing runway r
        end if
    end for
    if d(t,r′) ≤ d_max ∀ r′ ∈ C
        O ← O + {C}
    end if
end for
```

Algorithm 3: Snow removal option generation

4.2.5 De-ice management based on flight planning

The de-icing service provider is mostly interested in handling as much aircraft in as little time as possible, thus maximising profit. From a modelling perspective, it is important to know that de-icing is requested from a pilot. The decision making of the pilot is influenced by the airline's policy, but does not consist of an objective rule. The general process is as follows:

1. Pilot requests de-icing from service provider
2. Service provider determines moment of de-icing
3. Service provider requests de-icing procedure from ATC
4. ATC updates schedule
5. If remote de-icing: de-icing is scheduled and prior to the event, the plane taxies to remote location

6. Else: Plane is de-iced at the gate at the scheduled moment and pushed back for taxi and take-off

4.2.5.1 De-icing decision process

Due to the unpredictable nature of this process, a consistent model is hard to define. There is some forecasts for de-icing demand in place, which is, amongst others, determined based on the forecasted temperature. Assuming this is present, the abstraction of Figure 24 can be used.

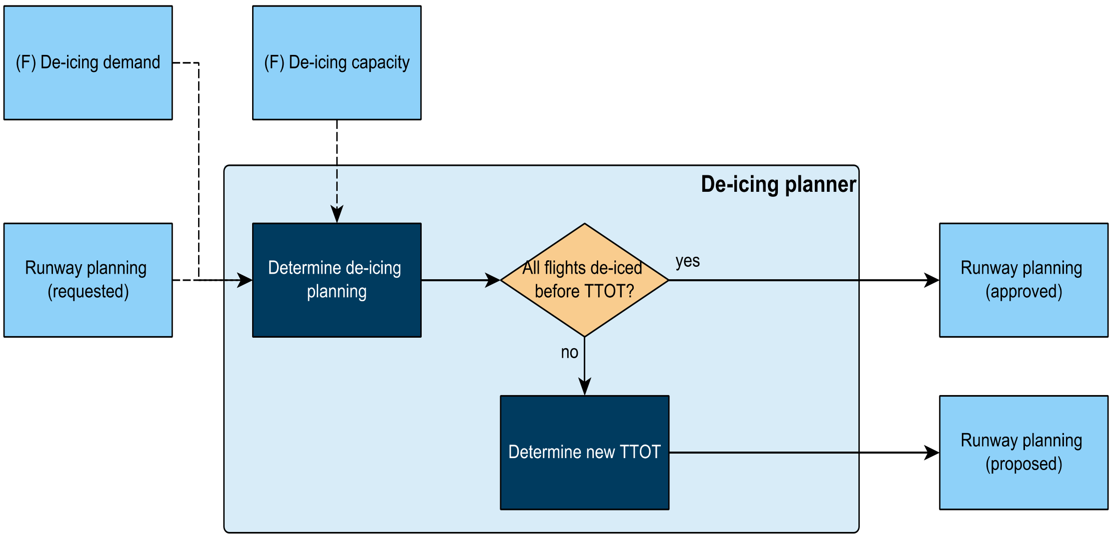


Figure 24: De-ice service provider decision flow

4.2.5.2 Cost of de-icing

The de-ice operator charges for each time aircraft de-icing is performed, at the request of the pilot. There is no large incentive to schedule operations in a shorter time-frame. Whether an airplane is de-iced 15 minutes earlier or later, does not have a large impact on the costs of the operator. The big inefficiency as a result of bad planning is for the airlines whom experiences delay as a result of inefficient de-ice planning. The delay, in turn, leads to large costs for the airline.

The main incentive for the de-icing operator is to minimize operating cost. This can be expressed as shown in eq. (41). Here, C_{dk} is the de-icing cost in time slot k, C_d is the unit operating cost of de-icing 1m^2, and S_{dk} is the surface area that is de-iced in time slot k. The operating costs include staffing, fuel, and other direct costs. Also see section 2.4 regarding de-icing capacity, which is forecasted in the units m^2/hr.

$$C_{dk} = S_{dk} C_d \qquad \text{eq. (41)}$$

4.2.5.3 De-icing planning option generation

The de-icing process is the matching of planes to de-icing stations or vehicles. Both are generalized and referred to as vehicles. Early departures are prioritized and therefore de-icing vehicles are matched to aircraft sorted by their scheduled departure times. The option generation algorithm used is Algorithm 4, based on the work of Verboon [31].

If there is more than one vehicle available i.e. $V \neq \emptyset$, assign the aircraft to one of the vehicles v^* and remove that station from the set of available vehicles. This is done through $V \backslash \{v^*\}$ being the vehicles V, excluding the just assigned vehicle v^*. The de-icing vehicle schedule V' is then updated with the newly assigned vehicle v^*.

In the case that no vehicle is available i.e. $V = \emptyset$, check which vehicle will be available at the soonest and assign that vehicle to the aircraft.

$V \leftarrow$ vehicles
$V' \leftarrow \emptyset$
$P \leftarrow$ planes sorted by scheduled departure time
for all $p \in P$ **do**
    v^*
    if $V \neq \emptyset$ **then**
        $v^* \leftarrow$one element of V
        $V \leftarrow V \backslash \{v^*\}, V' \leftarrow V' + \{v^*\}$
    else
        sort V by non-decreasing completion time of activities
        $v^* \leftarrow$first element in V
    end if
    assign p to v^*
end for

Algorithm 4: De-icing option generation, based on [31]

4.2.6 Airline decision making based on flight planning

With the little margins that exist in the airline business, plans are optimized to reduce costs as much as possible whilst still maintaining favourable level of service to its customers. The event of winter conditions is therefore definitely not appreciated by the airlines as each minute of delay counts.

4.2.6.1 Airline decision process

The only decision that airlines make to reduce delays, is cancelling flights to provide breathing space for other flights. This flow is depicted in Figure 25. As can be seen in the figure, the airline does not invent options itself, but merely acts based on the requested runway planning during the negotiation process.

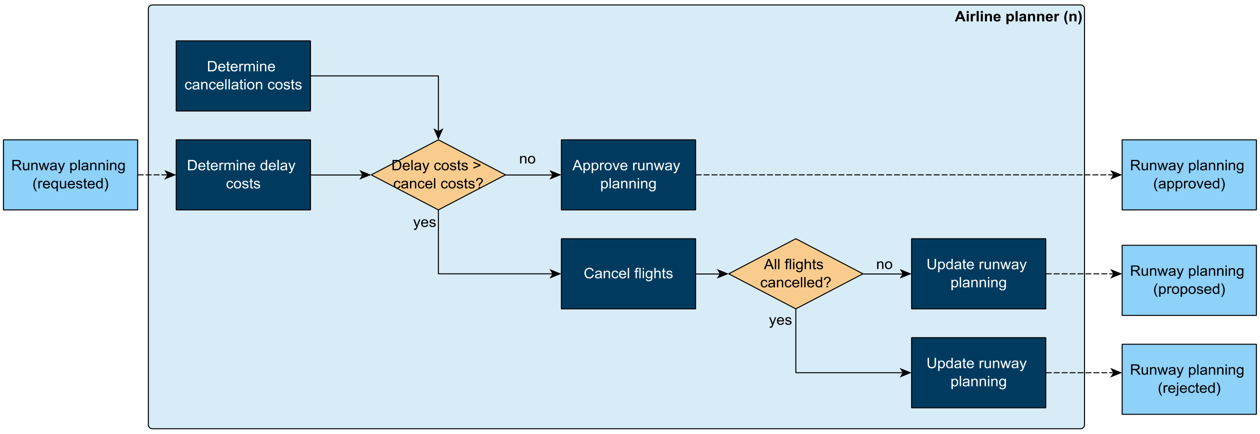


Figure 25: Airline decision flow

The determination whether a flight needs to be cancelled, can be simplified to checking what costs more: a delayed flight or cancelled flight? With $C_{1/ak}$ being the cost of delaying flight k of airline a and $C_{2/ak}$ being the cancellation cost, then the decision value x_{ak} of whether to cancel the flight is can be defined with the relation of eq. (42).

$$x_{ak} = \begin{cases} 1, & if\ C_{2/ak} > C_{1/ak} \\ 0, & elsewhere \end{cases} \qquad \textit{eq. (42)}$$

4.2.6.2 Cost of flight delays

In eq. (43) the total operation costs is shown as defined by Janic [32]. When only assessing the delay costs, this can be rewritten to eq. (44). In the latter, the operational costs have been removed. Apart from the delay duration, the delay costs are now only a factor of the passenger revenue and operational costs during the delay period.

$$C_{1/\mathrm{ak}} = n_{ak}C_{ak} + f_{ak}d_{ak}(n_{ak})[c_{ak} + \phi_{ak}S_{ak}\alpha_{ak}] \qquad \textit{eq. (43)}$$

$$C_{1/ak} = f_{ak}d_{ak}[c_{ak} + \phi_{ak}S_{ak}\alpha_{ak}] \qquad \textit{eq. (44)}$$

More specifically, the variables of eq. (43) are defined as:

- n_{ak} =prospectively affected flights during (k)th cycle
- C_{ak} =operating cost of a flight scheduled at affected airport during (k)th cycle.
- f_{ak} = delay multiplier at affected airport in (k)th cycle
  - If delay causes delay in next flight with same aircraft, impact is two-fold.
- $d_{ak}(n_{ak})$ =total delay of n_{ak} prospectively affected flights scheduled at given airport in (k)th cycle
- c_{ak} = unit cost of delay of flight scheduled at affected airport in (k)th cycle, variable costs such as:
  - Fuel costs
  - Crew costs
- ϕ_{ak} =average load factor of flight scheduled at affected airport in (k)th cycle

- S_{ak} = capacity of flight scheduled at affected airport in (k)th cycle
- α_{ak} =average cost of a unit of passenger time of flight scheduled at the affected airport in (k)th cycle
    - Leisure: \$31.96 [33]
    - Business: \$55.00 [33]

4.2.6.3 Cost of cancellations

When considering all costs that are introduced by a cancellation onto the overall system, as done in Janic [32], the costs are a factor of flight revenue, passenger wait costs, and social value costs. Passenger wait costs compromises the amount passengers need to be compensated for delays, as is compulsory for airlines by law. Social value costs refer to the added value the flight and its passengers bring to an airport region. Additionally, it also compensates for the operational costs i.e. the flight that does not need to be operated, so the airline saves – to some extent – fuel costs and crew costs. This is shown in eq. (45).

Rewriting the costs of the overall system to costs for an airline, social value is not taken into account as it is assumed that airlines decision making does not involve the value passengers bring to the airport region. Airlines are profiting little to none from the social value. Additionally, we can compute flight revenue based on the yield and distance of that specific flight. This also can be done for the avoidable operational costs, which can be computed based on the flight time and the unit operation costs. The rewritten formula is shown in eq. (46).

$$\begin{aligned} C_{2/ak} &= 2n_{ak}[(R_{ak} + CP_{ak} - C^*_{ak}) + W_{ak}] \\ &= 2n_{ak}[\phi_{ak}S_{ak}(r_{ak} + q_{ak}\alpha_{ak}D_{ak}) - C^*_{ak} + W_{ak}] \end{aligned} \qquad \textit{eq. (45)}$$

$$C_{2/ak} = 2[\phi_{ak}S_{ak}(\gamma_{ak}s_{ak} + q_{ak}\alpha_{ak}D_{ak}) - c_{ak}t_{ak}] \qquad \textit{eq. (46)}$$

The variables of eq. (45) are defined as:

- R_{ak} =average revenue per flight scheduled at affected airport in (k)th cycle
- CP_{ak} =cost of passenger time lost while waiting for flight scheduled at affected airport in (k)th cycle
- C^*_{ak} =avoidable cost of the flight scheduled at the affected airport in (k)th cycle
- r_{ak} = airfare of flight scheduled at affected airport in (k)th cycle
- q_{ak} =ratio of passenger waiting for flight scheduled at affected airport in (k)th cycle
- D_{ak} =average time, which the passengers have waiting for the flight scheduled at affected airport during (k)th cycle, before cancellation
- γ_{ak} = average yield per passenger-kilometre
- s_{ak} = distance of flight scheduled at affected airport during (k)th cycle
- t_{ak} = duration of flight scheduled at affected airport during (k)th cycle
- W_{ak} =social value of flight scheduled at affected airport during (k)th cycle

The duration of a flight t_{ak} can be estimated by dividing the distance over the cruising velocity of the aircraft operating the flight. Between two airport locations that can be expressed in their respective latitude ϕ and longitude λ, the distance can be computed by using the haversine formula as shown in eq. (47). Here, R equal to 6371km (the Earth's radius).

$$s_{ak} = 2R\arcsin\left(\sqrt{\sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + \cos(\phi_1)\cos(\phi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right) \qquad \text{eq. (47)}$$

4.2.6.4 Airline cancellation model assumptions

- Delay propagation is modelled through the delay multiplier f_{ak}, which may be inaccurate for individual cases. For example, long distance flights that have large times between arrival at the destination and the departure of the next flight, will be impacted less. Flights with tight turn-around times, will be impacted more.
- Rebooking is not taken into account. With a load factor less than 1 on other flights, this would definitely be possible. Therefore it is expected that cancellations are performed less than in reality.
- Flight distance is the great circle distance between the origin and destination airports. Due to regulations, wind conditions, or other optimizations actual distance may be longer. This results in a longer flight time and thus decrease cancellations costs.
- Transferring passengers that might miss their next flight is not taken into account. It is expected that therefore cancellation costs are higher, and less cancellations are performed in reality.

4.2.6.5 Cancellation policy analysis

To give better insight when cancellations occur according to eq. (43) and eq. (45), Figure 26 shows costs for 3 flight distances and aircraft capacity combinations. Namely: 500 km with 100 passenger aircraft capacity (e.g. flight to London with an Airbus 318), 6000km with 250 passenger capacity (e.g. a flight to Dubai with a Boeing 787), and 10.000km with a 450 passenger capacity (e.g. a flight to Johannesburg with a Boeing 747).

The distance s_{ak} is 500, 6000 or 10.000km for each scenario with a seat capacity S_{ak} of 100, 230, and 400 respectively. Based on the work of Janic [32], where the equations originate, the following assumptions are made. A delay multiplier $f_{ak} = 4$, unit operating costs $c_{ak} = \$1574/hr$, passenger wait ratio $q_{ak} = 0.5$, and passenger wait time $D_{ak} = 5hrs$. Based on [33] , the passenger unit wait cost is assumed to be $\$40/hr$. Lastly, the general assumptions are made that the flights will have an average load factor of $\phi_{ak} = 0.8$ and fly at an average speed of $v_{ak} = 900km/h$. Additionally, it is assumed that an average revenue of $r_{ak} = \$0.08/RPK$ is gained.

The delay and cancellation cost for delay durations between 0 and 10 hours is illustrated in Figure 26 for each scenario. The shortest flight in question has an intersection of 1:05 hr, the medium-haul flight is deemed feasible to cancel from 5:35 hrs, and the long-haul flight can be cancelled from 9:30 hrs. Logically, the further a flight its destination is and thus the more revenue a flight contributes, the longer delay is acceptable before it is cancelled.

The three scenarios produce expected cancellation results and thus the assumed parameter values are acceptable.

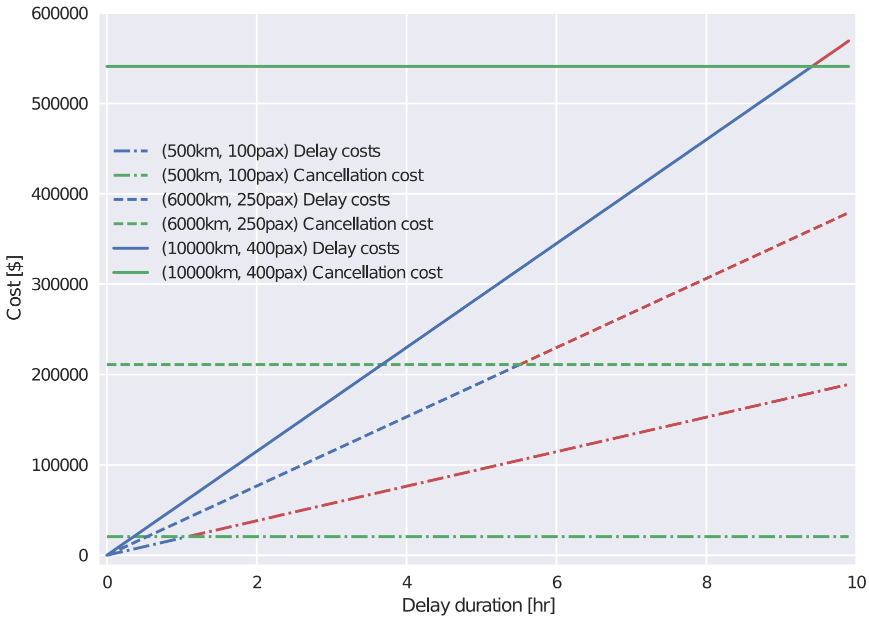


Figure 26: Cancellation versus delay costs for various flight distance and aircraft capacity settings

5 Simulation and integration of airport collaborative planning

One of the goals of this research is to show that collaboration benefits airport operations. In order to do so, a simulation was performed that integrates the negotiation process as described in chapter 4.

5.1 Simulation setup

The airport that will be used for simulation purposes is Amsterdam Schiphol Airport. Whilst the model is applicable to any airport, this one has been chosen for the following reasons:

1. It is a large airport with more than 2 runways, which increases the runway configuration selection significantly – especially in winter conditions
2. Weather forecast data was obtained from the KNMI and was the only detailed, historical forecast data that could be obtained [34]. The data only applies to the Netherlands.

The KNMI data description can be found in Appendix B. This section will provide an overview of the parameters used in the simulation with respect to the possible runway configurations and snow removal times.

5.1.1 Runway configuration setup

In the simulation, the possible runway configurations that were used are shown in Table 4. Additionally, their respective capacity levels (aircraft per hour) for both arrivals and departures are indicated for each visibility level.

For the visibility conditions, the following definitions were used.

- Good visibility: runway visual range > 5000m and cloud base > 1000ft
- Marginal visibility: runway visual range > 1500m or cloud base > 300ft
- LVP A: runway visual range > 550m or cloud base > 200ft
- LVP B: runway visual range > 350 or cloud base < 200
- LVP C/D: runway visual range > 200

Table 4: Runway configurations and respective arrival and departure capacities [35]

Priority	Configuration (ARR/DEP)	Capacity (ARR/DEP) [ac/hr]				
		Good	Marginal	LVP A	LVP B	LVP C/D
1	18R+18C / 09	68 / 40	68 / 35	56 / 24	44 / 30	34 / 23
2	06 / 36L+09	33 / 77	32 / 67	28 / 52	22 / 52	17 / 40
3	18C / 24	38 / 37	32 / 32	32 / 30	22 / 30	16 / 20
4	27 / 24	38 / 37	38 / 35	32 / 30	22 / 30	16 / 20
5	18C / 18C	22 / 22	20 / 20	17 / 17	15 / 15	10 / 10
6	27 / 27	22 / 22	20 / 20	17 / 17	15 / 15	10 / 10
7	- / -	0 / 0	0 / 0	0 / 0	0 / 0	0 / 0

5.1.2 Snow removal setup

Amsterdam Schiphol Airport makes use of Zaugg AG Eggiwil snow ploughs and sweepers. The largest variety, which is very likely used and is recommended for large airports, is the P21 SXL snow sweeper-plough combo. It has a clearing speed of $V = 50\mathrm{km/h}$, and a blade of $b_a = 6.3\mathrm{m}$ at $\alpha = 32°$ (thus an effective blade $b_e = 5.343\mathrm{m}$). This gives a clearing speed of 267 000m^2/h. A typical runway with its taxi ways covers about 900 000m^2, with a runway width of 40-45m. With the specific blade length, this means 7 ploughs are required in parallel to cover the runway once.

Using eq. (7) with the efficiency factor $\eta_s = 0.7$ as per [17] and combining this with the above specification, it results in a clear time of 41min. Schiphol states a 40min clearing time for their runways and main taxiways, with the exception of the Polderbaan (18R-36L), which requires 60min [36]. Our estimate is therefore valid. Based on the 60min Polderbaan clearance, it can also be derived this covers about 2 625 000m^2 of area to be cleared. This is vastly larger, but is mainly due to the increased runway width of the Polderbaan, being 75m. The increased width results in more parallel ploughs, namely 14.

5.1.3 De-icing setup

For each aircraft used in the simulation, the de-ice time is determined based on the de-ice category of the aircraft. The categories are defined in the AEA de-icing recommendations [18]. Herein, it provides an overview for the majority of aircraft with the associated de-ice category. A brief overview can be found in Appendix H.

For each de-icing category a de-icing time is defined. For Amsterdam Schiphol Airport, these are assumed to be as shown in Table 5.

Table 5: De-icing times per aircraft de-ice category [31]

Aircraft de-ice category	De-ice time
A	6
B	11
C	12
D	12
E	13
F	14

5.2 Assessing simulation model performance

Unfortunately, it was not possible to obtain actual data to validate the simulation model or assess the performance of the model. This section describes how the performance would otherwise be assessed.

Within SESAR, multiple key performance areas (KPAs) are defined to assess technological advancements [37] [38]. The KPAs are *qualitative* measures that are associated with Key Performance Indicators (KPIs), which are *quantitative* measures. The related KPAs to this research are:

- Airport Capacity: throughput, movements per hour
- Efficiency: actual performance as ratio of capacity
- Predictability: variance in forecasted and actual flight plans
- Resilience: avoided loss of capacity

Table 6: Mapped Key Performance Area (KPA) with associated Key Performance Indicator (KPI) units [37]

KPA ->	Capacity	Efficiency	Predictability	Resilience
KPI ->	Capacity Shortage	Delay	Punctuality	Avoidable loss
Airport	W movements	X min	Y percent	Z percent

In assessing the performance of the proposed model and the use of forecasting capacity, supporting information transparency, and increased collaboration, the KPAs that will be analysed are efficiency, predictability, and resilience. Therefore, airport capacity is not assessed. The airport capacity is not assessed, because the capacity is not improved or altered in any way, only forecasted.

5.2.1 Assessing KPA Efficiency; KPI Delay

Generally delay is the comparison between actual and scheduled time stamps of an event. For a passenger on a flight, the delay is usually the difference between the scheduled on- or off-block times and the actual times. However, the issue is that multiple processes influence these times, such as en-route delay or delay due to issues such as technical difficulties. In the assessment, it is therefore best to compare forecasted and intentional times as the indicator for delay. Here, the forecasted times include additional information such as weather forecasts, while the intended times do not. Additionally, the most restraining factor is used as the assessment process, which is the runway.

Delay will be computed for each arrival or departure and can be summed or averaged as a single value KPI output. Early flights, negative delay, do not contribute to the delay propagation. This computation is shown in eq. (48) as is defined in SESAR [37]. Here, FLDT and FTOT refer to the forecasted landing and take-off times and ILDT and ITOT refer to the intended landing and take-off times. Intended and forecast times are used as a generic comparison of times. This means one has to compare the same type of times. In this case the scheduled landing and take-off times (SLDT and STOT) are used as values for ILDT and ITOT. If off-block time was forecasted, the scheduled off-block times could be used as intended time for the delay computation.

$$\begin{aligned} D_{DEP} &= FTOT - ITOT \\ D_{ARR} &= FLDT - ILDT \end{aligned} \qquad \text{eq. (48)}$$

5.2.2 Assessing KPA Predictability; KPI Punctuality

The predictability of operations refers to the ability control flight operation variability and disruption effects, such as winter conditions as used as a use-case in this research. Predictability includes arrival, turn-around, departure predictability as well as flight cancellations and aircraft changes. For this research, arrival and departure predictability and the prediction of flight cancellations can be assessed.

During the assessment of the KPIs, the threshold (TH) can be varied. Currently, it is usual to have a threshold of 15min. The assessment can be done through utilizing eq. (49) and eq. (50), as defined within SESAR [37]. Additional to the definition of section 5.2.1, RLDT and RTOT refer to the reference landing and take-off times. Similar to ILDT and ITOT, for both the SLDT and STOT are used. Again, comparing forecasted and reference times have to be the same type of time. Meaning when off-block time is forecasted, the reference times would consist of off-block times.

$$ARRp = CNT([FLDT - RLDT] < TH)$$
$$DEPp = CNT([FTOT - RTOT] < TH) \qquad \text{eq. (49)}$$

$$P_{ARR} = \frac{ARRp}{ARR}$$
$$P_{DEP} = \frac{DEPp}{DEP} \qquad \text{eq. (50)}$$
$$P = \frac{ARRp + DEPp}{ARR + DEP}$$

5.3 Simulation Scenario: February 2, 2012

At the 2nd of February in 2012 there was a major snowfall event on Amsterdam Schiphol Airport. The majority of snow fell around between 11:00 and 13:00, but snow fell from 9:00 till 15:00. Not only the airport is affected, but also roads endure heavy traffic jams – at its peak 800km – and trains are delayed or cancelled. Flights are delayed by an average of 45 minutes; that is, if they are not cancelled [39].

The forecasts of that morning are shown in Figure 27, using the accumulation formulas of section 3.2.1, and show how snowfall may develop throughout a day. Forecast MOS data is provided by KNMI [34]. It is assumed to be 9:00, when snow just starts falling, what happens next?

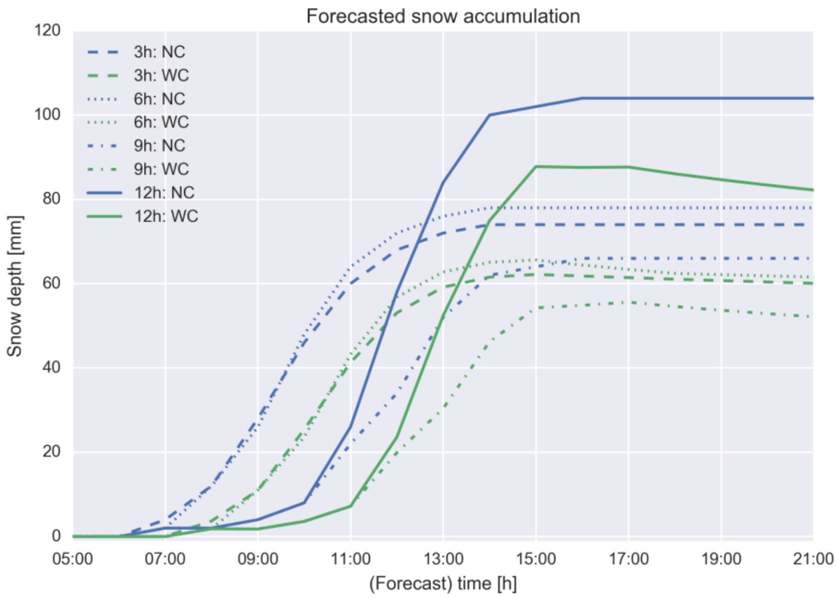


Figure 27: Comparison of snow accumulation as forecasted on 03:00, 06:00, 09:00 and 12:00 with (WC) and without compaction (NC) corrections

In generating possible configuration and scheduling options, the limiting factors are runway feasibility and configuration capacity. Wind directions and wind speeds determine runway feasibility, the visibility and cloud base conditions determine configuration capacity levels and snowfall determines runway feasibility as a result of snow removal operations.

5.3.1 Meteorological runway feasibility

To visualize the impact of the forecasts, Figure 28 provides an overview of runway feasibility due to wind limitations for all runway possibilities that result from the runway configurations of Table 4. Here, the tailwind limit was set to 10kts and the crosswind limit was set to 20kts.

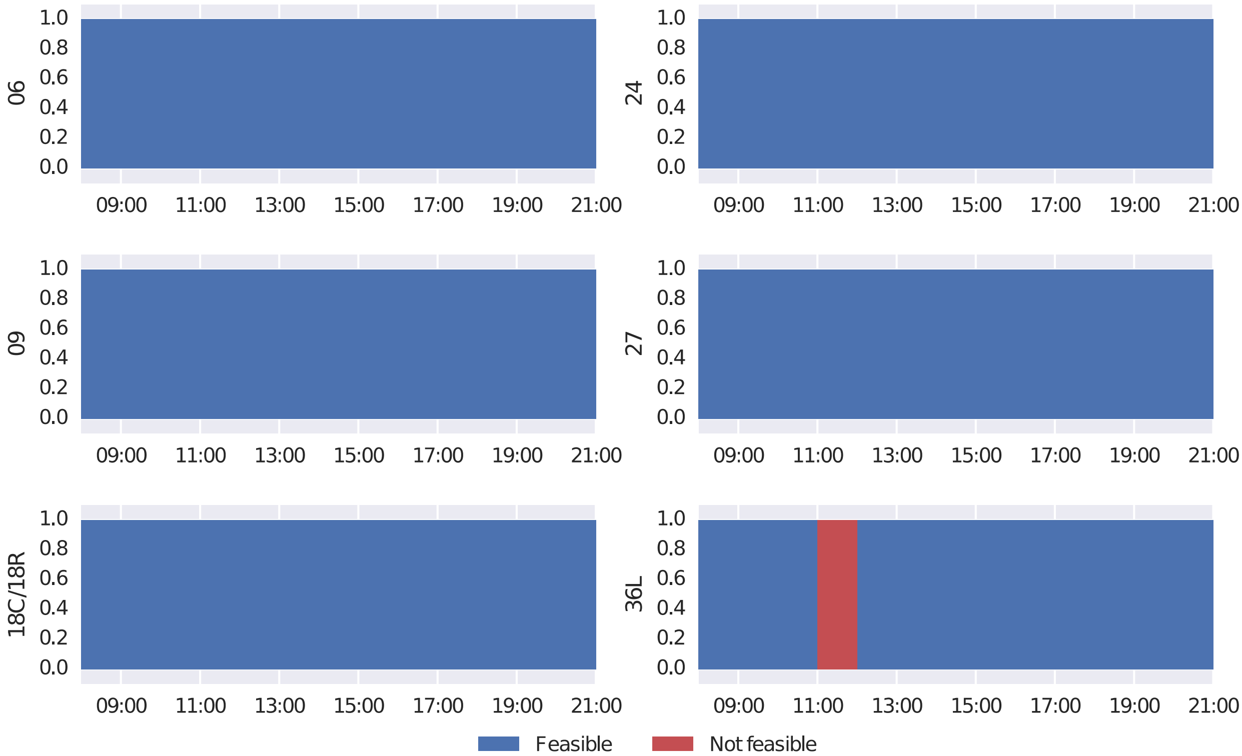


Figure 28: Runway feasibility due to tailwind and crosswind limitations

A similar overview is shown in Figure 29. Here, the runway configurations from Table 4 are shown along with their respective forecasted capacity values based on forecasted visibility and cloud base conditions, as through the process as shown in section 2.2.2. With capacity levels only slightly lower during the snowfall period (11:00 – 14:00), it can be concluded that visibility has only minor impact on the runway capacity.

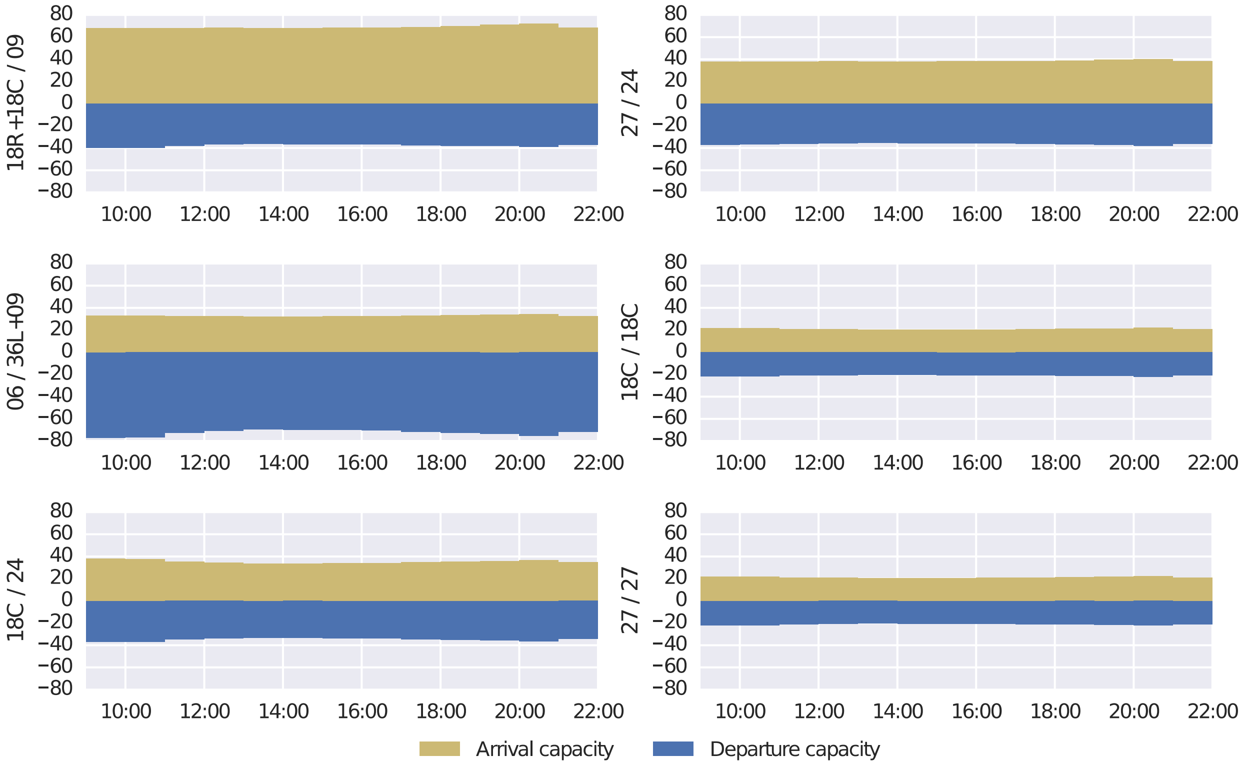


Figure 29: Forecasted capacity values for each configuration based on visibility and cloud-base conditions

Even though the runways are feasible in terms of wind and visibility conditions, they may not be due to the forecasted snowfall. Based on the snow removal process as described in section 3.2, Figure 30 shows the planned snow removal procedures, which is the result of the negotiation model.

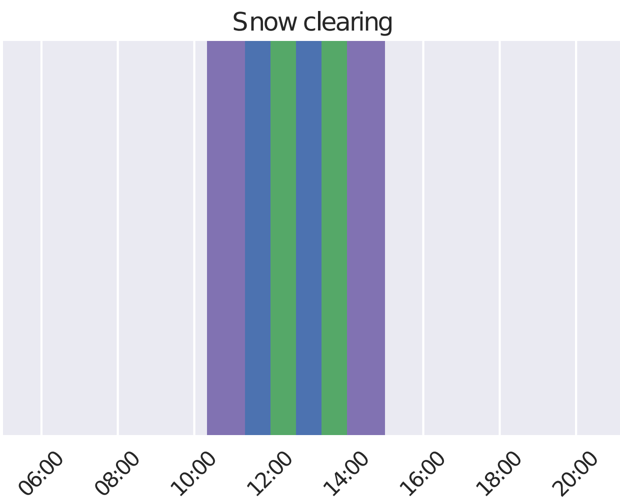


Figure 30a: Snow clearing operations

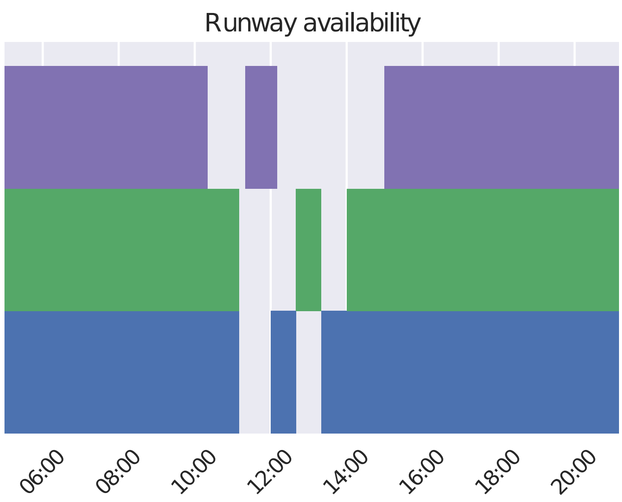


Figure 30b: Runway availability

Figure 30: Runway availability up to 3 separate runways (blue, green, and magenta); colours in both plots correspond to the same runway

5.3.2 Delay and cancellations

The performance of the capacity manager and the airline managers can be shown through analysing the delay propagation of the flight planning. Herein, the difference between the planned times of arrival or departure is compared with the scheduled times of arrival or departure. Performing this analysis will indicate two factors: it shows if the runway configuration is fitting for the inbound and outbound flights, but also the effect of flight cancellations and how much delay this prevents.

Figure 31a shows the delay accumulation for inbound and outbound flights for the regular model as well as when airlines will perform all of their scheduled flights and do not cancel any. One can conclude that cancelling flights lead to lower amounts of delay. Additionally, the effect of preventive cancelling of flights is substantial. The final accumulated delay is 100hrs less with preventive cancellations for both inbound and outbound flights.

The graph of Figure 31a also shows the behaviour of the runway configuration and flight planning techniques. Namely, the sum of total delay (i.e. inbound and outbound delay) is minimized. Both delay levels are balanced, which is shown by the fact that the areas under the both delay curves are nearly equal.

The analysis of delay accumulation is useful in comparing trends between different scenarios, but lack in visualizing the actual delay each flight is subject to. In Figure 31b the average delay for each flight is shown using a moving average over 20 flights. With the majority of snowfall during the time period between 11:00 and 14:00, delays increase dramatically. It takes up to 19:30 before outbound delays are at acceptable levels of an average of 15 minutes per flight. However this does not last for long, as a new outbound peak causes more outbound demand than there is capacity available. Average inbound delay levels remain high.

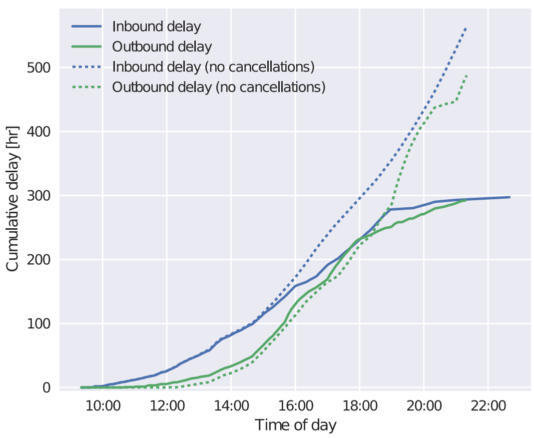


Figure 31a: Cumulative delay

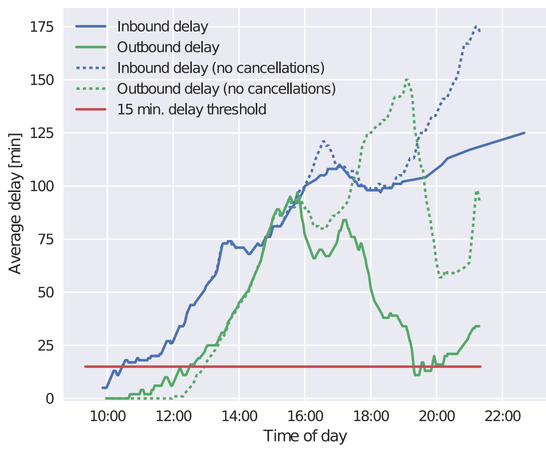


Figure 31b: Average delay

Figure 31: Delay propagation for inbound and outbound flights w.r.t. flight schedule

The decrease in delay in the new flight planning is achieved with only a minor number of cancellations for most airlines. Figure 32b shows the distribution in cancellations as a ratio of their total number of flights that day. Whilst major airlines that connect Amsterdam Schiphol Airport, such as KLM (KLM), Aer Lingus (BEE), and EasyJet (EZY), cancel the most flights they are not impacted solely. The aforementioned airlines have both higher (e.g. Aer Lingus) and lower (e.g. KLM) ratios. This shows the effect of the airline decision making model (see section 4.2.5.3) that makes a cost-benefit analysis per flight, and thus no airline is benefitting more than another.

The right section of the graphs shows (almost) no cancellations (TFL to DAL). This can be explained due to the fact that these flights were mostly in the morning, where little delay was accumulated and therefore no reason to cancel. This can also be seen in Figure 32a, where the most flights are cancelled just after the snow period i.e. the period when delays are accumulated too much and therefore delay costs are higher than the cancellation costs.

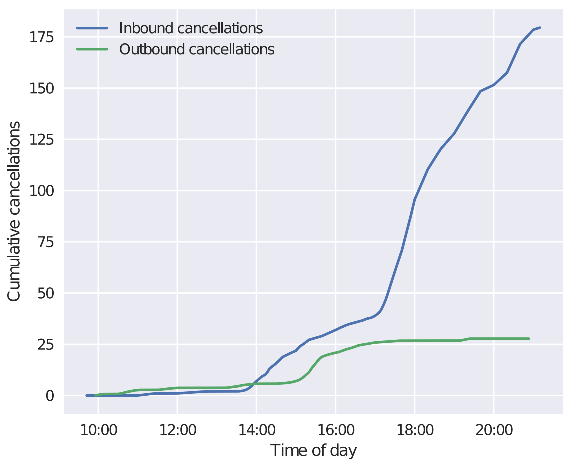


Figure 32a: Cumulative cancellations w.r.t. original scheduled time of arrival/departure

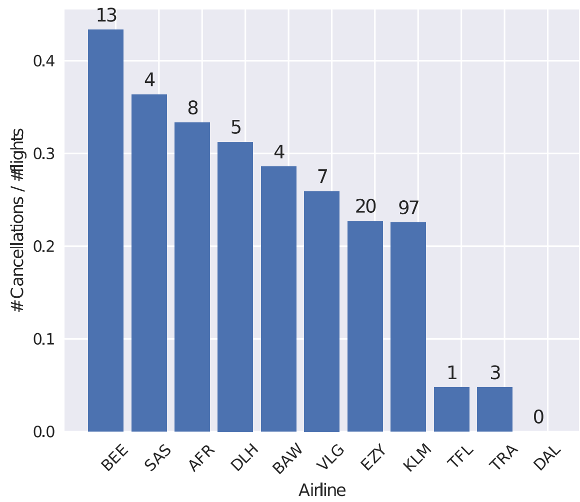


Figure 32b: Cancellation / flight ratios for airlines with at least 10 flights (abbreviations, see Appendix I*)*

Figure 32: Cancellations for simulated scenario of 2 Feb. 2012

5.3.3 Negotiation performance

Negotiation as a means for distributed planning is potentially a powerful approach to increase efficiency and predictability. In that case, one would like to evaluate the performance of the negotiation. This can be measured by the acceptance rate of the agents. Recalling from section 4.1, at each round, the negotiation is stopped when an agent rejects or proposes an alternative. The negotiation is then started again.

In total, 121 agents were involved in the negotiation. This number is mostly determined by the number of airlines involved as 117 agents are airlines. The acceptance rate is determined by dividing the accepting agents per negotiation round by the total number of agents (121). Naturally, the last round results in 100% acceptance rate as the negotiation stops when every party agrees on the proposed option.

The acceptance rate at each iteration is shown in Figure 33a. Two things are notable: there are some flat lines where no increase in acceptance rate occurs for some time (e.g. iteration 25 to 800) and the fact that there are a lot of iterations (1673). On average, 13.8 iterations are required for a proposal to be accepted for each agent. Both are the result of the set-up of the negotiation simulation because of the following two points.

Firstly, because an airline cancels flights, the runway flight planning (and possibly the runway configuration) needs to be re-computed and is thus again proposed. As airline cancel flights often (see second point), the re-computing leads to a lot of additional iterations.

Secondly, airlines can only cancel a maximum of one inbound and one outbound flight at a time, as the airline agent is modelled to be 'smart enough' to determine the impact of the cancellation. Cancelling a flight, namely, decreases the delay of other flights, which impacts the decision making of the airline.

If both factors were to be accounted for in the model or assumed to be accounted for in a real-life scenario, the real negotiation performance is much closer to Figure 33a. Considering 121 agents are negotiating, 70 iterations is a fair performance.

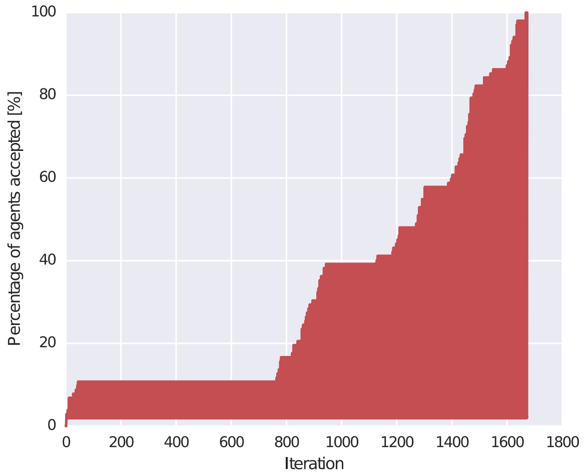


Figure 33a: Negotiation performance

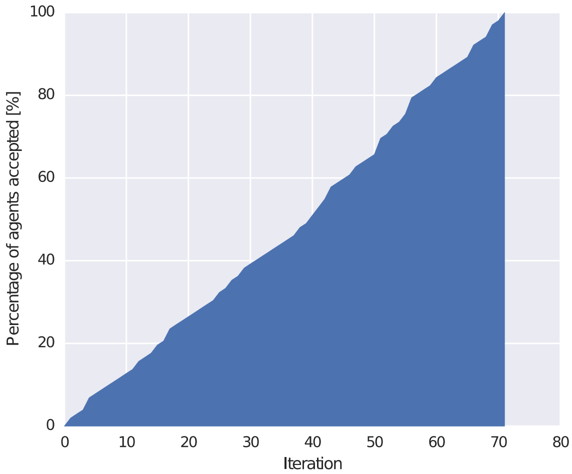


Figure 33b: Adjusted negotiation performance

Figure 33: Acceptance performance per iteration of negotiation

5.4 Airline delay and cancellation cost sensitivity

In the simulation, the capacity is forecasted as introduced in section 2.2.2. In the negotiation, it is then assumed by the airlines that they have to respect that capacity. Air Traffic Control, however, might not be eager to share runway capacity information, in the fear of over- or underestimating it. Therefore when capacity data is shared in the current situation, it tends to be conservative. Using the simulation of the negotiation process, it is possible to evaluate the impact of over- or underestimating the runway capacity.

The newly forecasted capacity that will be used in runway planning and runway configuration selection is the adjusted capacity C_A, as described in eq. (51). A factor f denotes the confidence in the estimated capacity forecast, with a negative value leading to an underestimation and a positive value to an overestimation of capacity.

An underestimation means that all other parties think there is less capacity, but in the execution there will be more. As a result, expected delays will be larger than what will be in the execution. For overestimations, the expected delay is smaller than what is most probable. Expected is that airlines will cancel more flights in the case of underestimating capacity and fewer flights cancelled when overestimating capacity.

$$C_A = C(1 + f) \qquad \textit{eq. (51)}$$

5.4.1 Airline decision making cost sensitivity

The results of the negotiation under the confidence levels between -15% and +15% is shown in Figure 34. Measuring the impact of the confidence level is done by computing the total delay and cancellation costs for all involved airlines. The impact is then normalized with respect to the realized planning, which corresponds with $f = 0$. For example, a cost impact of 0 means the costs are equal to the costs of the realized planning and a cost impact of 1 implies that the costs are doubled (+100%).

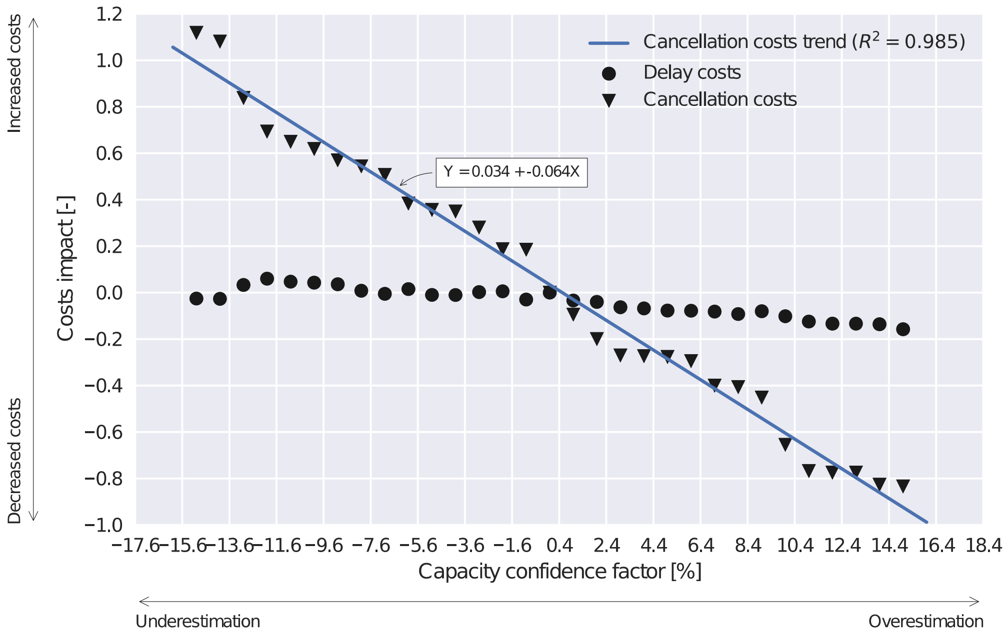


Figure 34: Airline delay and cancellation costs for capacity confidence levels

It shows that the delay costs do not change a lot with the various confidence factors, whilst the cancellation costs increase with a lower confidence factor and decrease with higher factors. Having sufficient demand, underestimations of capacity means that delay accumulates faster. For each flight, airlines assess if cancelling a flight might be a cheaper option than accepting the delay as is described in section 4.2.5.3. This means that the chance of cancelling a flight increases at lower confidence levels. It is thus logical that delay costs for all airlines in the simulated scenario do not change a lot with respect to the confidence factors, as a further increase in delay lead to unacceptable levels and cancellations are the result.

The default case exhibits a total cost of $22.18M, consisting of $6.05M in cancellation costs and $16.82M in delay costs. As expected, there is a clear, negative trend between the confidence level and the cost impact, with lower costs at higher confidence levels. The trend can be linearly estimated and is also shown in Figure 34 that exhibits a fitting accuracy R^2 of 0.985. It is important to note that the trend line is only valid for cost impact values larger than -1. A cost impact of -1 means there are no costs, so values smaller than -1 would imply that airlines gain revenue by cancelling or delaying a flight.

5.4.2 Airline cost sensitivity due to capacity imbalance

The above is definitely valid from the airline perspective, but the reality will turn out differently than expected. When capacity is overestimated, airlines cancel fewer flights as delay is expected to be less. However, in the execution of the planning, delay levels will be a lot higher, as capacity was overestimated.

It is expected that the increase in actual delay costs will be at least that of the decrease in cancellation costs. This is due to the decision making of the airline, where flights are cancelled once delay levels are too high. Applying this principle to the total costs of the airlines, namely the delay and cancellation costs, results in Figure 35.

Again, the costs vary with the capacity confidence factor, with the realized planning at $f = 0$. Thus in Figure 35 an increase in costs for both under- and overestimations can be seen. This is completely to be expected, namely that either an underestimation or overestimation never leads to an optimal planning. This in turn results in associated increase in costs. Interestingly, the impact of overestimating capacity increases faster than the impact of underestimating capacity when deviating from the default case ($f = 0$).

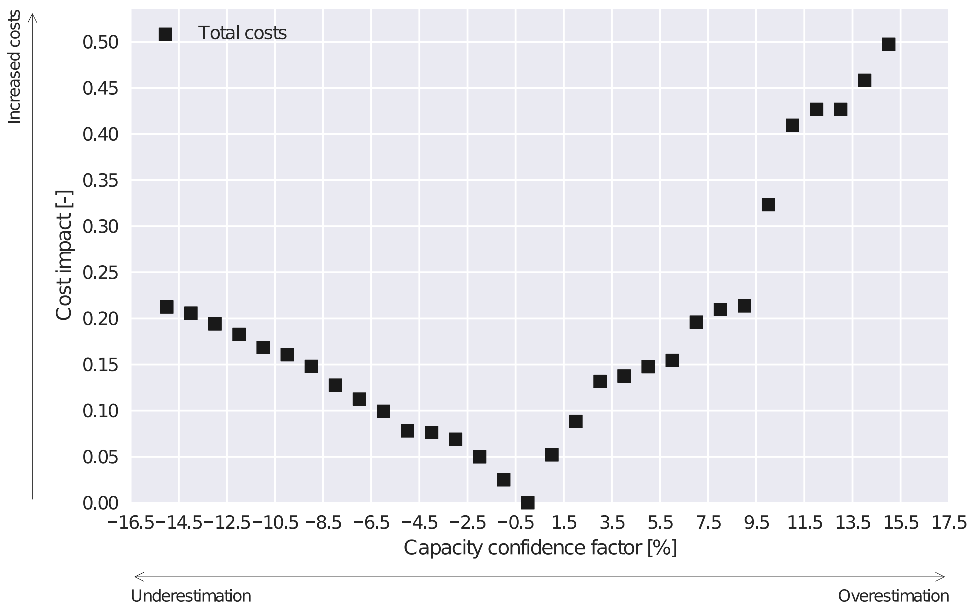


Figure 35: Airline total costs (delay and cancellation costs) for capacity confidence factors

5.4.3 Airline cost sensitivity due to capacity forecasts

The visibility category was modelled as a random variable. At each time step a random number was generated between 0 and 1. The random number is then compared with the probabilities of a visibility category occurring, as forecasted in the KNMI MOS forecast data. The negotiation model was run 1000 times.

In Figure 36 the distribution of delay costs, cancellation costs, and total costs is shown. Here, the costs are normalized with respect to the respective costs associated with the forecasted runway capacity. The latter also corresponds with the default 0 case of the previous section 5.4.2. Additionally, the associated histograms and probability density functions can be found in Appendix D.

What Figure 36 shows is that the forecasted capacity is mostly on-par. However, for both the delay and total costs, there is a higher probability of lower costs i.e. the area under the curve is larger for normalised cost < 0. Most significantly is the difference in cancellation costs. Here, the median cancellation costs are 5% lower than expected. The median total costs are 2% lower. Both seem rather insignificant, yet when combined with the normal total costs of $22M: it is not. The 2% cost reduction is an impact of $440.000.

It implies that in more cases the costs are lower than expected. This means that an airline should cancel fewer flights than predicted, thus decreasing costs and increasing customer satisfaction.

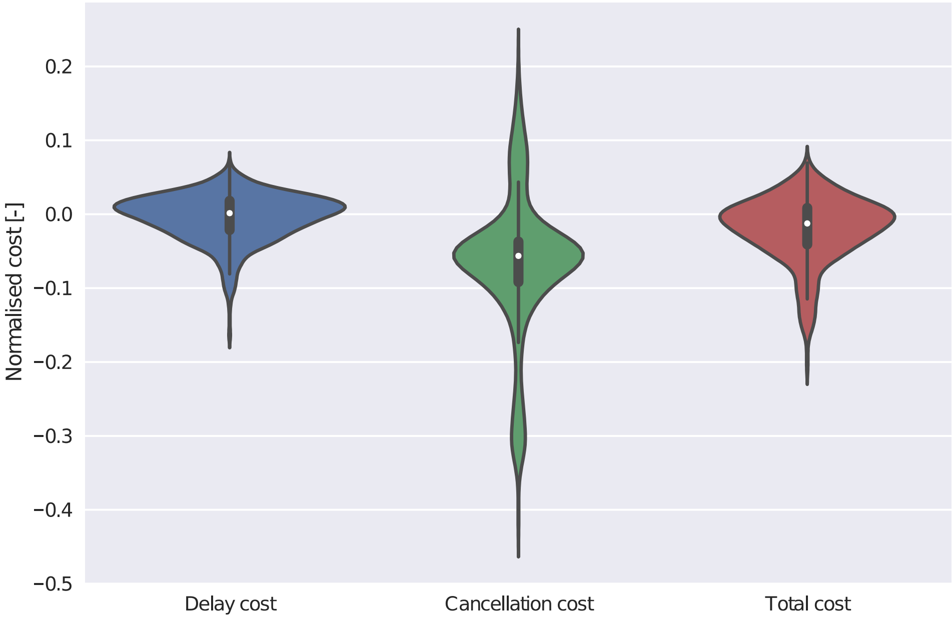


Figure 36: Violin plots of delay, cancellation and total costs over 1000 Monte Carlo runs

5.4.4 Operational impact of erroneous capacity estimations

Previously the impact of overestimating or underestimating was measured in terms of costs for airline. However, there are also some practical aspects that are the result of either over- or underestimating capacity. Both cases reveal their own issues.

Capacity underestimations

During the execution of a planning that is based on an underestimated capacity, delay levels are suddenly much lower than planned.

Advantages include:

- More slack time that can deal with unexpected issues i.e. robustness increases
- Expected delay costs are lower

Disadvantages include:

- Too many flights may be cancelled than necessary.
- Lower efficiency of available capacity. Parties have more slack time, therefore may operate at a lower rate.
- There is room to speed up operations, such that delay with respect to original scheduled arrival/departure times is minimized. However, if stakeholders try to achieve this, it leads to less organized executions, decreases efficiency and requires more communication between parties.

Capacity overestimations

When overestimating capacity, flights are planned with less delay than during the realisation. This means that parties are constantly behind schedule.

Advantages include:

- Less cancelled flights
- More passengers reach their destinations

Disadvantages include:

- More delay
- Decreased passenger experience
- Increased workload for all parties, most specifically:
    - Air traffic control
    - De-ice operators
    - Ground handling operators
- Increase crew fatigue

6 Conclusions and recommendations

Collaboration is the future of operational airport planning. With current airport stakeholders being hesitant to share information, a transition to increased collaboration is difficult. Research is required to prove the benefits of collaboration compared with the current situation. A part of this effort was done in this thesis, which had the following objective and goals.

Research objective
"To increase predictability in the (pre-)tactical airport airside operational processes through integrating capacity forecasting and decision support for air traffic control, the airport and service providers under winter conditions."

At the core of the objective are the 2 main goals:

1. To extend current capacity forecasting models to include winter conditions, thus allowing for all-weather capacity forecasting.
2. To develop a decision support facility that evaluates the effect of capacity forecasting and integrates the collaborative planning of runway management, de-icing, and snow-removal operations.

In order to achieve the objective, this thesis contributed the following:

- Snow removal and de-icing capacity forecasts
- Snow removal planning optimization model
- A negotiation model for distributed airport operational planning, with respect to
    - Runway configuration planning
    - Runway flight planning
- Decision models for each of the stakeholders:
    - Air traffic control
    - Snow removal
    - De-icing service provider
    - Airlines
- A simulation framework that integrates all of the above

6.1 Conclusions

This thesis has been a step towards modelling collaboration for complex operational planning processes by integrating capacity forecasts. The modelling is done through a multi-agent negotiation technique, where each stakeholder proposes and assesses planning options. In this case, stakeholders collaboratively work towards the most appropriate runway configurations and runway flight planning using the principled negotiation protocol. This was done whilst still adhering to the respective safety regulations and possible preferences.

The collaborative operational planning is based on the forecasted capacity. This thesis extends current runway capacity forecasting models with the ability to cope with winter scenarios. Not only runway capacity, but also snow removal and de-icing capacity forecasting were done.

With forecasting runway capacity in place, flight schedules are updated and results in the impact in terms of flight delay. This means that airlines have the possibility to cancel flights much earlier on. The earlier they can decide whether to cancel, the better. Namely, early decision leaves more time available for rebooking passengers. This improves passenger experience and reduces the costs for airlines.

During winter conditions, flight handling (from arrival to turn-around to take-off) is a less common practice, which increases the variability in performance and decreases the situational awareness. Increasing the predictability of operations and improving shared situational awareness through distributed planning, limits the adverse effects.

A simulation was run for February 2, 2012 when Amsterdam Schiphol Airport was hit by snowfall. The simulation shows that working collaboratively on the flight planning shows significant delay minimization. Over a period of 12 hours, cumulative delays are reduced by 100 hours. The reduction is achieved due to the cancellation of flights that are expected to have high delay levels.

In the simulation 121 agents participated and agreement is reached within 1670 iterations. This is an average of 13.8 iterations per agent. The agreement was reached within 20 seconds computation time and is thus very suitable for real-time operations. Especially given the fact that it is a multi-agent system, where computation time increases linearly instead of exponential [40]. We can additionally conclude principled negotiation is suitable as a distributed planning protocol. Aside from its performance, it is beneficial that this protocol always reaches agreement.

Furthermore, the system can be easily up-scaled using the same type of agents, but also new agents can be added with ease. New agent types can be developed without any required knowledge of the decision making of the other agents, as long as the same variables are negotiated. New variables can be added independent of the decision making of other agents and thus allows for easy extension of the system.

Apart from real-time planning possibilities, the system proves to be able to work inter-organisational through the use of the multi-agent system. Due to the distributed nature of the system, it is not a problem to implement across multiple locations / organisations. In terms of security or privacy this is extra beneficial, as only global data is shared and local data for decision making remains at the respective organisation.

With airline decision making being dependent on the capacity forecasts, it is most important that the forecasts are not underestimated or overestimated in any way as both lead to decreased predictability and increased costs. Air traffic control is not very eager to share capacity information. If the information is shared it is not unthinkable that capacity levels might be estimated more conservatively. From simulations it can be concluded that estimating more conservatively is at least beneficial compared to overestimating capacity. It shows that underestimation lead to an increase of airline cost of approximately 1.5 times the confidence factor. That is to say, if capacity is 10% estimated more conservatively (underestimated), airline costs grow with 15%. On the other hand, overestimations increase with a factor 2.25.

With the used capacity forecasting methods, the capacity tends to be somewhat higher in most cases. The forecasting is thus a little conservative. Combined delay and cancellation costs are generally 2% lower than expected.

6.2 Recommendations

In this thesis it was not possible to validate the results with the reality. Therefore, the recommendation is to obtain runway configuration and flight planning data to compare results with. In order to do a proper validation, delay and cancellation data is required. Preferably the reasoning to delay or cancel a flight would be available too, in order to validate the model within the bounds of the model assumptions.

In this thesis, a simulation was performed that automates the collaboration of stakeholders. The same ruleset of proposing and accepting options may also be applied in an operational environment with humans in the loop. A decision support tool that facilitates the negotiation for stakeholders is thinkable. Additionally, impact of decisions can be evaluated though computing what-if scenarios. This allows for a more quantitative argumentation compared to expert judgement decisions.

With a large part of the thesis focussing on collaboration and distributed planning, some forecasting methods are not as advanced as is done in other literature. More sophisticated methods such as machine learning algorithms as introduced by Udo [41] or To70/KLM [42] may provide more accurate forecasts and would increase the benefit of the negotiation. Using model techniques such as machine learning helps to provide forecasts in cases that are not specifically modelled, which was the approach in this thesis. The disadvantage from ML models is that it requires a fair amount of data. It is therefore advised to research a generalized approach, which could even use data from a multitude of airports. If doing so, the model will likely perform better in unseen cases.

The choices by the stakeholders are modelled deterministic. In some scenarios, it may occur that stakeholders have a different reasoning process than is currently modelled. To account for this, one could include stochasticity in the decision modelling. Once that is done, the performance of the model can be re-evaluated with respect to its robustness to the stochastic nature.

The scope of this work was limited to the runway configuration and runway flight planning based on forecasted runway capacity, snow removal capacity, and de-icing capacity. Including more components such as taxiway, stand, push-back and ground handling will increase the accuracy of the flight planning and enhance collaboration further. Also, if the opportunity arises it would be beneficial to connect airside and landside capacity by integrating terminal capacity and processes such as check-in, passport control, and security.

This thesis work has focussed itself to the collaboration with respect to the runway configuration and runway flight planning. The same method may very well be applied to other planning processes. This could be in the aviation environment, but applications can also be in other logistical domains such as seaports or (truck) vehicle routing [1]. Generally the used multi-agent approach is valuable in contexts with a multitude of stakeholders.

References

[1] N. Lang, H. M. Moonen, F. J. Srour and R. A. Zuidwijk, “Multi Agent Systems in Logistics: A Literature and State-of-the-art Review,” Rotterdam, 2008.

[2] J. Dedrick and K. L. Kraemer, “The impacts of IT on firm and industry structure: The personal computer industry,” *California Management Review,* vol. 47, pp. 122-142, 2005.

[3] NLR, ENAC and GESAC, “Airport Capacity Forecast: Operational Concept Description,” 2013.

[4] NLR, ENAC and GESAC, “Airport Capacity Forecast: System Architecture Description,” 2014.

[5] A. T. Wells, Airport planning and management, 6 ed., Mcgraw-Hill Education - Europe, 1992.

[6] M. Janic, Air transport system: analysis and modelling, 1 ed., Amsterdam, the: Gordon and Breach Science Publishers, 2000, p. 318.

[7] M. Bazargan, K. Fleming and P. Subramanian, “A simulation study to investigate runway capacity using TAAM,” in *Winter Simulation Conference*, 2002.

[8] N. J. Ashford, S. Mumayiz and P. H. Wright, Airport Engineering: Planning, Design and Development of 21st Century Airports, 4 ed., Hoboken, New: John Wiley & Sons, 2011.

[9] H. Hesselink and J. Nibourg, “Probabilistic 2-Day Forecast of Runway Use,” in *Ninth USA/Europe Air Traffic Management Research and Development Seminar*, 2011.

[10] A. Heidt and O. Gluchshenko, “From uncertainty to robustness and system's resilience in ATM: a case-study,” in *Third International Air Transport and Operations Symposium*, Delft, 2012.

[11] H. R. Glahn and D. A. Lowry, “The Use of Model Output Statistics (MOS) in Objective Weather Forecasting,” *Journal of Applied Meteorology,* vol. 11, no. 8, pp. 1203-1211, 12 1972.

[12] L. Li and J.-P. Clarke, “Airport configuration planning with uncertain weather and noise abatement procedures,” in *29th Digital Avionics Systems Conference*, 2010.

[13] J. M. Nibourg, H. H. Hesselink and Y. A. J. R. van de Vijver, “Environment-aware runway allocation advice system,” in *26th International congress of the aeronautical sciences*, 2008.

[14] NLR, ENAC and GESAC, “Capacity model descriptions,” 2014.

[15] H. H. Hesselink, J. M. Nibourg, L. d'Estampes and P. Lezaud, “Airport Capacity Forecast - Short-term Forecasting of Runway Capacity,” in *Fourth SESAR Innovation Days*, 2014.

[16] D. J. Tighe, L. A. Garland and J. C. Caird, “An Analysis of Airport Snow Removal and Ice Control,” Ottawa, 1970.

[17] FAA, “AC 150/5220-20A: Airport Snow and Ice Control Equipment,” 2014.

[18] Association of European Airlines (AEA), "Recommendations for De-Icing / Anti-Icing of Aircraft on the Ground," 2008.

[19] T. Myers, M. Andrews and J. Krozel, "Winter Weather Airport Capacity Model," in *Proceedings of Twelth AIAA Aviation Technology, Integration, and Operations (ATIO) Conference*, Indianapolis, 2012.

[20] Weather Forecast Office (WFO) Buffalo; Iowa State University, "What is compaction?," [Online]. Available: http://www.meteor.iastate.edu/~ckarsten/bufkit/compaction.html. [Accessed 8 2016].

[21] Q. Wu, Y. Andreopoulos, S. Xanthos and S. Weinbaum, "Dynamic compression of highly compressible porous media with application to snow compaction," *Journal of Fluid Mechanics,* vol. 542, pp. 281-304, 2005.

[22] M. Wooldridge, An introduction to multiagent systems, John Wiley & Sons, 2009.

[23] S. Franklin and A. Graesser, "Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents," in *International Workshop on Agent Theories, Architectures, and Languages*, 1996.

[24] S. Kraus, "Automated negotiation and decision making in multiagent environments," *Multi-agent systems and applications,* 2001.

[25] F. Wu, S. Zilberstein and X. Chen, "Online planning for multi-agent systems with bounded communication," *Artificial Intelligence,* vol. 175, no. 2, pp. 487-511, 2011.

[26] S. Kraus, "Negotiation and cooperation in multi-agent environments," *Artificial Intelligence,* vol. 94, no. 1-2, pp. 79-97, 7 1997.

[27] R. Fisher, W. L. Ury and B. Patton, Getting to yes: Negotiating agreement without giving in, 3 ed., Penguin Books, 2011.

[28] J. P. Wangermann and R. F. Stengel, "Principled negotiation between intelligent agents: a model for air traffic management," *Artificial Intelligence in Engineering,* vol. 12, pp. 177-187, 1998.

[29] E. Bonabeau, "Agent-based modeling: Methods and techniques for simulating human systems," in *Proceedings of the National Academy of Sciences*, 2002.

[30] FAA, "AC 150/5200-30D: Airport Field Condition Assessments and Winter Operations Safety," 2016.

[31] R. S. Verboon, "Deicing scheduling," 2016.

[32] M. Janic, "Modeling Airport Operations Affected by a Large-Scale Disruption," *Journal of Transportation Engineering,* vol. 135, no. 4, pp. 206-216, 2009.

[33] P. Anand, H. Ceylan, K. Gkritza, P. Talor and V. D. Pyrialakou, "Cost comparison of alternative airfield snow removal methodologies," Ames, 2014.

[34] KNMI, *TAF Guidance MOS 2009-2015 [data set].*

[35] Amsterdam Schiphol Airport CORRECT, *QRC09 - Baancombinaties en capaciteitscijfers, geldig m.i.v. 23-12-2016.*

[36] Schiphol Group, “Schiphol in de winter,” [Online]. Available: http://schipholjunior.nl/schiphol-hoe-werkt-dat/schiphol-in-de-winter.html. [Accessed 03 01 2017].

[37] EUROCONTROL, SEAC, DFS and AENA, “DCB Preliminary OSED,” 2012.

[38] EUROCONTROL and AENA, “Indentify Airport KPIs and Performance Drivers for the selected KPAs/Focus Areas: Predictability,” 2010.

[39] NOS, “3 februari: overlast door sneeuw,” 2012. [Online]. Available: http://nos.nl/artikel/337035-3-februari-overlast-door-sneeuw.html. [Accessed 10 01 2017].

[40] L. C. Lee, H. S. Nwana, D. T. Ndumu and P. De Wilde, “The stability, scalability and performance of multi-agent systems,” *BT Technol J,* vol. 16, pp. 94-103, 1998.

[41] E. M. Udo, “Forecast model for the declared runway capacity,” 2014.

[42] A. De Leege and C. Janssen, “Probabilistic Runway and Capacity Forecasting using Machine Learning to Support Decision Making,” in *Sixth SESAR Innovation Days*, Delft, 2016.

[43] E. P. Gilbo, “Airport capacity: Representation, estimation, optimization,” *Control Systems Technology, IEEE Transactions on,* 1993.

[44] NLR, ENAC and GESAC, “Demonstrator,” 2014.

[45] R. M. Rasmussen, J. Vivekanandan, J. Cole, B. Myers and C. Masters, “The Estimation of Snowfall Rate Using Visibility,” *Journal of Applied Meteorology,* vol. 38, no. 10, pp. 1542-1563, 10 1999.

[46] N. Subbotin and S. Gardner, “Takeoff and Landing Performance Assessment Validation Effort of the Runway Condition Assessment Matrix,” 2013.

[47] J. P. Wangermann and R. F. Stengel, “Optimization and Coordination of Multiagent Systems Using Principled Negotiation,” *Journal of Guidance, Control, and Dynamics,* vol. 22, no. 1, pp. 43-50, 1 1999.

[48] J. Rapajic, Beyond airline disruptions, Ashgate, 2009, p. 169.

[49] NLR, ENAC and GESAC, “Operational Concept Description,” 2013.

[50] LVNL, *EHAM ATA / ATD 03-02-2017.*

Appendix A Airport capacity forecast decision support

The negotiation of the agents is programmed in a web-based environment using Java, running on a Tomcat server enabled by the libraries JavaServerFaces and Primefaces. The last two are used for rendering the output. This is built as a demonstrator and initial set-up for a decision support facility for forecasted capacity and operational planning negotiation. This chapter elaborates upon the facility architecture and the methods of visualizing capacity forecast information.

Appendix A.1 Facility architecture

The facility consists of two major parts:

- Negotiation framework (see Figure 37)
- Capacity forecasting framework (see Figure 38)

The negotiation framework is shown in Figure 37, which is based on the negotiation definition from section 4.1.4. The negotiation is modelled as the communication of Messages between Agents. A message is a Request, Proposal, Acceptance, or Rejection and contains one or many Options, which is currently negotiated between the Agents. When all Agents agree upon the Option, it is formalized as a Plan to be executed. Each Option consists of one or many Actions.

In case of a Rejection, limitations may be communicated. An example of a limitation could be that a configuration is infeasible due to wind limitations. The limitations are communicated through the use of ActionLimits. When an ActionLimit is communicated, other Agents may use this in their option generation process.

The communication is done through a Messenger, which enables the possibility to communicate easily to each Agent without each Agent having to know what other Agents are involved in the negotiation process. Additionally, it can facilitate the negotiation across multiple servers and enable asynchronous communication. The advantage of asynchronous communication is that an Agent can propose options to all other Agents at the same time, without having to wait for a response. It will avoid scenarios such as waiting for a long time until one agent has generated its best options, only for the initial proposal to be rejected by another Agent. Asynchronous communication thus means that the negotiation process is more efficient.

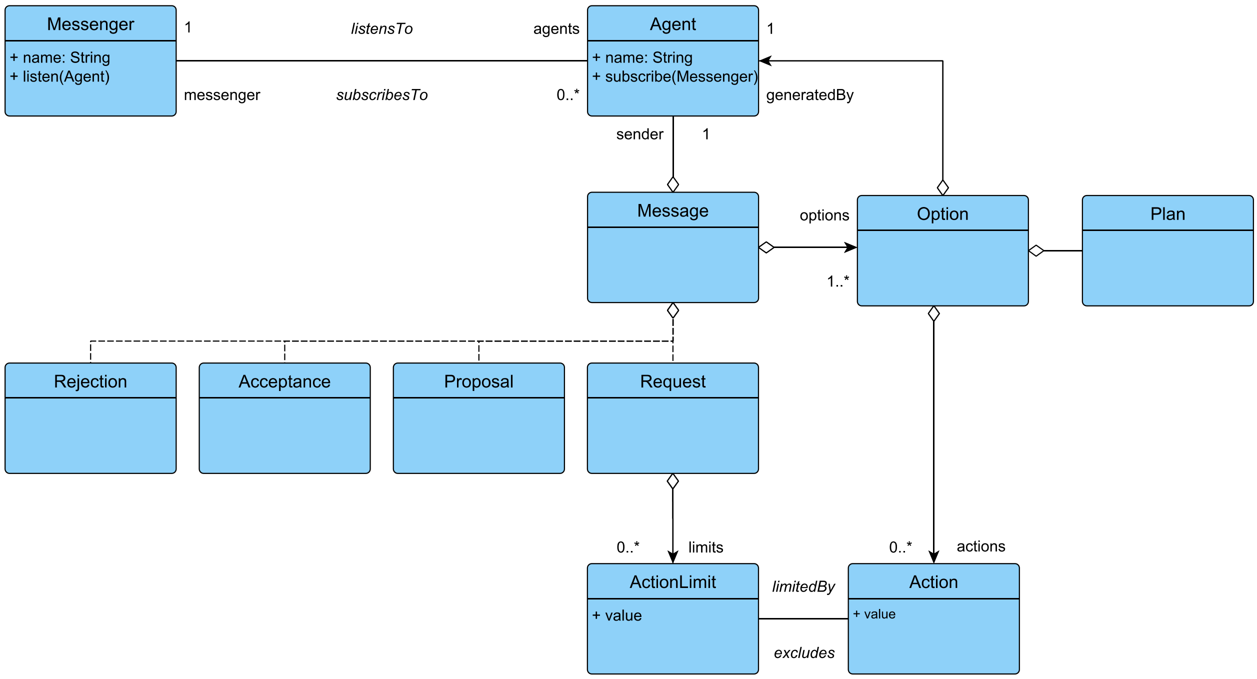


Figure 37: Negotiation framework class diagram

The capacity forecasting framework is set up using two elements: the capacity manager models and the meteorological forecast models. The main MeteoForecastModel retrieves the meteorological forecast data and transforms data to SI units. Other forecast models such as the WindForecastModel, VisilityForecastModel, SnowForecastModel, and DeIceForecastModel extend the base MeteoForecastModel and expose the appropriate data and additional helper functions. The RunwayForecastModel integrates wind and visibility information for feasibility checking (if safety limitations are not exceeded). The FlightForecastModel retrieves the inbound and outbound flight schedules, including relevant information such as aircraft data (type, capacity, etc.).

The main CapacityMgr model implements the Agent model and thus allows for negotiation as described previously; see Figure 37. This main model is then extended by the AirlineMgr, RunwayConfigurationMgr, RunwayPlanningMgr, SnowRemovalMgr, and DeIcingMgr. Each integrates the decision flows and heuristics of section 4.2 and uses the previously described forecasting model through the relationships shown in Figure 38.

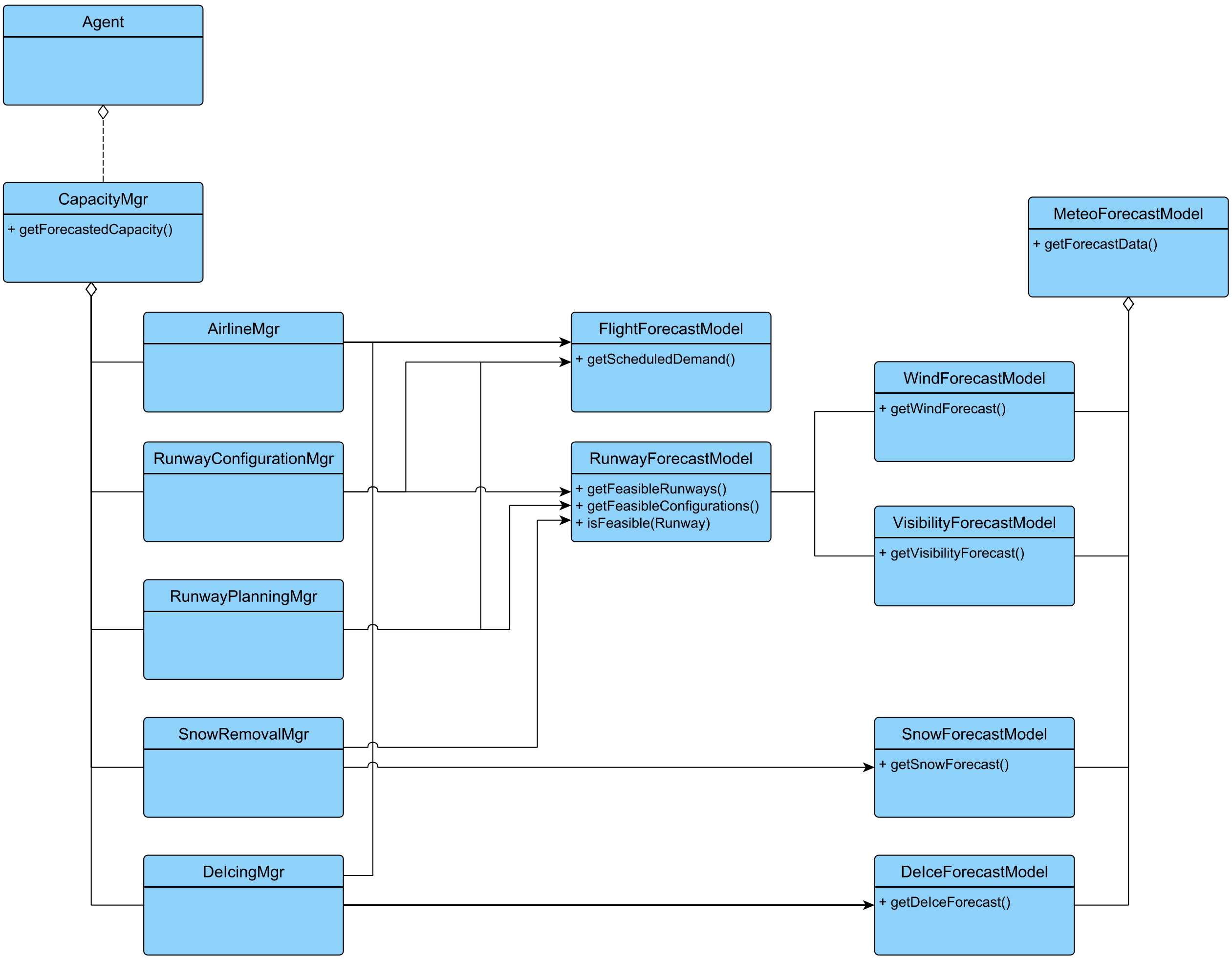


Figure 38: Capacity forecasting class framework

Appendix A.2 Capacity forecast visualization

Runway capacity is usually expressed through a Runway Capacity Curve Envelope (RCCE); an example can be seen in Figure 39. In this figure capacity is shown per 15min, but it is not uncommon to have capacity defined per 20 or 60 minutes. The data points correspond with arrival and departure empirical data over a longer period of time. Plotting a curve over all extreme data points lead to Curve 1, however is not realistic as it includes outliers with a very low frequency of occurrence. Curve 2 shows a more realistic curve, excluding outliers, and is used to determine the declared capacity.

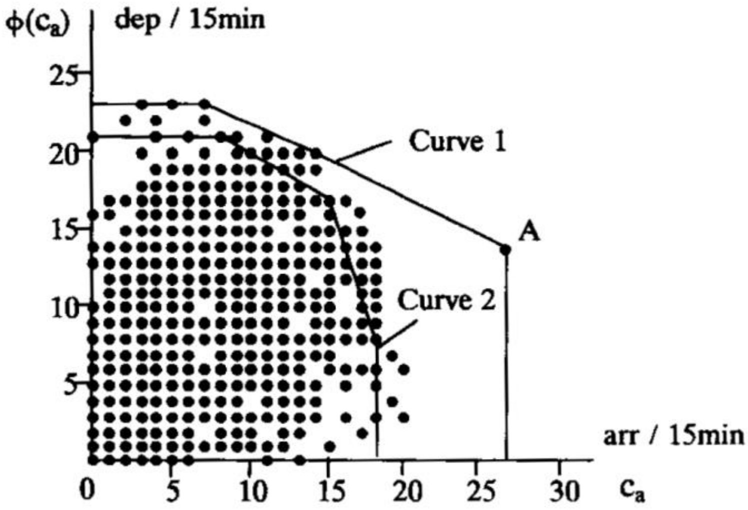


Figure 39: Historical airport performance data and capacity curves [43]

When displaying forecasted information in a decision support system, there are a few factors of importance. The main question is whether or not the demand can be met. This can be measured through the difference between the forecasted capacity and the demand. Due to the nature of the forecast, the forecasted capacity has inaccuracies and thus need to be taken into account. This leads to the following required values to represent:

- Forecast value
- Forecast inaccuracy
- Forecasted demand
- Applicable time period

For a certain runway configuration, the main drivers for capacity are the forecasted visibility conditions. More specifically, cloud base and runway visibility. With a forecast probability for each category, one can combine the forecast with capacity levels to reach a forecast as seen in Figure 40. Here, the forecast values and inaccuracies are incorporated through plotting the forecasted capacity versus the chance of achieving that capacity level. Additionally, the required demand is shown as well. In this example, the demand can be met with a 75% chance, which is indicated by the intersection between the forecasted capacity and demand. It is then up to the ATC to determine whether the levels may be acceptable or not. Additionally, one could extend the plot through including demand requirements for various delay settings.

$$C(p) = \begin{cases} C(G) & if & 0 \leq p < P(G) \\ C(M) & else\ if & P(G) \leq p < P(M) \\ C(I) & else\ if & P(M) \leq p < P(I) \\ C(II) & else\ if & P(I) \leq p < P(II) \\ C(III) & else\ if & P(II) \leq p < P(III) \\ 0 & else\ if & P(III) \leq p \leq 1 \end{cases} \qquad \textit{eq. (52)}$$

The forecast of Figure 40 is computed through multiplying the probability of a visibility category and the capacity for that category. These values are then linearly interpolated. This is shown in eq. (52). Here, p is the chance of achieving the capacity level, C is the capacity level, $C(V)$ is the capacity at visibility category V, and $P(V)$ is the forecasted probability of at least experiencing visibility category V. It is thus required that $\sum_{v \in \boldsymbol{V}} P(v) = 1$. In this example $\boldsymbol{V} \in [G, M, A, B, C/D]$.

In Figure 41b, the forecast is only shown for one runway configuration. One can extend the same principle by combining runway configuration forecasts with the above described method such that $\sum_{c \in \boldsymbol{C}} \sum_{v \in \boldsymbol{V}} P(c)P(v) = 1$, where $\boldsymbol{C}$ denotes the set of possible runway combinations.

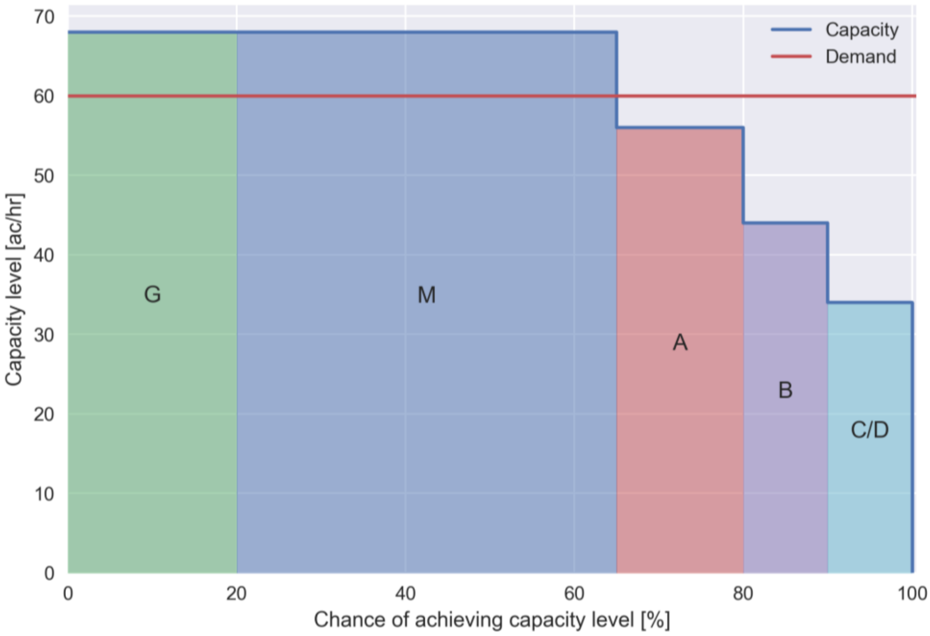


Figure 40: Capacity forecast based on visibility categories

One issue with forecasting is that not only one point in time is of interest, but the overall picture as well. Namely the demand and capacity figures are changing over time. Thus instead of comparing demand and capacity at a single moment in time, they will need to be assessed for a certain look-ahead period. When doing so, trends become possible to spot, along with moments of under- or overcapacity. These are therefore the required qualifiers for the capacity visualization:

- Trends
- Undercapacity
- Overcapacity

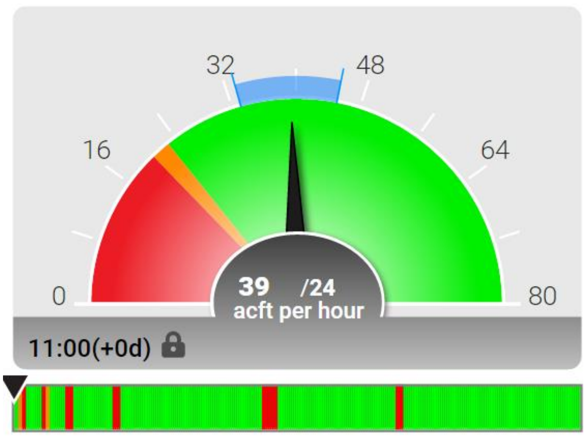


Figure 41a: Option 1 – Gauge [44]

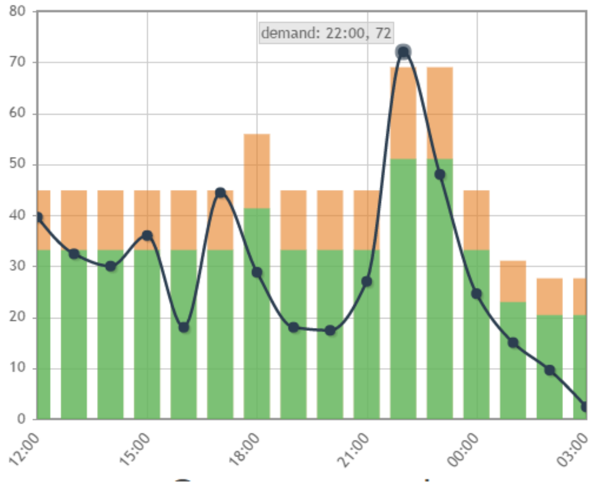


Figure 41b: Option 2 – Bar/line plot

Figure 41: Capacity visualization options

Various options to visualize the data are possible. In Figure 41, two options are shown. Here, option 1 was introduced in the ACF project [44] and option 2 is first proposed in this document. With respect to the required values and qualifiers, Table 7 assesses each visualization option.

Table 7: Comparison chart of capacity visualization options

	Metric	Option 1 (Gauge)	Option 2 (bar/line plot)
Values	Forecast value	• Needle	• Minimum is green, maximum is orange
	Forecast inaccuracy	• Blue margin around needle	• Orange area spanning from minimum to maximum forecasted capacity
	Demand	• Green area starts at demand – 5% • Yellow area starts at demand – 15% • Red area starts at 0	• Black line with markers
	Time period	• Time shown below gauge • Initial and minimum time instant corresponds with 'now' • Look-ahead time requires interaction	• Time span below plot • Minimum time instant corresponds with 'now' • Look-ahead time at a glance • Hover confirms time period

Qualifiers	Trends	• Gradient displayed under gauge	• Forecast: differences between bars • Demand: slope of line
	Under- / overcapacity	• Green *may indicate* overcapacity • Red represents undercapacity	• Difference between line and bar chart
Notes		Inaccuracy is displayed twice by showing forecast inaccuracy and a custom defined yellow region	

Appendix B KNMI Model Output Statistics (MOS) weather forecast data

Table 8: KNMI Model Output Statistics (MOS) parameter description

Element number	Element name	Description	Unit
		Temperature	
1005	T2m	2m temperature	0.1 °C
		Wind	
1001	DD	Wind direction (10-min. average)	Deg
1002	FF/kt___00	Wind speed (10-min. average)	Kts
1243	FF(WX)__00	Wind speed in precipitation	Kts
1096	SD_DD	Standard deviation wind direction	Deg
1097	SS_FF	Standard deviation wind speed	Kts
1206	P_FF>15_00	Probability of wind speed more than 15 kts	%
1207	P_FF>25_00	Probability of wind speed more than 25 kts	%
1208	P_FF>35_00	Probability of wind speed more than 35 kts	%
1250	FX_X____00	Maximum gust	Kts
1251	P_FX>25_00	Probability of gusts more than 25 kts	%
1252	P_FX>40_00	Probability of gusts more than 40 kts	%
1253	P_FX>55_00	Probability of gusts more than 55 kts	%
		Visibility	
1036	VIS/100m	Visibility	100 m
1248	VIS(WX)	Visibility in precipitation	100 m
1304	P_BZO<=M	Probability of BZO Phase less or equal to M	%
1305	P_BZO<=A	Probability of BZO Phase less or equal to A	%
1306	P_BZO<=B	Probability of BZO Phase less or equal to B	%
1307	P_BZO<=C	Probability of BZO Phase less or equal to C	%
		Precipitation	
1270	RR1__mm/10	Total amount of precipitation over recent hour	0.1 mm
1025	Pw_Any_LMH_1	Probability of any precipitation over recent hour	%
1260	Pw_Liq_LMH_1	Probability of liquid precipitation over recent hour	%
1023	Pw_Frz_LMH_1	Probability of freezing precipitation over recent hour	%
		De-icing	
1082	%1-Deic_3h	Percentage of planes to de-ice 3h	%

Appendix C US Model Output Statistics (MOS) weather forecast data

Model output statistics is a prediction method of forecasting weather data for each item in a gridded area. Doing so, a prediction for a specific site can be computed. In Figure 42 a sample using the MOS output scheme is shown. In Table 9 the abbreviations of output along with the description and units are elaborated upon.

Sample Message

```
KDEN   GFS MOS GUIDANCE    3/04/2010  1200 UTC
DT /MAR   4/MAR   5                /MAR   6                /MAR   7
HR   18 21 00 03 06 09 12 15 18 21 00 03 06 09 12 15 18 21 00 06 12
N/X                    27          53          28          51    24
TMP  48 52 51 40 35 32 30 35 47 50 48 40 38 35 32 36 45 48 45 31 27
DPT  25 25 27 29 29 27 25 25 21 17 18 20 21 21 20 21 21 22 22 23 21
CLD  BK SC SC SC SC OV OV OV BK BK BK SC BK SC SC SC SC SC SC SC SC
WDR  19 14 13 16 20 20 25 25 28 28 28 22 23 23 22 21 12 10 10 17 21
WSP  05 12 11 08 08 07 07 07 08 10 11 08 08 07 07 07 07 10 10 08 07
P06         1     6    14    20    14    25     8     4     2  3  2
P12                    15          27          26           4     3
Q06         0     0     0     0     0     0     0     0     0  0  0
Q12                     0           0           0           0     0
T06      5/11  1/ 2  0/ 1  1/ 2  8/ 3  1/ 1  0/ 0  0/ 0  2/ 8  0/ 0
T12            7/11        1/ 2        8/ 4        0/ 1     2/ 8
POZ   1  1  3  2  2  7  8  3  4  2  3  0  3  3  4  6  3  1  2  0  3
POS  27 16 18 24 28 65 74 72 31 20 37 57 94 87 95 65 41 18 28 50 91
TYP   R  R  R  R  R  S  S  S  R  R  R  S  S  S  S  S  R  R  R  R  S
SNW                     0                       0                 0
CIG   8  8  8  8  8  8  8  7  8  8  7  8  8  8  8  8  8  8  8  8  8
VIS   7  7  7  7  7  7  7  1  7  7  7  7  7  7  7  7  7  7  7  7  7
OBV   N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N  N
```

Figure 42: Model Output Statistics (MOS) example

Table 9: US Model output statistics (MOS) parameter description

Abbr.	Description	Unit[, categorical values]
DT	The day of the month, denoted by the standard three or four letter abbreviation	[-]
HR	Hour of the day in UTC time. This is the hour at which the forecast is valid, or if the forecast is valid for a period, the end of the forecast period.	[-]
N/X	Night-time minimum/daytime maximum surface temperatures.	[F]
TMP	Surface temperature valid at that hour.	[F]
DPT	Surface dew point valid at that hour.	[F]
CLD	Forecast categories of total sky cover valid at that hour.	• CL: clear • FW: few • SC: scattered • BK: broken • OV: overcast
WDR	Forecasts of the 10-meter wind direction at the hour, given in tens of degrees.	[D]
WSP	Forecasts of the 10-meter wind speed at the hour, given in knots.	[kts]
P06	Probability of precipitation (PoP) during a 6-h period ending at that time.	[%]
P12	PoP during a 12-h period ending at that time.	[%]
Q06	Quantitative precipitation forecast (QPF) category for liquid equivalent precipitation amount during a 6-h period ending at that time.	• 0: no precip • 1: 0.01-0.09 • 2: 0.10-0.24 • 3: 0.25-0.49 • 4: 0.50-0.99 • 5: 1.00-1.99 • 6: 2.00+ [inches]
Q12	QPF category for liquid equivalent precipitation amount during a 12-h period ending at the indicated time.	See **Q06**

SNW	Snowfall categorical forecasts during a 24-h period ending at the indicated time.	• 0: no snow • 1: 0-2 • 2: 2-4 • 4: 4-6 • 6: 6-8 • 8: 8+ [inches]
T06	Probability of thunderstorms/conditional probability of severe thunderstorms during the 6-hr period ending at the indicated time.	[%]
T12	Probability of thunderstorms/conditional probability of severe thunderstorms during the 12-hr period ending at the indicated time.	[%]
POZ	Conditional probability of freezing pcp occurring at the hour.	[%]
POS	Conditional probability of snow occurring at the hour.	[%]
TYP	Conditional precipitation type at the hour.	• S: snow (grains) • Z: any mixed with freezing precip • R: rain (with snow)
CIG	Ceiling height categorical forecasts at the hour.	• 1: 0-200 • 2: 200-400 • 4: 500-900 • 4: 1000-1900 • 5: 2000-3000 • 6: 3100-6500 • 7: 6600-12000 • 8: 12000+ [feet]
VIS	Visibility categorical forecasts at the hour.	• 1: 0.0-0.5 • 2: 0.5-1.0 • 3: 1.0-2.0 • 4: 2.0-3.0 • 5: 3.0-5.0 • 6: 6 • 7: 6+ [miles]
OBV	Obstruction to vision categorical forecasts at the hour.	• N: none of below • HZ: haze, smoke • BR: mist (VIS>=5/8M) • FG: fog (VIS<5/8M) • BL: blowing dust / sand / snow

Appendix D Capacity forecasting distribution

In the Figure 43, Figure 44, and Figure 45 costs are normalized with respect to the costs associated with the forecasted runway capacity.

Figure 43: Delay cost distribution over 1000 Monte Carlo runs

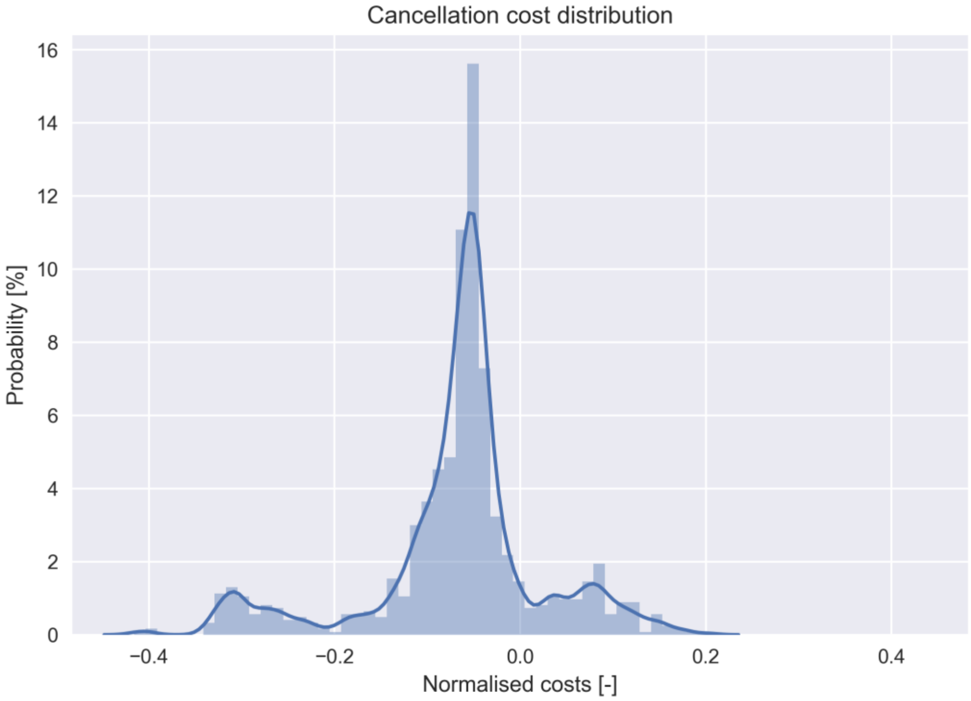


Figure 44: Cancellation cost distribution over 1000 Monte Carlo runs

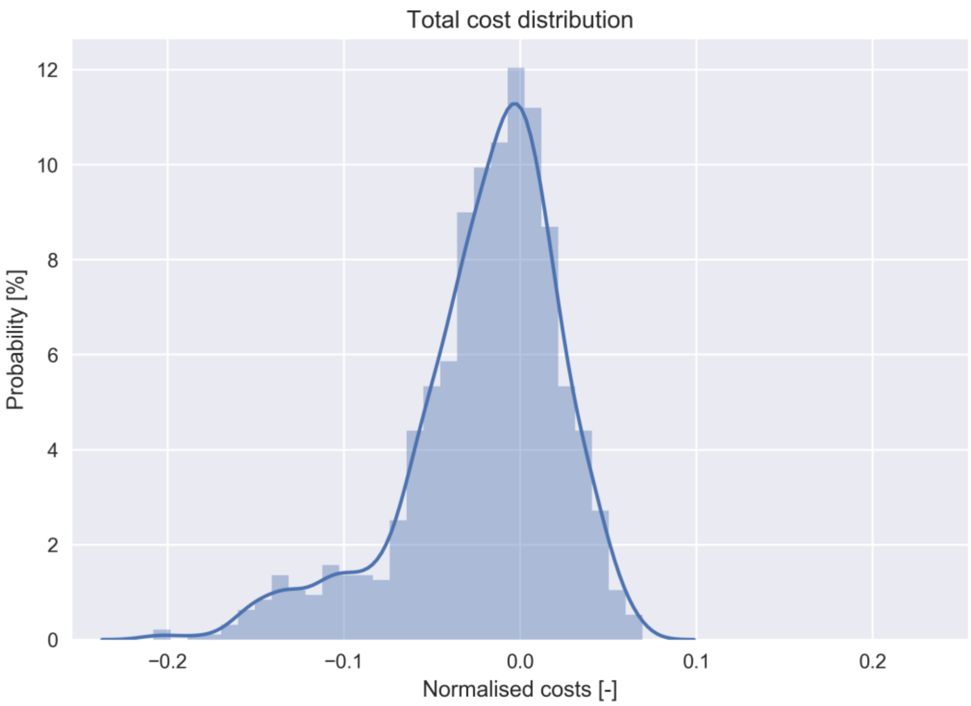


Figure 45: Total cost distribution over 1000 Monte Carlo runs

Appendix E Forecasting snowfall

Not all airports have the luxury to have a rain/snow intensity sensor installed. This is often the case across Europe. Therefore it can be very useful to derive snowfall from other parameters. An alternative, as researched by Rasmussen et al. [45], is the ability to derive snowfall rates from visibility conditions. In order to do this, we have to recognize the fact that multiple variants of snowflakes exist and are commonly categorized in either dry or wet snow. Dry snow is described as snow that falls apart when trying to form a snowball. Due to the minimum water contents, snow particles do not stick very well. Thus whilst dry snow is a lot less dense than wet snow and thus with the same flake size, its terminal velocity is lower of dry snow than wet snow.

Table 10: Snow density and terminal velocity for different snow types

	C_3 [gr/cm^2]	V_t [cm/s]
Dry snow	0.017	100
Wet/rimed snow	0.072	200

The relationship defined in [45] is shown in eq. (53).

$$I = \frac{1.3C_3\,\overline{V_t}}{Vis} \qquad \text{eq. (53)}$$

Additionally, it has to be recognised that the concept of visibility changes as a function of available light. It means that the equivalent visibility during the night is lower. This relation can be expressed as in eq. (54) and is plotted in Figure 46.

$$V_d = \frac{ln(\epsilon)\,V_n}{ln\left(\frac{C_{DB}V_n}{I_O}\right)} \qquad \text{eq. (54)}$$

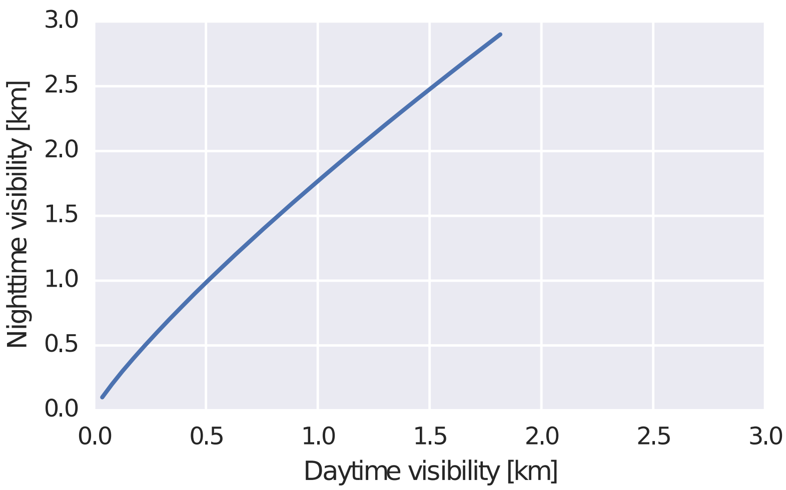


Figure 46: Daytime versus night-time visibility

With snowfall intensity data available in the US, METAR data of Minneapolis-St. Paul airport (KMSP) has been analysed throughout 2015 to compare visibility with snowfall. Precipitation data is widely available in METAR data in the USA. Minneapolis is used due to the high snowfall numbers for US standards as it is located at high latitude, close to the Canadian border. It is expected that the intensity sensors already account for day/night issues. In Figure 47, violin plots are shown for various snow conditions grouped by the visibility conditions (day or night).

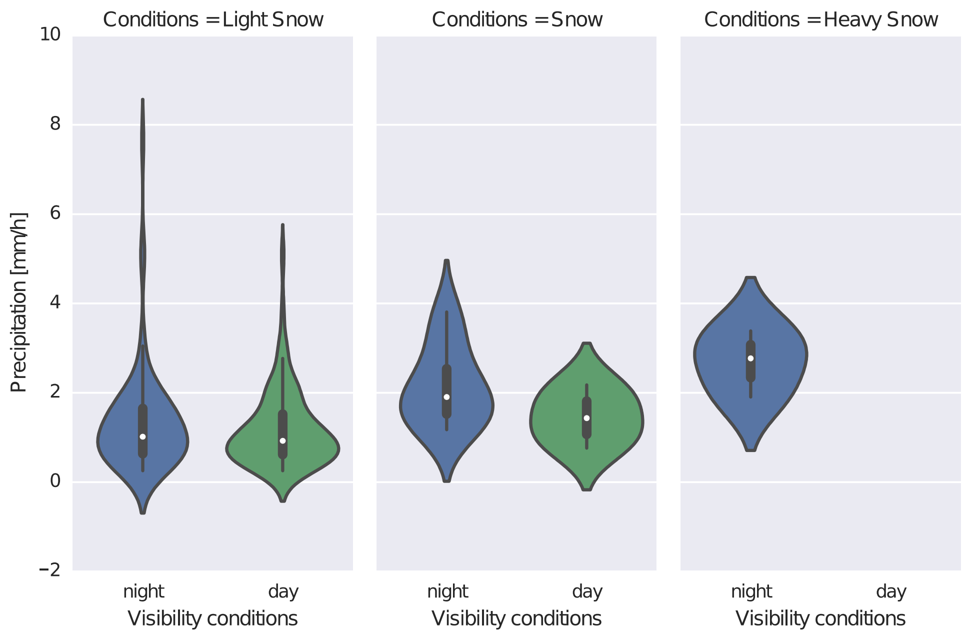


Figure 47: Violin plots comparing Snowfall intensity between snowfall and day/night conditions

Notably in Figure 47 it can be seen that heavy snow does not occur during the day. Additionally, it can be seen that during night times higher precipitation rates occur, but the weight is around the same levels of precipitation. This is likely due to the fact that night-time is usually colder and thus snow formation occurs more often. This can be seen in comparing Figure 48a and Figure 48b, where the similar precipitation rates occur under lower temperatures.

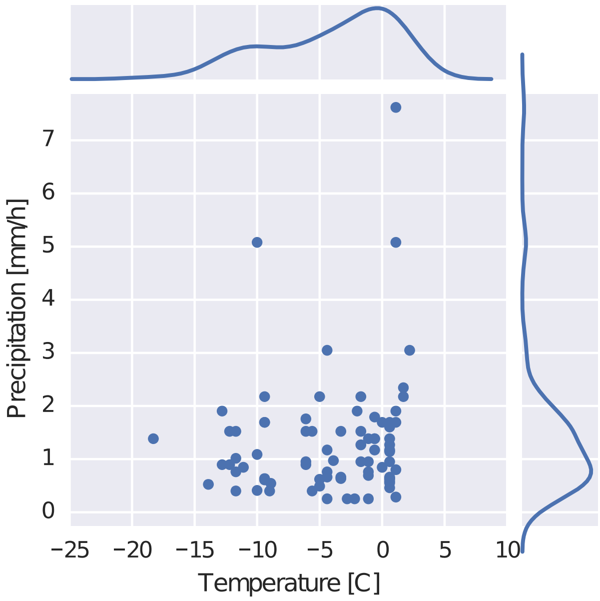


Figure 48a: Night-time

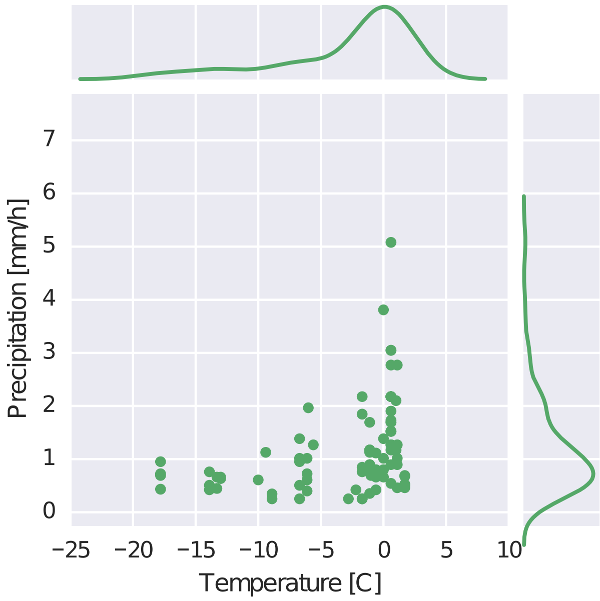


Figure 48b: Day-time

Figure 48: Light snow precipitation distribution for various temperature levels comparing day- and night-time

Within the MOS data, the probability of precipitation in a 6hr forecast is given by the parameter *P06* with the associated quantity *Q06*. Note that the quantities are given in QPF categories (see Appendix A) and need to be translated to actual values. At a forecast time t, both will be further referred to as $P(P)_t$ and $Q(P|S)_t$, respectively. If precipitation occurs, the parameter *POS* indicated the probability of snow i.e. *POS* is a dependent variable. At a forecast time t, this will be referred to as $P(S|P)_t$.

To find the probability of snow, Bayes' rule is applied and rewriting gives eq. (56). Here, $P(P|S) = 1$ as per definition that precipitation always occurs given that it snows.

$$P(S|P) = \frac{P(P|S)P(S)}{P(P)} \qquad \textit{eq. (55)}$$

$$\therefore P(S) = \frac{P(S|P)P(P)}{P(P|S)} = P(S|P)P(P) \qquad \textit{eq. (56)}$$

The intensity of snowfall is defined as the quantity of snow times the probability that it will actually snow. This is shown in eq. (57).

$$I_t = Q(P|S)_t P(S)_t = Q(P)_t P(S|P)_t P(P)_t \qquad \textit{eq. (57)}$$

Appendix F Take-off And Landing Performance Assessment (TALPA) matrix

Runway Condition Assessment Matrix (RCAM)					
Assessment Criteria		Downgrade Assessment Criteria			
Code	Runway Condition Description	**Mu (μ)** [1]	**Vehicle Deceleration Or Directional Control Observation**	**PIREP**
6	• Dry		---	---
5	• Frost • Wet (Includes Damp and1/8" or less depth of Water) ***1/8" or less depth of:*** • Slush • Dry Snow • Wet Snow	40 or Higher	Braking deceleration is normal for the wheel braking effort applied AND directional control is normal.	Good
4	***-15°C and Colder outside air temperature:*** • Compacted Snow	39 to 30	Braking deceleration OR directional control is between Good and Medium.	Good to Medium
3	• Wet ("Slippery when wet" runway) • Dry Snow or Wet Snow (Any depth) over Compacted Snow ***Greater than 1/8" depth of:*** • Dry Snow • Wet Snow ***Warmer than -15°C outside air temperature:*** • Compacted Snow		Braking deceleration is noticeably reduced for the wheel braking effort applied OR directional control is noticeably reduced.	Medium
2	***Greater than 1/8" depth of:*** • Water • Slush	29 to 21	Braking deceleration OR directional control is between Medium and Poor.	Medium to Poor
1	• Ice [2]		Braking deceleration is significantly reduced for the wheel braking effort applied OR directional control is significantly reduced.	Poor
0	• Wet Ice [2] • Water on top of Compacted Snow [2] • Dry Snow or Wet Snow over Ice [2]	20 or Lower	Braking deceleration is minimal to non-existent for the wheel braking effort applied OR directional control is uncertain.	Nil

Figure 49: Runway condition assessment matrix as input for take-off and landing requirements [46]

Appendix G EUROCONTROL DDR2 database

The DDR2 database of EUROCONTROL contains all flights in and out of Europe. The SO6 data files contain flight information on a segment level. Table 11 shows a few lines of data from an SO6 file. Table 12 describes the data format.

Table 11: Example SO6 data from airport ENZV to waypoint LUKEX on the way to airport ENGM; operated by SAS

Columns 1 through 10									
ENZV_$SyWQ	ENZV	ENGM	B736	145600	145622	0	25	0	SAS4028
$SyWQ_$SyWR	ENZV	ENGM	B736	145622	145721	25	41	0	SAS4028
$SyWR_$SuDo	ENZV	ENGM	B736	145721	145742	41	50	0	SAS4028
$SuDo_$SyWU	ENZV	ENGM	B736	145742	145823	50	69	0	SAS4028
$SyWU_$SyWW	ENZV	ENGM	B736	145823	145900	69	90	0	SAS4028
$SyWW_$SuDs	ENZV	ENGM	B736	145900	145922	90	102	0	SAS4028
$SuDs_LUKEX	ENZV	ENGM	B736	145922	145932	102	110	0	SAS4028
Columns 11 through 20									
150101	150101	3532.6	338.2667	3532.45	339.25	183076961	1	0.529957	0
150101	150101	3532.45	339.25	3532.3	340.25	183076961	2	0.538261	0
150101	150101	3532.3	340.25	3532	342.2167	183076961	3	1.06009	0
150101	150101	3532	342.2167	3531.25	347.1667	183076961	4	2.667379	0
150101	150101	3531.25	347.1667	3530.633	351.1167	183076961	5	2.134341	0
150101	150101	3530.633	351.1167	3530.183	354.0833	183076961	6	1.599635	0
150101	150101	3530.183	354.0833	3529.733	357.05	183076961	7	1.599954	0

Table 12: DDR2 SO6 data format description

Column #	Field	Comment
1	Segment identifier	First point name "_" last point name
2	Origin of flight	ICAO code
3	Destination of flight	ICAO code
4	Aircraft type	
5	Time begin segment	HHMMSS
6	Time end segment	HHMMSS
7	FL begin segment	
8	FL end segment	
9	Status	0=climb, 1=descent, 2=cruise
10	Callsign	

11	Date begin segment	YYMMDD
12	Date end segment	YYMMDD
13	Latitude begin segment	
14	Longitude begin segment	
15	Latitude end segment	
16	Longitude end segment	
17	Flight identifier	
18	Sequence id	Starts at 1 for every flight and increments each segment
19	Segment length	In nautical miles
20	Segment parity/color	0=NO, 1=ODD, 2=EVEN, 3=ODD_LOW, 4=EVEN_LOW, 5=ODD_HIGH, 6=EVEN_HIGH, 7=general red, 8=general orange, 9=general yellow

Appendix H Aircraft data sheet

Table 13: Aircraft capacity overview

Aircraft type	Capacity [# seats]	De-ice category	Aircraft type	Capacity [# seats]	De-ice category
A306	266	D	**B789**	230	E
A310	218	D	**C25A**	6	B
A318	107	C	**C25B**	6	B
A319	124	C	**C680**	8	B
A320	150	C	**CL30**	8	C
A321	186	C	**CL35**	8	C
A332	256	E	**CRJ2**	50	C
A333	335	E	**CRJ7**	70	C
A343	263	E	**CRJ9**	90	C
A388	555	F	**D228**	15	B
B733	128	C	**D328**	30	B
B735	108	C	**DH8D**	70	B
B737	110	C	**E145**	50	B
B738	162	C	**E170**	70	C
B739	177	C	**E190**	98	C
B744	416	E	**E35L**	10	B
B748	467	F	**F100**	107	C
B752	202	D	**F2TH**	8	B
B763	210	D	**F70**	79	C
B764	245	D	**F900**	13	B
B772	305	E	**GLEX**	19	C
B77L	305	E	**H25B**	6	B
B77W	386	E	**MD11**	323	D
B788	230	E	**RJ85**	85	C

Appendix I ICAO airline codes

Table 14: ICOA airline reference table

Airline ICAO abbreviation	Airline name	Airline country
ADR	Ryanair	Ireland
AFL	Arkefly	Netherlands
AFR	Turkish Airlines	Turkey
AZA	Alitalia	Italy
BAW	Vueling Airlines	Spain
BCY	Flybe	United Kingdom
BEE	Aer Lingus	Ireland
CND	CityJet	Ireland
DAL	easyJet	United Kingdom
DLH	Scandinavian Airlines	Sweden, Denmark and Norway
EIN	British Airways	United Kingdom
EZS	Aero Continente Dominicana	Dominican Republic
EZY	Delta Air Lines	United States
KLM	Aeroflot Russian Airlines	Russia
NAX	Adria Airways	Slovenia
RYR	Transavia Holland	Netherlands
SAS	TAP Portugal	Portugal
TAP	Norwegian Air Shuttle	Norway
TFL	Air France	France
THY	easyJet Switzerland	Switzerland
TRA	KLM	Netherlands
VLG	Lufthansa	Germany

NLR

Anthony Fokkerweg 2

1059 CM Amsterdam, The Netherlands