Professional MBA
Entrepreneurship & Innovation

Decision support for air traffic management based on probabilistic weather forecasts

A Master's Thesis submitted for the degree of
“Master of Business Administration”

supervised by
Univ.Prof. Mag. Dr. Sabine Theresia Köszegi

Mag. Dr. Martin Steinheimer

09902451

Vienna, 28.06.2019

Affidavit

I, **MAG. DR. MARTIN STEINHEIMER**, hereby declare

1. that I am the sole author of the present Master's Thesis, "DECISION SUPPORT FOR AIR TRAFFIC MANAGEMENT BASED ON PROBABILISTIC WEATHER FORECASTS", 79 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

Vienna, 28.06.2019

Signature

Abstract

European air traffic is continuously growing and now reaching the airspace capacity limits even in normal weather conditions. Adverse weather can considerably reduce airspace capacity, as a result suitable measures need to be taken to ensure air traffic is kept safe and reliable under such conditions. Air traffic regulations are the main measure taken to avoid that arrival traffic is exceeding the available airport capacity. Under such a regulation aircraft which would arrive in the regulated period are delayed on ground at the origin. The delay is not only inconvenient for passengers, but also a major cost factor for airlines.

Weather forecasts are inherently uncertain. An adequate way to represent these uncertainties are probabilistic weather forecasts. For optimal implementation of such forecasts in air traffic management decision making, a suitable decision support framework is required. Previous work on weather integration in air traffic management is reviewed as a basis for proposing a decision support framework for the air traffic flow and capacity management at airports.

Two utility measures are developed for decision making. The first measure is based on a cost model which uses flight delay and flight diversions derived from air traffic simulations as input. The second measure represents the balance of traffic entering an airspace volume with the available capacity and is obtained from traffic demand and expected weather scenarios.

In case studies the suitability of the utility measures for decision making is investigated. A simple cost-loss decision making approach and a more complex approach based on evaluating expected utility for a range of decisions and weather scenarios are applied. Results show that cost of delay is very sensitive to small variations of input data, while the traffic-capacity balance is more robust.

Contents

1 Introduction

After a period of stagnation and even decline from 2008 to 2013 as a result of the economic crises, air traffic is now growing again considerably. In Europe 2018 was a new record year for traffic volumes after growing by 3.8% compared to 2017 (EUROCONTROL, 2019a). The medium-term outlook given by EUROCONTROL (2019a) forecasts a traffic growth of 15% from 2018 to 2025 for the baseline (i.e. most probable) scenario, that corresponds to an average annual growth rate of 2%. The forecast is subject to a range of uncertainties, most importantly the economic growth in Europe, where factors such as a possible hard Brexit and the uncertainty of the Turkish economic development must be considered. The uncertainties are accounted for by forecasting low and high growth scenarios in addition to the baseline scenario. These scenarios result in a traffic growth forecasts from 2018 to 2025 of 5% and 25%, respectively.

Long term forecast up to 2040 (EUROCONTROL, 2018a), give a similar outlook. The most probable scenario results in an average annual growth rate of 1.9% (47% more traffic in 2040 compared to 2018) with considerable uncertainty indicated by the results for a high growth rate scenario, resulting in 2.7% annual growth rate, and a low growth rate scenario with only 0.5% annual growth rate. Again the economic development is the dominating uncertainty factor in the estimates, but on the longer time scales also other factors become important, for example developments with regards to free trade agreements, expected cost of CO_2 emission trading or new/improved high-speed rail connections.

The increase in air traffic puts further pressure on the air traffic network. In Europe, airspace and airports are already now hitting capacity limits during traffic peaks, especially in summer. Average delay per flight reported by airlines in 2018 increased by 2.3 minutes compared to 2017, reaching 14.7 minutes (European Commision Network Manager, 2019b). For the most likely scenario EUROCONTROL (2018a) estimates a further increase of delay to 20.1 minutes per flight on average in 2040. The forecast shows a long tail in the delay distribution with a significant increase of flight delay between 60 and 120 minutes by a factor of 7 until 2040. This corresponds to 470,000 passengers who are delayed between 60 and 120 minutes per day. Considering the planned increase in airport capacity there is still a major gap between forecasted demand and traffic which can be accommodated. In the most likely scenario it is estimated, that 1.5 million flights per year, 8% of the forecasted demand, can not be accommodated, resulting in 160 million passengers who are not able to fly (EUROCONTROL, 2018a). In addition to the traffic growth it is expected that climate change will have negative effect on air traffic capacity (EUROCONTROL, 2018a). Besides expected shifts of traffic flow because of changes in tourism demand, it is expected that changes in weather patterns will affect capacity. This includes increased frequency of strong thunderstorms and increased clear air turbulence.

Air traffic congestion and the related delay are not only inconvenient for passengers but also a major source of cost for airline operators. As a consequence delay originating by Air

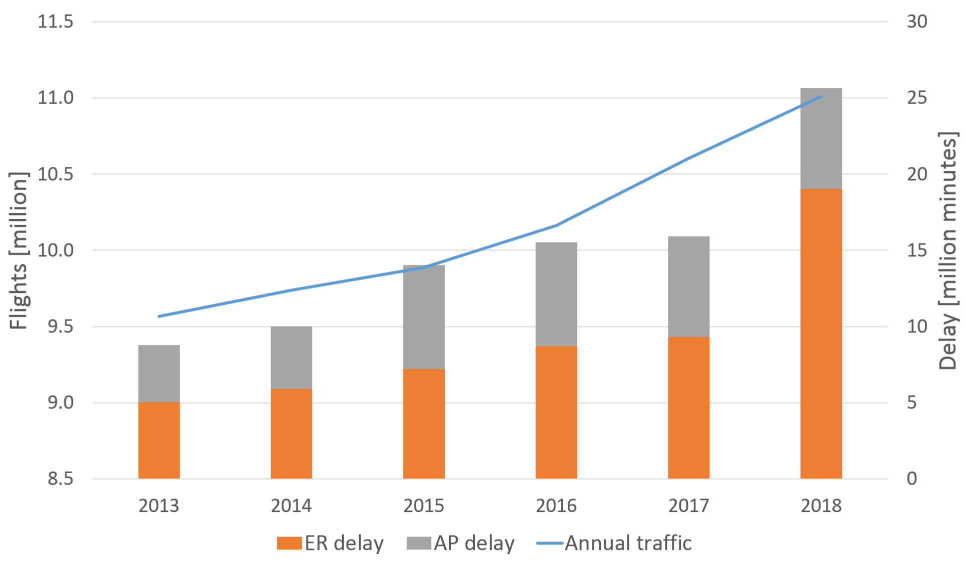

Figure 1: Traffic and ATFCM-delay of the European air traffic network for the years 2013 to 2018 (Data from Figure 9 in European Commision Network Manager, 2019b).

Traffic Flow and Capacity Management (ATFCM) measures taken by Air Navigation Service Providers (ANSPs), so called ATFCM regulations, is an important performance target for ANSPs imposed by European legislation (European Commision, 2014). ATFCM regulations are issued by ANSPs to match the air traffic load to the available air space and airport capacity (for a detailed description see Section 3.1). This is a prerequisite to ensure the workload for air traffic controllers is on acceptable levels to facilitate safety and efficiency. Given that role ATFCM-delay is the central element of performance reports, such as the Network Operations Report (European Commision Network Manager, 2019b) or the CODA Digest (Walker, 2019) which are issued on a regular basis by the European Network Manager.

Total average delay per flight in 2018 as reported by airlines (Walker, 2019) was 14.7 minutes. Out of this, 6.7 minutes were so called reactionary delay. This delay results from the late arrival of an aircraft on its previous flight. Two types of reactionary delay are distinguished, rotational delay, i.e. the delay of an aeroplane on its next flight because of late arrival from the previous flight, and non-rotational delay, i.e. another aeroplane being delayed because of connecting passengers, crew or freight from a delayed flight. The second largest contribution to total delay is airline related delay, 3.6 minutes per flight on average in 2018. ATFCM-delay reported by airlines in 2018 has been 2.78 minutes per flight. The remainder of the total delay is related to delay outside of the control of the airline operation and ANSPs, e.g. caused by weather, government or other reasons. Figure 1 shows the evolution of European traffic and ATFCM-delay from 2013 to 2018. A steady growth of both traffic and en-route delay is apparent, while airport delay is more or less constant since 2015. The rapid increase of en-route ATFCM-delay in 2018 is a strong concern for all aviation stakeholders as a similar or even worse situation is expected in summer 2019 (cf. Pasquini, 2019). On average an ATFCM delay minute is estimated to induce a cost of 100 Euro for airlines (EUROCONTROL, 2018c), translating into a cost of more than 250 million Euros in 2018. EUROCONTROL (2018a) estimates a further growth of ATFCM-delay, reaching 6.2 minutes per flight in 2040, 31% of total delay by then.

Total weather delay, ATFCM and others, reported by airlines accounted for 0.63 minutes per flight (Walker, 2019). That means 4.3% of total delay is related to weather. Looking only at ATFCM-delay weather is responsible for a considerable higher share. European Commision Network Manager (2019b) reports total ATFCM-delay of 2.33 minutes per flight in 2018 of which 0.76 minutes, or 33%, are accounted to weather.[1] Weather is after Air Traffic Control capacity the second largest contribution to en-route ATFCM-delay (26%) and is responsible for the largest contribution to airport ATFCM-delay (52%). Taking a local view the importance of weather is even more apparent. At more than half of the 20 European airports with the most ATFCM airport delay in 2018 weather was the largest contributor to the delay. The high impact of weather on ATFCM-delay is also directly highlighted by European Commision Network Manager (2019b, p.7):

> The year was marked by a record number of adverse weather events, especially CB cells, which started early in the summer and continued throughout the season, disrupting operations both on the ground and en-route. As a result, regulation delays allocated to weather have doubled comparing to 2017, and were one third of all ATFM delays.

Although weather delay can not be avoided entirely, because weather cannot be changed, effort is put into reducing the delay by making optimum use of weather forecast information. This is also highlighted by the fact, that improved weather management is one point in a seven-point programme of EUROCONTROL's Network Manager to optimise scarce aviation capacity in 2019 (Pasquini, 2019).

This work focuses on how the intrinsic uncertainty of weather forecasts can be best anticipated in Air Traffic Management (ATM) decision making for airport arrivals. The goal is to improve the current decision making process (see Section 3.3) through objective support tools to reduce the dependence on the subjective interpretation of the individuals involved in the decision making process. This will be done by making use of probabilistic weather forecast in

[1] The ATFCM-delay reported by Walker (2019) differs from the numbers reported in European Commision Network Manager (2019b). Total ATCFM delay reported by airlines is 2.78 minutes while the Network Manager reports 2.33 minutes. The difference can be explained by different calculation methods, airlines report the actual experienced ATFCM-delay, while the Network Manager numbers are based on flight plan delay (European Commision Network Manager, 2019b). In addition the airline data coverage is only 70% of all flights while the Network Manager covers all flights. As the Network Manager data is also available via an online database access (EUROCONTROL, 2018b) for more detailed evaluation, ATCFM delay evaluations presented in this study are based on Network Manager data.

combination with economic considerations to identify the relevant probability thresholds for taking the decisions. A general overview of weather and Air Traffic Management including a review of international research towards better integration of weather forecasts in Air Traffic Management procedures is given in Section 2. Air Traffic Management decision support systems are reviewed in Section 3 including a general overview of decision making based on weather forecasts. Based on these analyses a decision making framework for weather regulations in ATFCM is proposed for Vienna International Airport (LOWW) (Section 4). Case studies putting the proposed decision support tool to test are discussed in Section 5.

The work presented was done in the framework of the MET4LOWW and PROB4LOWW projects (for a brief overview of the projects, see Appendix A), and extends the results presented by Steinheimer et al. (2016) and Steinheimer et al. (2019). Besides a more detailed view on the aspects reported by Steinheimer et al. (2016) and Steinheimer et al. (2019) an alternative utility function based on the traffic and capacity balance rather than on airline cost is introduced (Section 4.3.2). Additional sensitivity studies were performed and included in the case studies (Sections 5.1 and 5.2). A decision framework based on weather scenarios is introduced in addition to the probability threshold based procedure in Section 4.1 and tested in Section 5.3.3.

2 Air traffic management and weather

2.1 Weather phenomena impacting air traffic management

The importance of weather for air traffic management was highlighted in the discussion of ATFCM-delay in Section 1. The impact of weather on capacity can be large, both for en-route traffic and traffic in the arrival and departure phase. The weather phenomena impacting capacity differ between en-route and airport traffic. For en-route traffic the most important factor is deep convection,[2] in aviation referred to as Cumulonimbus (CB) or Thunderstorm (TS), during the summer months. Various hazards, severe turbulence, heavy precipitation including hail, are connected to convective clouds, hence convection needs to be avoided by aircraft. The deviations from the planned routes mean considerably increased workload for the Air Traffic Controllers (ATCOs). The increased workload together with the reduced usable space in the air traffic sector mean considerable reduced capacity. But not only the sectors where convection occurs are affected, also neighbouring sectors can be considerably impacted, if diverting traffic is entering leading to exceedance of sector capacity.

Other factors in the en-route phase are turbulence[3] and mountain-waves,[4] which can result in the need for increased vertical spacing between aircraft. Increased spacing has direct deteriorating impact on capacity. In addition flights will request to change altitude to avoid the affected levels, this increases traffic complexity and ATCO workload.

The hazards described for the en-route phase are of course also relevant for arriving and departing traffic at airports. As in the terminal airspace[5] traffic is more restricted to follow prescribed routes, more vertical movement is involved and traffic density is higher, movements to avoid convection are even more problematic. In addition strong surface winds and rapid changes of wind direction connected to convection, can raise the need for the change of the arrival runway in an anyway complex traffic situation. If strong convection is located at the airport or directly on the final approach path of the landing runway, there can result times where no arrivals are possible at all with major impact on arrival capacity.

Strong wind, snow, aircraft icing and low visibility are other weather phenomena which can have major impact on arrival capacity. At the majority of airports traffic is separated based on distance, that means in case of strong headwinds, when aircraft need more time to fly the

[2] In Meteorology deep convection refers to thermally driven vertical motions of the atmosphere. Deep convection is convection which spans a considerable part of the atmosphere from the lower part up to levels where it also affects air traffic.

[3] Depending on severity the impact of turbulence spans from minor inconvenience to passengers up to serious accidents with injury to crew and passengers or even damage to the airframe.

[4] Mountain-waves, a meteorological phenomenon, are vertically oscillating motions induced by disturbances of the horizontal wind by mountains. The vertical motions can be so strong, that aircraft are not able to maintain their altitude and unexpectedly leave their assigned fligthlevel. Severe turbulence is also often associated to mountain-waves.

[5] The airspace around airports, where traffic departing and arriving is controlled, is referred to as terminal airspace.

Table 1: LVP states in use at LOWW.

LVP state	RVR		Ceiling	Separation	Capacity
normal				2.5NM	>40
LVP	<600m	or	<200ft	4NM	25
LVP CATIII	<350m			6NM	18

Reproduced from Table 2 in Steinheimer et al. (2016)

separation distance, the arrival capacity is negatively impacted (for more details see Treve, 2016). Depending on the runway configuration of the airport strong wind can have additional deteriorating impact on capacity, because the usage of certain runways or procedures might no longer be possible because of too high cross- or tailwind. Snow affects the air traffic system in multiple ways. Strong snowfall reduces visibility, which can raise the need for increased separation. Snow on the ground reduces the braking effectiveness, with the need to increase separation on final approach to allow landed aircraft more time to leave the runway before the next landing. Snow needs to be cleared from the runway if it accumulates too much, with the need to close the runway for the duration of the clearing. If no other runway is available, because of the wind situation or on single runway airports, that means that no departures and arrivals are possible for this duration. Apart from affecting the runway capacity, snow can also be a problem for ground handling processes. For example, aircraft stands need to be cleared of snow, cleared snow needs to be stored and might block ground handling areas. In certain weather conditions when ice builds up on aircraft while on ground or there is the possibility of ice building up during departures, aircraft need to run through a de-icing procedure, where they are sprayed with a de-icing fluid prior to departure. Besides the time needed for the de-icing process limited availability of de-icing facilities might reduce the capacity. In case of low visibility or low cloud base so called Low Visibility Procedures (LVP) are set into force. That means the separation between aircraft on final approach needs to be increased to ensure that landed aircraft have left the sensitive area of the instrument landing ground equipment before successive aircraft arrive. The increased separation has major impact on arrival capacity. Table 1 shows the Runway Visual Range (RVR)[6] and ceiling[7] thresholds for the LVP states at LOWW plus the related separation and arrival capacity. In case of very low visibility (LVP CATIII) the arrival capacity is reduced more than 50% to 18 arrivals per hour from more than 40 arrivals in normal conditions.

6 Runway Visual Range: Distance over which the pilot can see the runway lightning.
7 Height of lowest cloud layer base covering more than half of the sky.

2.2 Impact of capacity reduction on aviation stakeholders

In the previous section weather phenomena with adverse impact on the air traffic system have been described. All phenomena impact air traffic capacity, either directly, as for example in the case of LVP due to the need for increased spacing, or indirectly because of increased ATCO workload due to deviation from the planned route to avoid the weather. If traffic demand exceeds the available capacity, action needs to be taken in order to keep ATCO workload on acceptable levels and avoid excessive airborne waiting of flights in holding patterns. Taking action to match traffic to the available capacity is the responsibility of Air Traffic Flow and Capacity Management (ATFCM). Measures taken by local Flow Management Positions (FMPs) at the national ANSPs are coordinated on European level by the Network Manager.[8] If a FMP anticipates that the traffic demand exceeds the available capacity in an airspace volume a so called ATFCM-regulation is issued, which states the acceptable airspace capacity for the regulation period. Traffic which has not departed and would enter the airspace in the regulation period is then hold on ground long enough to ensure the capacity is not exceeded. The ATFCM-regulation process is described in detail by Matos and Ormerod (2000) and will be discussed in more detail in Section 3.1.

That means impact of weather for passengers, besides discomfort when entering areas of turbulence, translates into delay. Depending on the length of delay it can be a minor inconvenience or a major disruption of plans, if an onward connection or appointment is missed.

Airlines face additional cost by the impact of weather in various ways. The need to avoid areas with adverse weather increases the flight distance and time, which increases operating cost. If a flight is directly hit by weather, e.g. severe turbulence or lightning, additional maintenance and inspection cost can be the result. Capacity limitations lead to ATFCM delays, these induce cost for crew overtime, passenger compensation, cost for alternative modes of travel for connecting passengers who miss the onward flight, and can mean additional airport charges for leaving the gate late. If flights are often delayed indirect costs can accrue due to negative impact on an airline's image and related decline of passenger numbers.

For ANSPs the effect of weather on capacity means that action needs to be taken to match the traffic load to the available capacity. As beside ensuring safe air traffic also efficiency is a concern for ANSPs, it is important to set ATFCM regulations in a way to make best use of the available capacity. The delay resulting from ATFCM regulations is an important performance target for ANSPs imposed by European legislation (European Commision, 2014). Depending on the weather phenomenon on hand and whether en-route or arrival traffic is impacted, additional cost is incurred by measures to increase capacity in adverse conditions. For example, if convection is affecting en-route traffic, opening additional air traffic sectors by calling in staff

[8] EUROCONTROL was nominated as Network Manager by European Commission Decision (European Commision, 2011)

on overtime can improve the capacity situation. In case of arrivals and departures where mostly the runway throughput is limiting capacity, for example in case of LVP, ANSPs have no means to increase capacity, hence the impact is only on workload and not economic.

2.3 Delay situation at Vienna International Airport

In 2017 Vienna International Airport (LOWW) was one of the European top-20 airport ATFCM-delay locations, it was the location with the 12th most airport delays (European Commision Network Manager, 2018a). An overview of the traffic development and ATFCM-delays for the years 2013 to 2017 is given in European Commision Network Manager (2018b). Traffic was going down slightly from 2013 to 2017, while the delay shows a relatively large variation over the years between one-hundred- and one-hundred-and-fifty-thousand minutes. Also the distribution of delay into the various delay reasons used by the Network Manager are given by European Commision Network Manager (2018b). In all years the dominating reason for delay was weather, followed by aerodrome capacity, while other reasons only contributed very little to total delay. In 2017 88.5% (86.4% in 2016) of all airport delays were due to weather (European Commision Network Manager, 2018b). The trend of a growing relative contribution of weather to total delay was present over the last years. The large contribution of weather to total delay also explains the variation of total delay between the individual years, as the occurrence of adverse weather conditions shows considerable variation between years.

Splitting weather delay into the contributions of various weather phenomena makes the variability of weather apparent. The dominating adverse weather phenomena at LOWW are thunderstorms (CB / TS) and low visibility events. The delay caused by these phenomena varies from year to year based on the occurrence frequency and whether the events happen during traffic peak hours or not. For example, in 2017 41% of total ATFCM-delay in LOWW was caused by convection and 15.8% by low visibility (European Commision Network Manager, 2018b). In 2016 convection was responsible for 55% and low visibility for 33.8% of total ATFCM-delay. Snow can also have big impact. In 2013 delays caused by snow were the second largest contribution to total weather delays. Because heavy snow events were rare at LOWW in the last years, snow did not have considerable impact in the other years. A single adverse weather event, e.g. an all day heavy snow or low visibility event, can cause up to 10.000 delay minutes alone. So a single event can be responsible for around 10% of total annual delay at LOWW, which explains the variability in delays also for weather phenomena, which are less rare than snow events. In addition to the reduced runway throughput in case of strong head winds (for information on wind impact on capacity see Treve, 2016), the runway configuration in LOWW with crossing runway centre lines adds to the vulnerability to capacity reduction due to winds. Under certain strong wind conditions, not that exceptional for LOWW, only one runway can be used both for departures and arrivals, which means capacity is almost halved.

2.4 Air Traffic Management related weather research

The big range of research on weather impact on aviation underlines the significance for all stakeholders. An important aspect in ATM specific weather research is to incorporate the inherent uncertainty of weather forecasts, mostly in form of probabilistic weather forecasts. This section gives a brief overview and discussion of this topic.

One field which is covered by broad research is convection in en-route airspace and how the weather forecasts can be translated into ATM impact. This topic is covered in literature primarily for north America. DeLaura et al. (2008) studied the avoidance of convection by flights. By comparing actual flight tracks to the route filed in the flight plan and relating those deviations to observations from weather radar showed that echo top height[9] is the best predictor for en-route flights to deviate convection. Sheth et al. (2009) and Sheth et al. (2013) investigated the traversal of aircraft trajectories through probabilistic convective weather forecast areas on a regional basis, i.e. for each of the 20 en-route control centres in the United States. The results indicated that above a certain probability threshold the forecast areas were mostly avoided by flights. This threshold was called the Probability Cut-off Parameter (PCP) and differs of course with forecast lead time. As the forecasts have not been available to the airlines or pilots, the analysis of the PCP can be seen as a kind of forecast verification and the derived values be used in a forecast application. This was done in the study by Sheth et al. (2009) and shown that re-routing flights locally within the area of a control centre based on these forecasts is beneficial, with regards to additional fuel used and traffic congestion in the related centre, compared to do the re-routing on a national level.

Song et al. (2009) propose a method to derive weather impact on sector capacity based on 2D and 3D weather data. Three measures are derived and compared. A 2D sector coverage is derived from vertically integrated liquid water contend weather radar data. In combination with echo top information to also account for the height dimension a 3D Weather Avoidance Altitude Field (WAAF) is generated. Based on a mincut algorithm a flow-based reduced-sector-capacity-ratio is derived from the WAAF as third measure. The indices were then compared with an estimate of the actual sector capacity for 48 US high altitude sectors. None of the three indices performed best in all sectors, but a dependence of performance on the traffic patterns could be identified. In all sectors with dominant flow directions the reduced-sector-capacity-ratio showed the strongest correlation to actual sector capacity.

The studies of Wang and Sridhar (2010) and Reiche et al. (2014) focus on finding suitable evaluation methods of convective forecasts in ATM application in addition to established verification methods used in meteorology. The measures derived in both studies, and suggestions how to best combine different forecast products yielded useful insights for ATM decision makers, aviation meteorologists, as well as for designing automated decision support systems.

[9] Cloud height derived from weather radar observation

Matthews et al. (2009) and Matthews et al. (2015) look into the translation of weather avoidance fields into air traffic impact. They look into the blockage of air space routes by convection and possible avoidance actions. The airspace permeability, the degree to which traffic flows are restricted, was identified as suitable measure to translate forecasts into impact on various scales, from single routes to whole airspace regions. In Matthews et al. (2015) a machine learning approach was taken to forecast airspace permeability and related uncertainty. For that a machine learning algorithm was used to combine various forecast sources in one decision support metric for 0-12 hour forecast lead times. Matthews et al. (2015) conclude, that the understanding of the interrelations of permeability, achievable flow rates, workload and forecast uncertainty need to be further refined for future application in decision support systems.

The need to translate weather ensemble forecasts into ensembles of aviation-relevant information was highlighted by Steiner et al. (2010). As a proof of concept they translated each weather prediction ensemble member forecast into a forecast of available flow capacity to create a distribution of possible capacity outcomes. Such an ensembles can be a useful input for decision support tools and informs the user about possible best and worst situations to expect. The need to accurately calibrate such ensemble forecasts was also emphasized by the shown example, which over-predicted the capacity reduction by about a factor of two. The presented approach can be universally extended from the presented en-route application in case of convection also to other hazards or applications in terminal airspace, such as low visibility or snow, if adequate ensemble prediction systems covering these hazards are available.

An application of this approach to airport weather is discussed by Steiner et al. (2015) where ensemble forecasts are employed to do airport snow predictions, which are, for example, translated to pavement condition forecasts.

Another phenomenon of importance to airports, lightning, is discussed by Steiner et al. (2014). The measures taken for lightning are not based on forecasts, but on observation data. Nevertheless, the decision process does still involve uncertainty. Besides the uncertainty related to the detection of lightning by the observation system, human factors lead to uncertainty, because implementation of action can be delayed by distraction or consciously disregarding procedures. All these aspects need to be observed when implementing decision procedures.

Kicinger et al. (2016) evaluate the impact of different weather forecast input on results of an airport capacity model. The model used provides probabilistic airport capacity estimates based on predicted traffic demand, weather forecasts and airport specifics, such as runway layout and ATM procedures. The results showed no statistically significant difference of results depending on the weather input, i.e. deterministic forecasts, deterministic forecasts in combination with an error model and ensemble forecasts gave comparable results. Kicinger et al. (2016) stressed however, that ensemble forecasts are valuable to provide information on the possibility of different scenarios, which is not available from the other forecast approaches.

3 Decision support for air traffic management

In the previous sections the importance of weather for the ATM system was presented and research on weather in the context of ATM discussed. This section is focused on the decision making process in ATFCM. After a description of the basic processes in ATFCM, literature on relevant research will be reviewed.

3.1 Air traffic flow and capacity management

Baumgartner (2007) reviews the history of aviation and air traffic control in Europe from its beginning in the early 20th century up to the current complex system with thousands of flights per day. With growing traffic airspace capacity started to become a limiting factor and the need for ATFCM started to arise. Starting in the seventies first flow management units were set up locally within national states in Europe (Matos and Ormerod, 2000), but it soon became apparent that flow management measures need to be done on a coordinated basis on larger scales to be effective. In the eighties ATFCM services were started to be implemented, beginning with an European central database to collect and share flight data and information (Matos and Ormerod, 2000). In the mid nineties finally the Central Flow Management Unit (CFMU) at Eurocontrol became fully operational to take care of ATFCM services in Europe. Later the Air Traffic Flow Management (ATFM) became part of European legislation and Eurocontrol's CFMU was nominated to provide this service (European Commision, 2011). In the course of this CFMU evolved into the Network Manager Operations Centre (NMOC).[10] The core mission of the NMOC is to "improve the performance of the European ATM Network" (EUROCONTROL, 2019b). The core services to achieve this goal are according to EUROCONTROL (2019b):

- Flow and Capacity Management
- ATM Access Gateway and Flight Planning Operations
- Information Management Domain
- Crisis and Contingency Management
- Post-operations analysis and reporting

Of these services Air Traffic Flow and Capacity Management (ATFCM) has the most relevance for ATM decision making. A detailed description of the ATFCM procedures is given by European Commision Network Manager (2019a). The objectives of ATFCM are summarized by European Commision Network Manager (2019a, p.21):

> ATFCM is a service that is enhancing ATFM with the objective of managing the balance of demand and capacity by optimising the use of available resources and

[10] https://www.skybrary.aero/index.php/Network_Manager_Operations_Centre_(NMOC)

coordinating adequate responses, in order to enhance the quality of service and the performance of the ATM system.

ATFCM is split into four phases (European Commision Network Manager, 2019a), the strategic phase, which happens more than seven days before the day of operation, is concerned with early identification of demand-capacity imbalances, e.g. in case of major sport events. A Network Operations Plan is set up to optimise capacity to match demand as good as possible in such a situation. In the pre-tactical phase, from six days until one day before the day of operation, a daily plan is developed to optimise efficiency and balance demand and capacity upfront. On the day of operations tactical flow management adjusts the measures taken in the strategic and pre-tactical phase to unforeseen disturbances, such as weather or staffing problems. The final phase is the post operational analysis, where the measures taken during the previous phases are reviewed by the network manager under involvement of all stakeholders. From the review lessons learnt and best practices are derived to improve the processes for the future.

Decision making based on weather is relevant for the tactical phase. The predictability of the weather phenomena affecting the ATM system is not sufficient on timescales necessary to be successfully used in the strategic and pre-tactical phase.

In the tactical phase the Flow Management Positions (FMPs) at the ANSPs monitor the traffic situation and external factors to make sure that the traffic demand can be handled with the available capacity. In case that the traffic demand exceeds the available capacity measures must be taken. The FMP and the Air Traffic Control (ATC) supervisor coordinate the available capacity based on available staff, weather forecasts and other external information. Based on this the FMP issues an ATFCM regulation with the NMOC. An ATFCM regulation sets the acceptable number of aircraft which can be handled in a given airspace volume in a certain period of time. The flow management process in general is set up as collaborative decision making process between the NMOC, ANSPs, aircraft operators, military authorities and airport authorities (European Commision Network Manager, 2019a). The final decision on which regulations to implement are the responsibility of the ANSPs, while the final decision on the measures to be taken to adhere to the regulation is the responsibility of the NMOC.

The measures which can be taken by NMOC include rerouteing, level capping and ground delays. In case of rerouteing traffic flows are diverted from areas with capacity limitation to areas with free capacity. Level capping means that flights between certain airports are only allowed below certain levels. This measure is taken between busy airports which are located relatively close to each other.[11] Besides reducing the number of flights in higher levels, this measure also avoids the complexity connected to climbing and descending flights and hence reduces ATCO workload. The most effective, but also most disruptive, measures are ground

[11] Aircraft operators try to operate at the optimum cruising altitude to minimize operating cost, which usually result in relatively high requested cruising altitudes even for short distances.

delays. In this case flights are hold on ground at their origin to delay their arrival in areas with capacity limitations. In this way traffic is spread out more evenly over time to keep the traffic load within the capacity limits. In case of capacity limits at the destination airport ground delay is the only measure which can be taken. Delaying flights on ground at the origin is usually more cost effective for aircraft operators than waiting in holding patterns close to the arrival airport. Ground delays are implemented by the NMOC by issuing so called slots to the individual flights. For each regulation NMOC builds a list of slots corresponding to the regulated capacity and regulation time. These slots are then assigned to the planned flights on a ”First Planned - First Served” basis, i.e. the slots are allocated to the flights in the order they were planned to arrive at the regulated airspace without the regulation (European Commision Network Manager, 2019a). Based on the slot assigned to the flight its take-off time is calculated and communicated to the aircraft operator and the ATC unit in charge. If a flight is affected by more than one regulation, i.e. different airspaces along its planned route are regulated, the slot is assigned based on the most penalising regulation. Various additional mechanisms are in place which allow the NMOC to handle changes in flight plans, allow aircraft operators to switch slots between aircraft in case more than one flight is affected by the same regulation, or react to new or changes in existing traffic regulations.

Various research on improvements to the flow management procedures is carried out. The research ranges from looking into mathematical models to optimize the regulations (Agustín et al., 2010) to proposals for new optimization targets. Dmochowski and Skorupski (2017) proposes to use air traffic smoothness as measure rather than only matching traffic demand and capacity. The rational is that smooth air traffic, i.e. traffic which follows the previously agreed plan without additional manoeuvres, results in less workload for the ATCO and hence is easier to handle. That means capacity for smooth traffic is higher and regulations need to be less strict for smooth traffic. Ivanov et al. (2017) extend the view from the ATFCM delay of a single flight to the propagation of delays to later flights. They conclude that because of buffers in the schedule the minimization of ATFCM delay for individual flights is not necessarily in the best interest of aircraft operators to achieve their operational goals and to increase network predictability. One important factor of ATFCM is however to ensure fairness and equal treatment of all aircraft operators. Optimization targeting the network level often results in potentially unfair distribution of delays. For example, if buffers in the schedule are considered when distributing delays, as proposed by Ivanov et al. (2017), flight operators with longer planned buffer times could face a larger share of delay.

3.2 Review of ATM decision support systems

Research published in literature on decision theory and on decision support is exhaustive (e.g. Berger, 1985; Valencia-García et al., 2018; Burstein and Holsapple, 2008a; Burstein and Holsapple, 2008b; Munier et al., 2019; Druzdzel, 1993; Obwegeser, 2011). Full coverage of decision theory and decision support systems in multiple fields is beyond the scope of this study. An overview of research on decision support in ATM will be given and related to decision support in other fields where appropriate. Also in the field of ATM focus will be set on decision support related to ATFCM and weather, other specific fields such as support tools in the air traffic control systems to support ATCOs with ensuring aircraft separation will not be discussed.

With NextGen[12] in the United States and SESAR[13] in Europe two large scale initiatives are focused on modernizing the air transportation system. Given the high impact that weather can have on capacity, as outlined in previous sections, weather integration into ATM decision making processes is an important component of both NextGen and SESAR. FAA (2016) outlines the plans for better integration of weather into ATM decision making within NextGen. The focus is on integrating weather information into decision support processes and tools to reduce the subjectivity of weather interpretation as it is present today. Effort is focused on improving weather forecasts and the translation of weather data into aviation impact and constraints. Also an increased level of data fusion between flight data, weather data and ATM information is anticipated to enable knowledge-based decision processes. Another component is to facilitate easy sharing of and access to data for all stakeholders to ensure a consistent and joint basis for the individual decision making processes. This will be achieved trough System Wide Information Management (SWIM), a concept which is aimed at enabling easy and secure access to all relevant data by all stakeholders.

Flathers et al. (2013) developed a framework for an ATM-weather integration concept for the United States which targets at including meteorological information in the logic of decision processes and tools to take the effect of weather into account when ATM decisions are made. The rational is to try to reduce weather delays as far as possible. As reported by Flathers et al. (2013) the Federal Aviation Administration (FAA) considers that two-thirds of weather delay is potentially avoidable. The four primary elements of the ATM-Weather integration were summarized in a chart, which is informally called the ”Ketchup-Mustard Chart”. A simplified version of this chart is reproduced in Figure 2. The Weather Information element includes all meteorological data, i.e. observations, analyses and forecasts, available to national weather services. This data is made available to the FAA weather experts and other stakeholders. The second element, Weather Translation (yellow box in Figure 2), comprises the translation of the weather information into airspace system constraints and threshold events, by considering the weather

[12] Next Generation Air Transportation System, for more details see https://www.faa.gov/nextgen/
[13] Single European Sky ATM Research, for more details see https://www.sesarju.eu/

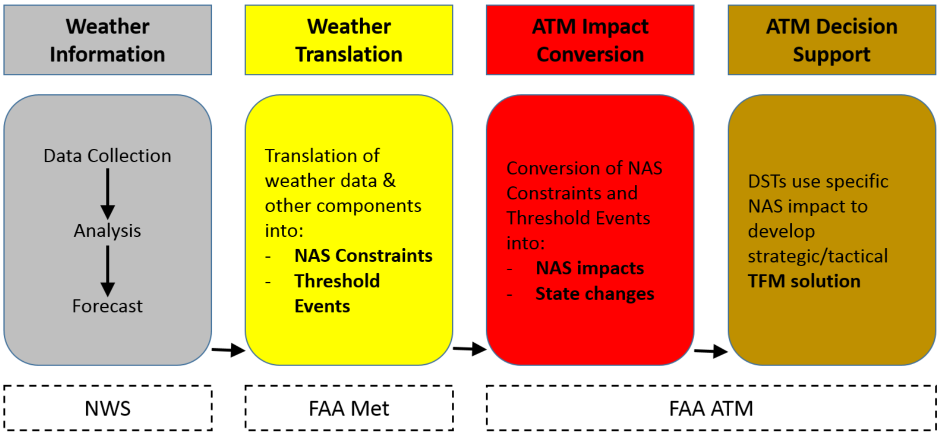

Figure 2: "Ketchup-Mustard Chart" reproduced from Figure 1-1 in Flathers et al. (2013). Primary elements of weather integration in ATM decision processes. Abbreviations: NAS: National Airspace System, TFM: Traffic Flow Management, FAA Met: FAA meteorology experts, FAA ATM: FAA ATM experts, DST: Decision Support Tool, NWS: National Weather Service.

effects in the light of safety regulations, operating limitations and standard operating procedures. Airspace system constraints and threshold events are expressed in non-meteorological parameters highlighting the weather impact on capacity. Threshold events are connected to changes in minimum spacing at airports related to changes of weather parameters, for example if visibility or ceiling is falling below certain limits. Impact of adverse weather leading to reduced airspace permeability are expressed as airspace system constraints which can be used to derive capacity limits. In the third component, the ATM Impact Conversion (red box in Figure 2), the translated weather information is merged with ATM specific data, such as traffic demand and flight specifics, to derive the impact on the ATM system in the light of the specific traffic situation. This is then the input to the fourth component, the ATM Decision Support (brown box in Figure 2), where ATM measures, e.g. flow management regulations, are derived. At the bottom of the chart the main responsibilities for the components are given. Flathers et al. (2013) highlight however, that the ATM-Weather integration problem cannot be solved keeping the communities separate, but that the collaboration of weather and ATM community is essential to achieve optimal results. Only in that way requirements of the ATM community can be best matched by the capabilities of the weather community.

In Europe within the SESAR initiative similar objectives are pursued. The much more fragmented organization on national levels complicates the approach. There is not one national weather service but weather information needs to be gathered from many services. The translation and implementation of the weather information into air traffic impact and decision support is then done differently and at various levels of sophistication by the national ANSPs. The NMOC coordinates the national decision outcomes on European level which can be difficult because of the different input data used and varying decision processes. There have been

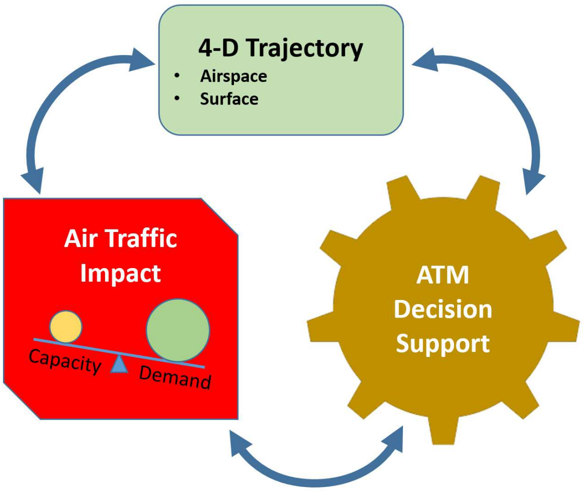

Figure 3: ATM decision cycle reproduced from Figure 2-3 in Flathers et al. (2013).

various attempts by the NMOC to introduce consolidated weather information for use by all stakeholders, but so far with limited success.

The elements shown in Figure 2 are not simply in a linear relationship as it might appear on first sight. Flathers et al. (2013) point out that air traffic impact by weather, ATM decision support and traffic build a decision cycle as those three elements are closely interrelated. Figure 3 depicts this relation. Air traffic is represented by the 4-D trajectory. The future concepts of ATM build on these 4-D trajectories, where each flight is seen as its path depicted by position, horizontal and vertical, and its time. These trajectories are defined from gate-to-gate and are the basis for all planning and decision processes. Before departure the trajectory is based on the planned flight details and after departure it is updated on a continuous basis. The concept is also referred to as trajectory based operations and builds on the automatic and constant exchange of 4-D trajectories between all stakeholders. In the decision cycle the 4-D trajectories build the basis for demand specification, if an imbalance of demand and capacity is detected in the impact evaluation, actions defined by the ATM decision support will alter a number of trajectories. The updated traffic will than again be subject to the impact analysis, completing the decision cycle. Although, often the ATM measures will have impact on the traffic, e.g. due to imposed ground delays, short-term capacity management measures, such as sector configuration changes, can increase capacity without affecting traffic. In this way the ATM decision support is directly changing the air traffic impact. Also flight operators are aware of the air traffic impact and might in turn apply changes to their planed trajectories, with impact on the capacity-demand balance and eventually on the ATM decision support process.

The basic definition of ATM decision support of Flathers et al. (2013) is the collection of tools available to decision makers, which ingest capacity-demand analyses to develop plans for mitigation of capacity reduction. The result are various mitigation strategies presenting possible solutions which are defined by ATM actions, their timing and associated risk. The ultimate selection of the actions to take is then done by human decision makers.

The main shortfalls for implementation of the ATM weather integration were identified by Flathers et al. (2013) to be related to the primary components (refer to Figure 2) weather information, weather translations, air traffic impact and decision support. Although the required weather forecasts for the elements of interest do exist, it is unclear whether the accuracy is sufficient to be useful for the further process. Also for weather translation methodologies exist, e.g. weather avoidance fields (cf. Section 2.4), but it is not yet clear if these methodologies are the most appropriate translations. When it comes to deriving air traffic impact a functionality needs to be developed to detect conflicts between flight trajectories and weather constraints. Once such a conflict is detected appropriate algorithms are required to determine the impact associated to this conflict, potentially on a flight by flight basis. For the decision support various different types of required support tools and functionalities were identified. These include weather conflict resolution on a flight by flight basis defining how aircraft respond to the conflict, recommendation for airspace configuration to optimize capacity in the given weather situation, recommendations for alternative airport runway configurations in the given weather situation and a combination of these components to give the decision maker a selection of appropriate mitigation strategies.

Even so the analysis of Flathers et al. (2013) dates already back more than half a decade the identified shortfalls are not satisfactorily solved and still in the focus of research and development. The implementation in operations is an ongoing step by step process based on various attempts to implement individual decision support tools.

Evans (2001) discusses a decision support tool for rerouteing in case of convection both for en-route and terminal traffic. The tool uses a combination of automated systems and human forecaster input. These forecasts together with observation data from weather radars are displayed for the ATM decision maker. For terminal airspace a forecast loop was displayed from the past 30 minutes to the forecast time of maximum 60 minutes. In the weather integration concept of Figure 2 this system is located somewhere between grey and yellow, as it contains an element of translating weather into areas of interest, but on a very basic level.

The concept for terminal areas was further refined and presented by Evans et al. (2006). In the so called Route Availability Planning Tool (RAPT) for the New York airports a concept was developed to translate convective forecasts into a prediction of the availability of departure routes. To achieve that, thunderstorm forecasts are combined with a model for pilot avoidance of convective weather in combination with the departure route layout of the New York airports. By also considering nominal flight times the route availability can be forecasted as function of take-off time, which enables decision makers to focus on the departure planning instead of interpreting thunderstorm forecast in relation to the departure routes. RAPT was designed to answer three questions (Evans et al., 2006, p. 85):

> Will a candidate future departure encounter hazardous weather at some point along its intended path?
> Will there be opportunities to route the aircraft through significant gaps in evolving weather?
> If so, at what times can the aircraft depart to be able to utilize the gaps?

The RAPT display for users consists of a departure route map with an overlaid weather forecast loop. Each departure route is labelled with the number of planned departures on this route. Below the map a coloured timeline is given for each departure route. The colours depict the route status for the given departure time. RAPT distinguishes blocked departure, red, impacted routes, yellow, partially clear routes, dark green and clear departures, light green.

Operational evaluation was carried out along with the usage of RAPT by checking operational logs, interviews of ATC personnel, observation of ATC operations during convection and user feedback received by e-mail. A lot of positive feedback was recorded about reduced delays in some cases. However, there were cases when RAPT reported closed departure routes when pilots used the departure routes without diversion. This was credited partly to pilots overflying convection and consequently the RAPT forecast was extended to also consider cloud tops. Continuing over-warning showed the need to further improve the convection avoidance model as, depending on the life-cycle of thunderstorms, flights were observed to fly through the storms in their decaying phase. Another inhibiting factor identified was, that the en-route ATC units could not accept the additional departures, because they were as well affected by convection and did not have support tools, such as RAPT available, and RAPT could not be extended to the en-route application with the available forecasts. Another drawback identified was, that RAPT did only give information on blocked routes but did not support the search for alternative routes. This had to be done manually, including also checking for possible congestions resulting from re-routing flights and other impacts such as increased flight distance which needs to be considered by flight operators.

In the weather integration framework shown in Figure 2 RAPT as described by Evans et al. (2006) clearly does ATM impact conversion, but as the evaluation showed could be even more helpful if it would be closer integrated in the decision cycle (Figure 3) to also help with selecting ATM measures and anticipating their impact.

Weber et al. (2007) addressed the evaluation outcome and extended the RAPT tool with a Departure Sequencing Program (DSP). The DSP shows the RAPT timeline for each flight's planned departure route. Alternative routes can be automatically evaluated by selecting a flight. The alternative route calculation is based on four factors: route blockage, flying time, and two measure for en-route capacity. This extension is clearly a step in the direction of further integration of the weather impact in the decisions cycle (Figure 3). In addition Weber et al. (2007)

propose a further step for future development, *departure flush* procedures. In situations with adverse impact of convection these procedures would favour departures from major congested airports with large departure delays over departures from minor airports without delays. In this way major disruptions could be avoided, however, it must be ensured that this does not result in disproportionate delays at airports without adverse weather. In order to successfully implement such procedures suitable decision support tools are a prerequisite because of the major complexity involved to select and coordinate the ATM measures at the airports and the adjacent en-route sectors.

Further evaluation and enhancements of RAPT were discussed by Robinson et al. (2009) underlining the continuous improvement based on performance evaluation. The most promising enhancements identified were to add information on impact trends to inform decision makers about possible changes and information on missed departure opportunities when a route is usable again after a disruption, to focus the attention of decision makers on such events to make better use of opportunities in the future.

A similar tool to RAPT for en-route application was presented by Matthews et al. (2015) and Matthews et al. (2017). Impact of convection on airspace capacity is derived based on a permeability metric which takes into account severity and scale of convection in relation to aircraft trajectories. Based on this permeability metric the airspace routes are assigned an impact level, impassable (red), uncertain (yellow), passable with acceptable storm-avoiding deviations (dark green) and passable (green). The convection impact on the airspace is then derived using a weighted average of the route impacts traversing the sector. For permeability forecasts which include also uncertainty information a machine learning based algorithm to combine multiple sources of weather forecasts was developed. The impact forecasts were then visualized in a Traffic Flow Impact application for decision makers. The main display shows a geographic map where the impact forecast is displayed. In addition a timeline, similar to RAPT, of the expected impact on individual air traffic sectors is shown. By selecting a sector detailed information on the permeability forecast is given including uncertainty information. The application is intended for the use by air traffic managers to support the selection of ATM measures. The display was evaluated for one season including on-site observation studies and end of season feedback collection. Overall the tool was rated to be helpful in understanding weather impacts. It was also concluded that the tool helps to improve communication between various stakeholders, which highlights the need to make such information available to all stakeholders and integrate it better in decision processes. The uncertainty information was observed to be beneficial in cases where high uncertainty led to less aggressive but more flexible measures for later adjustment.

Evans and Crowe (2019) give an overview about 30 years of decision support development for convective weather in ATM. In the centre of the 30 year development was a benefit-driven design process building on the provision of operational prototype systems. The prototypes allow to iterate the functionality of the decision support to optimize the operational benefits based on operational user feedback and objective benefit assessment. These feedback loops, qualitative and quantitative have been identified as key features of successful decision support development. Another important factor for prototype based development highlighted by Evans and Crowe (2019) is training. Standard training was used to give users an understanding of the new product, including information on the strength, weaknesses and uncertainties of the provided information. Based on the decision making process characteristics, such as time pressure, personal responsibility and high impact of the decision outcome, the weather related ATM decision making was characterised as a ”Recognition-Primed Decision” according to Klein (2001) (cited in Evans and Crowe, 2019). That means that decision makers relate the situation to prior experience and hence only consider decision support information that has been available in the past disregarding new decision support information. To work around this Evans and Crowe (2019) integrated past situations in the training to get users familiar with the new product in a known setting. Another integral part of the training was to collect user input on required improvement steps.

The quantitative feedback loop evolved over time. At the start it was mostly based on end-of-season interviews with users who estimated the benefit of the decision support tool in hindsight. Later, operational benefits studies were conducted. For these, observers watched the decision making process during weather events and evaluated how the tools were used, user statements during decision making and feedback what alternative decisions would have been made without the tools available. A further refinement was to introduce objective automatically derived measures based on recorded flight tracks and the forecasted impact. The outcome of the benefit analysis was translated into improvements of the decision support tools, which were then evaluated based on the same metrics. Another important insight from the benefit analyses was, that a widespread availability of the decision support tools to all stakeholders increased the benefits measurable due to the shared situational awareness.

Overall Evans and Crowe (2019) conclude that the ongoing prototype centric process with a qualitative feedback loop based on user feedback and a quantitative feedback loop based on objective measures is an effective approach to improve decision support in case of adverse weather.

Most work on weather integration into decision support tools is reported from the United States with a strong focus on convection. Other weather phenomena which were addressed are low ceiling and visibility. Evans et al. (2006) describes a low stratus-cloud forecast system for San Francisco airport, where during times with low stratus-cloud arrival capacity is only half the fair weather capacity. This capacity reduction is resulting in major ground-delays during the arrival peaks. Based on forecasts for the end of the low stratus periods it was envisioned that the ground delay measures could be ended in time for traffic to arrive once capacity is available again. In this way the periods where less traffic is arriving than could be accommodated by available capacity could be reduced compared to the case where the ground delay measures are only ended once the low stratus ended. In practice decision processes are too conservative adding too much safety margin, which results in limited improvements, although the forecast performance is good. Various reasons have been identified for this outcome. The possible result of too many aircraft holding in the arrival sectors in case the low-stratus does not end is rated as severe by the decision makers, i.e. a very high cost is assigned to this outcome. Also, the decision makers were not trained how to properly use probabilistic information in decision making. A third identified reason was that the provided forecast information was not suitable for decision making under uncertainty. As a consequence Evans et al. (2006) proposed to increase the awareness of all stakeholders, that a properly applied probabilistic forecast could improve their utility. In addition a more sophisticated risk mitigation process was proposed in case too many aircraft arrive. The idea was to set up a process with all stakeholders whose flights would need to divert in case of overfilled holding patterns.

Reynolds et al. (2012) reports on the impact of changes to procedures at San Francisco airport, namely setting ground delays with a variable rate, i.e. higher accepted rates in the later hours of the forecasts, and rather than setting a fixed length of the ground delay program the length is set collaboratively between ATC, weather forecasters and airline representatives. These new procedures showed considerable improvements, i.e. reduced ground delays. Further improvement potential was shown in a retrospective analysis of previous seasons. The analysis showed that 29% of total delay could have been avoided compared to the actual observed delay by using probabilistic forecasts together with an appropriate cost model described by Cook and Wood (2009). So a clear potential for improvement based on probabilistic forecasts was identified.

Outside the United States, Zhang et al. (2018) investigated rerouteing and capacity forecasts in case of convection at Shanghai Airport. Results of a theoretical model and simulations are compared. The presented route optimization considered multiple constraints, including ATCO workload, fuel consumption, delay and route length. The proposed dynamic rerouteing showed improvements in the constraints, suggesting that the presented method could be beneficial for use in decision support systems to optimize capacity.

The Hong Kong Observatory implements and continuously improves decision support tools for Hong Kong International Airport in collaboration with airport and aviation authorities. The Graphical Situation Display visualizes windshear and turbulence alerts from Hong Kong Observatory's windshear and turbulence warning system (Chan and Hon, 2016). Another example is the MET-ATM Integrated Monitoring tool, which combines weather information and air traffic flow data in a dashboard view to support collaborative decision making at Hong Kong International Airport (Hon, 2018). A significant convection forecast product is supporting weather briefings for ATFCM. The product combines display of weather observations, such as weather radar images and lightning data, with weather forecasts for significant areas, e.g. location of holding patterns, around Hong Kong airport (Cheung, 2011).

In Europe the Single European Sky ATM Research (SESAR) project ONBOARD (Alvarez et al., 2011; Clare and Richards, 2012; Clare et al., 2012; Clare and Richards, 2013; Escartin and Martinez, 2013) investigated how uncertainty can be best considered in ATFCM planning to improve ATM performance. Sector capacity was optimized using a Mixed-Integer Linear Programming approach, which was adapted to include probabilistic constraints (Clare and Richards, 2012). Simulated test cases showed that using the probabilistic constraints did reduce the frequency of sector capacity violations compared to a deterministic reference model. The capacity optimizer model was then coupled to an Airline Operation Centre algorithm which rerouted and rescheduled flights based on the ATFCM constraints optimizing fleet assignment and airline cost (Escartin and Martinez, 2013). The approach which closely coupled the Airline Operation Centre algorithm and the ATFCM algorithm showed that delay could be reduced without introducing additional capacity breaks.

In addition to the discussed decision support tools there is a range of other decision support tools developed on national level with limited coverage in the literature. Section 3.3 discusses examples from Austria.

3.3 Current decision making process at Vienna International Airport

As described in Section 3.1 the FMP and the ATC supervisor are responsible to monitor the available capacity based on available staff, weather forecasts and other external information and take measures to ensure that the traffic load stays within the available capacity. The final decision if and which measures are implemented is made by the ATC supervisor. The decision making process is based on the guidelines laid out in the ATC procedures (Eder, 2018). Weather products issued for all aviation stakeholders are regulated by the International Civil Aviation Organization (ICAO), among others these are TAF[14], SIGMET[15] and aerodrome warnings. In addition to these products bespoke weather information for ATFCM is provided to FMP and the ATC supervisor. The most important information for decision making at LOWW are expected convection in the air traffic control approach sectors, the occurrence of LVP and wind. These information is summarized in the so called Significant Weather Bulletin, a weather information dashboard. Figures 4 and 5 show examples of this dashboard for cases with expected LVP and convection, respectively. The product is issued every hour between 0400 and 1900 UTC by a forecaster at LOWW and amended in between in case of significantly different weather development. To ensure the information can be easily and efficiently perceived, it is displayed

[14] Terminal Aerodrome Forecast (more information at https://www.skybrary.aero/index.php/Weather_Forecast)
[15] Weather warning product (more information at https://www.skybrary.aero/index.php/SIGMET)

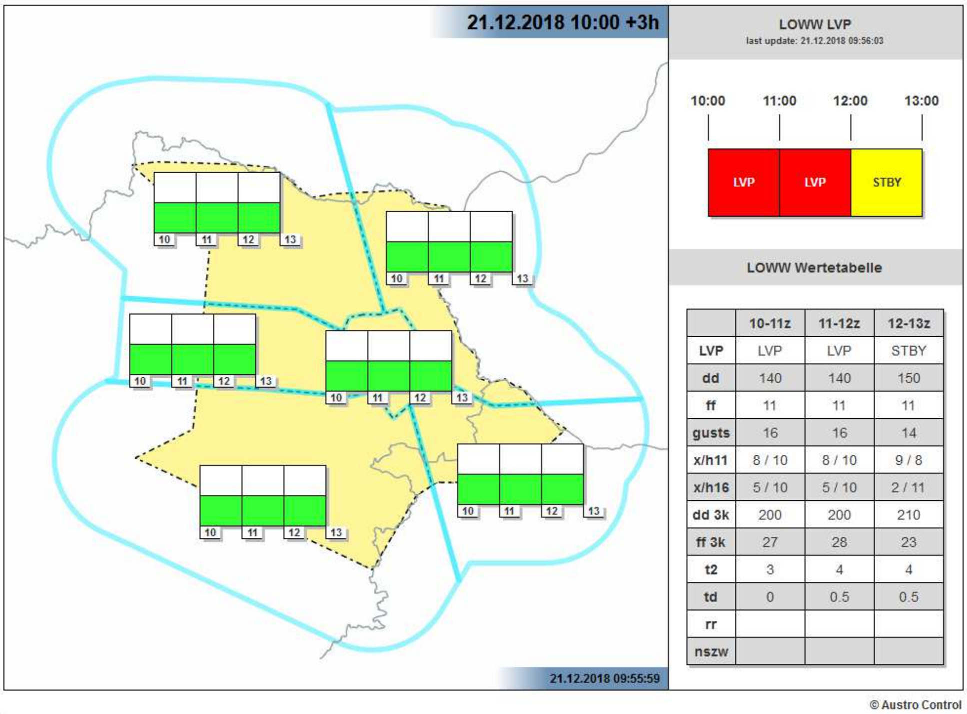

Figure 4: Significant Weather Bulletin: Weather information for ATC-Supervisor and FMP. Example with expected LVP.

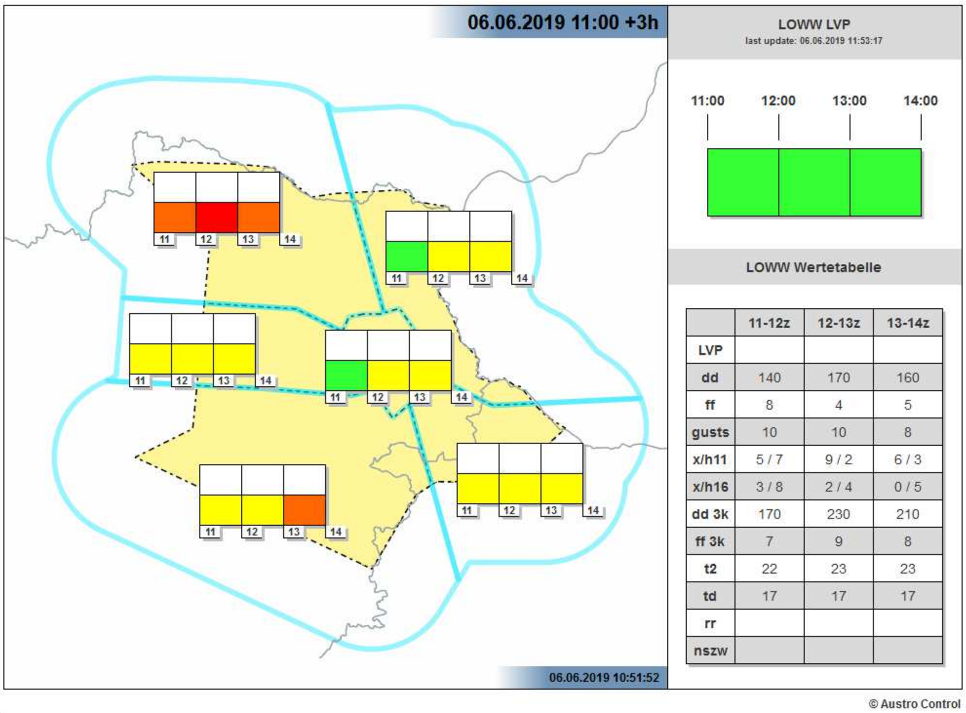

Figure 5: Significant Weather Bulletin: Weather information for ATC-Supervisor and FMP. Example with expected convection.

using a simple traffic light colour scheme. Information on expected occurrence of LVP is given in the top right corner of the dashboard (cf. Figure 4) for the next three hours. For each hour a coloured box indicates the expected LVP state according to Table 1. If normal conditions are expected the box is green, in case of expected LVP or LVP CATIII the box is red with the status information given as text in the box. In addition to states affecting capacity also the state LVP stand-by (STBY) is indicated by yellow. Under these conditions the arrival rate is not affected but procedures must be set up in order to be able to switch to LVP operation at any time. The forecast for convection is presented in a similar way. The traffic volume around LOWW is split into six regions for which convection forecasts are made. Again the state for the next three hours is indicated by colours. Green indicates that no convection is expected. If convection is expected the colour (yellow, orange or red) indicates the organisation of convection, yellow for isolated convective cells which normally can easily be avoided by air traffic up to red, where major impact of convection on air traffic must be expected due to the organization of convection. The product is however defined in meteorological terms, i.e. the forecaster issuing the product only considers the organization of the convection without taking into account impact related information such as location on arrival routes, expected traffic counts and others. Information on the expected wind situation is given in the table in the lower right part of Figures 4 and 5. In the ATM weather integration framework of Figure 2 the product is at the interface of the grey weather information and yellow weather translation elements. Wind and LVP forecasts are based on the relevant thresholds affecting ATM procedures and hence can be considered as basic translation into impact. For convection the translation into ATM impact is more difficult and although the organization categories used are related to expected general impact, other key elements important for impact translation are not considered.

In addition to the provided weather products periodic telephone calls between the ATC supervisor and the weather forecaster support the decision making process. During these phone calls additional information which is not covered by the forecast products is discussed, for example the uncertainty of the provided information or whenever possible more details on the temporal evolution. These briefings are an essential element of the current decision making process, but although a general framework for the process is given by the operational procedures the resulting decisions still rely on the risk aversion of the involved parties, both on ATC and weather side.

Once the expected course of the weather was determined as described, the ATC supervisor evaluates the expected impact on operations by considering the ATC specific factors, such as traffic demand and available staff. Together with the FMP the necessary measures, for example traffic regulations, are decided. The measures are based on general procedures (Eder, 2018) but can be adjusted on the supervisor's discretion to fit the specific circumstances.

Overall weather forecasts are well integrated in the decision making process, but translation

Table 2: Cost matrix for cost-loss ratio decision model.

		adverse weather	
		yes	no
protective action taken	yes	C	C
	no	L	0

into ATM impact is currently done solely on a manual basis relying on separate information systems for weather and ATM data. A higher integration of weather and ATM data to improve impact translation could provide improved decision support for the ATC supervisor and FMP.

3.4 Decision making based on weather forecasts

Katz and Lazo (2012) discuss decision making based on weather forecasts from an economic point of view. It is highlighted that the most common decision model used in context of meteorology is the cost-loss ratio model. This model is rather simple by only considering two available options for the decision maker, to take protective action against adverse weather or to not take protective action. Similarly, there are also only two possible weather states, adverse weather happens or adverse weather does not happen. For each of the possible outcomes an expense is defined. The cost-loss decision model is a special case of the general utility theory in decision making, where the decision maker is assumed to maximize expected utility (for a detailed discussion of utility theory see Berger, 1985). In the simplest form of the model a cost C is incurred if protective action is taken and a loss L is incurred if the adverse weather occurs and no protective action has been taken. Table 2 shows the expense matrix of the model. The decision maker is assumed to take action in a way to minimize the expected expense. In case of a well-calibrated probability forecast that means to take action if the forecasted probability of adverse weather p is higher than the cost-loss ratio, i.e. $p > C/L$ (Katz and Lazo, 2012). According to Katz and Murphy (1997) the cost-loss model was introduced by Thompson (1952), while the basic idea goes back even further to Thompson (1950). This basic cost-loss model is called *static* by Katz and Murphy (1997) and complemented by two *dynamic* versions, one with finite horizon and one with infinite horizon. The dynamic versions consider that current and previous actions and their consequences have influence on future actions and consequences, in contrast to the static version where consecutive decisions are treated entirely independent. Finite horizon means, that the expected expense is minimized over a finite time horizon, e.g. a season, while in the case of infinite horizon the decision process continuous indefinitely, or at least many years. The dynamic models are much more complicated than the static model and are solved using a stochastic dynamic programming approach. Katz and Murphy (1997) discuss further extensions to the model. One of these extensions is to consider also temporal autocorrelation of weather variables, as the state of the weather usually shows a tendency to persist, depending of course on the time scales of interest. In addition generalization of the model to account for insufficiencies of the weather forecast, e.g. not being well calibrated, is discussed.

Another aspect is, that in most work the cost-loss ratio is defined in pure monetary terms, i.e. it is assumed that economic value is the only decision criteria. Other aspects, such as risk aversion, are not considered although this was already suggested years ago by Shorr (1966). Matte et al. (2017) pick up this thought and integrate risk-aversion of decision makers in the evaluation of economic value of streamflow forecasts for flood protection. The results show that the value of a forecast is strongly dependent on the risk aversion of the decision maker, as for example over forecasting of adverse weather has strong impact on the economic value of forecasts for risk averse decision makers.

Overall the simple static cost-loss ratio approach shows to be popular, this is probably because the more sophisticated models described above are much more difficult to handle, while still relying on major simplification compared to actual weather based decision processes.

4 Decision support for Vienna International Airport

Based on the analyses presented in the previous sections possibilities for improved weather related decision support at LOWW will be explored. The impact of weather cannot be eliminated altogether as restrictions, such as capacity reduction through increased spacing on final approach in case of LVP (cf. Table 1), are unavoidable even if the weather would be known exactly in advance. As weather forecasts have an intrinsic uncertainty and need to be translated into discrete ATM decisions, an appropriate decision model is required. Currently this translation is, somehow subjectively, done by the ATM decision maker based on weather briefings (for more details see section 3.3). Weather uncertainty is communicated in the briefing by the forecaster, these uncertainties are mainly based on the forecaster's subjective estimation. In this study weather uncertainty is considered in the light of objective probabilistic weather forecasts. Such forecasts can be based on statistical models, for example as discussed by Dietz et al. (2018) and Kneringer et al. (2019) for LVP, or on ensemble prediction systems. Ensemble prediction systems represent the forecast uncertainties by running numerical weather forecast models multiple times with altered initial conditions, to represent the uncertainties of the initial state, and model uncertainty representation (a detailed description of ensemble forecasting is given by Leutbecher and Palmer, 2008). In this study the weather forecasts are considered as external input and the decision making evaluated under the assumption that these forecasts are well-calibrated, i.e. that an event which is forecasted with a probability of p is happening p times in the long run. Adjustments to consider forecast insufficiencies are left for future research.

4.1 Methodology

The methodology employed here was previously discussed by Steinheimer et al. (2016) and Steinheimer et al. (2019). It is based on the evaluation of weather impact on the ATM system using fast time, i.e. quicker than real-time, air traffic simulations. The simulation allows to run multiple scenarios of weather and decision combinations and examine the outcomes. Figure 6 shows the structure of a simulation experiment. The main inputs are weather, forecasted (FCST) and observed (OBS), and traffic demand. Traffic demand is the air traffic planned by the airspace users. For the simulation experiments randomly generated traffic can be used, or traffic demand of an undisturbed situation, i.e. a day without adverse weather or other air traffic restriction, is used. Based on traffic demand and the weather forecast ATM measures are applied. Here only ATFCM measures for arrival traffic are considered, that means arrival capacity restrictions are set which are executed by delaying traffic on ground (cf. section 3.1). In principle also other ATFCM measures, e.g. re-routing, could be implemented if the methodology was applied to en-route traffic. In terms of the decision making process considered here, setting the ATM measures is the crucial step, because here preventive actions is taken, while later operation

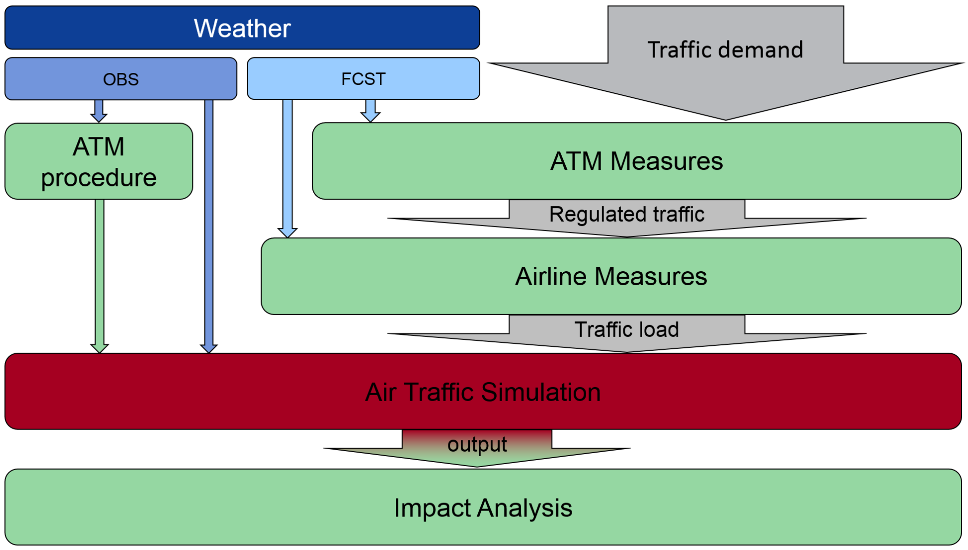

Figure 6: Schematic of the air traffic simulation experiment design (adapted from Figure 1 in Steinheimer et al., 2016).

is executed following predefined procedures. Outcome of the ATM measure step is the so called regulated traffic where the arrival times have been shifted according to the applied traffic regulation. Traffic is then subject to airline measures where in addition to the outcome of the ATM measures also weather forecasts are taken into account. Airline measures considered here are additional fuel carried to allow for longer delays in holding patterns. Other measures such as flight cancellations or re-routing in case of en-route traffic could also be implemented, but are not used in the evaluations presented here. If such airline measures which change the timing of the flights would be used, a feedback loop back to the ATM measures would be required. After ATM and airline measures have been applied, the traffic input for the air traffic simulation is finished. Weather input to the simulation is the observed[16] weather in the simulated scenario. The weather affects the simulation directly, e.g. in case of TS areas which are avoided by air traffic in the simulation, and indirectly via applied ATM procedures. Weather dependant ATM procedures considered here are the choice of the used runway, depending on the wind situation, and the aircraft separation on final approach, depending on visibility and cloud ceiling. Based on the traffic, weather and ATM procedure input the simulation is performed and detailed data collected to be used in the impact analysis. The individual steps are described in more detail in the course of the further discussion.

The impact derived for various weather scenarios under various preventive actions, i.e. decisions, taken is evaluated for its usefulness as basis for developing decision support for ATFCM. Two principle levels of integrating the air traffic simulation and weather forecasts in the decision making process can be distinguished. The basic level is to employ the simulation to derive

[16] Observed does not mean that the weather was actually observed in reality but refers to what is considered to happen in the respective simulation scenario.

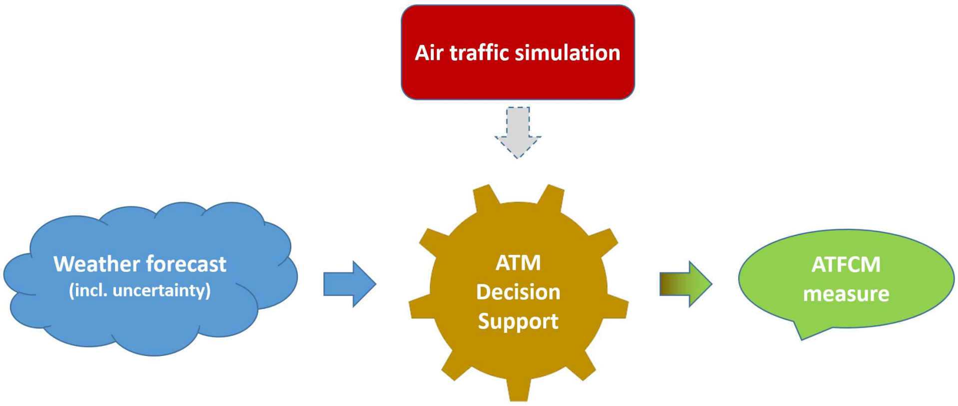

Figure 7: Basic level of weather and air traffic simulation integration in decision support systems.

Table 3: Utility matrix for the simplest form of the basic integration decision support model.

		adverse weather	
		yes	no
protective action taken	yes	U_{pe}	U_{pn}
	no	U_{ue}	U_{un}

decision criteria based on weather forecasts and their uncertainties. Forecast uncertainty can be represented by the probability that an event will occur or a distribution of possible weather outcomes. That means the air traffic simulation is only used in the design phase of the decision support system and is not required to run routinely for providing decision support (Figure 7). For the ATFCM regulation measures considered this means that based on the weather forecast the decision support system suggests the accepted arrival rate to be set by the regulation. In contrast to this basic integration of weather and air traffic simulation, in the full level of integration the air traffic simulator is used to derive the decision utility for all combinations of forecasted possible weather outcomes and decisions made. The resulting expected utilities are then provided as support to the decision maker (Figure 8). In the light of the weather integration concept introduced in Section 3.2 (Figure 2) the air traffic simulation is responsible for the ATM impact conversion. While this is rather static in the basic level integration, as this conversion is only done in the design phase and hence needs to be restricted to a limited number of typical scenarios, the full level integration allows for detailed integration of specific weather and traffic situations. In that way it better represents the ATM decision cycle presented in Figure 3.

The basic level of integration is a variant of the full integration based on a number of simplifying assumptions. In its simplest form, i.e. when weather input is only considered as the probability of a specific adverse weather event happening or not, and the protective action taken in case such an event is expected is predefined, it is equivalent to the cost-loss ratio decision model discussed in Section 3.4. Table 3 shows the cost-loss decision model shown in Table 2

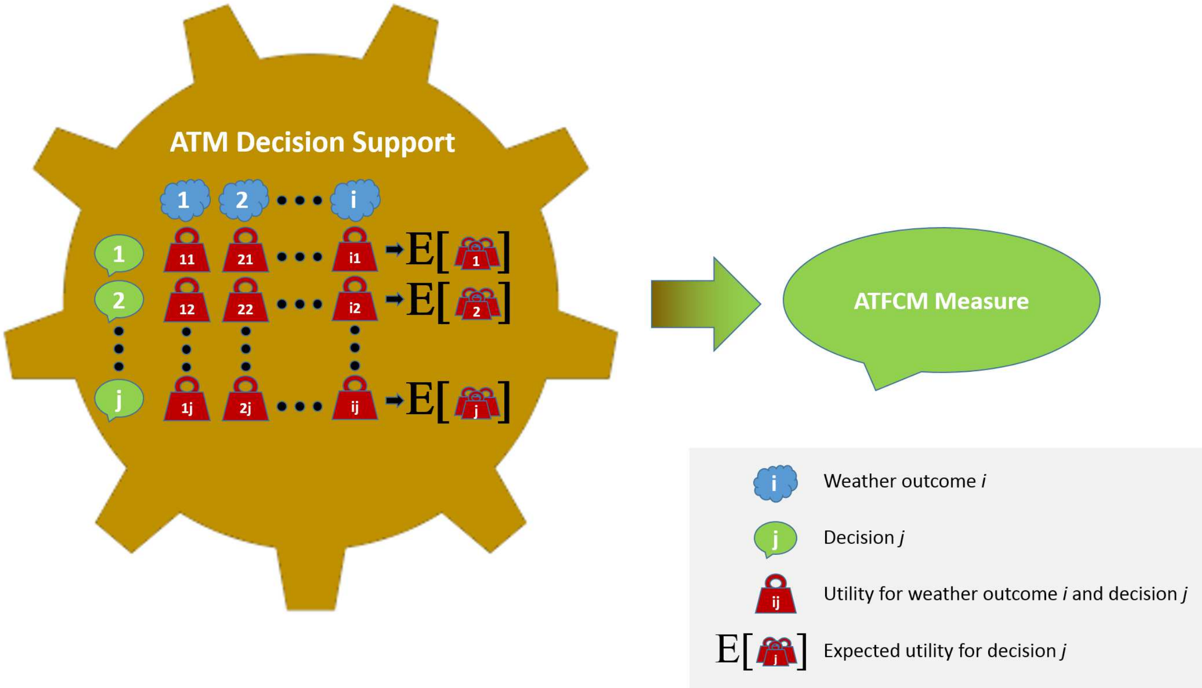

Figure 8: Full integration of weather and air traffic simulation in decision support systems.

formulated more generally in terms of utility instead of expenses. From the four utility values, for the event happing with protection U_{pe}, the event happening unprotected U_{ue}, the event not happening when protection was taken U_{pn}, and the event not happening and no protection was taken U_{un}, the expected utilities for the decision options, to protect or not protect, can be derived:

$$\mathbb{E}\left[U_p\right] = p_e U_{pe} + (1 - p_e)\, U_{pn} \tag{1}$$
$$\mathbb{E}\left[U_u\right] = p_e U_{ue} + (1 - p_e)\, U_{un} \tag{2}$$

The probability of the adverse weather event happening is denoted by p_e. The threshold probability for taking action or not taking action p_{th}, i.e. where the utility outcome is the same in both cases, can be derived by equating Equations (1) and (2):

$$\begin{aligned} \mathbb{E}\left[U_p\right] &= \mathbb{E}\left[U_u\right] \\ p_{th} U_{pe} + (1 - p_{th})\, U_{pn} &= p_{th} U_{ue} + (1 - p_{th})\, U_{un} \\ p_{th} &= \frac{U_{pn} - U_{un}}{U_{ue} - U_{pe} + U_{pn} - U_{un}} \end{aligned} \tag{3}$$

That means in the long run it is beneficial to take action whenever the probability that the event will happen exceeds p_{th}. To build a decision support system upon this various prerequisites must be met. Foremost a suitable utility function representing the interests of all stakeholders must be defined which can be derived from the air traffic simulation. In addition meaningful combinations of weather events and ATM conditions must be identified for which p_{th} can be derived for later use. This combinations must be universal enough, i.e. not too sensitive to weather and traffic variations, to not raise the need for too many different combinations. For example, ideally it is enough to consider events like *LVP during the morning traffic peak*, without the need to account for LVP duration and various traffic demand levels.[17] Further a well calibrated forecast of the event must be available for operational application.

For the full level of integration the prerequisites are similar. It also requires a suitable utility function and well calibrated forecasts. It does not share the need for limiting the scenarios, as the individual scenario is simulated in the operational application. However, it still is important that the resulting utilities' sensitivity to uncertainties both in the weather forecast and the traffic[18] is limited. For operational application it must be feasible to run the required number of simulations in adequate time.

For both levels of integration it is important to have suitable means to present the decision support data to the decision maker as well as to share it with all stakeholders. Possible ways of presentation are discussed in Section 4.4.

4.2 Air traffic simulator

For the methodology presented the derivation of suitable utility values for weather and traffic scenarios is a prerequisite. Using air traffic simulation is a way to investigate the impact of decisions, given varying weather and air traffic situations. To achieve meaningful results it is important that the air traffic simulation is a realistic realization of the real air traffic system. In this study the NAVSIM[19] simulation platform is used. In course of the MET4LOWW and PROB4LOWW projects (cf. Appendix A) NAVSIM was extended to realistically represent the ATM procedures in LOWW and support for the relevant weather phenomena was implemented. A detailed description of the simulator's capabilities is given by Steinheimer et al. (2016), here only the functionality relevant for the case studies in Section 5 is described.

The simulation is based on traffic which is initialized at the endpoints of the four Standard Arrival Routes (STARs). From these points flights are following three basic arrival modes to the arrival runway. Figure 9 shows the three modes. The *direct mode* is applied in case of low traffic, aircraft are directed on the shortest route to the final approach. If traffic density is too high for the direct mode, aircraft need to follow the transition. Due to the longer flight path in

[17] Traffic demand varies between weekdays and also shows seasonal fluctuations. In addition traffic is growing significantly at LOWW.

[18] On the timescales to take meaningful action, i.e. around two hours in advance, also the traffic demand shows considerable levels of uncertainty

[19] NAVSIM ATM/ATC/CNS Tool is developed by Mobile Communications Research & Development Forschungs GmbH in co-operation with University of Salzburg

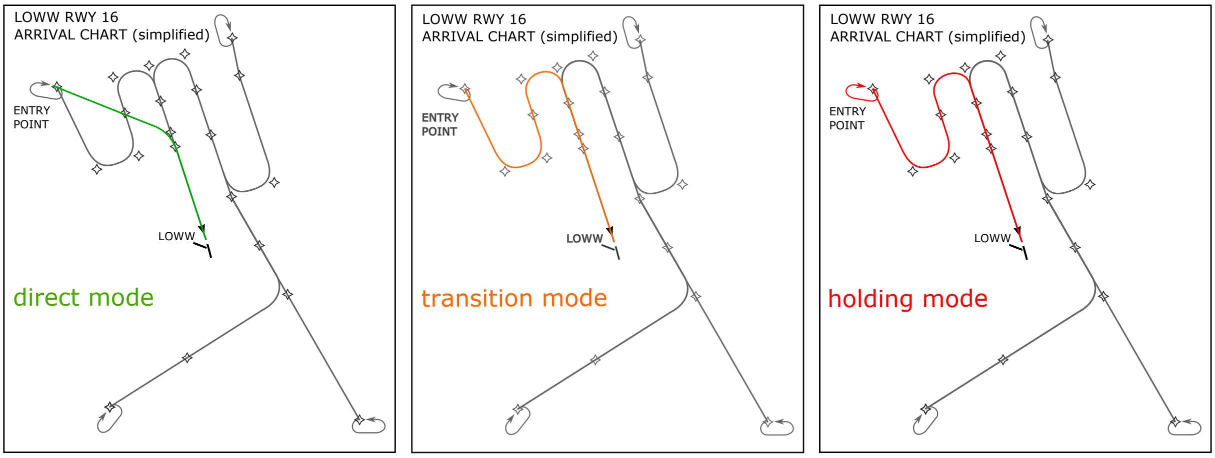

Figure 9: Traffic arrival modes. Transitions from STAR endpoints to the arrival runway are shown in grey.

this *transition mode* more flights can be handled in the arrival airspace. If traffic counts exceed what can be handled in transition mode, aircraft operation is switched to *holding mode*. In this mode aircraft need to wait in a holding pattern at the beginning of the transition until their approach can be facilitated. In addition, the maximum holding time of every aircraft is part of the traffic input and flights are diverted to an alternate aerodrome if their expected holding time exceeds the maximum.

To simulate the impact of weather the simulator was extended to include the impact of wind on the simulated flight tracks. A weather avoidance algorithm was implemented which routes the aircraft around polygons of adverse weather. This algorithm is used to simulate the impact of thunderstorms. LVP can be accounted for by setting the minimum separation between aircraft on the final approach. The arrival runway can be configured and changed in the course of a simulation. Also times with no arrival runway are handled by keeping all flights in a holding or divert them based on their maximum holding time. In that way a runway closure, e.g. in the case snow clearing is needed on the runway, can be simulated.

To facilitate the impact analysis extensive output is recorded from the simulation. Data, such as entry time into the traffic volume, landing time, distance flown in the arrival airspace, time and distance spent in holding patterns, and many more, is recorded for every flight. Also the radio communication between the ATCO and the individual flights is simulated and recorded to support workload evaluation.

To make sure the simulation results are adequately realistic validation experiments were carried out. In these validations the simulation was initialized from recorded real traffic trajectories and the observed flight paths compared to the simulated paths. Figure 10 shows a screenshot of a validation experiment. The observed flights are represented by yellow, simulated flights by light blue triangles. As can be seen in the figure simulated and observed flights are not

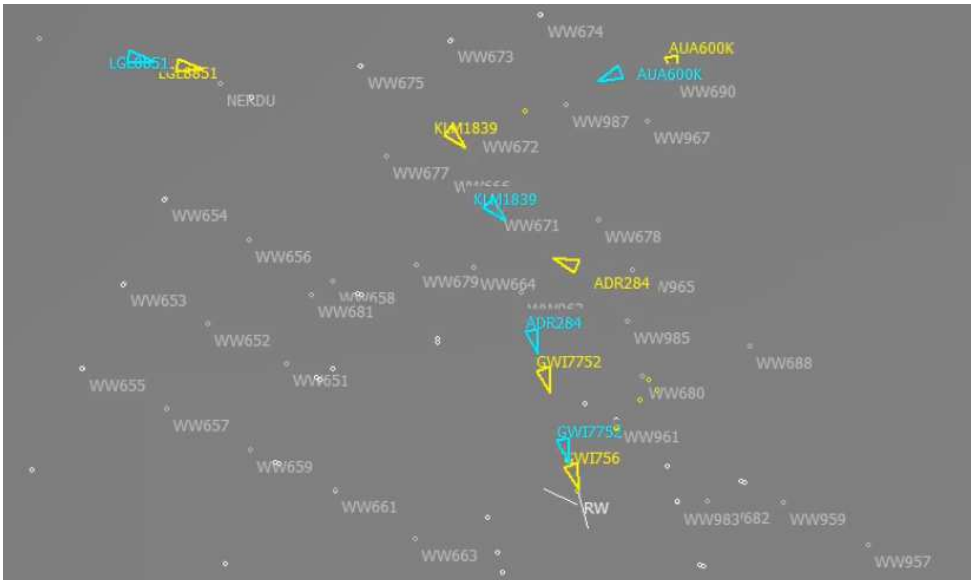

Figure 10: Screenshot of air traffic simulator validation experiment. Yellow triangles depict observed flights, light blue triangles represent simulated flights.

completely identical, but the traffic patterns look very similar. For the validation ATCOs were watching the simulations and certified that the simulated flight paths are realistic. Based on this assessment it was concluded, that the simulation is a realistic representation of arrival traffic and hence can be used for evaluating weather impact and derive utilities for decision support purposes.

4.3 Utility functions

For both levels of data integration in the decision support methodology presented in Section 4.1 a utility function representing the decision criteria is a prerequisite. The utility function has to account for the interests of all involved stakeholders. For decisions in ATFCM as considered here these interests are partly contradictory (Steinheimer et al., 2016). An airline is interested in minimizing cost by maximizing capacity, while an ANSP is interested in optimizing ATCO workload. These two goals are contradictory as the decisions for optimization either of them will usually not be the same. In the light of the primary objective of all aviation stakeholders, to ensure safety, the general joint objective to maximize accommodated traffic[20] while maintaining acceptable workload can be formulated. This can be translated into specific utility functions in different ways.

Steinheimer et al. (2016) proposed to use a suitably weighted combination of key performance indicators which adequately represent all stakeholders' interests. This proposal to follow

[20] Accommodated traffic in this context refers to the number of flights able to land/accepted in the airspace in a given time span

a Multi-Criteria Decision Making approach turned out to be too complex as a first step. Reasons for that are that a high sensitivity to some criteria must be expected and also some criteria, foremost workload, are not well defined. In addition such an approach is complicated by the *Decision-Making Paradox* (Munier et al., 2019), which means that different mathematical approaches can yield different decisions for the same optimization criteria.

Steinheimer et al. (2019) reduced the complexity by looking only into impact of weather phenomena where ATCO workload is of secondary concern, i.e. LVP and runway closure for snow clearing.[21] Under these assumptions *cost of delay* was considered as suitable optimization criteria by Steinheimer et al. (2019). The cost model used is outlined in Section 4.3.1.

Another more general optimization criteria, the balance between traffic and available capacity, is discussed in Section 4.3.2. This approach is potentially less sensitive to external factors and implicitly also accounts for workload.

4.3.1 Cost of delay

As outlined in Section 1 flight delays are a major cost factor for airlines. The cost for one minute of ground delay due to ATFCM measures is estimated to be 100 Euro on average for the European air traffic system (EUROCONTROL, 2018c). Such an average value is however not sufficient for the use as utility in decision making, because the actual cost of delay is a non-linear function of delay time and heavily depends on the specific aircraft type. For quantifying the impact of weather and the decision taken, not only ground delay, but also in-flight delay needs to be considered. A further cost component which needs to be included in the cost of delay model are flight diversion. A flight needs to divert to a different airport if congestion at its arrival airport is leading to longer in-flight waiting time as can be achieved with available fuel. The difference in cost for ground delay compared to in-flight delay or diversion is the governing factor for differences in utility between decisions under the same weather scenario.

Delay cost is derived using the cost estimates given by Cook and Tanner (2015) for a range of aircraft types. Cost for types not covered are mapped to cost of similar types in the case studies. The delay cost for an Airbus A320 is shown in Figure 11 for ground delay and in-flight delay. The difference between in-flight and ground delay is linear (blue line in Figure 11). This additional in-flight cost is mainly attributable to fuel and the flight time dependent maintenance cost. The stepwise evolution of cost is caused by cost components which increase rapidly in case of certain events. One major contribution is cost due to missed connection flights. As long as passengers reach their connection flight the delay does not cause passenger related cost, but if the connection is missed alternative transportation needs to be arranged causing the rapid

[21] In these situations traffic exceeding the arrival capacity must wait in holding patterns. Holding patterns are a well defined procedure, hence impact on ATCO workload is limited. In cases where traffic is highly exceeding the available capacity workload would still be noticeably affected. Such cases are neglected for the time being.

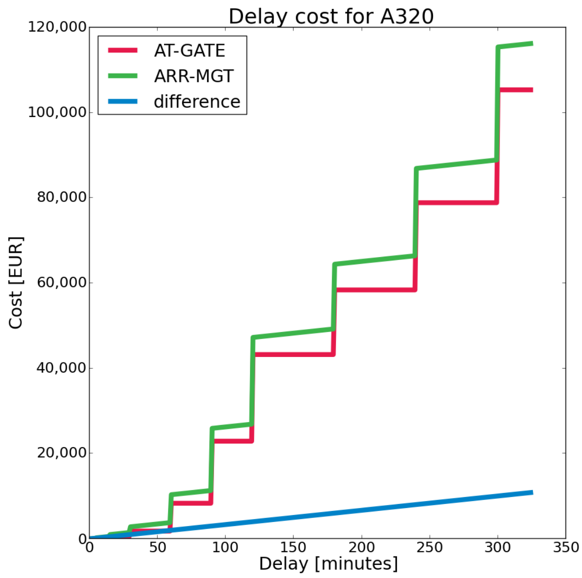

Figure 11: Airbus A320 delay cost based on Cook and Tanner (2015). Ground delay cost (AT-GATE) is shown in red, in-flight delay cost (ARR-MGT) in green and the difference in blue.

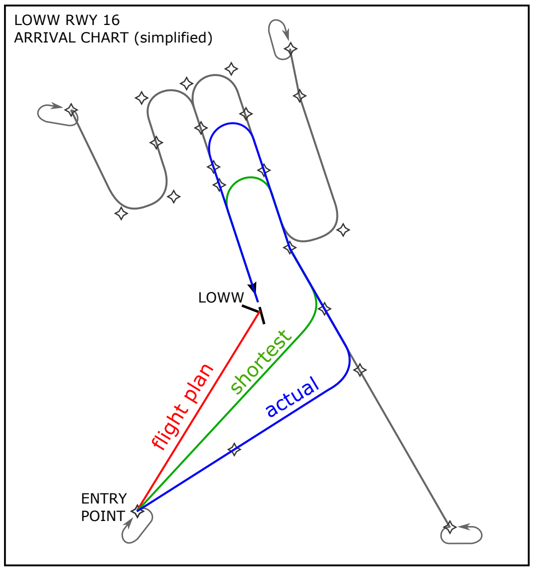

Figure 12: In-flight delay schematic. The red route indicates the flight route between entry into the arrival traffic volume and the airport considered in flight planning, the green route is the shortest possible route and blue shows an example of an actual flown route.

increase of cost. Similar events are related to reactionary delays, e.g. if due to the delay the following flight of the aircraft is also delayed, or if delay exceeds the threshold for passenger compensation based on European Union regulation. As these threshold events vary significantly between individual flights the delay cost of Cook and Tanner (2015) represents only an average value which needs to be considered in the interpretation of results. A more detailed cost estimate considering the individual situation of each flight is not possible with the current available data, because airlines do not disclose information such as number of transfer passengers.

Cost of diversion is even harder to estimate on a general basis because it heavily depends on the individual situation of a flight. A short stopover at another airport when passengers can stay on board and the final destination is reached with limited delay can cause lower cost than spending the same time in a holding pattern at the destination. If however the flight can not continue promptly, e.g. in case crew duty time is exceeded and a replacement crew must be organized, or alternative means of transport need to be organized, considerably cost can be accrued. Again not enough information is available to account for this cost on a detailed level and general estimates must be used. EUROCONTROL (2018c) gives cost estimates for diversion of regional, continental and intercontinental flights. These are used for the case studies (Section 5) using the assumption that aircraft types can be mapped to the type of flight.

The cost for every flight in a scenario can be derived from the air traffic simulation output. If a flight is diverted in the simulation its cost is the cost of diversion, which in case the flight was first subject to ground delay is increased by the associated ground delay cost. For other flights the total delay is derived from the difference of the actual arrival time and the planned arrival time. To account for the non-linearity in the delay cost, the cost is derived using the ground delay cost value for the total delay duration and adding the variable in-flight cost (blue line in Figure 11) for the in-flight delay duration. The in-flight delay is given by total delay reduced by a possible ground delay. It must be noted that based on this calculation method every flight is subject to at least some in-flight delay. This is based on the fact, that the planned arrival time taken from the flight plan considers a direct route between entry into the traffic volume and the airport because the runway in use is not known at the time of filing the flight plan. This direct route is shorter than the shortest possible route. So at least the difference between this planned route and the shortest possible route is counted as in-flight delay. Figure 12 shows an example of this difference for one entry point and runway combination. As this bias is present for all simulated scenarios the impact on the overall interpretation is expected to be limited. In the case studies the sensitivity of the results to using the arrival time from the flight plan opposed to in-flight delay calculation accounting for the shortest possible route will be investigated.

4.3.2 Traffic-capacity balance

Although the cost of delay presented above is an alluring optimization measure, as airlines are most effected by weather impact, the various simplifications necessary because of limited available data and the fact that ATCO workload is not reflected are limiting factors. Another issue with optimizing delay cost is that this approach could be unfairly beneficial for some airlines and discriminate others. For example, missed connection flights are contributing highly to the cost of delay, so optimizing this cost could favour airlines with many transfer passengers (i.e. network carriers) over airlines with few transfer passengers (i.e. low cost airlines). A detailed consideration of fairness and regulation optimization is done by Montlaur and Delgado (2018). Their study however investigates alternative ways of implementing ATFCM measures on network level, i.e. how the traffic slots are allocated to individual flights. Here only decisions about applied accepted rates in the current ATFCM framework are considered.

Coming back to the general joint objective to maximize accommodated traffic while maintaining acceptable workload identified above, an alternative optimization measure is derived. Starting from the assumption, that the future course of weather is known, i.e. a perfect forecast is available, it is reasonable to assume that the traffic regulation would be applied in a way that the number of aircraft entering the traffic volume in a given time equals the number of aircraft which can efficiently land while maintaining acceptable workload in this time span. That means the *accommodated traffic* (flights accepted to enter the traffic volume, i.e. the ATFCM regulation rate) and the *available capacity* (flights which can be efficiently handled maintaining acceptable workload) are balanced. For decision making under uncertainty the balance of traffic and available capacity, from here on referred to as *traffic-capacity balance*, seems to be a suitable basis for defining a utility function.

The initial step for defining the utility function is to derive the available capacity for a given scenario. For some weather scenarios the available capacity is obvious, e.g. for LVP it is given by the achievable landing rate[22] (cf. Table 1). In other cases, such as convection, it is not that straight forward to define the available capacity because it does not depend mainly on procedural requirements but on ATCO workload which is highly dependent on the situation. In such cases the available capacity needs to be defined by expert judgement, which is difficult if it needs to be done for many different weather scenarios, or could be derived iteratively from air traffic simulation if suitable workload diagnostics are available.

When the available capacity is known the utility function can be formulated in multiple ways. In the simplest case it could be the absolute value of the traffic-capacity difference:

$$U[D_j, W_i] = |T[D_j] - C_a[W_i]| \tag{4}$$

Where $U[D_j, W_i]$ is the utility given decision D_j and weather scenario W_i, $T[D_j]$ is the traffic entering the traffic volume for D_j, and $C_a[W_i]$ is the available capacity, i.e. in case of arrival traffic the number of possible landings, given W_i. U, T, C_a of course depend strongly on the time period considered.

To be more meaningful Equation (4) should be adjusted to also consider traffic demand, because in case there is less traffic demand than available capacity, traffic is smaller than the capacity independent of the decision taken. In order to account for this, accumulated traffic is introduced. This is calculated by accumulating the entry counts for each time interval κ from the start of the considered time span up to time k:

$$\mathrm{ACC}(T[D_j])_k = \sum_{\kappa=1}^{k} T[D_j]_\kappa \tag{5}$$

With that, Equation (4) can be transformed to an entry-capacity imbalance I, representing too much entries compared to available capacity (positive) and unused capacity, i.e. less entries than capacity (negative):

$$I[D_j, W_i] = \max\Big(T[D_j] - C_a[W_i], \quad \mathrm{ACC}(T[D_j]) - \mathrm{ACC}(T_d)\Big) \tag{6}$$

T_d is the original traffic demand without considering D_j or $C_a[W_i]$. A graphical representation of the imbalance and the involved terms is given for two different weather scenarios in

[22] Depending on the wind situation only one usable runway for both departures and landings might be available, in which case the landing rate needs to be further reduced to accommodate also departures.

Figures 13, 15 and 14, 16. The left graphs in Figures 13 and 14 show the sector entry counts for original traffic demand (orange bars), the traffic regulated to match the available capacity $C_a[W_i]$ of the weather scenario (green bars) and the traffic regulated according decision D_j (blue bars). The available capacity and the capacity according D_j are given by the green and blue lines, respectively. The traffic is shown for eighteen time intervals with a traffic peak from steps four to seven. When considering an interval length of ten minutes entry counts of 3, 4 and 7 relate to the capacities of LVP procedures (Table 1). The first variant (Figure 13) shows no weather impact, i.e. full capacity, for the first six intervals and high restrictions due to weather thereafter. The second variant (Figure 14) is inverted with traffic restrictions due to weather in the beginning and no restrictions later on. The impact of weather can be seen in the sector entry counts, which are spread out by the regulations over more time intervals. These shifts in traffic correspond to ground delay introduced by ATFCM measures. The right graphs in Figures 13 and 14 show the entry counts accumulated over time. Also here the ground delays are visible from the differences between the curves for the regulated traffic (green according $C_a[W_i]$, blue according D_j) and the original traffic demand (orange). The entry-capacity imbalance introduced in Equation (6) and its components are shown in the left graphs of Figures 15 and 16. The red bars show the imbalance which results from the difference of the traffic entering the sector and the available capacity (grey line) and the traffic which was planned to arrive already at the respective time in the original demand but is delayed due to the regulation ($\mathrm{ACC}(T[D_j]) - \mathrm{ACC}(T_d)$ shown in blue). In both weather situations it is obvious, that at the beginning and end of the period the difference between traffic and available capacity is big and would have unintended impact on utility if not adjusted with traffic demand to the shown imbalance. Based on the imbalance various utility functions can be derived from a simple linear variant based on the absolute value, along what was shown in Equation (4), to more complex function with different weights for positive and negative imbalances or non-linear functions to weight larger imbalances stronger than small ones.

The imbalance is a measure how close the regulation of the considered decision matches the available capacity. That means it is only a measure for how well the entry rate matches the landing capacity at a given time, but does not consider congestions effects in case the entry rate exceeds the landing capacity over a longer period of time. In order to account for the congestions the number of aircraft in the sector exceeding the landing capacity could be used. The dark blue lines in the right graphs of Figures 15 and 16 show this exceeding traffic count:

$$A[D_j, W_i]_\kappa = \begin{cases} \max\Big(0; \quad T[D_j]_\kappa - C_a[W_i]_\kappa\Big) & : \kappa = 1 \\ \max\Big(0; \quad A[D_j, W_i]_{\kappa-1} + T[D_j]_\kappa - C_a[W_i]_\kappa\Big) & : \kappa > 1 \end{cases} \tag{7}$$

It is however not suitable as a stand-alone measure for utility, because it would favour the introduction of ground delay, because ground delay and the connected reduction of entry rates

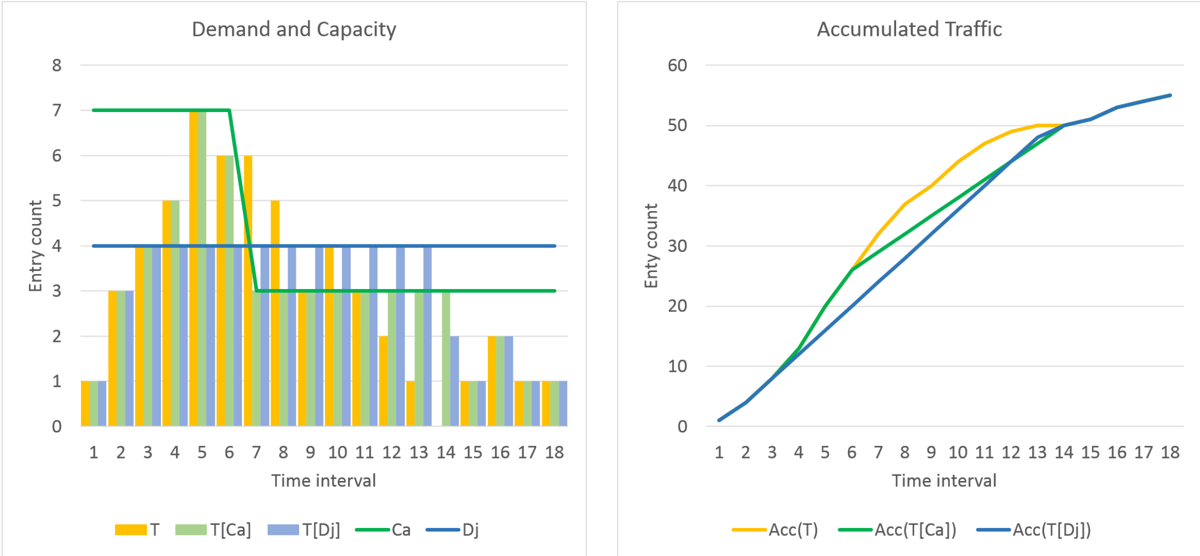

Figure 13: *Left:* Available capacity $C_a[W_i]$ (green line), accepted capacity for decision D_j (blue line) and traffic (entry counts) for original traffic demand (orange bars), traffic regulated to match $C_a[W_i]$ (green bars) and traffic according to D_j (blue bars). *Right:* Accumulated traffic for original demand (orange), according $C_a[W_i]$ (green) and according to D_j (blue).

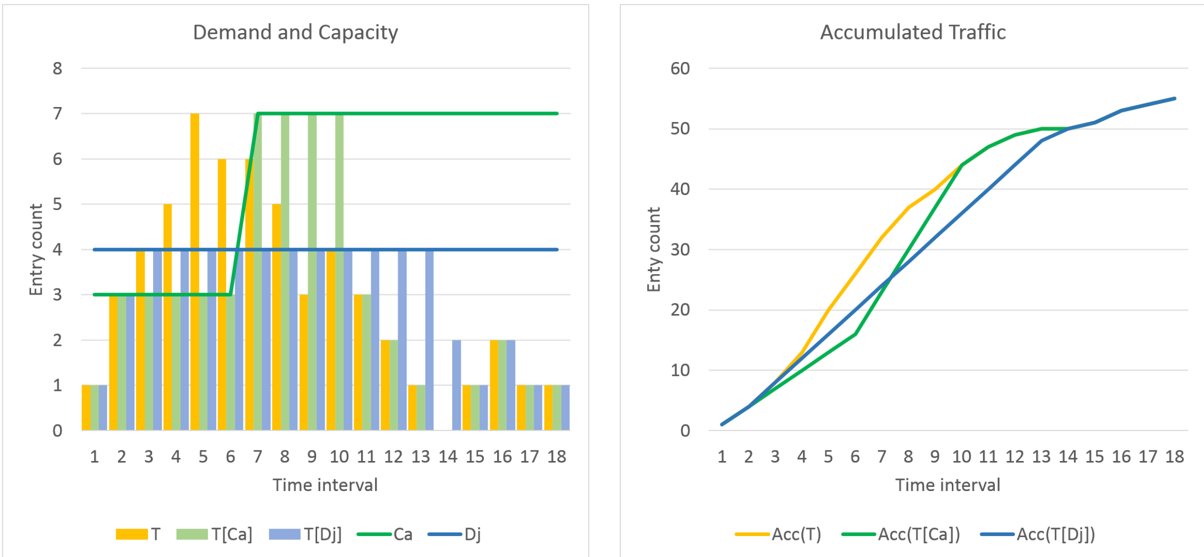

Figure 14: Same as Figure 13 for different W_i.

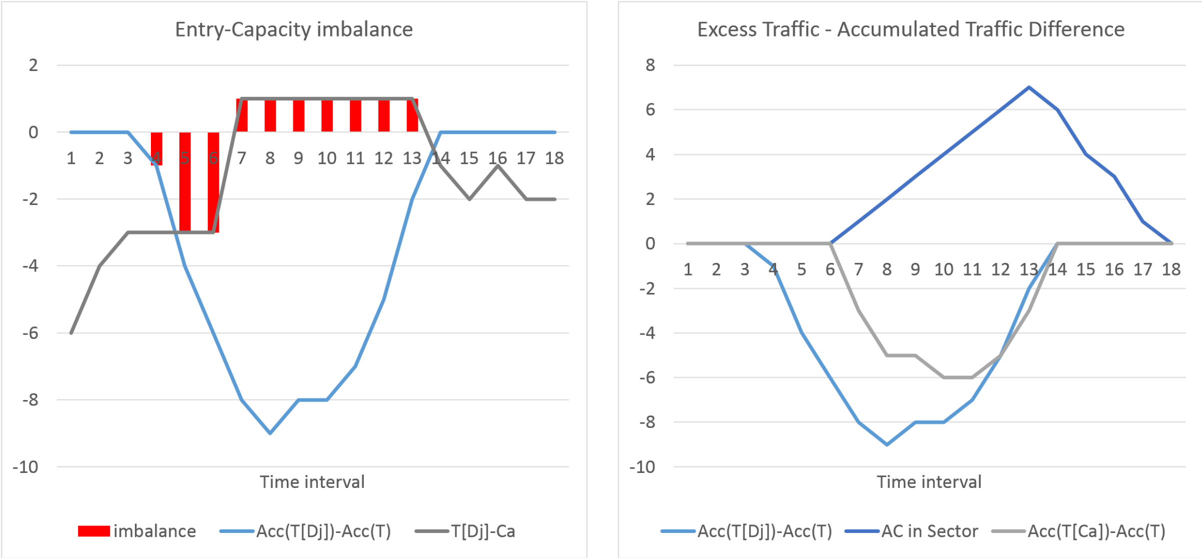

Figure 15: *Left:* Entry-capacity imbalance according Equation (6) (red bars), difference of traffic entering the airspace under decision D_j and available capacity $C_a[W_i]$ (grey line) and difference of accumulated traffic under decision D_j and original demand (blue line). *Right:* Aircraft in sector exceeding landing capacity under decision D_j (dark blue), difference of accumulated traffic under decision D_j and original demand (light blue) and difference of accumulated traffic regulated to match $C_a[W_i]$ and original demand (grey).

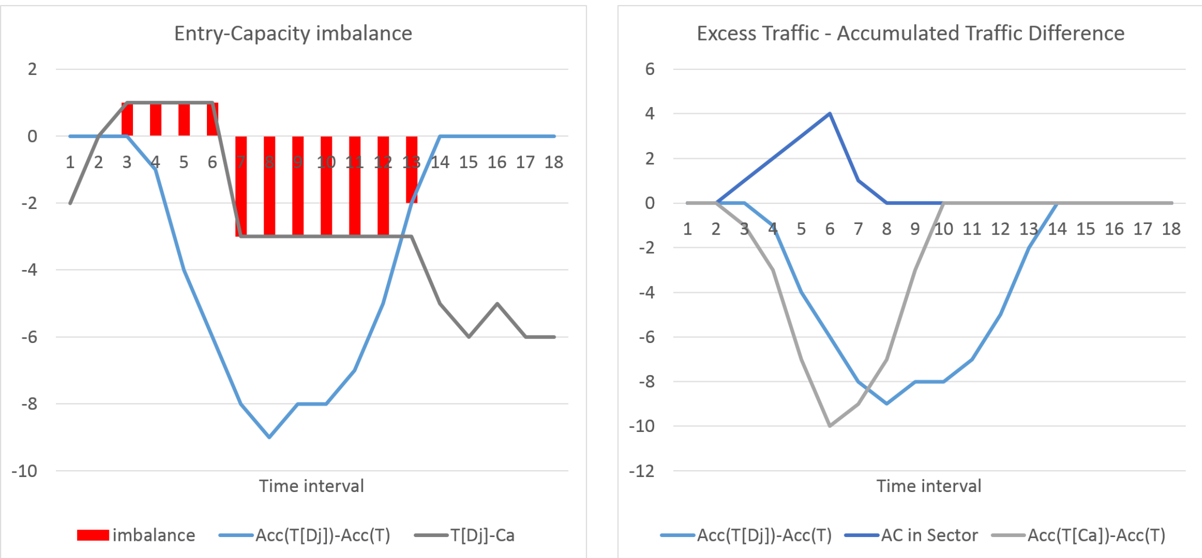

Figure 16: Same as Figure 15 for different W_i.

helps to avoid the build up and accelerates the reduction of the excess traffic count. That means it could be optimized by simply always introducing restricting regulations. To avoid the introduction of excess ground delay, it can be combined with a measure for representing ground delay. Ground delay could be used directly, another possible measure easier to derive is the difference between accumulated traffic regulated according D_j and accumulated original traffic (light blue lines in the right graphs in Figures 15 and 16). This measure says how many aircraft have not yet arrived in the arrival sector, which would have arrived without D_j. As comparison also the difference between accumulated traffic regulated according $C_a[W_i]$ and accumulated original traffic (grey lines) is shown in Figures 15 and 16 (right graphs). For the regulation according $C_a[W_i]$ there are no excess aircraft in the sector by definition (compare Equation (7)). The excess traffic is a measure for the in-flight delay, as well as for workload, because the number of aircraft in a sector correlates with ATCO workload. A simple utility function based on excess traffic and the accumulated arrival count difference would be:

$$U[D_j, W_i] = \alpha \left(\sum_{\kappa} A[D_j, W_i]_\kappa \right) + \sum_{\kappa} \Big(\mathrm{ACC}(T[D_j]) - \mathrm{ACC}(T_d) \Big)_\kappa \tag{8}$$

Where α is a weight allowing to adjust the relative importance of the two components and the sum over time intervals κ is computer for the time span of interest. To better reflect the workload implication of $A[D_j, W_i]$ a non-linear approach seems appropriate, where the utility is considerably increasing once the excess traffic count is higher than the number of aircraft which can usually be handled in the holding patterns.

The discussed utility functions will be used in the evaluation for the case studies presented in Section 5.3.

4.4 Decision support presentation

In addition to a sound theoretical basis, it is also important to present the decision support information in a suitable way. The user must be able to conceive the information quickly as decisions need to be taken timely. Further, the user must believe and trust the support information, i.e. it is important that the decision support is not restricted to a simple *yes*, *no* or traffic rate number to apply, but that also information supporting the suggestion is available. It is important to translate the support information into the users' mental model (Tabachneck-Schijf and Geenen, 2009), especially for probability based decision models, to make sure to tab the full potential of the method.

A detailed discussion and development of a decision support user interface is beyond the scope of this study, only a brief overview of concepts discussed with users so far will be given.

Possible concepts can be clustered with respect to their level of weather and ATM integration. The various levels of integration will be discussed based on LVP but could in similar way be extended to other relevant weather events. Based on the primary integration levels shown in Figure 2, on the basic level weather forecasts could be simply presented including information on their uncertainty. For example the expected visibility and cloud-ceiling information could be presented including error bars to support decision making regarding LVP. On the next level of integration the LVP state would already be derived from visibility and ceiling and the expected LVP state could be presented including uncertainty information to the ATM decision maker. While such a presentation would be certainly an advantage over pure deterministic information, presenting a time series of LVP states with uncertainties lacks the crucial information about temporal correlations, i.e. it gives information of the uncertainty at each point in time, but does not carry the information if the uncertainty is about occurrence overall or the expected timing of occurrence. A further step would be to translate expected weather scenarios into ATM impact, e.g. to identify relevant weather scenarios and derive the expected impact. This impact could, for example, be presented in form of expected exceeding aircraft count defined in Equation (7) if no measures are taken. Another possibility would be to display the expected traffic situation for the scenarios in a simulation framework mimicking the ATCO traffic display. In that way the decision maker could see the impact in a familiar form. Impact visualisation could also be the basis for the final level of integration in a decision support system. The effect of implementing recommended actions based on the decision framework discussed above could be presented in that way. By giving the decision maker the possibility to change the action taken and display the outcome for the expected weather scenarios, a decision cycle as shown in Figure 3 could be realized.

A crucial prerequisite for success at any level of integration will be the training of the user. Only if the user is familiar with the support tool and the presented information, an efficient and beneficial application is possible. As there is only limited time for taking the decision it is important to reduce the presentation to the essential information. Hence, the selection of presented weather scenarios and decision options needs to be appropriate. User integration in the development process for the decision support system and its user interface is key for operational acceptance and success. The findings of Evans and Crowe (2019) regarding a prototype centric approach discussed in Section 3.2 are a valuable basis for this process.

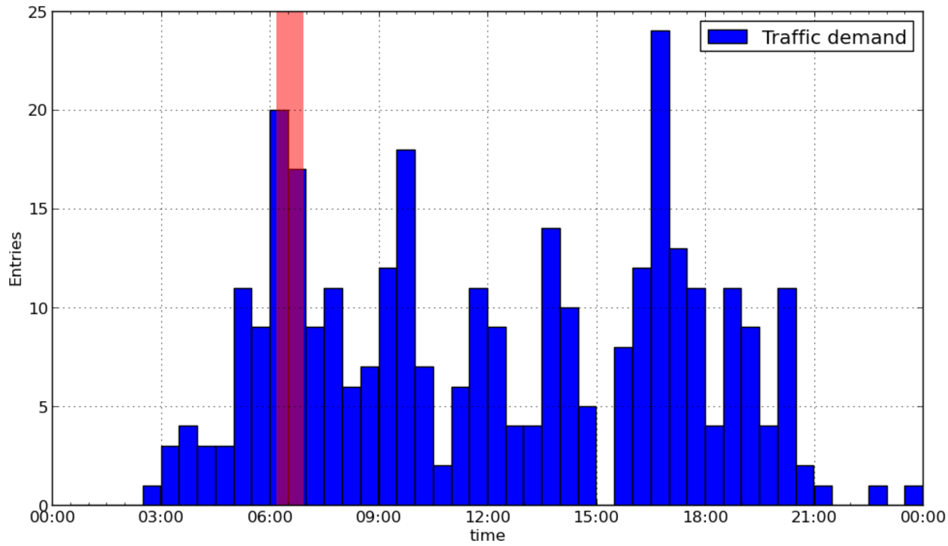

Figure 17: Sector entry counts of traffic demand in the runway closure case study. The time span highlighted in red is the time where the runway is closed.

5 Case studies

Three case studies will be presented. The first two case studies are based on the *cost of delay* utility described in Sector 4.3.1, while in the last one utilities based on the *traffic-capacity balance* concept discussed in Section 4.3.2 will be applied.

5.1 Runway closure - Cost of delay

This case study is based on a synthetic example introduced by Steinheimer et al. (2019) for a snow event which happens during a morning traffic peak hour. In addition to heavy snow also strong winds are assumed, so that only one runway is suitable to be used. Due to strong snow accumulation it is necessary to close the runway for 45 minutes for snow clearing. For the case study the traffic demand of a day without disturbance at LOWW was used (5.4.2016). The entry counts in 30 minute intervals are shown in Figure 17. The time span where the runway is closed for snow clearing is highlighted in red. As can be seen in the figure, the runway closure coincides with the morning traffic peak. The impact of weather and the decision taken is evaluated based on the basic utility matrix shown in Table 3. Only two weather events are considered, the snow event happens or it does not happen, no further uncertainties or variations are considered. Also only two decision options, to take action or to not take actions are taken into account. The goal of the evaluation is to derive the probability threshold for taking action according Equation (3) in the considered situation.

The evaluation scenarios defined in Table 3 are outlined in Table 4. In case measures are

Table 4: Scenario definitions for the runway closure case study.

protected event (S_{pe}):	Runway closed
ATM measures:	Traffic regulation issued at 05:00 with acceptance rate zero between 06:10 and 06:55.
Airline measures:	Average maximum holding time increased from 20 to 30 minutes.
protected non-event (S_{pn}):	Runway not closed
ATM measures:	Traffic regulation issued at 05:00 with acceptance rate zero between 06:10 and 06:55.
Airline measures:	Average maximum holding time increased from 20 to 30 minutes.
unprotected event (S_{ue}):	Runway closed
ATM measures:	No traffic regulation applied.
Airline measures:	None.
unprotected non-event (S_{un}):	Runway not closed
ATM measures:	No traffic regulation applied.
Airline measures:	None.

taken an ATFCM regulation for the expected duration of the runway closure is issued with a leadtime of one hour and 10 minutes. The lead time of the regulation is crucial as only flights not yet departed can be regulated. Also airline measures in form of increased maximum holding time are considered, as airlines carry extra fuel when adverse weather is forecasted. The maximum holding time of the individual flights in the scenario are randomly assigned from a gamma distribution (shape=1.5, scale=4.0, an offset is applied to achieve mean=average maximum holding time as given). A simplification is included in the S_{ue} and S_{pn} scenarios, where normally a regulation would be issued once the event happens or a present regulation would be cancelled if the event does not occur, respectively. Given the short duration of the considered event, the impact of this simplification on the results is expected to be limited.

Following the evaluation method outlined in Figure 6 the scenarios were run with the air traffic simulator and cost of delay was derived from the output as outlined in Section 4.3.1. The results are shown in Table 5. The unprotected non-event scenario S_{un} shows the lowest cost, while the cost for the protected non-event S_{pn} is already twice as high. The unprotected event S_{ue} shows by far the highest cost. By taking action based on the weather forecast, here a forecast perfectly predicting the exact time span, this cost can be clearly reduced as shown by the result for the protected event S_{pe}. The results in Table 5 suggest, that by acting according the forecast €50,604 total cost can be saved compared to the event happening unprotected. This value can be considered to be the upper bound for possible savings, as both the actual duration of clearing the snow as well as the weather forecast are subject to uncertainty. In addition also the inaccuracy of the cost model, due to the taken assumptions (cf. Section 4.3.1), adds to the uncertainty of the results.

The total cost from Table 5 applied to Equation (3) gives a probability threshold for taking

Table 5: Results for the runway closure case study (adapted from Table IV in Steinheimer et al., 2019). Results are based on 75 flights in 2.5 hours of simulation time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}
Diversions	0	0	15	3
Holding time [min]	46	71	239	291
ATFCM delay [min]	0	823	0	823
ATFCM delay cost [€]	0	19,710	0	19,710
Airborne delay cost [€]	40,063	63,856	52,268	82,754
Total delay cost [€]	40,063	83,566	52,268	102,464
Diversion cost [€]	0	0	124,500	23,700
Total cost [€]	**40,063**	**83,566**	**176,768**	**126,164**

action of 0.46 for this specific event. That means given a probabilistic forecast for the event, it would be beneficial to take action if the forecasted probability is above 0.46.

In order to test the sensitivity of the result individual components of the evaluation are slightly altered. Traffic, start of runway closure and the delay calculation method are varied independently to get an impression of the impact an individual component has on the results.

The results for varying the traffic demand are shown in Table 6. Traffic entry times were randomly shifted with magnitudes from one to ten minutes using a uniform distribution. The offsets were chosen to be zero averaged over all flights. Considerable variation in total cost results from these rather small shifts in entry times. The variation affects all scenarios, but as can be seen from the cost difference to the reference scenario S_{un}, given in the lower lines for every time offset, the impact is not uniform. As a consequence the resulting probability threshold shows strong variation. In case of nine minute offset the probability threshold even exceeds one, i.e. the unprotected event scenario S_{ue} had lower cost than the protected event scenario S_{pe}, which means it would not be beneficial to take protective action in that case. Given the many external factors which impact the actual arrival time of the individual aircraft compared to the planned time in the traffic demand, e.g. late departure due to passenger delay or congestion on the departure airport, the identified sensitivity to small shifts in the traffic entry times poses a problem for deriving a suitable probability threshold for taking action. A closer investigation of the cost variations showed, that the variability is, at least partly, related to the non-linearity of the delay costs (cf. Figure 11). A small shift of the arrival time of a flight can result in a slightly longer delay, which, due to the non-linearity of cost, can mean considerably higher incurred cost. In the total cost over all flights this effect cancels out to a certain extend, but is still noticeable.

Table 7 shows also results for the traffic variation, but in-flight delay was calculated with respect to the shortest possible route instead of relative to the flight plan route (cf. Figure 12 in Section 4.3.1). The results differ significantly from Table 6, not only for the absolute cost

Table 6: Results for the runway closure case study with random variation to the sector entry times. Total cost is given in the first line, the second line shows total cost difference to reference scenario S_{un}. Results are based on 75 flights in 2.5 hours of simulation time.

Traffic	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	40,063 0	83,565 43,503	176,768 136,706	126,164 86,101	0.46
Demand +/- 1min	35,712 0	84,491 48,780	168,179 132,467	134,420 98,709	0.59
Demand +/- 2min	37,167 0	73,452 36,285	165,760 128,593	134,657 97,490	0.54
Demand +/- 3min	34,766 0	76,207 41,440	177,978 143,211	131,329 96,563	0.47
Demand +/- 4min	36,389 0	83,331 46,943	175,492 139,104	150,862 114,474	0.66
Demand +/- 5min	39,308 0	97,152 57,844	166,996 127,688	160,089 120,781	0.89
Demand +/- 6min	31,719 0	76,292 44,573	173,049 141,330	133,977 102,258	0.53
Demand +/- 7min	33,260 0	77,639 44,380	165,784 132,525	133,608 100,349	0.58
Demand +/- 8min	33,801 0	68,172 34,372	152,539 118,739	105,644 71,843	0.42
Demand +/- 9min	41,746 0	99,619 57,872	157,464 115,718	160,860 119,114	1.06
Demand +/- 10min	52,722 0	96,762 44,040	193,564 140,842	168,584 115,862	0.64

Table 7: Same as Table 6 but in-flight delay calculation based on shortest possible route.

Traffic	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	18,482 0	32,404 13,922	154,601 136,119	70,318 51,837	0.14
Demand +/- 1min	16,611 0	35,973 19,362	149,695 133,084	75,901 59,290	0.21
Demand +/- 2min	18,424 0	35,664 17,239	141,441 123,017	73,999 55,574	0.20
Demand +/- 3min	16,888 0	34,866 17,977	158,019 141,131	81,939 65,051	0.19
Demand +/- 4min	19,285 0	38,260 18,975	154,231 134,946	94,105 74,820	0.24
Demand +/- 5min	21,167 0	37,086 15,919	144,302 123,134	75,048 53,881	0.19
Demand +/- 6min	16,191 0	32,054 15,863	149,114 132,923	79,970 63,779	0.19
Demand +/- 7min	17,488 0	31,907 14,419	143,860 126,372	75,997 58,509	0.17
Demand +/- 8min	20,452 0	33,516 13,063	130,821 110,369	57,361 36,909	0.15
Demand +/- 9min	24,845 0	37,765 12,920	141,880 117,035	86,192 61,347	0.19
Demand +/- 10min	32,484 0	41,341 8,856	173,444 140,960	93,084 60,600	0.10

Table 8: Results for the runway closure case study with variation of the event start time. Results are based on 75 flights in 2.5 hours of simulation time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -30min	40,063 0	68,056 27,993	110,042 69,980	118,898 78,836	1.46
Event start offset -20min	40,063 0	95,740 55,678	138,780 98,718	138,127 98,064	0.99
Event start offset -10min	40,063 0	91,781 51,718	157,283 117,220	128,249 88,186	0.64
Event start offset	40,063 0	83,565 43,503	176,768 136,706	126,164 86,101	0.46
Event start offset 10min	40,063 0	63,773 23,710	180,788 140,725	139,094 99,032	0.36
Event start offset 20min	40,063 0	60,212 20,149	198,617 158,554	145,631 105,569	0.28
Event start offset 30min	40,063 0	61,705 21,642	185,989 145,926	161,589 121,527	0.47

Table 9: Same as Table 8 but in-flight delay calculation based on shortest possible route.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -30min	18,482 0	21,044 2,562	90,343 71,861	60,496 42,014	0.08
Event start offset -20min	18,482 0	31,454 12,972	118,734 100,252	71,220 52,738	0.21
Event start offset -10min	18,482 0	37,379 18,897	130,941 112,459	73,829 55,347	0.25
Event start offset	18,482 0	32,404 13,922	154,601 136,119	70,318 51,837	0.14
Event start offset 10min	18,482 0	25,191 6,710	164,849 146,367	91,995 73,513	0.08
Event start offset 20min	18,482 0	29,272 10,791	177,547 159,065	116,603 98,121	0.15
Event start offset 30min	18,482 0	31,029 12,547	163,958 145,477	129,013 110,531	0.26

values, where it is expected given the change in in-flight delay calculation, but also for the resulting probability thresholds. The cost for the reference scenario is approximately halved for all traffic offsets, showing a big impact of the changed in-flight delay calculation. The derived probability thresholds are also considerably smaller. They show now less absolute variation between the different traffic realisation, but the highest found value (0.24) is still 2.4 times the lowest found value (0.10). The strong impact of the in-flight delay calculation on the probability threshold results suggest that it is important to use the more realistic calculation based on the shortest possible route rather than the simpler calculation from the flight plan arrival time.

The sensitivity of the results to the start of the adverse weather event in relation to the traffic peak was investigated by shifting the onset of the event ten, twenty and thirty minutes back and forth. The results are shown in Tables 8 and 9 for in-flight delay calculation according to flight plan arrival time and accounting for shortest possible route, respectively. As before strong variation is found in total cost and in the resulting probability thresholds. Variation is again more pronounced for the simple in-flight delay calculation based on flight plan arrival time. Here the probability threshold exceeds one for one event start time and is very close to one for another, suggesting that no action should be taken even in case it is certain the event will happen. In contrast the probability threshold calculated based on in-flight delay relative to shortest route are 0.08 and 0.21 for the same event start times, suggesting action should be taken even in case of low probability that the event will happen. Also for the variation of the event onset the results based on the more realistic in-flight delay calculation seem to be more robust, while still showing high relative variation for the probability threshold. The variation between different event start times is not surprising as it was expected that the impact of an event depends on the traffic situation during the adverse event. So it seems reasonable to use different probability thresholds for the same event depending on the timing. A strong variation for relatively small time offset however means that it is difficult to derive a set of probability threshold for operational use in advance.

An overall high sensitivity was identified for all considered variations. The sensitivity to the timing of the event relative to traffic was expected. The strong sensitivity on the in-flight delay calculation shows, that the derived probability thresholds are highly sensitive to the used utility function. Based on the results which show higher consistency of the results for the in-flight delay calculation considering the shortest possible route, this seems the more appropriate choice. However, the underlying cost model needs to be evaluated in more detail to make sure it is a suitable representation of the decision criteria. The sensitivity to small variations in traffic could be a limiting factor for the applicability of a probability threshold based decision framework, as traffic has a considerable uncertainty at the time of taking the decision. As discussed this variability arises, at least partly, from the non-linearity of the cost model. Small variations in traffic unrelated to the decision taken can have high impact on the resulting utility.

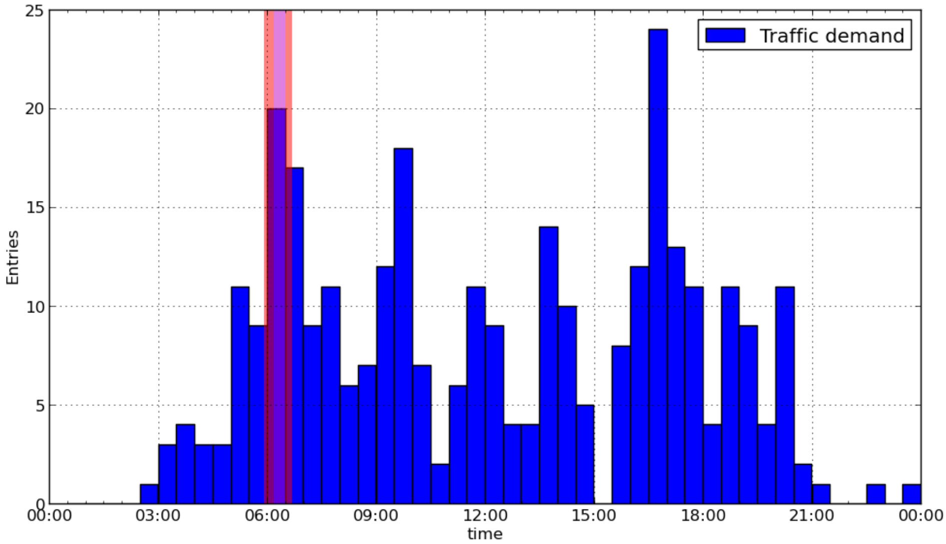

Figure 18: Sector entry counts of traffic demand in the LVP case study. The time spans highlighted in red and magenta are the times where four and six nautical miles spacing had to be applied, respectively.

5.2 LVP - Cost of delay

The case investigated here is based on an observed LVP event during the morning rush hour (see also Steinheimer et al., 2019). At the onset of the event the visibility situation required an increased spacing of four nautical miles. The visibility situation became worse later on requiring a spacing of six nautical miles, severely impacting available capacity (cf. Table 1). To exclude any impact of actually taken decisions the traffic used in the case study is taken from a day without traffic restrictions at LOWW. Figure 18 shows the traffic demand (sector entry counts in 30 minutes intervals), the times impacted by LVP are highlighted in red (4 miles spacing) and magenta (6 miles spacing). As in the runway closure case study, the evaluation is based on the basic utility matrix (Table 3), i.e. only two decision options, to take action or not, and only two weather scenarios, i.e. the event happens or not, are considered. The details of the four scenarios are outlined in Table 10. In case preventive action is taken, an ATFCM regulation is issued one hour in advance with an arrival rate of 30 flights per hour. It is a common procedure to issue the regulation with a higher rate for a forecasted event to account for forecast uncertainty. The regulation is then adjusted to reflect the actual achievable arrival rate at the onset of the event. In the S_{pe} scenario the arrival rate is updated to 25 once the LVP need to be applied. As in this scenario a well forecasted event is assumed, the arrival rate is not further reduced when 6 miles spacing needs to be applied, because the short duration is anticipated. In the unprotected event scenario S_{ue} a regulation with 25 arrivals per hour is issued at the onset of the event, which is then updated to 18 arrivals when spacing needs to be increased to 6 miles, as for this scenario it

Table 10: Scenario definitions for the LVP case study.

protected event (S_{pe}):	LVP situation happens.
ATM measures:	Traffic regulation with arrival rate 30 issued one hour before the expected event for the forecasted duration. Updated to arrival rate 25 once the spacing needs to be increased to 4 nautical miles.
Airline measures:	None.
protected non-event (S_{pn}):	LVP situation does not happen.
ATM measures:	Traffic regulation with arrival rate 30 issued one hour before the expected event for the forecasted duration.
Airline measures:	None.
unprotected event (S_{ue}):	LVP situation happens.
ATM measures:	Regulation with arrival rate 25 issued at the onset of the event for the entire duration of the traffic peak. Updated to arrival rate 18, when the spacing needs to be increased to 6 nautical miles.
Airline measures:	None.
unprotected non-event (S_{un}):	LVP situation does not happen.
ATM measures:	No traffic regulation applied.
Airline measures:	None.

Table 11: Results for the LVP case study (adapted from Table V in Steinheimer et al., 2019). Results are based on 103 flights in 4.5 hours of simulation time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}
Diversions	0	0	0	0
Holding time [min]	54	33	77	35
ATFCM delay [min]	0	172	211	191
ATFCM delay cost [€]	0	1,010	3,790	1,590
Airborne delay cost [€]	56,936	54,758	60,534	56,422
Total delay cost [€]	56,936	55,768	64,324	58,012
Diversion cost [€]	0	0	0	0
Total cost [€]	**56,936**	**55,768**	**64,324**	**58,012**

is assumed that no suitable forecast is available.

The four scenarios were simulated using the methodology outlined in Figure 6 to derive cost of delay as outlined in Section 4.3.1. Table 11 shows the results for the 4.5 hours of simulation including 103 flights. As the event is short there is no diversion in any scenario. The difference in cost is also rather small between all scenarios. What is striking however, is that the cost is lowest in the protected non-event scenario S_{pn}, which results according Equation (3) in a negative probability threshold of -0.23 for taking action. That means based on the used cost model it would be beneficial to always take action, even if no event happens. This can be explained by the fact, that the relatively low cost for ATFCM delay, most of the affected flights are delayed for less than 10 minutes, in S_{pn} is outweighed by greater savings in in-flight delay by smoothing out the traffic peak and thereby reducing congestion in the arrival airspace. Airlines are very cost sensitive, so it is likely that there is a reason that airlines are not spreading out the flights more evenly to reduce the traffic peak. Most probably marketing reason are the driving force. An earlier scheduled arrival time can be advantageous if customers compare flights and hence increase sales. Also, even short shifts in scheduled arrival time could result in transfer times falling below the airport limit, so that certain connections could not be offered. Such marketing considerations are not reflected in the used cost model and it would be very hard to do so without airline internal knowledge.

To check the robustness of the results the same sensitivity tests as for the runway closure case study were performed. Table 12 shows the results for the traffic variation. As in the runway closure case a random offset was applied to the traffic to investigate the impact of traffic uncertainty. In addition to the random traffic variation the evaluation was also done for traffic load, i.e. based on actual observed entry times. The traffic variation translates into strong variations of the results. The probability threshold varies from negative values to values above one. Given this high sensitivity to the small changes in traffic it must be concluded that the methodology is not suitable for decision making in this case. In the runway closure case study the calculation of in-flight delay considering the shortest possible route (cf. Figure 12) showed more robust results. Results based on this method are given in Table 13. Also here the results are more consistent in showing now a negative probability threshold for all input traffic. However, the values are highly fluctuating. Here also the protected event scenario S_{pe} shows lower cost than the reference scenario for many of the traffic variations, suggesting that in case of an LVP event the cost for related ground delay is less expensive than in-flight delay in the reference scenario. The high fluctuation can be related to the event's limited duration and related limited impact, however the consistently lower cost for the protected non-event scenario S_{pn} indicates that the used cost model does not reflect real cost appropriately.

The results testing the sensitivity to moving the event onset relative to the traffic peak are shown in Tables 14 and 15 for the two variants of calculating in-flight delay. The results are

Table 12: Results for the LVP case study with random variation to the sector entry times (adapted from Table VI in Steinheimer et al., 2019). Results are based on 103 flights in 4.5 hours of simulation time.

Traffic	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	56,936 0	55,768 -1,167	64,323 7,388	58,012 1,076	-0.23
Demand +/- 1min	50,778 0	54,195 3,417	58,652 7,873	55,825 5,047	0.55
Demand +/- 2min	50,650 0	52,563 1,913	60,256 9,606	57,948 7,298	0.45
Demand +/- 3min	51,063 0	55,548 4,485	65,170 14,107	58,060 6,997	0.39
Demand +/- 4min	50,051 0	52,375 2,324	58,715 8,664	57,226 7,175	0.61
Demand +/- 5min	54,348 0	55,684 1,336	67,916 13,568	58,051 3,702	0.12
Demand +/- 6min	46,582 0	49,509 2,927	60,205 13,623	55,480 8,898	0.38
Demand +/- 7min	47,900 0	50,937 3,037	60,015 12,114	53,078 5,178	0.30
Demand +/- 8min	52,904 0	56,613 3,709	58,324 5,419	59,570 6,666	1.51
Demand +/- 9min	53,760 0	55,254 1,494	69,953 16,192	61,039 7,278	0.14
Demand +/- 10min	63,799 0	66,135 2,336	71,028 7,229	66,977 3,178	0.37
Load	19,573 0	19,121 -453	27,382 7,808	20,380 807	-0.07

Table 13: Same as Table 12 but in-flight delay calculation based on shortest possible route.

Traffic	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	29,703 0	23,509 -6,193	34,138 4,435	25,680 -4,022	-2.74
Demand +/- 1min	25,664 0	21,589 -4,075	29,777 4,113	24,744 -921	-4.25
Demand +/- 2min	26,570 0	23,233 -3,337	31,765 5,195	25,858 -712	-1.30
Demand +/- 3min	25,690 0	22,179 -3,511	34,861 9,171	25,174 -516	-0.57
Demand +/- 4min	25,300 0	21,902 -3,399	31,103 5,803	25,053 -247	-1.28
Demand +/- 5min	27,786 0	23,253 -4,533	33,282 5,496	23,590 -4,196	-0.88
Demand +/- 6min	24,579 0	20,685 -3,894	31,005 6,425	24,749 169	-1.65
Demand +/- 7min	25,917 0	23,019 -2,898	33,964 8,047	26,002 85	-0.57
Demand +/- 8min	32,684 0	29,403 -3,280	34,611 1,927	30,588 -2,096	-4.42
Demand +/- 9min	30,883 0	30,200 -683	39,825 8,941	34,431 3,548	-0.14
Demand +/- 10min	38,427 0	33,064 -5,363	42,774 4,347	33,565 -4,862	-1.39
Load	7,551 0	4,724 -2,827	12,993 5,443	6,170 -1,380	-0.71

Table 14: Results for the LVP case study with variation to the onset of the LVP period. Results are based on 103 flights in 4.5 hours of simulation time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -15min	56,936 0	57,131 195	69,458 12,522	61,962 5,026	0.03
Event start offset -10min	56,936 0	55,711 -1,224	68,285 11,350	61,532 4,596	-0.22
Event start offset -5min	56,936 0	59,113 2,177	67,789 10,853	61,189 4,254	0.25
Event start offset	56,936 0	55,768 -1,167	64,323 7,388	58,012 1,076	-0.23
Event start offset 5min	56,936 0	63,790 6,855	69,605 12,669	65,306 8,371	0.61
Event start offset 10min	56,936 0	58,688 1,753	67,652 10,717	62,613 5,677	0.26
Event start offset 15min	56,936 0	64,278 7,342	67,127 10,191	69,241 12,305	1.40

Table 15: Same as Table 14 but in-flight delay calculation based on shortest possible route.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -15min	29,703 0	24,278 -5,424	35,126 5,424	28,464 -1,238	-4.38
Event start offset -10min	29,703 0	24,421 -5,282	35,795 6,093	29,519 -184	-5.31
Event start offset -5min	29,703 0	23,619 -6,083	33,136 3,433	25,016 -4,686	-2.99
Event start offset	29,703 0	23,509 -6,193	34,138 4,435	25,680 -4,022	-2.74
Event start offset 5min	29,703 0	23,581 -6,121	36,266 6,563	25,218 -4,485	-1.24
Event start offset 10min	29,703 0	25,431 -4,272	36,328 6,626	28,167 -1,535	-1.10
Event start offset 15min	29,703 0	27,135 -2,567	36,183 6,481	30,273 571	-0.77

consistent with the results for the traffic variation in the sense, that there are high fluctuations in cost and derived probability threshold. For the in-flight delay calculation considering the shortest possible route the probability threshold is negative for all event offsets, while it changes sign for the other calculation.

The overall high sensitivity and negative probability threshold results indicate, that the used cost model is not suitable for supporting decisions in this case. The identified shortcomings of the cost model to not reflect possible marketing consideration puts the model's usefulness in question, also for other applications. The high variation in probability thresholds also indicates that the methodology of integrating probabilistic weather information in that way (cf. Figure 7) is not a feasible approach, but that a more integrated approach (cf. Figure 8) is needed.

5.3 Traffic-capacity balance

The results for the case studies presented in the previous sections showed considerable shortcomings in the used cost model. Also the approach of integrating probabilistic weather information in the decision making process by computing probability thresholds in advance for later application seems to be questionable because of the identified high sensitivity to uncertainties in other input. In this section the probability threshold approach will be revisited to evaluate its usefulness based on the utility function introduced in Equation (8). Based on this utility function also the fully integrated approach outlined in Figure 8 will be applied in a case study.

5.3.1 Runway closure

For evaluation of the runway closure case study presented in Section 5.1 based on the utility function given in Equation (8) the regulations defined for the individual scenarios in Table 4 were applied to the traffic demand. The available capacity required for the calculation of the excess traffic defined in Equation (7) is set to zero in the period with closed runway for the event scenarios S_{ue} and S_{pe} and to 42 arrivals per hour otherwise. From original and regulated demand together with the available capacity the utility function can be calculated for each scenario. The evaluations presented here were done based on ten minute intervals for calculation of the utility function. The results when using weight $\alpha = 1.25$ are given in Table 16 for the same traffic variations as in Table 6. While the utility values vary considerably between traffic variations the resulting probability thresholds are almost constant. The same applies to the results with variations of the event start times shown in Table 17. The results are more robust for the traffic-capacity utility function than for the cost model used before. However, the results depend strongly on the weight α used. In Table 18 results are shown for $\alpha = 2$ resulting in clearly smaller probability thresholds. For an operational application in decision support a suitable value for α needs to be derived together with the users based on the evaluation of past

Table 16: Results for the runway closure case study based on utility function introduced in Equation (8) for $\alpha = 1.25$ with random variation of the sector entry times.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	1.25	83.0	255.0	238.0	0.83
	0.0	81.75	253.75	236.75	
Demand +/- 1min	0.0	83.0	241.25	224.25	0.83
	0.0	83.0	241.25	224.25	
Demand +/- 2min	1.25	80.75	252.5	235.75	0.83
	0.0	79.5	251.25	234.5	
Demand +/- 3min	1.25	80.0	257.5	240.0	0.82
	0.0	78.75	256.25	238.75	
Demand +/- 4min	0.0	87.75	252.5	235.25	0.84
	0.0	87.75	252.5	235.25	
Demand +/- 5min	4.5	96.25	258.25	238.75	0.82
	0.0	91.75	253.75	234.25	
Demand +/- 6min	10.0	86.0	250.0	233.5	0.82
	0.0	76.0	240.0	223.5	
Demand +/- 7min	1.25	77.0	240.0	224.5	0.83
	0.0	75.75	238.75	223.25	
Demand +/- 8min	3.5	78.0	239.75	223.0	0.82
	0.0	74.5	236.25	219.5	
Demand +/- 9min	3.5	64.75	216.0	202.25	0.82
	0.0	61.25	212.5	198.75	
Demand +/- 10min	6.75	94.25	266.75	246.75	0.81
	0.0	87.5	260.0	240.0	

Table 17: Results for the runway closure case study based on utility function introduced in Equation (8) for $\alpha = 1.25$ with variation of the event start time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -30min	1.25	93.25	231.25	213.25	0.84
	0.0	92.0	230.0	212.0	
Event start offset -20min	1.25	123.5	275.0	249.75	0.83
	0.0	122.25	273.75	248.5	
Event start offset -10min	1.25	141.5	282.5	252.75	0.82
	0.0	140.25	281.25	251.5	
Event start offset	1.25	83.0	255.0	238.0	0.83
	0.0	81.75	253.75	236.75	
Event start offset 10min	1.25	72.5	226.25	210.0	0.81
	0.0	71.25	225.0	208.75	
Event start offset 20min	1.25	74.0	182.5	167.75	0.83
	0.0	72.75	181.25	166.5	
Event start offset 30min	1.25	38.5	138.75	129.75	0.81
	0.0	37.25	137.5	128.5	

Table 18: Same as Table 16 for $\alpha = 2$.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	2.0	92.0	408.0	340.0	0.57
	0.0	90.0	406.0	338.0	
Demand +/- 1min	0.0	92.0	386.0	318.0	0.57
	0.0	92.0	386.0	318.0	
Demand +/- 2min	2.0	89.0	404.0	337.0	0.56
	0.0	87.0	402.0	335.0	
Demand +/- 3min	2.0	86.0	412.0	342.0	0.55
	0.0	84.0	410.0	340.0	
Demand +/- 4min	0.0	99.0	404.0	335.0	0.59
	0.0	99.0	404.0	335.0	
Demand +/- 5min	6.0	106.0	412.0	334.0	0.56
	0.0	100.0	406.0	328.0	
Demand +/- 6min	13.0	95.0	397.0	331.0	0.55
	0.0	82.0	384.0	318.0	
Demand +/- 7min	2.0	86.0	384.0	322.0	0.57
	0.0	84.0	382.0	320.0	
Demand +/- 8min	5.0	84.0	383.0	316.0	0.54
	0.0	79.0	378.0	311.0	
Demand +/- 9min	5.0	70.0	345.0	290.0	0.54
	0.0	65.0	340.0	285.0	
Demand +/- 10min	9.0	101.0	425.0	345.0	0.54
	0.0	92.0	416.0	336.0	

events. Potentially it will be necessary to use a more sophisticated utility function than given in Equation (8), for example to better reflect the impact when excess traffic exceeds the capacity of the holding patterns.

5.3.2 LVP

Equivalent to what was presented in the previous section for the runway closure case study, the LVP case study was conducted based on the traffic-capacity utility function (Equation (8)). The results for various traffic variations are shown in Table 19. The variation in utility values with varying traffic is more pronounced here than in the runway closure case, but much more robust than the results based on the cost model (Tables 12, 13). This is also reflected in the probability threshold which still shows considerably more variation as in the runway closure case but is not turning negative or exceeding one. The sensitivity to changes in the start time of the event is also considerably reduced (see Table 20). Also here the probability threshold is now positive for all considered start time offsets. Overall the results based on the traffic-capacity utility function seem to be more suitable for use with the basic approach of weather integration in the decision process (Figure 7). As pointed out in the discussion of the runway closure case study the suitability of the utility function as basis for decision support needs to be evaluated together with the stakeholders.

Table 19: Results for the LVP case study based on the utility function introduced in Equation (8) for $\alpha = 1.25$ with random variation of the sector entry times.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Demand	1.25 0.0	31.25 30.0	82.0 80.75	59.75 58.5	0.57
Demand +/- 1min	0.0 0.0	34.25 34.25	84.5 84.5	65.25 65.25	0.64
Demand +/- 2min	1.25 0.0	24.25 23.0	81.25 80.0	62.0 60.75	0.54
Demand +/- 3min	1.25 0.0	43.25 42.0	88.0 86.75	72.75 71.5	0.73
Demand +/- 4min	0.0 0.0	32.25 32.25	77.5 77.5	63.75 63.75	0.70
Demand +/- 5min	4.5 0.0	34.25 29.75	93.25 88.75	74.0 69.5	0.61
Demand +/- 6min	10.0 0.0	41.25 31.25	90.5 80.5	71.0 61.0	0.62
Demand +/- 7min	1.25 0.0	34.25 33.0	84.0 82.75	65.75 64.5	0.64
Demand +/- 8min	3.5 0.0	27.25 23.75	68.5 65.0	57.5 54.0	0.68
Demand +/- 9min	3.5 0.0	24.25 20.75	72.25 68.75	54.0 50.5	0.53
Demand +/- 10min	6.75 0.0	34.25 27.5	82.5 75.75	65.75 59.0	0.62

Table 20: Results for the LVP case study based on utility function introduced in Equation (8) for $\alpha = 1.25$ with variation of the event start time.

	S_{un}	S_{pn}	S_{ue}	S_{pe}	p_{th}
Event start offset -15min	1.25 0.0	9.25 8.0	73.0 71.75	66.25 65.0	0.54
Event start offset -10min	1.25 0.0	27.5 26.25	75.0 73.75	59.75 58.5	0.63
Event start offset -5min	1.25 0.0	17.75 16.5	71.25 70.0	64.25 63.0	0.70
Event start offset	1.25 0.0	31.25 30.0	82.0 80.75	59.75 58.5	0.57
Event start offset 5min	1.25 0.0	18.0 16.75	78.75 77.5	62.0 60.75	0.50
Event start offset 10min	1.25 0.0	26.0 24.75	90.25 89.0	66.5 65.25	0.51
Event start offset 15min	1.25 0.0	17.5 16.25	75.25 74.0	63.25 62.0	0.57

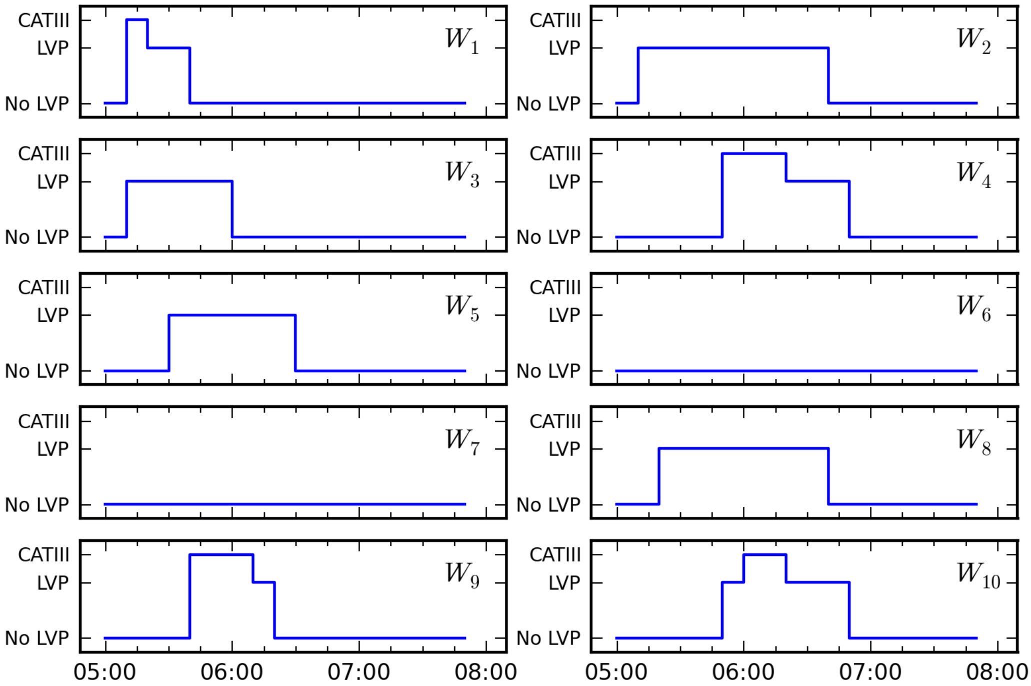

Figure 19: LVP ensemble forecast members.

5.3.3 Full integration of weather in the decision framework

To fully integrate probabilistic weather forecasts in the decision support framework, as described in Section 4.1 and outlined in Figure 8, the utility needs to be derived for all possible weather scenarios under all suitable decisions to derive the expected utility for each decision. In meteorology ensemble forecasts are used to represent the possible weather outcomes. In this case study a synthetic ensemble with ten members is used. To create the ensemble members a forecast generator was built, which is based on random distributions for onset and duration of LVP periods. For this example settings were used to create an ensemble with a probability of 0.2 that no LVP will occur and duration and onset parameters were chosen to be consistent with the LVP case study in Section 5.2. The members of the ensemble used here are shown in Figure 19. One member (W_{10}) is very similar to the case considered in the LVP case study, starting with a short period of *LVP* status changing briefly to *LVP CATIII* and back to *LVP*. Each ensemble member is considered to be equally likely, i.e. the probability of every member is assumed to be 0.1.

The selection of suitable decisions is not as straight forward, because the variety of different decisions is vast. Possible regulation rates range from 18 to 42 arrivals per hour. For a time step of ten minutes there are 18 steps in the three hour interval considered here. The resulting number of different decisions is 25^{18}, i.e. more than 10^{25}. Even when reducing the number of arrival rates to 18, 25, 30 and 42 and looking at half hour intervals the number of different possible decisions, 4096, is too high to evaluate the expected utility for each decision in reasonable time. For an operational application a suitable selection algorithm for appropriate decisions would be required. Jones and Glina (2019) discuss methods based on integer-programming and reinforced learning for a similar problem with promising results. Here only the principle framework is discussed and therefore a simple approach for selecting the decisions is taken. The optimal regulations for each ensemble member, i.e. the available capacity given the LVP state at each time step of the member, are selected as decisions. In addition regulations with constant rate over the full three hour period for all arrival rates from 18 to 42 are used. For each of these 35 decisions the utility is derived for every ensemble member to eventually obtain the expected utility. Utilities derived following Equation (8) and resulting expected utilities are given in Table 21. The lowest expected utility among the considered decisions is found for applying a regulation according to the available capacity in weather scenario five $C_a[W_5]$. What was not taken into account in the evaluation is, that in the actual application the decision is not static, i.e. the regulation is adjusted when new information is available or an LVP situation occurs. The adjustment could be integrated in the evaluation by adapting the respective regulation at the time of LVP onset in the individual weather scenario. However, the duration for which the adjustment should be applied is not clear at the time the initial decision is made. Setting the duration of the adjustment is a new decision to be made under uncertainty based on the information available at that later time. This information is not available at the time of the initial decision, so it is up to further research to find an appropriate way to integrate a regulation update in the decision framework. Taylor et al. (2019) discuss an adaptive decision making process under weather forecast uncertainty evolution from an aircraft operator's perspective. The basic idea is to incur the cost of taking a decision under uncertainty as late as possible as new available information can help to further optimize the overall cost. An approach along this line is already in place for the current deterministic decision framework for LVP at LOWW where, as described in Section 5.2, a forecast of LVP triggers a rate reduction to 30 arrivals per hour and the rate is only further reduced once the event happens. The efficiency of ATFCM regulations taken depends on the time when they are issued, as only flights not yet departed can be delayed. Such timing effects need to be considered in the decision framework.

Coming back to the case study results, where the expected utility was only evaluated for a limited number of selected decisions without a methodology to find the optimum from the vast decision space, selecting the decision simply based on minimum expected utility might not be the optimal choice. Instead of taking decision $C_a[W_5]$ it could be beneficial to take decision *Rate 31* with only slightly higher expected utility but more room for later adjustment.

Table 21: Utilities for weather scenario and decision combinations.

	W_1	W_2	W_3	W_4	W_5	W_6	W_7	W_8	W_9	W_{10}	$\mathbb{E}[U]$
$C_a[W_1]$	11	95	11	157	61	1	1	95	63	137	63.2
$C_a[W_2]$	53	53	53	115	43	43	43	53	53	95	60.4
$C_a[W_3]$	11	95	11	157	61	1	1	95	63	137	63.2
$C_a[W_4]$	81	81	81	87	71	71	71	81	71	87	78.2
$C_a[W_5]$	41	65	41	127	31	31	31	65	41	107	58.0
$C_a[W_6]$	11	95	11	157	61	1	1	95	63	137	63.2
$C_a[W_7]$	11	95	11	157	61	1	1	95	63	137	63.2
$C_a[W_8]$	53	53	53	115	43	43	43	53	53	95	60.4
$C_a[W_9]$	42	96	42	126	60	32	32	96	32	126	68.4
$C_a[W_{10}]$	72	72	72	96	62	62	62	72	68	76	71.4
Rate 18	264	264	264	256	254	254	254	264	254	256	258.4
Rate 19	217	217	217	215	207	207	207	217	207	215	212.6
Rate 20	167	167	167	187	157	157	157	167	167	175	166.8
Rate 21	153	153	153	173	143	143	143	153	153	161	152.8
Rate 22	143	143	143	163	133	133	133	143	143	151	142.8
Rate 23	128	128	128	148	118	118	118	128	128	136	127.8
Rate 24	124	124	124	144	114	114	114	124	124	132	123.8
Rate 25	91	97	91	129	83	81	81	97	91	115	95.6
Rate 26	72	88	72	128	70	62	62	88	78	112	83.2
Rate 27	66	82	66	122	64	56	56	82	72	106	77.2
Rate 28	60	76	60	120	58	50	50	76	66	102	71.8
Rate 29	55	71	55	115	53	45	45	71	61	97	66.8
Rate 30	47	71	47	121	51	37	37	71	57	103	64.2
Rate 31	31	75	31	137	45	21	21	75	49	117	60.2
Rate 32	22	84	22	146	50	12	12	84	52	126	61.0
Rate 33	22	84	22	146	50	12	12	84	52	126	61.0
Rate 34	22	84	22	146	50	12	12	84	52	126	61.0
Rate 35	22	84	22	146	50	12	12	84	52	126	61.0
Rate 36	17	89	17	151	55	7	7	89	57	131	62.0
Rate 37	11	95	11	157	61	1	1	95	63	137	63.2
Rate 38	11	95	11	157	61	1	1	95	63	137	63.2
Rate 39	11	95	11	157	61	1	1	95	63	137	63.2
Rate 40	11	95	11	157	61	1	1	95	63	137	63.2
Rate 41	11	95	11	157	61	1	1	95	63	137	63.2
Rate 42	11	95	11	157	61	1	1	95	63	137	63.2

6 Conclusions

The impact of adverse weather on the ATM system was analysed. A general overview of relevant weather phenomena and how they impact aviation was given, including a brief discussion how various stakeholder are affected. The need for adequate weather integration into ATM decision processes is obvious from the large share weather delay has in total delay. Although the impact of weather cannot be avoided altogether, as weather cannot be changed, incorporating weather forecasts in the decision making process can contribute to mitigate the negative consequences. The importance of weather integration is also obvious from literature covering this topic. An overview over relevant work was given.

Based on the literature review, decision frameworks for integrating weather in the ATFCM decision process were discussed using the example of Vienna International Airport. Two levels of integration were considered. The more complex approach is based on utility-theory, where for a range of expected weather scenarios the utilities related to possible decisions are calculated. The expected utility for each decision is derived to identify the most appropriate course of action. The second approach is a simplification, where only two decisions, to take action or not, and two weather outcomes, a specific events happens or not, are considered. Based on these assumptions probability thresholds for taking action were derived.

The selection of a suitable utility function is essential for both approaches. In a decision problem involving multiple stakeholders it is important that the utility function represents the interests in a balanced way. The first utility function explored was airline cost of delay. For cases where ATCO workload is of secondary importance airline delay cost is a suitable optimization criteria as it indirectly also includes passenger disruption. This is because a large part of the cost is related to passenger compensation and arranging alternative transportation in cased of missed connections. Fast time air traffic simulation was used to estimate delay for a given weather situation and decision. The delay was then translated using a cost model. The case studies and the performed sensitivity experiments showed however considerable variation in the estimated costs, even for small changes to other input data. For example, small changes to the traffic input in the range of a few minutes had big impact on the estimated cost and the derived probability thresholds. This variation can be attributed to the non linear nature of delay cost, as cost depends highly on delay exceeding certain threshold times, e.g. when a connection flight is missed. It should also be noted, that the cost model itself is subject to considerable uncertainty. It is only based on average cost estimates, because online data on transfer passengers is not available, so the cost of a specific flight can not be evaluated in detail. It was also identified, that the current cost model seems to lack certain cost elements. The outcome of the case studies showed, that smoothing out traffic peaks reduces cost, yet airline schedules of network carriers build on traffic peaks to offer attractive connections. Marketing cost related to this is not considered in the cost model at the moment. Further research is necessary to investigate whether the cost model can be improved to be more realistic. The success for that also depends on data availability and it is not clear if airlines are willing to share required information. Given the non linear nature of delay cost with step wise cost increase when certain thresholds are exceeded, it must be expected that even with an improved cost model the high sensitivity to small traffic variations will persist. Traffic is inherently uncertain due to factors such as late departures, so cost of delay could turn out to be inappropriate for use as utility measure.

The second approach explored for defining a utility function was based on balancing traffic and available capacity. A basic formulation of this concept was introduced and tested in the case studies. It showed much more robust results in the sensitivity studies than the cost of delay, especially the derived probability thresholds were more consistent. Also the calculation is much more simple because no air traffic simulation is required, at least for the basic formulation used in this study. However, more work is needed before it can be used in a decision support system. It must be evaluated if the current form represents the decision criteria in a suitable way or if adjustments are necessary. For example, the measure of excess traffic in the airspace volume is only represented in a linear way, while it must be expected that the impact on ATCO workload is considerably higher once the capacity of the holding patterns is exceeded. Based on stakeholder insights and further case studies the formulation needs to be refined and the applicability needs to be further investigated.

The case study investigating the more complex decision framework revealed that this approach, while better representing the decision process and the weather scenarios, is much more demanding regarding the evaluation. As the range of possible decisions is vast, it is not computationally feasible to calculate the expected utility for each possible decision. In the case study presented a set of decisions was manually defined, for an operational application a suitable algorithmic framework must be set up to find the optimal decision with reasonable effort. This would be even more relevant, if a more complex utility function would be used, especially if for its derivation air traffic simulation is required.

One aspect, which is not well represented by either of the decision frameworks considered, is the dynamic nature of the ATM decision process. ATFCM decision making is not based on one-off decisions which are independent, but decision taken previously can have considerable impact on later decisions. In current practice the regulations for a specific event, e.g. a LVP event, are often implemented in steps. Given the uncertainty in the weather forecasts, regulations are implemented less restrictive at the beginning and then updated when new information becomes available. On the one hand it is of course beneficial to delay the decision to not introduce unnecessary delay, on the other hand only traffic not yet departed can be delayed, so a decision taken too late can be ineffective. The temporal component of the decision process needs to be considered in further development of decision support.

Also other aspects need to be addressed in future work. Weather forecasts were seen as external input in this study under the assumption that they are of high quality and reliable in a statistical sense, i.e. that the forecast probability corresponds to the actual probability of the forecasted event. This is however often not the case, as most of the adverse weather events impacting the ATM system are difficult to predict. A decision support system must be able to account for the weather forecast insufficiencies or suitable weather forecast calibration is required. Another thing which needs to be investigated is the risk aversion of the stakeholders. Especially when cost is used as utility the level of loss the stakeholders are willing to accept could be important.

This study must be seen as a starting point for ATM decision support development building the foundation for further research. Valuable insights on the decision frameworks and utility functions investigated were obtained. Based on these insights further research and development activities will be carried out. While the cost of delay derived from air traffic simulation showed to be of limited applicability in the current implementation, the air traffic simulation proofed to be a valuable tool for validation activities. As user acceptance is a prime success criterium for any support tool, the simulator plays an important role in demonstrating the usefulness of new development based on historic cases.

Although the presented evaluations were focused on Vienna International Airport (LOWW), the methods can be transferred to other airports with limited adaptation. The extension of the basic principles to en-route traffic is also possible, but more effort will be required to account for the different procedural framework.

Given the ongoing traffic growth and related increased weather impact, a reliable weather management is crucial to ensure efficient air traffic in the future. Ongoing research in the field of meteorology to improve the quality of weather forecasts, especially in the field of probabilistic prediction, will provide the basis for improved weather dependent decision making. A suitable decision support framework can support ATM decision makers to fully benefit from this information.

Appendix

A Research Projects

The results presented are based on the MET4LOWW and PROB4LOWW projects. These projects have received funding from Take Off programme. Take Off is a Research, Technology and Innovation Funding Programme of the Austrian Federal Ministry for Transport, Innovation and Technology (BMVIT). The Austrian Research Promotion Agency (FFG) has been authorized for the Programme Management.

A.1 MET4LOWW

Abstract

Wind and adverse / severe weather have significant impact on air traffic management (ATM). Various, partly contradictory, performance figures like safety, capacity, cost-efficiency and environment have to be considered and optimized. The complex ATM-system is currently based on strictly deterministic information, while it would be more reasonable to use a probabilistic approach to account for the intrinsic uncertainty of the meteorological (MET) information. The objective of this project is to integrate the uncertainty of weather and strictly deterministic ATM procedures into a holistic ATM / MET approach for optimal arrival and departure management.

Basic Arrival / Departure Manager (AMAN/DMAN) ideas, i.e. sequencing based on time of overflight estimates for waypoints, are used to evaluate the impact of weather on approach and departure. This includes the study of impact of wind and avoidance of weather objects (e.g. thunderstorms) by aircrafts. The quantitative assessment is based on ATM key performance indicators (KPI) derived from fast time simulations. In addition the simulated traffic is qualitatively assessed by air traffic controllers. Based on these two assessments the ATM / MET procedures are optimized.

To do the simulations standard arrival and departure procedures (Vienna airport is used as showcase in this project) and handling of wind and weather objects are integrated in University of Salzburg's ATM / ATC simulator NAVSIM. Important tasks are to implement realistic avoidance algorithms for weather objects (e.g. thunderstorms) and accurately simulate the impact of wind on aircraft separation on final approach. In addition the calculation of ATM performance indicators based on the simulation results is implemented. It is aspired that the simulation results help to improve weather information for ATM, both in deterministic form for current ATM procedures and in probabilistic form for future ATM procedures where weather information should be an integral part.

The potential of integrated ATM / MET procedures can be evaluated from different perspectives by the applied approach. Areas with highest potential through improved weather information can be identified by sensitivity studies of weather impact on KPIs. The required accuracy of weather forecasts in terms of temporal / spatial resolution as well as forecasted thresholds can be assessed. The use of probabilistic weather information to improve efficiency on average, while retain safety in each individual case can be investigated.

The project results are the prerequisite for future planning and implementation of new procedures to better integrate weather information into the operational ATM-system in order to improve the overall safety and efficiency.

Project team

Austro Control

Markus Kerschbaum
Martin Steinheimer
Carlos Gonzaga-Lopez
Christian Kern
Lukas Strauss

University of Salzburg

Kurt Eschbacher
Martin Mayr
Carl-Herbert Rokitansky

A.2 PROB4LOWW

Abstract

Weather phenomena such as thunderstorms, strong winds and fog are responsible for 80-90% of all delays at Vienna Airport. To provide forecasts of these weather events at the spatial and temporal accuracy required by the air traffic management (ATM) system, however, is generally not possible. This has to do with the very nature of weather phenomena, which, because of their small scale and high temporal variability, do not permit to be forecast precisely. Due to this apparent shortcoming, the estimation of capacities in arrival and departure management still relies on the subjective judgment of flight planners and approach supervisors. Uncertainties, inherent in all weather information, are thus insufficiently taken into account in ATM decisions.

Probabilistic weather predictions aim at incorporating forecast uncertainties using probabilities for the occurrence of a relevant weather event. In the proposed exploratory project, a concept for the integration of probabilistic meteorological information in arrival and departure management for capacity optimization shall be devised. Experts in aviation operations, flight planning, ATM, air traffic simulation, and aviation meteorology will identify and analyse all weather-related ATM decisions. Flight planning and operation guidelines as well as detailed simulations of air traffic will be used to determine the costs incurred at the occurrence of a given weather event (”loss”) and to compare them with the costs of the protective actions against the event’s impact. In the framework of economic decision models, the so-obtained cost-loss ratio is then used to determine the optimal probability thresholds required to set arrival and departure rates at the occurrence of individual weather events. With this multi-disciplinary and cost-based approach, probabilistic weather information will be translated into an integrated in deterministic decision-making processes beneficially in order to sense of reducing flight delays, improving predictability and planning and managing workload of air traffic controllers.

The use of probability information underlines the fact that decisions, made on the basis of uncertain input information, are found to be incorrect at times. To mitigate this unavoidable risk, an adaptive decision-support procedure will be devised, refining the forecast information and any measure derived from it with the current state of the weather. The goal of this exploratory project is to provide evidence that exploiting probabilistic weather information for arrival and departure management is both worthwhile and feasible and that its benefits can be suitably quantified.

Project team

Austro Control

Markus Kerschbaum
Martin Steinheimer
Christian Kern
Matthias Moder
Alexander Schiemer
Karin Hennermann
Johannes Sachsperger
Lukas Strauss

University of Salzburg

Kurt Eschbacher
Carl-Herbert Rokitansky
Fritz Zobl

Flightkeys

Georg Schiefer
Raimund Zopp

List of abbreviations[23]

ANSP	Air Navigation Service Provider
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATFCM	Air Traffic Flow and Capacity Management
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
CB	Cumulonimbus
CFMU	Central Flow Management Unit
CODA	Central Office for Delay Analysis
FAA	Federal Aviation Administration
FMP	Flow Management Position
ICAO	International Civil Aviation Organization
LOWW	Vienna International Airport
LVP	Low Visibility Procedures
NextGen	Next Generation Air Transportation System
NMOC	Network Manager Operations Centre
RVR	Runway Visual Range
SESAR	Single European Sky ATM Research
STAR	Standard Arrival Route
SWIM	System Wide Information Management
TS	Thunderstorm

[23] A detailed description for most terms can be found at http://www.skybrary.aero

List of Figures

List of Tables

References

Agustín, A., A. Alonso-Ayuso, L. Escudero, and C. Pizarro-Romero (Jan. 2010). "Mathematical Optimizationg models for Air Traffic Flow Management: A review." In: *Stud. Inform. Univ.* 8, pp. 141–184.

Alvarez, L. J., J. Cegarra, and A. G. Richards (2011). "Network Management under uncertainty, The ONBOARD project: research objectives and current status". In: *Proceedings of the 1st SESAR Innovation Days*.

Baumgartner, M. (2007). "The Organisation and Operation of European Airspace". In: *European air traffic management*. Ed. by A. Cook. Ashgate. Chap. 1, pp. 1–34.

Berger, J. O. (1985). *Statistical decision theory and Bayesian analysis*. eng. 2. ed. Springer series in statistics. New York, NY: Springer. ISBN: 9780387960982.

Burstein, F. and C. H. Holsapple (2008a). *Handbook on Decision Support Systems 1. Basic Themes*. Ed. by F. Burstein and C. H. Holsapple. Springer, Berlin, Heidelberg.

— (2008b). *Handbook on Decision Support Systems 2. Variations*. Ed. by F. Burstein and C. H. Holsapple. Springer, Berlin, Heidelberg.

Chan, P. and K. Hon (Feb. 2016). "Observation and Numerical Simulation of Terrain-Induced Windshear at the Hong Kong International Airport in a Planetary Boundary Layer without Temperature Inversions". In: *Advances in Meteorology* 2016.

Cheung, P. (2011). "Development of significant convection forecast product and service for air traffic flow management in Hong Kong". In: *Proceedings of the 91st American Meteorological Society Annual Meeting*.

Clare, G. and A. Richards (July 2013). "Disturbance feedback for handling uncertainty in Air Traffic Flow Management". In: *2013 European Control Conference (ECC)*, pp. 3246–3251.

Clare, G. and A. Richards (2012). "Air Traffic Flow Management Under Uncertainty: Application of Chance Constraints". In: *Proceedings of the 2Nd International Conference on Application and Theory of Automation in Command and Control Systems*. ATACCS '12. London, United Kingdom: IRIT Press, pp. 20–26. ISBN: 978-2-917490-20-4.

Clare, G., A. Richards, J. Escartin, D. Martinez, J. Cegarra, and L. J. Alvarez (2012). "Air Traffic Flow Management Under Uncertainty: Interactions Between Network Manager and Airline Operations Centre". In: *Proceedings of the 2nd SESAR Innovation Days*.

Cook, A. and G. Tanner (Dec. 24, 2015). *European airline delay cost reference values, updated and extended values*. Version 4.1.

Cook, L. S. and B. Wood (2009). "A Model for Determining Ground Delay Program Parameters Using a Probabilistic Forecast of Stratus Clearing". In: *Proceedings of the 8th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2009*. EUROCONTROL.

DeLaura, R., M. Robinson, M. Pawlak, and J. Evans (2008). "Modeling convective weather avoidance in enroute airspace". In: *Proceedings of the 13th Conference on Aviation, Range and Aerospace Meteorology*.

Dietz, S. J., P. Kneringer, G. J. Mayr, and A. Zeileis (Nov. 2018). "Correction to: Forecasting Low-Visibility Procedure States with Tree-Based Statistical Methods". In: *Pure and Applied Geophysics*. ISSN: 1420-9136.

Dmochowski, P. A. and J. Skorupski (2017). "Air Traffic Smoothness. A New Look at the Air Traffic Flow Management". In: *Transportation Research Procedia* 28. INAIR 2017, pp. 127–132. ISSN: 2352-1465.

Druzdzel, M. J. (1993). "Probabilistic Reasoning in Decision Support Systems: From Computation to Common Sense". PhD thesis. Department of Engineering and Public Policy of CarnegieMellon University.

Eder, A. (2018). *Manual FMP Vienna*. Austro Control internal document. Austro Control.

Escartin, J. and D. Martinez (2013). *ONBOARD Final Project Report*. SESAR Joint Undertaking.

EUROCONTROL (2018a). *EUROPEAN AVIATION IN 2040. CHALLENGES OF GROWTH*. Edition 2. EUROCONTROL.

— (Apr. 27, 2018b). *NMIR User Guide*. EUROCONTROL.

— (2018c). *Standard Inputs for EUROCONTROL Cost-Benefit Analyses*. Edition Number 8.0, January 2018. Eurocontrol.

— (2019a). *EUROCONTROL Seven-Year Forecast February 2019. Flight Movements and Service Units 2019-2025*. EUROCONTROL.

— (May 29, 2019b). *Network Operations*. URL: `www.eurocontrol.int/network-operations` (visited on 05/29/2019).

European Commision (July 7, 2011). *2011/4130: COMMISSION DECISION of 7.7.2011 on the nomination of the Network Manager for the air traffic management (ATM) network functions of the single European sky*.

— (Mar. 12, 2014). "2014/132/EU: Commission Implementing Decision of 11 March 2014 setting the Union-wide performance targets for the air traffic management network and alert thresholds for the second reference period 2015-19 Text with EEA relevance". In: OJ L 71, pp. 20–23.

European Commision Network Manager (2018a). *Network operations report 2017*. Eurocontrol.

— (2018b). *Network operations report 2017 ANNEX III - AIRPORTS*. Eurocontrol.

— (May 1, 2019a). *ATFCM USERS MANUAL*. 23.0. Eurocontrol.

— (2019b). *Network operations report 2018*. Eurocontrol.

Evans, J. (2001). "Tactical Weather Decision Support To Complement "Strategic" Traffic Flow Management for Convective Weather". In: *Proceedings of the 4th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2001*. EUROCONTROL.

Evans, J. and B. Crowe (2019). "Development of Benefits-Driven Convective Weather Decision Support Systems for Improving Safety and Efficiency in the ATC System through 30 Years of Continuous Use of Real-Time Functional Prototypes". In: *Proceedings of the 99th American Meteorological Society Annual Meeting 2019*.

Evans, J., M. Weber, and W. Moser (2006). "Air Traffic Management Decision Support". In: *Lincoln Laboratory Journal* 16.1, pp. 81–96.

FAA (June 1, 2016). *The Future of the NAS*. U.S. Department of Transportation, Federal Aviation Administration.

Flathers, B., M. Fronzak, M. Huberdeau, C. McKnight, M. Wang, and G. Wilhelm (2013). *A FRAMEWORK FOR THE DEVELOPMENT OF THE ATM-WEATHER INTEGRATION CONCEPT*. The MITRE Corporation, unpublished.

Hon, K. (Mar. 2018). "Big data opportunities in high-impact public and aviation weather at the Hong Kong Observatory". In: *Proceedings of CBS TECO 2018*.

Ivanov, N., F. Netjasov, R. Jovanovic, S. Starita, and A. Strauss (2017). "Air Traffic Flow Management slot allocation to minimize propagated delay and improve airport slot adherence". In: *Transportation Research Part A: Policy and Practice* 95, pp. 183–197. ISSN: 0965-8564.

Jones, J. C. and Y. Glina (2019). “Estimating Flow Rates in Convective Weather: A Simulation-Based Approach”. In: *Proceedings of the 13th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2019*. EUROCONTROL.

Katz, R. and J. Lazo (Jan. 2012). “Economic Value of Weather and Climate Forecasts”. In: *The Oxford Handbook of Economic Forecasting*.

Katz, R. W. and A. H. Murphy (1997). “Forecast value: prototype decision-making models”. In: *Economic Value of Weather and Climate Forecasts*. Ed. by R. W. Katz and A. H. Murphy. Cambridge University Press, pp. 183–218.

Kicinger, R., J.-T. Chen, M. Steiner, and J. Pinto (2016). “Airport Capacity Prediction with Explicit Consideration of Weather Forecast Uncertainty”. In: *Journal of Air Transportation* 24.1, pp. 18–28.

Klein, G. (Jan. 2001). *Sources of Power: How People Make Decisions*. Vol. 1.

Kneringer, P., S. J. Dietz, G. J. Mayr, and A. Zeileis (May 2019). “Probabilistic Nowcasting of Low-Visibility Procedure States at Vienna International Airport During Cold Season”. In: *Pure and Applied Geophysics* 176.5, pp. 2165–2177. ISSN: 1420-9136.

Leutbecher, M. and T. Palmer (2008). “Ensemble forecasting”. In: *Journal of Computational Physics* 227.7. Predicting weather, climate and extreme events, pp. 3515–3539. ISSN: 0021-9991.

Matos, P. L. de and R. Ormerod (2000). “The application of operational research to European air traffic flow management - understanding the context”. In: *European Journal of Operational Research* 123.1, pp. 125–144. ISSN: 0377-2217.

Matte, S., M.-A. Boucher, V. Boucher, and T.-C. Fortier Filion (June 2017). “Moving beyond the cost-loss ratio: Economic assessment of streamflow forecasts for a risk-Averse decision maker”. In: *Hydrology and Earth System Sciences* 21, pp. 2967–2986.

Matthews, M., R. DeLaura, M. Veillette, J. Venuti, and J. Kuchar (Dec. 15, 2015). *Airspace Flow Rate Forecast Algorithms, Validation and Implementation*. ATC-428. MIT Lincoln Laboratory.

Matthews, M., M. Veillette, J. Venuti, R. DeLaura, and J. Kuchar (2017). “Translating Convective Weather Forecasts into Strategic Traffic Management Decision Aids”. In: *Proceedings of the 12th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2017*. EUROCONTROL.

Matthews, M., M. Wolfson, R. DeLaura, J. Evans, and C. Reiche (2009). “Measuring the uncertainty of weather forecasts specific to air traffic management operations”. In: *American Meteorological Society Special Symposium on Weather – Air Traffic Integration*.

Montlaur, A. and L. Delgado (2018). “Arrival Trade-offs Considering Total Flight and Passenger Delays and Fairness”. In: *Proceedings of the 8th SESAR Innovation Days*.

Munier, N., E. Hontoria, and F. Jiménez-Sáez (2019). *Strategic Approach in Multi-Criteria Decision Making : A Practical Guide for Complex Scenarios*. eng. International Series in Operations Research & Management Science 275. Cham: Springer International Publishing Imprint: Springer. ISBN: 9783030027261.

Obwegeser, N. (2011). “Adoption of multi criteria decision support systems”. eng. PhD thesis. Wirtschaftsuniversität Wien , Department of Information Systems and Operations, Institute for Information Business.

Pasquini, L. (2019). “EUROCONTROL’S NETWORK MANAGER TAKES URGENT ACTION TO PREPARE FOR SUMMER 2019”. In: *Skyway magazine* 70. Ed. by L. Pasquini.

Reiche, C., M. Robinson, V. Klimenko, S. Percic, M. Kay, and R. Kicinger (2014). "EVALUATION OF CONVECTIVE WEATHER FORECAST PERFORMANCE BY OPERATIONALLY RELEVANT METEOROLOGICAL CHARACTERISTICS". In: *Proceedings of the 94th American Meteorological Society Annual Meeting*.

Reynolds, D. W., D. A. Clark, F. W. Wilson, and L. Cook (2012). "Forecast-Based Decision Support for San Francisco International Airport: A NextGen Prototype System That Improves Operations during Summer Stratus Season". In: *Bulletin of the American Meteorological Society* 93.10, pp. 1503–1518.

Robinson, M., R. DeLaura, and N. Underhill (2009). "The Route Availability Planning Tool (RAPT): Evaluation of Departure Management Decision Support in New York during the 2008 Convective Weather Season". In: *Proceedings of the 8th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2009*. EUROCONTROL.

Sheth, K., T. Amis, and S. Gutierrez-Nolasco (2009). "Analysis of Probabilistic Weather Forecasts for Use in Air Traffic Management". In: *Proceedings of the Aviation, Range and Aerospace Meteorology Special Symposium on Weather-Air Traffic Management Integration*.

Sheth, K., T. Amis, S. Gutierrez-Nolasco, B. Sridhar, and D. Mulfinger (2013). "Development of a Probabilistic Convective Weather Forecast Threshold Parameter for Flight-Routing Decisions". In: *Weather and Forecasting* 28.5, pp. 1175–1187.

Shorr, B. (1966). "The Cost/Loss Utility Ratio". In: *Journal of Applied Meteorology* 5.6, pp. 801–803.

Song, L., D. Greenbaum, and C. Wanke (2009). "The Impact of Severe Weather on Sector Capacity". In: *Proceedings of the 8th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2009*. EUROCONTROL.

Steiner, M., R. Bateman, D. Megenhardt, Y. Liu, M. Xu, M. Pocernich, and J. Krozel (Oct. 2010). "Translation of Ensemble Weather Forecasts into Probabilistic Air Traffic Capacity Impact". In: *Air Traffic Control Quarterly* 18, pp. 229–254.

Steiner, M., W. Deierling, K. Ikeda, E. Nelson, and R. Bass (June 2014). "Airline and airport operations under lightning threats - Safety risks, impacts, uncertainties, and how to deal with them all". In: *Transactions of Japanese Society for Medical and Biological Engineering*. Vol. 51. ISBN: 978-1-62410-291-2.

Steiner, M., A. R. S. Anderson, S. Landolt, S. Linden, and B. R. J. Schwedler (Sept. 2015). "Coping with adverse winter weather - Emerging capabilities in support of airport and airline operations". In: *The Journal of Air Traffic Control* 57, pp. 36–45.

Steinheimer, M., C. Gonzaga-Lopez, C. Kern, M. Kerschbaum, L. Strauss, K. Eschbacher, M. Mayr, and C.-H. Rokitansky (2016). "Air traffic management and weather: the potential of an integrated approach". In: *Proceedings of the International Conference on Air Transport*. University of Zilina, Air Transport Department, Zilina, Slovakia.

Steinheimer, M., C. Kern, and M. Kerschbaum (2019). "Quantification of Weather Impact on Arrival Management". In: *Proceedings of the 13th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2019*. EUROCONTROL.

Tabachneck-Schijf, H. J. and P. L. Geenen (2009). "Preventing knowledge transfer errors: Probabilistic decision support systems through the users' eyes". In: *International Journal of Approximate Reasoning* 50.3. Special Section on Bayesian Modelling, pp. 461–471. ISSN: 0888-613X.

Taylor, C., S.-L. Tien, E. Vargo, and C. Wanke (2019). “Strategic Flight Cancellation under Ground Delay Program Uncertainty”. In: *Proceedings of the 13th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2019*. EUROCONTROL.

Thompson, J. C. (1950). “A NUMERICAL METHOD FOR FORECASTING RAINFALL IN THE LOS ANGELES AREA”. In: *Monthly Weather Review* 78.7, pp. 113–124.

— (1952). “On the Operational Deficiences in Categorical Weather Forecasts”. In: *Bulletin of the American Meteorological Society* 33.6, pp. 223–226.

Treve, V. (2016). *Time-Based Separation Fact Sheet*. EUROCONTROL.

Valencia-García, R., M. A. Paredes-Valverde, M. d. P. Salas-Zárate, and G. Alor-Hernández (2018). *Exploring Intelligent Decision Support Systems. Current State and New Trends*. Ed. by R. Valencia-García, M. A. Paredes-Valverde, M. d. P. Salas-Zárate, and G. Alor-Hernández. Cham: Springer International Publishing. ISBN: 978-3-319-74002-7.

Walker, C. (Mar. 8, 2019). *CODA Digest 2018. All-Causes Delay and Cancellations to Air Transport in Europe -2018*. EUROCONTROL.

Wang, Y. and B. Sridhar (Oct. 2010). “Convective weather forecast accuracy analysis at center and sector levels”. In: *29th Digital Avionics Systems Conference*, 2.B.2-1-2.B.2–17.

Weber, M. E., J. E. Evans, W. R. Moser, and O. J. Newell (2007). “Air Traffic Management Decision Support During Convective Weather”. In: *Lincoln Laboratory Journal* 16.2, pp. 263–275.

Zhang, M., X. Kong, K. Liu, and X. Li (2018). “A Novel Rerouting Planning Model for the Terminal Arrival Routes under the Influence of Convective Weather”. In: *Journal of Advanced Transportation* 2018.

Acknowledgements

The research leading to the presented results has received funding from Take Off programme. Take Off is a Research, Technology and Innovation Funding Programme of the Austrian Federal Ministry for Transport, Innovation and Technology (BMVIT). The Austrian Research Promotion Agency (FFG) has been authorized for the Programme Management.

The simulations within this study were performed on the NAVSIM simulation platform provided and brilliantly supported by Professor Rokitansky and Kurt Eschbacher from the Aerospace Research Group of University of Salzburg within the frame of the MET4LOWW and PROB4LOWW projects. Also the valuable discussions and input of the entire MET4LOWW and PROB4LOWW project teams contributed to the success of this work. Special thanks go to Markus Kerschbaum for continuing support of the conducted research.