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Abstract

This is the final report of the *Integrating weather prediction models into ATM planning ('IWA')* PhD, which was awarded funding through the Engage KTN's Call for PhDs and post-graduate theses. This report provides a summary of the research in advance of the published PhD thesis, which can be accessed directly from Linköping University (the link is provided in Section 11.1).

SESAR Engage KTN – PhD final report

PhD title:	Integrating Weather Prediction Models into ATM planning (IWA)
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1. Abstract

Weather has a strong impact on ATM. Inefficient weather avoidance procedures and inaccurate prognosis lead to longer aircraft routes and, as a result, to fuel waste and increased negative environmental impact. A better integration of weather information into the operational ATM-system will ultimately improve the overall air traffic safety and efficiency.

Covid-19 pandemics affected aviation severely, resulting in an unprecedented reduction of air traffic, and gave the opportunity to study the flight performance in non-congested scenarios. We discovered noticeable inefficiencies and environmental performance degradation, which persisted despite significant reduction of traffic intensity. The PhD thesis proposes a methodology that allows us to distinguish which factors have the highest impact on which aspects of arrival performance in horizontal and vertical dimensions.

Academic Excellence in ATM and UTM Research (AEAR) group operating within the Communications and Transport Systems (KTS) division at Linköping University (LIU), together with the Research and Development at Luftfartsverket (LFV, Swedish ANSP) develops optimization techniques to support efficient decision-making for aviation authorities.

In this thesis, we apply probabilistic weather modelling techniques, taking into account the influence of bad weather conditions on the solutions developed in our related projects and integrate them into the corresponding optimization frameworks. First, the PhD student enhanced the optimization framework for arrival route planning in TMA, with the convective weather avoidance technique. Next, the probabilistic weather products were used to obtain an ensemble of staffing solutions, from which the probability distributions of the number of necessary ATCOs were derived. The modelling is based on the techniques recently developed within several SESAR projects addressing weather uncertainty challenges. The proposed solutions were successfully tested using the historical flight data from Stockholm Arlanda airport and five airports in Sweden planned for remote operation in the future.

2. Objective of the study

This PhD pursues the following scientific goals:

- Study the impact of weather on different aspects of airspace operation, assess the impact of various weather phenomena on the flight efficiency (TC3 Efficient provision and use of meteorological information in ATM).
- Incorporate the weather impact into optimization frameworks developed in LIU-LFV related projects (CAPMOD, ODESTA). Refine the developed optimization frameworks, making them more robust with respect to weather uncertainties.
  - Part 1. Weather in TMA Route Planning (TC2 Data-Driven Trajectory Prediction, TC3 Efficient provision and use of meteorological information in ATM).
  - Part 2. Weather in Remote Tower Staff Planning (TC3 Efficient provision and use of meteorological information in ATM)

3. Motivation

Commercial aviation provides a vital component of the transportation sector, facilitates international trade and economic growth. But it also has its drawbacks, such as deleterious greenhouse gas emissions. The carbon emissions from the commercial aviation are still only a small fraction of total anthropogenic emissions, but the share of greenhouse gases contributed by aviation is growing rapidly.

The minimum possible pollution is produced if the aircraft keeps CCOs and CDOs (Fricke, Seiss, & Herrmann, 2015), (Wubben & Busink, 2000) during climb and descent phases, which provide optimal vertical trajectory without levelling-off. CCOs and CDOs trajectories are also optimal in terms of fuel consumption. Additional fuel burn of actual aircraft trajectories, comparing to the optimal ones, costs millions of euros per year.

Aircraft deviations from planned trajectories can cause air traffic delays. Frequent and long delays may induce large tactical and strategic costs for airlines, airports and passengers. With all these environmental and financial issues, air transport efficiency is one of the major concerns for all the aviation stakeholders.

Weather and ATFM are among the main factors influencing aircraft trajectories. Flight routes can be altered to avoid convective weather, such as thunderstorms (Hernandez, Valenzuela, & Rivas, 2016) . Severe weather causes delays and cancellations (Borsky & Unterberger, 2019). Airport capacity can be reduced considerably by low visibility, strong winds, thunderstorms in the terminal area and runway closures. Snowy weather causes major disturbances in airport operation, resulting in reduced visibility, slippery runway conditions and the necessity to free runway for snow cleaning.

A better integration of weather information into the operational ATM-system will ultimately improve the overall air traffic safety and efficiency. For example, current ATCO working regulations do not even take seasonal variations into account. This often yields overstaffing during low-traffic months and staff shortages during high-traffic months. Thus, a good estimate of the necessary number of ATCOs, which account traffic intensity and weather forecast, results in a higher safety level.

4. Advances this work has provided with regard to the state of the art

Impact of Weather on Flight Efficiency in TMA

EUROCONTROL developed the methodology used by its Performance Review Unit (PRU) for the analysis of flight efficiency within the areas of safety, capacity, cost-effectiveness and environment, reflected in the yearly assessment reports, reviewing the flight efficiency within TMA at the top 30 European airports (EUROCONTROL, 2020).

Pasutto, Hoffman & Zeghal (2020) analyse the factors affecting vertical efficiency in descent at the top 30 European airports. The paper reveals an increase of the vertical deviation with the horizontal deviation, and a dispersion of the vertical deviation for the same horizontal deviation. The analysis also reports a very significant disparity among airports, with some indicators ranging by a factor of 5 or more. Zanin (2020) evaluates the efficiency of flights landing at an airport using open large-scale data sets of aircraft trajectories. The author focuses on understanding the efficiency of different airspaces and on comparing them.

Estimation of the flight inefficiencies in terms of extra fuel burn calculated based on the algorithm proposed in Chatterji (2011) was considered in the scope of APACHE project (a SESAR 2020 exploratory research project) (Prats, et al., 2018a), (Prats, Agui, Netjasov, Pavlovic, & Vidosavljevic, 2018b), but mostly for en-route flight phase. Later Prats, Dalmau & Barrado (2019) proposed a family of performance indicators to measure fuel inefficiencies.

In Ryerson, Hansen & Bonn (2014) fuel consumption is evaluated for terminal areas with a Terminal Inefficiency metric based on the variation in terminal area fuel consumed across flights, reported by a major U.S. airline. Using this metric, they quantify the additional fuel burn caused by ATM delay and terminal inefficiencies. Furthermore, in Fricke, Seiss & Herrmann (2015) and Wubben & Busink (2000), fuel savings of the CDOs with respect to conventional procedures are analysed. A reduction in fuel consumption of around 25-40% by flying CDOs was reported.

Quantification of the impact of different weather phenomena on airport operation is reflected in many recent research activities. Schultz, Lorenz, Schmitz & Delgado (2018) used the ATMAP algorithm, published by EUROCONTROL's PRU, which transforms the METAR data into the aggregated weather score weighting the different weather factors. They analysed the correlation of the on-time performance of flight operations with the ATMAP score at major European airports.

Within SESAR, new models for weather forecasts and their integration in planning problems, e.g., in trajectory planning, have been developed in several projects, e.g., IMET (2013), FMP-MET (2020-2022), PNOWWA (2016-2018). The staple technique for capturing the uncertainty in weather predictions is retrieving probabilistic weather data from an EPS. An EPS quantifies weather uncertainty by generating a range of weather forecasts, referred to as members, which represent a sample of the possible states of the actual weather outcome (World Meteorological Organization, 2012).

Impact of deep convection and thunderstorms is also subject to ongoing research, e.g. Steiner et al. (2010), Steiner, Deierling, Ikeda, Nelson & Bass (2014) and Song, Greenbaum & Wanke (2009) investigated their implication both on the en-route flow management and on terminal area operations. Klein, Kavoussi & Lee (2009) used a high-level airport model to quantify the impact of weather forecast uncertainty on delay costs.

Steiner (2015) discusses the crucial effect of accurate forecasts of high-impact winter weather for efficient management of airport and airline capacity and highlight the need of data sharing and integrated decision making between stakeholders. Recent works (Reitmann, Alam, & Schultz, 2019), (Steinheimer, Kern, & Kerschbaum, 2019) confirmed the relevance and emphasized the importance of quantification and analysis of the weather impact on airport operation.

Van den Bergh et al. (2013) presented a literature review of modern techniques for personnel scheduling problems. They processed 291 articles from 2004 onwards and classified the optimizations tasks and their solution methods from different perspectives. The authors developed a number of recommendations, some of which are used in our work, and other ones are left for future research.

In our work, we propose a methodology that allows us to distinguish which factors have the highest impact on which aspects of arrival performance in horizontal and vertical plane. In particular, we introduce WIF (Weather Impact Factor) and TIF (Traffic Impact Factor), a unified condition metrics representing the current weather and traffic situations, which can be applied in regression analysis in order to determine what factor influence the chosen PI most.

TMA Route Planning

One of the solutions to reduce aircraft environmental impact in TMAs is the use of CDOs, which allows reduced aircraft fuel consumption, pollutant emissions and noise nuisance, while bringing major economic benefits and without any adverse effect in safety. But in reality, CDOs are barely applied in busy TMAs due to many reasons. ATCOs usually apply larger separation buffers to handle CDOs, leading to airspace and runway-capacity losses that are not desirable in major TMAs, especially during peak hours. ATCOs tend to issue open-loop instructions (i.e., radar vectoring) to maintain safe separation between aircraft and to maximize the throughput in these static routes (Sáez, Prats, Polishchuk, & Polishchuk, 2020).

In the previous work (Andersson Granberg, Polishchuk, Polishchuk, & Schmidt, 2016), (Polishchuk, et al., 2020), our group proposed a Mixed-Integer-Programming-based (MIP-based) approach for automatic generation of STARs and optimized arrival routes to enable CDOs for all arriving aircraft. We assumed aircraft could arrive within a time window at the TMA entry point, which could be achieved by adjusting the speed during the en-route phase. Then, in this most recent work (Sáez, et al., 2021), the concept of operations was developed to show the applicability of the proposed optimization framework in the current air traffic operations system. The methodology was tested on different scenarios with different traffic levels/distributions, we assess the sensitivity of our solution to the size of the entry-point time window and we analyse the effect that different traffic mixes have on the optimized arrival routes.

We extend the optimization framework from Andersson Granberg, Polishchuk, Polishchuk & Schmidt (2016) for constructing operationally feasible obstacle-avoiding static STARs, to handle obstacles changing with time (e.g. hazardous weather regions) and to output morphing STARs that never change abruptly (so controllers and pilots may easily see how the STARs evolve over time).

Remote Tower Staff Planning

The RTC concept aims to provide air traffic service simultaneously to multiple airports with ATCOs at a remote location (NORACON, 2013). A variety of aspects of this concept has been studied: Möhlenbrink et al. (2010) and Papenfuss et al. (2010) considered usability within the novel remote-control environment. Wittbrodt, Gross & Thuring (2010) emphasized the role of radio communication for RTCs.

Meyer, Vogel & Fricke (2010) provided a safety assessment of the RTC concept, where they suggest functional hazard analyses and pinpoint the issue of getting reliable probability values for the models. Oehme & Schulz-Rueckert (2010) suggested sensor-based solutions that alleviate the dependency on visibility conditions and tower location. In addition, Friedrich, Pichelmann, Papenfuss & Jakobi (2017), Möhlenbrink, Papenfuss & Jakobi (2012), Möhlenbrink & Papenfuss (2011), Manske & Schier (2015), Papenfuss & Friedrich (2016) studied work organization and human performance issues in the context of remote towers. The authors proposed several methods to control two airports from a single RTC and investigated how the monitoring performance may influence the system design and behavioural strategies, in particular, they presented results on the design of the novel RTC workplaces.

Rostering of ATCOs naturally inherits some features from other related staff scheduling problems, e.g., from nurse scheduling (Burke, De Causmaecker, Berghe, & Van Landeghem, 2004), university course timetabling (Chiarandini, Birattari, Socha, & Rossi-Doria, 2006) or multi-skilled staff planning (Li &

Womer, 2009). However, for ATCO rostering schedule requirements are much stricter. Arnvig et al. (2006) provide an overview on early results in shift scheduling in ATM and detail European regulations and policies connected to ATCO work organization.

Various methods have been used for rostering ATCOs. In a survey, Conniss (2015) names, amongst others, Linear Programming, Tabu Search, Simulated Annealing, Constraint Programming, and Case-Based Reasoning. Stojadinovic (2014) proposed to solve the ATC shift scheduling by using various exact methods: CSP, SAT, Partial MaxSAT, SMT, ILP and PB. The results indicate that SAT-related approaches outperform other methods for the problem described. Conniss, Curtis & Petrovic (2014) suggested an effective greedy heuristic to solve the problem. The authors of all these studies aimed to provide rosters for ATCOs in a conventional tower. Their problem description is close to the one we formulate, but naturally lacks constraints related to the RTO.

Gultepe et al. (2019) described current knowledge available for aviation operations related to meteorology and provided suggestions for necessary improvements in the measurement and prediction of weather-related parameters to serve safe aviation operations. The authors claim that some weather-related events such as fog, precipitation, clear-air and in-cloud turbulence, wind shear, gust, or icing may be related to changing climate conditions, and emphasize the importance of considering aircraft flying conditions to improve future aviation operations.

Taszarek, Kendzierski & Pilguj (2020) investigated spatial and temporal variability of situations with limited visibility, thunderstorms, low-level wind shear, and snowfall that cause disruptions in airline traffic and airport operations. They used environmental parameters derived from the ERA5 database (European Centre for Medium-Range Weather Forecasts, 2020) and determined threshold values for meteorological metrics to distinguish between hazardous and non-hazardous situations, some of which we use in our work.

The problem of analysing and quantifying the effects of meteorological uncertainty in Trajectory-Based Operations was studied in Hernandez, Valenzuela & Rivas (2016), Rivas, Vazquez & Franco (2016). The authors considered two types of meteorological uncertainty: wind uncertainty and convective zones. New probabilistic radar-based nowcasting methods to support ATM challenged by winter weather were proposed in Pulkkinen, Van Lerber, Saltikoff & Hagen (2017), Saltikoff, Hagen, Juntti, Kaltenböck & Pulkkinen (2018).

To the best of our knowledge, there were no published attempts to quantify the effect of different weather phenomena on controllers taskload or workload. We proposed a method to account for weather impact on ATCO work in RTC staff scheduling. We identified different sources for numerical thresholds for the impactful weather phenomena and used probabilistic weather products to obtain an ensemble of staffing solutions, from which we can derive probability distributions of the number of necessary ATCOs. To compute the ensemble of staffing solutions, we applied our prior MIP for RTC staff scheduling (Josefsson, Polishchuk, Polishchuk, & Schmidt, 2017) extended by a constraint requiring an airport with impactful weather occurrence to be operated in single mode. In addition, we presented a detailed sensitivity analysis for a set of cut-off values for the taskload-driven impact factor, exploring the trade-off between safety level and cost savings.

5. Methodology

Impact of Weather on Flight Efficiency in TMA

Horizontal inefficiencies during the climb and descent phases result from the deviation of flights from SIDs and STARs. Vertical inefficiencies are produced by the inability of flights to keep up CCO and CDO. E.g., during the descent phase VFE means aircraft leaves its cruising level at the optimum top of descent and avoids level-off segments after that. This type of operations enables the execution of a flight profile optimized to the operating capability of the aircraft, giving as a result optimal continuous engine-idle descents (without using speed-breaks), that reduce fuel consumption, gaseous emissions and noise nuisance.

ICAO propose a set of PIs to analyse the performance of arrivals and departures in TMA, such as Departure and Arrival punctuality, Additional time in terminal airspace, Additional fuel burn, Level-off during climb, Level-off during descent. EUROCONTROL Experimental Center develops new performance indicators targeting to capture different aspects of flight inefficiencies in TMA (Pasutto, Hoffman, & Zeghal, 2019). EUROCONTROL also proposed the techniques to calculate VFE PIs (EUROCONTROL, 2017). In order to capture different aspects of the TMA performance, we choose the following key performance indicators: Additional Time in TMA, Level-off during descent, Additional Distance in TMA and Additional Fuel Burn.

In Lemetti, Hardell & Polishchuk (2020), we introduce WIF, a unified condition metric representing the current weather situation, and apply it in an isolated scenario with low traffic flight performance. Similarly, we create TIF and investigate an isolated scenario of flight performance in good weather conditions, assuming the isolated scenario with no influence of weather.

In Lemetti, Polishchuk, Polishchuk, Sáez & Prats (2020), we aim at identifying the factors with high influence on the chosen PIs. We study this problem using statistical analysis, and the problem is an inference task. When inference is the goal, there are clear advantages of using simple and relatively inflexible statistical learning methods, such as linear regression. We use multiple linear regression and the method of Backward Selection to determine the statistically significant metrics.

TMA Route Planning

In Bulusu et al. (2020), we model the TMA by a rectangle (see Figure 1), where a square grid V of points is laid down inside the rectangle, and every grid point is connected to its 8 immediate neighbours North, East, South, West, NE, SE, SW, and NW (these connections may be used by the STAR to link the TMA entry points to the runway). The grid points V, together with the connections (denoted by E) form the graph $G = (V, E)$ which we will search for the paths. The graph is bidirected: for any two vertices $i, j \in V$, both directed edges ij and ji belong to E. The runway is in the middle of the square, with the landing direction pointing South. The airspace has four entry points: one on each side of the TMA. Such modelling is done only for simplicity, as our techniques work with arbitrarily shaped airspace (e.g., one way of handling an arbitrary-shape airspace may be to “carve it out” from the square by declaring as obstacles the parts of the square which do not belong to the airspace shape), any number of entry points (without restriction on their locations) and runway located anywhere. Basically, the model represents a generic TMA with entries from different directions and a runway somewhere inside.

In addition to the TMA with its entry points and the runway, the input to our problem consists of a set of moving obstacles: for any time step $t \in [1, . . ., T]$ within a given planning horizon T, we are given a set of polygons that affect the routes. In a pre-processing step, for every t we determine the subset $O_t \subseteq E$ of edges of G that overlap with the obstacles. Weights of the edges are the last input. We use ij to denote the weight assigned to edge $ij \in E$, the weights indicate the severity of the convective weather.

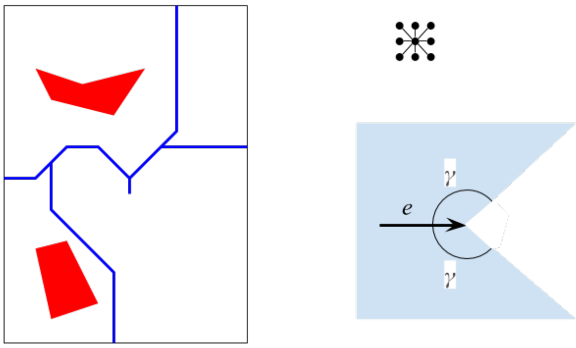

*Figure 1 : Left: The STAR (blue) avoiding the obstacles (red). Right: A grid vertex is connected to the 8 neighbours. The turn constraint means that if edge **e** is used by a STAR, then no other edge in the blue region $\boldsymbol{\Gamma_e}$ (i.e, an edge forming an angle less then **γ** with **e**) can be used in the STAR.*

As the output of our problem, we seek a sequence $(\mathcal{T}_1, . . ., \mathcal{T}_T)$ of arrival trees (STARs) in G, that merge the entries to the runway. That is, for every $t \in [1, . . ., T]$, the tree $\mathcal{T}_t$ should have the entries as leaves and the runway as the root (contrary to the common convention, we assume that the edges of the arborescence are directed from leaves to root). The STARs should be disjoint from the obstacles – i.e., identifying a tree with its edges, we require $\mathcal{T}_t \cap O_t = \emptyset$. Operational feasibility of the STARs is ensured by requiring that they satisfy the requirements outlined in Andersson Granberg, Polishchuk, Polishchuk & Schmidt (2016): at most two routes merging at a point (translating to the requirement that every vertex of the tree must have in-degree less than or equal to 2), and the turn constraints (no sharp change of direction at any node). Last but not least, we add the new requirement that the STARs should change "slowly"; we model it by requiring that $\mathcal{T}_{t+1}$ and $\mathcal{T}_t$ should differ by at most U edges, where U is a parameter given in the input: $| \mathcal{T}_{t+1} \Delta \mathcal{T}_t | \leq U$ (where Δ denotes the symmetric difference).

Similarly to Andersson Granberg, Polishchuk, Polishchuk & Schmidt (2016), we consider two objectives for any resulting tree: minimizing the total weight of the entry-to-runway paths in the tree and the total weight of all edges in the tree (the two objectives are different because some edges are used by paths from more than one entry; we call the two objective functions the *path length* and the *tree weight* respectively). The objective function in our IP is the sum, over all timesteps, of a linear combination of the path length and tree weight. Our resulting IP is a modification and extension of the IP from Andersson Granberg, Polishchuk, Polishchuk & Schmidt (2016) for finding one, static STAR: we add the time dimension to allow the STAR to morph and add constraints that assure consistency between the consecutive trees.

Remote Tower Staff Planning

To achieve our goal of integrating weather impact in RTC staff scheduling, we implement the following steps:

(1) Identify impactful weather phenomena for each considered airport
(2) Define threshold values for the impactful weather phenomena from step (1)
(3) Obtain weather data in form of EPS
(4) Obtain flight movements for all considered airports
(5) Calculate a distribution of the necessary number of ATCOs for staffing based on the input from Steps (1) to (4)

Probabilistic weather forecasts consist of predictive probability distributions of future weather quantities. Probabilistic weather forecasts are produced by major weather forecasting agencies using EPSs which consist of ensembles of deterministic numerical weather predictions.

Weather induced airports closure was incorporated into the staff scheduling optimization framework as an additional constraint of the developed MIP. Then, the probability distribution of the necessary number of ATCOs is obtained using the developed MIP and EPSs as follows. For each of the *M* EPS ensemble members, we solve the MIP and obtain the number Q_m, $m=1..M$ of ATCOs needed. Then the probability that at most k ATCOs are needed is:

$$P(Q \leq k) = \frac{1}{M}\sum_{m=1}^{M} X_m(k),$$

Where $X_m(k) = \begin{cases} 1 & if\ Q_m \leq k, \\ 0 & otherwise \end{cases}$

6. Description of the data the study relies on

Aircraft tracking information

- Demand Data Repository (DDR2) hosted by EUROCONTROL
  EUROCONTROL offers data in SO6 format that is delimiter separated values files which store flight trajectories (the lists of waypoints containing aircraft position, barometric altitude and identity). Files of SO6 m1 format are used as flight plans, SO6 m3 file format is for the actual trajectories.
  This source was used in early stage of the work (Lemetti, Polishchuk, Sáez, & Prats, 2019), (Lemetti, Polishchuk, Polishchuk, Sáez, & Prats, 2020), we studied its benefits and drawbacks in comparison to the Opensky Network data in Lemetti, Polishchuk & Sáez (2019).
- Historical Database of the OpenSky Network
  Opensky is a crowd-sourced network of ground sensors which collect air traffic data from aircraft transponder signals. We use aircraft state vectors (a summary of all tracking information) for every second of the trajectories inside TMA.

- FlightRadar24
  FlightRadar 24 is an Internet-based service that shows real-time commercial aircraft flight tracking information on a map. We use this data source for some additional investigation of flight inefficiency during the specific days.

Aircraft performance data

We use BADA version 4.2 (EUROCONTROL, 2014) for CDO trajectory generation and fuel consumption calculation. For aircraft types operated by the studied flights not available in BADA, we replace it by a type similar in performance and size.

Weather data

- METAR
  Current weather conditions are usually recorded at each airport in the form of METARs. In addition to information about the location, the day of the month and the UTC time, the METAR contains information about wind, visibility, precipitation, clouding, temperature, and pressure that are relevant for the air traffic, especially for the airport operations. We used METAR data in Lemetti, Polishchuk, Polishchuk, Sáez & Prats (2020).
- NOAA
  GRIB formatted files with 0.5 degrees granularity provided by the GFS through the NOMADS. This data was used to generate the longitudinal wind profiles as a function of the altitude (needed for the trajectory optimization) in Lemetti, Polishchuk & Sáez (2019) and Lemetti, Polishchuk, Polishchuk, Sáez & Prats (2020).
- ECMWF ERA5
  Reanalysis and ensemble datasets provided via the C3S Data Store in form of NetCDF files. The ERA5 database contains estimates of a large number of weather variables from year 1979 onwards. It covers the whole surface of the Earth with 137 vertical levels from the surface up to a height of 80 km. Data has been regridded to a regular lat-lon grid of 0.25 degrees for the reanalysis and 0.5 degrees for the uncertainty estimate.
  ECMWF ERA5 reanalysis dataset has temporal granularity of one hour. The dataset is used for evaluation of weather impact on flight efficiency as well as for fuel consumption calculation.
  ECMWF ERA5 ensemble dataset includes an uncertainty estimation in the form of a 10-member ensemble, which has a temporal granularity of three hours. The dataset is used to illustrate the capabilities of the developed methodologies, which incorporate the weather uncertainty into optimization frameworks.

7. Computational experiments

Impact of Weather on Flight Efficiency in TMA

Opensky Network provides very accurate but noisy aircraft tracking information. We performed a set of data wrangling procedures in order to clean and pre-process the trajectory data before PIs calculation. The following methods has been chained:

- Determine incorrect latitude or longitude (more than 0.1 degree distance from the previous record), fix all incorrect latitudes and longitudes using linear interpolation between the correct values
- Substitute fluctuations in altitude (more than 300 meters up and more than 600 meters down) with the previous value
- Use Gaussian filter to smooth the altitude
- Remove the trajectories for which latitude, longitude or altitude could not be fixed by means of the previous steps
- Remove the flights that go too far from the TMA border (more than 0.5 degree of latitude or longitude)
- Remove the trajectories that are incomplete within TMA and do not reach the runway (last altitude is larger than 600 meters)
- Remove the trajectories, which start from the altitude lower than 600 meters (departure and arrival at the same airport, mostly helicopters)
- Remove the trajectories, which represent the landings too far from the runway (detected visually)
- Remove the trajectories, representing the go around within TMA (detected visually)
- Remove the trajectories representing non-commercial flights (ICAOs consist of only letters, consist of only digits, shorter than four symbols, start with certain letters)

To evaluate the horizontal flight efficiency, we use the Additional Distance in TMA. For that we cluster the trajectories in each TMA using the methodology proposed in Pasutto, Hoffman & Zeghal (2019).

Next, we choose an ideal reference trajectory, constructing a user-preferred route tree inside the TMA as proposed in Polishchuk V. (2016). We identify the start of the reference trajectory as the point on the TMA border that is closest to each cluster centroid. The reference trajectory goes directly to the interception of the localizer for an ILS approach, with a 2 NM straight segment before the FAP.

TMA Route Planning

In Bulusu et al. (2020) we covered the TMA with a 66 NM x 90 NM rectangle and laid out an 11x15 grid *G* with distance 6 NM between the grid points (i.e., a grid pixel has side length of 6 NM). The grid edges outside the TMA were declared as permanent obstacles, to make sure the STARs stay within the TMA. We use hourly weather updates to define the obstacles O_t at every hour t and update the STARs every hour during a time horizon of T = 5 hours. We used CAPE metric, which is an indicator of the instability of the atmosphere and can be used to assess the potential for the development of convection, which can lead to heavy rainfall, thunderstorms and other severe weather. Note, that our method is universal, and CAPE can be replaced with any other indicator of the convective activity, or other weather phenomena evolving in time horizon. July 29, 2018 was chosen as the highest values of CAPE were recorded on this day (above 1000 J/kg). We took CAPE values for the $59^{\circ} - 61^{\circ}$N, $17^{\circ} - 19^{\circ}$E grid as it covers the Stockholm Arlanda TMA area.

The weather cells are given weight based on the severity, and paths with low weight (weather exposure) were sought. Weights to all possible links are assigned based on the location of the weather cells, and we assign higher weights to the links impacted by the higher activity weather. Since the weather cells granularity is not the same as the grid granularity, we assign weights of the nearest weather point to all links in the grid cell. Also, when one link is close to more than one weather cell, the highest weight of all close-by cells is assigned. In Figure 6 the weather-impacted links are colored as follows: a CAPE value below 800 is given a weight of 1 and is not shown in the figures (we assume low impact of the connective weather associated with these values), light yellow corresponds to a CAPE value of 800-899, yellow corresponds to a CAPE value of 900-999, orange corresponds to a CAPE value of 1000-1099, red corresponds to a CAPE value of 1100- 1199 and dark red corresponds to a CAPE value above 1200.

Remote Tower Staff Planning

To illustrate how the described strategy for integrating weather impact into ATCO staff scheduling can be used in practice, we perform an experimental study on the example of two days of the year 2020 for five Swedish airports (AP 1-5) in remote control.

We follow Steps (1)-(5) described in Section 5 as follows.

(1) Identify impactful weather phenomena for each considered airport
Our goal is to study the impact of weather on ATCOs and their workload. However, no measures or classifications for this exist. Hence, we performed structured interviews with three Swedish ATCOs working at five Swedish airports, which are either already operated remotely or considered for future remote operation. The main goal with the interviews was to obtain the additional tasks appearing for different strengths of various weather phenomena. Thereafter, we treated different weather phenomena separately: snow, low visibility, precipitation (excluding snow), wind (strong low-level and surface winds), and convective weather. We queried the occurrence of additional ATCO tasks in case of a light, moderate or severe occurrence of the weather phenomenon. Then, we transfer the ATCO's answers to numerical values. Taking the average of these values for all additional ATCO tasks associated with a weather phenomenon, we obtain average taskload-driven impact factors of light, moderate and severe occurrences of the weather phenomena. For easy visual differentiation of the airports, we transfer the numerical average taskload-driven impact factors to a heat value and present the resulting impact-heat tables for snow, low visibility, precipitation and strong winds in Figure 2.

These average taskload-driven impact factors allow us to differentiate the impact that different intensities of the weather phenomena have on the five airports. We need to decide what constitutes a threshold (cutoff) over which a weather phenomenon influences ATCO's work at an airport significantly. We perform a sensitivity analysis on this cutoff value: we use cutoff values of 0.2, 0.3, 0.4, 0.5, 0.6 and 0.7 and study the effect on staff scheduling for the RTC---namely, on the number of ATCOs needed to remotely control the five considered airports.

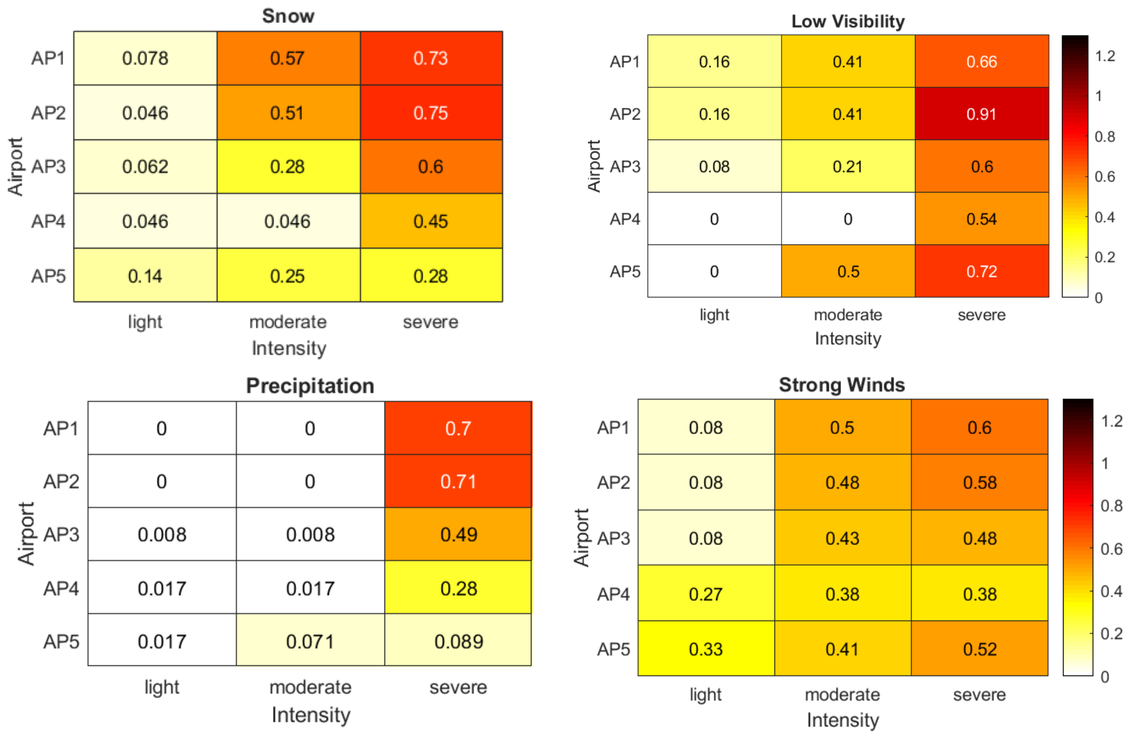

Figure 2 Impact-heat tables for snow, low visibility, precipitation, and strong winds

(2) Define threshold values for the impactful weather phenomena
We deduced threshold values for the impactful weather phenomena from the literature and ATCO’s answers.

(3) Obtain weather data in form of EPS.
We downloaded weather data from the ERA5 reanalysis database for February 2020 and July 2020 and chose two exemplary dates:

a. February 16, 2020: A winter day during which four out of the five considered weather phenomena occurred: snow, low visibility, strong wind and precipitation.
b. July 29, 2020: A summer day during which three out of the five considered weather phenomena occurred: low visibility, wind and precipitation.

As previously mentioned in Section 6, the ERA5 reanalysis ensemble presents weather data every three hours. We obtain the hourly weather variables as follows: for cumulative weather parameters (snowfall and precipitation), the accumulated quantity is divided by the length of the time interval (three hours); for instantaneous weather parameters, a linear interpolation is used to obtain the intermediate hourly values.

(4) Obtain flight movement data for all airports.
We obtained the number of movements per hour at each airport using FlightRadar24 historical flight data. We use only hours 6-14 for February 16, 2020, and 14-22 for July 29, 2020, that is, we provide rosters for nine hours of operation for each of the days. The movement data for February 16, 2020, and July 29, 2020, is shown in Figure 3.

Feb 16	6	7	8	9	10	11	12	13	14
AP1	0	0	1	0	1	0	1	2	1
AP2	1	1	1	1	1	2	2	2	2
AP3	0	0	0	0	0	0	0	3	0
AP4	0	0	0	0	0	0	1	1	1
AP5	1	4	0	3	3	4	2	6	4

Jul 29	14	15	16	17	18	19	20	21	22
AP1	1	1	0	1	1	0	0	0	0
AP2	1	0	3	0	2	3	2	1	2
AP3	0	1	1	0	0	0	0	0	0
AP4	0	0	0	0	0	0	0	0	0
AP5	3	4	0	0	1	4	0	0	2

Figure 3 The number of flight movements for the five Swedish airports during nine hours of operation on February 16, 2020, and July 29, 2020.

(5) Calculate a distribution of the necessary number of ATCOs for RTC staffing.

We use AMPL and Gurobi optimization software (for both TMA Route Planning and Remote Tower Staff Planning) installed on a very powerful Tetralith server (Linköping University, 2020), utilizing the Intel HNS2600BPB computer nodes with 32 CPU cores, 384 GiB, provided by the Swedish National Infrastructure for Computing. One problem instance of TMA Route Planning IP took ∼10 minutes to solve. The computational time of each run of Remote Tower Staff planning MILP varied between 0.08 and 3.03 seconds with an average value of 0.38 seconds.

8. Results

Impact of Weather on Flight Efficiency in TMA

To study the impact of traffic intensity and weather on arrival performance we investigate an isolated non-congested scenario and an isolated scenario with good weather conditions. We perform the regression analysis of PIs medians per hour onto the WIF and TIF using the data for the period of two years 2019 and 2020 at Stockholm Arlanda and Gothenburg Landvetter airports (see examples in Figure 4, Figure 5).

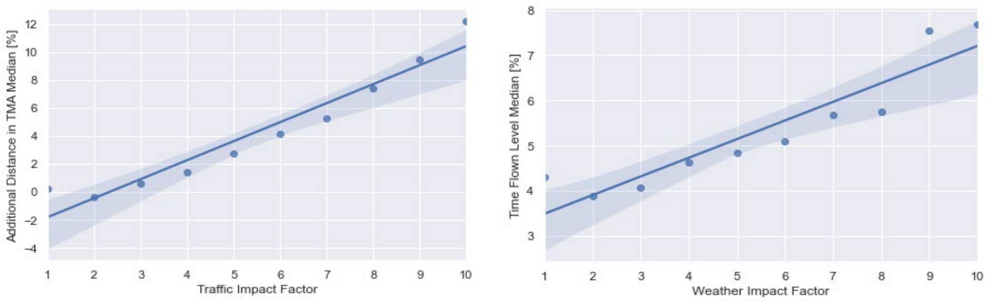

Figure 4 Regression of Additional Distance median values onto the TIF (R^2 = 0.93) (left) and Time Flown Level median values onto the WIF (R^2 = 0.73) (right) at Stockholm Arlanda airport

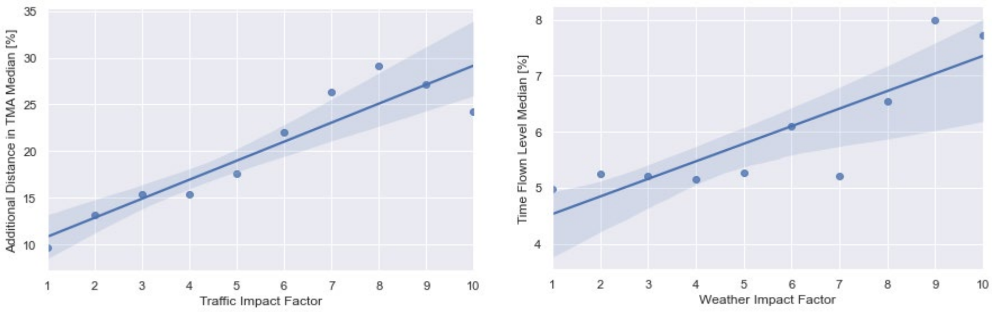

Figure 5 Regression of Additional Distance median values onto the TIF (R^2 = 0.86) (left) and Time Flown Level median values onto the WIF (R^2 = 0.93) (right) at Gothenburg Landvetter airport

To identify which of the individual factors have higher influence on each PI separately we apply Backward Selection method for regressing the PI (Average Additional Time in TMA, Average Time Flown Level, Average Additional Fuel Burn) onto normalized weather metrics and traffic intensity (Lemetti, Polishchuk, Polishchuk, Sáez, & Prats, 2020). An example of Backward Selection algorithm steps is presented in Table 1, that is three steps to identify the most significant factors for Additional Time in TMA. We identify traffic intensity, snow and wind gust as the most significant factors for Average Additional Time in TMA. For Average Time Flown Level, we identify only CAPE as an insignificant metric. The other individual factors have significant influence on the vertical efficiency PI, and together with the traffic intensity, snow and wind speed reveal strong influence, and hence, can be identified as the most important. For Additional Fuel Burn only wind gust is identified as a significant factor influencing additional fuel consumption within TMA. All the other factors with the corresponding higher p-values were disregarded by the algorithm.

Table 1 Backward Selection algorithm results for multiple linear regression of the average additional time in TMA versus impact factors

R^2_{adj}	F-stat.	Prob(F-stat.)	Traffic intensity		Snow		Visibility		Wind Gust		CAPE	
			coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value	coef.	p-value
0.18	18.71	7.58e-15	0.9746	0.0	0.9356	0.0	-0.0961	0.551	1.0680	0.0	0.3570	0.347
0.18	20.84	1.83e-15	0.9838	0.0	0.9926	0.0			1.0850	0.0	0.4363	0.22
0.18	27.24	6.65e-16	0.9629	0.0	0.9657	0.0			1.0758	0.0		

TMA Route Planning

In Bulusu et al. (2020), first, we set U = 5 in the experiment. Given such a low flexibility in the number of links the trees can be different in, and having all the trees optimized together in one program, the resulting routes are not always passing through the cells with the lowest weather activity (e.g. the route from the south entry in Figure 6(b)). With U = 20 (Figure 7), the difference between the trees is more noticeable. The resulting paths are better adjusted to the current weather conditions (e.g. for T = 2 in Figure 7 (b), the route from the south entry is now passing through the cells with the lowest weather activity). Another example is the rightmost STAR for T = 6, where in the first case (U = 5, Figure 6 (f)) the path from the south entry is passing through some weather-impacted regions, while in the second case (U = 20, Figure 7 (f)) safely avoids them.

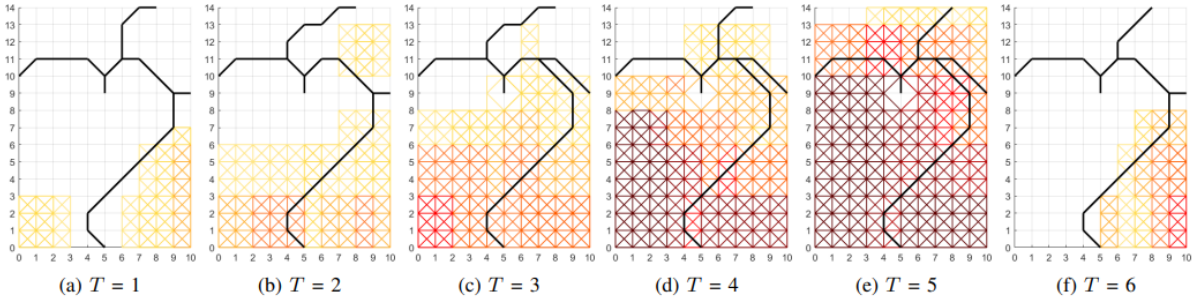

Figure 6 Optimized STARs with weighted links based on severity of the weather, for six different time steps T for U = 5. CAPE intensity is illustrated by the color of the links. The darker colors, the higher CAPE values.

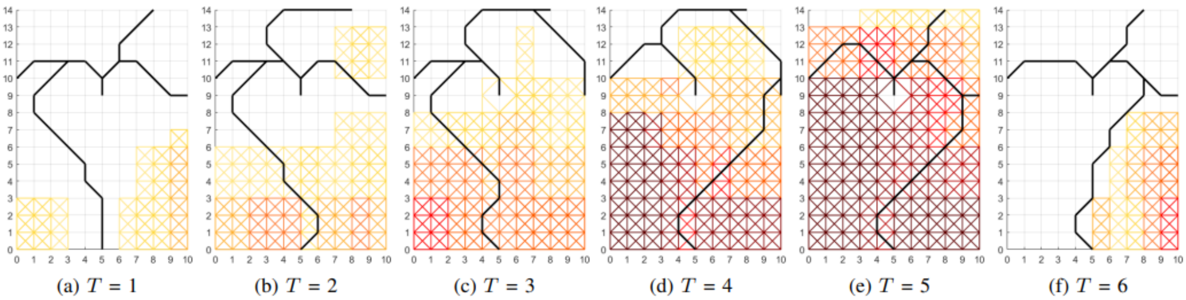

Figure 7 Optimized STARs with weighted links based on severity of the weather, for six different time steps T for U = 20. CAPE intensity is illustrated by the color of the links. The darker colors, the higher CAPE values.

Remote Tower Staff Planning

When we optimize the number of ATCOs for the 9-hour intervals on both considered dates without taking weather into account, we obtain staff schedules with 5 ATCOs (Hernandez-Romero, et al., 2022). Taking weather into account, we obtain different distributions of the number of necessary ATCOs depending on the cutoff value. Figure 8 shows the results as bar diagrams (red dots indicate the expected value for the necessary number of ATCOs, the red line indicates the trend of this expected value).

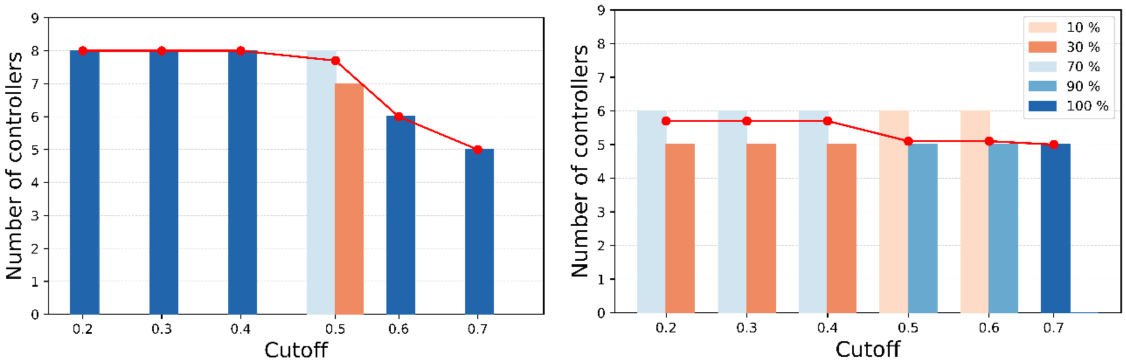

Figure 8 Distribution of the necessary number of ATCOs with different cutoff values for February 16, 2020 (left) and July 29, 2020 (right)

9. Analysis of the results

Impact of Weather on Flight Efficiency in TMA

We revealed in Lemetti, Hardell & Polishchuk (2020) that the additional distance flown by aircraft in TMA strongly correlates with the traffic intensity, while vertical flight efficiency depends more on weather conditions (see Figure 4, Figure 5). Horizontal flight efficiency has moderate or low correlation with WIF depending on the airport, while VFE has weak correlation with traffic intensity for both considered airports. With Additional Fuel Burn in TMA, we observe moderate correlation with weather conditions for both airports and strong correlation with traffic situation for Arlanda airport. Landvetter airport does not show correlation of Additional Fuel Burn with traffic intensity. That can be explained by smaller values of traffic intensity, as well as a smaller TMA.

Our results in Lemetti, Polishchuk, Polishchuk, Sáez & Prats (2020) show that wind gust and snow are the factors with the most significant impact on the majority of our PIs. Since convective weather is relatively rare event in our study area, our conclusion that CAPE alone does not fully reveal the influence of convective weather on inefficiencies within TMA may be of limited applicability.

TMA Route Planning

Results in Bulusu et al. (2020) demonstrate the clear trade-off between the total path length and the consistency between the trees objectives. We present the total path lengths for the resulting trees for different values of the STAR "smoothness" parameter *U* in Table 2 and visualize the Pareto-optimal solutions in Figure 9. High values of the total path lengths are resulting from the high weights of the tree edges belonging to the weather-impaired regions.

Table 2 Total weighted path lengths for the trees with different STAR "smoothness" parameter U

U	***T* = 1**	***T* = 2**	***T* = 3**	***T* = 4**	***T* = 5**	***T* = 6**	**Total**
5	87	1026	2019	4106	9300	532	17070
10	41	878	1971	3862	9350	135	16237
20	37	582	1834	3434	9400	37	15324
30	36	537	1729	3433	9300	36	15071

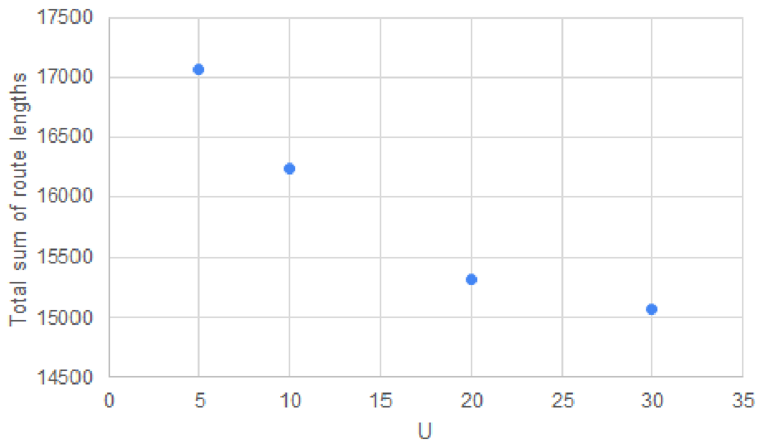

Figure 9 Pareto optimal solutions for two objectives: STAR "smoothness" and the total route lengths over all STARs.

Remote Tower Staff Planning

In Hernandez-Romero et al. (2022), we proposed a method to account for weather impact on ATCO work in RTC staff scheduling. We used probabilistic weather products to obtain an ensemble of staffing solutions, from which we then derived probability distributions of the number of necessary ATCOs. To compute the ensemble of staffing solutions, we applied our prior MIP for RTC staff scheduling extended by a constraint requiring an airport with impactful weather occurrence to be operated in single mode.

We presented a detailed sensitivity analysis on the cutoff value for the taskload-driven impact factor and could clearly highlight a trade-off between safety level and staffing need. Our experiments for five Swedish airports and days with three to four weather phenomena occurring clearly show the possible impact of weather: the five ATCOs that would be scheduled taking all legal and shift-related constraints into account on both days are not always sufficient for the RTC without possibly yielding situations compromising safety due to weather. Only for a cutoff value of 0.7, the scheduling of five ATCOs will avoid what is considered as a critical situation with that value.

10. Conclusions and look ahead

We revealed that weather conditions have a significant impact on vertical flight efficiency, while traffic intensity influences mostly the lateral efficiency. Our results show that wind gust and snow are the factors with the most significant impact on the majority of our PIs.

Our solution for TMA route planning entails extending an IP-based optimization framework for obstacle-avoiding STAR generation (Andersson Granberg, Polishchuk, Polishchuk, & Schmidt, 2016) to the case of moving obstacles. Our algorithms output slowly morphing STARs that avoid the obstacles and do not change too fast over time.

A standard assumption in all research on STAR design is that the runway configuration is specified, i.e., the landing runway is given in the input. It may be interesting to lift this assumption and extend our framework by allowing the configuration to be changed and land (possibly, part of) the traffic on another runway. This may be particularly useful if landing all aircraft to the single, given runway is infeasible. Given the huge impact of weather on ATM, it may be worth exploring how weather data granularity influences the arrival routes. For that, one could either take several weather data sources, or simply coarsen the given weather data by blurring it (i.e., considering it on a coarser grid). Then, for the STARs computed using the different-granularity weather, several performance indicators may be evaluated. The PIs may be compared both among the STARs and versus the real operational flights. The first tree $\mathcal{T}_1$ in our STAR sequence $(\mathcal{T}_1, \ldots, \mathcal{T}_T)$ is output by our IP. Alternatively, one could take some existing tree $\mathcal{T}_0$ as the input and require that also the first tree $\mathcal{T}_1$ does not differ too much from $\mathcal{T}_1$: $|\mathcal{T}_1 \Delta \mathcal{T}_1| \leq U$. This would be a straightforward addition to our framework.

For Remote Tower Staff Planning, we proposed a method to account for weather impact on ATCO work scheduling. We highlighted that no measures or classifications for weather impact exist and used structured interviews with experienced ATCOs to deduce taskload-driven impact factors for five weather phenomena at five Swedish airports. We identified different sources for numerical thresholds for these impactful weather phenomena and used probabilistic weather products to obtain an ensemble of staffing solutions, from which we then derived probability distributions of the number of necessary ATCOs. To compute the ensemble of staffing solutions, we applied our prior MIP for RTC staff scheduling extended by a constraint requiring an airport with impactful weather occurrence to be operated in single mode. In addition, we presented a detailed sensitivity analysis on the cutoff value for the taskload-driven impact factor and could clearly highlight a trade-off between safety level and staffing need.

Our experiments for five Swedish airports and days with three to four weather phenomena occurring clearly show the possible impact of weather: the five ATCOs that would be scheduled taking all legal and shift-related constraints into account on both days are not always sufficient for the RTC without possibly yielding situations compromising safety due to weather. Only for a cutoff value of 0.7, the scheduling of five ATCOs will avoid what is considered as a critical situation with that value.

We highlighted the importance of developing meteorological products with longer look-ahead horizon, tailored to the needs of airports staff planning. This is particularly important for remote towers.

One direction for future work is the practical validation of our work. This includes both (simulation) trials to assess the validity of our assignments and additional interviews to confirm the presented results. Often, with the occurrence of the considered weather event, the number of VFR movements reduces. Hence, it would be interesting to evaluate if this reduction has any influence on the impact on taskload associated with different weather phenomena.

11. References

11.1 Link to PhD thesis / repository

LiU DiVa (Digitala Vetenskapliga Arkivet) portal: https://liu.diva-portal.org/

11.2 Associated outputs and publications

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Annex I: Acronyms

Term	Definition
ANSP	Air Navigation Service Provider
ATC	Air Traffic Control
ATCO	Air Traffic Controller
ATFM	Air Traffic Flow Management
ATM	Air Traffic Management
CAPE	Convective Available Potential Energy
CCO	Continuous Climb Operations
CDO	Continuous Descent Operations
ECMWF	European Centre for Medium-Range Weather Forecasts
EPS	Ensemble Prediction System
FAP	Final Approach Point
GFS	Global Forecast System
GRIB	Gridded binary
ICAO	International Civil Aviation Organization
ILS	Instrument Landing System
IP	Integer Program
METAR	Meteorological Terminal Aviation Routine Weather Reports
MILP	Mixed-Integer Linear Program
NM	Nautical Mile
NOAA	National Oceanic and Atmospheric Administration
NOMADS	National Operational Model Archive and Distribution System
PI	Performance Indicator
PRU	Performance Review Unit
RTC	Remote Tower Center
RTO	Remote Tower Operation
SESAR	Single European Sky ATM Research
SID	Standard Instrument Departure Route
STAR	Standard Arrival Route
TMA	Terminal Manoeuvring Area
UTM	Unmanned Aerial Vehicle Traffic Management

Term	Definition
VFE	Vertical Flight Efficiency
VFR	Visual Flight Rules

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