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Integrating weather impact in air traffic controller shift scheduling in remote and conventional towers☆,☆☆

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ABSTRACT

Weather affects the work of air traffic controllers, however, for staff scheduling in Remote Tower Centers (RTCs) it has not been taken into account. We study the impact of various weather phenomena on air traffic controller (ATCO) taskload through structured interviews with ATCOs. We deduce taskload-driven impact factors and the corresponding thresholds for the intensity of the weather phenomena at several Swedish airports. To account for the uncertainty in the weather prediction, we obtain probabilistic weather data from Ensemble Prediction Systems (EPSs). Then we adjust our prior Mixed Integer Programming (MIP) model for RTC staff scheduling to account for uncertain impactful weather occurrences and yield a distribution for the necessary number of ATCOs for RTC staff scheduling. Our framework can be used for conventional towers as well.

We quantify the impact of weather by comparing the number of controllers necessary to operate at five Swedish airports from a remote tower during two example days in 2020, with and without taking weather events into account. In our calculations we use historical weather and flight data to show that ignoring weather impact may lead to significant understaffing at a RTC.

1. Introduction

Constructing rosters for ATCOs is a complex problem since a myriad of legal and operational requirements needs to be taken into account. ATCO rostering is more complicated than most shift-planning tasks because of very strict and legally binding regulations (Delgado et al., 2015): shifts may not be too short or too long, between two shifts a minimum rest interval must be kept, during a shift an ATCO must have breaks every so often, etc. Moreover, an ATCO can work at different airports and must hold an endorsement for each airport. To maintain such endorsements, controllers are supposed to spend a specified number of hours working at the corresponding airports. The number of constraints only increases in remote towers.

The first RTC opened in Sweden in 2015. The Swedish Air Navigation Service Provider Luftfartsverket (LFV) serves Örnsköldsvik Airport, Sundsvall-Midlanda Airport and Linköping SAAB Airport from the center. In an RTC an ATCO can work in the so-called "multiple" position (or multiple mode, or multiple operation), when the ATCO monitors traffic at more than one airport. While currently all service is provided in single mode (one ATCO controls one airport), multiple operation is planned in Sweden, as well as in other countries, as it will bring up significant cost savings. In Europe, usually two or three airports are considered for the multiple position.

Unions and regulatory bodies require additional safety assessment before approving multiple mode implementation. In particular, when assigning airports to ATCOs we need to ensure that no ATCO is confronted with traffic-inherent situations in the multiple airports, which would lead to an unacceptable workload for the ATCO. Such situations may stem from simultaneous movements (landings and take-offs) at two airports, or severe weather conditions in one or both airports may increase the ATCO's taskload. Weather affects the work of ATCOs through increased communication with ground traffic and pilots, through increased out-of-the-window observation, and through changes to the arrival and departure routes. For example, during our field study at Bromma airport tower, we observed the influence of a severe

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weather event on ATCO workload (Josefsson et al., 2020). With 4, 5, 9 and 27 movements during four hours, the average workload rating (self-assessed by the ATCOs using the adapted Cooper–Harper Scale from Papenfuss and Peters (2012)) was higher in the first three hours, during which regular snow sweeping with a convoy of 10–14 vehicles occurred, than in the final hour with peak traffic.

Weather disturbances have a noticeable influence on ATCOs working in a conventional tower, and they may have even higher impact on ATCOs in an RTC, in particular, when an ATCO monitors several airports simultaneously, possibly with different weather conditions. The impact of weather on ATCO work is significantly under-researched and is not taken into account in current operation and planning, neither in conventional towers nor in RTCs. Moreover, to the best of our knowledge, no good measures or classifications for weather impact on ATCOs and their workload exist. This yields a couple of research questions: How do different weather phenomena impact ATCO workload (at different airports)? How to quantify the resulting weather-induced capacity reductions? And how can we integrate this impact in RTC staff scheduling?

Our work contributes to a safety assessment for multiple mode by showing that during staff scheduling we can account for weather-induced increased taskload and ensure that ATCOs do not face safety-compromising situations. Specifically, we aim to quantify the impact of weather and integrate it into optimization of ATCO work at RTCs, in particular, into an automated staff scheduling—thus revealing another important application area for weather models for aviation. We provide a proof of concept using historical weather and aircraft movement data. The goal is to use our approach as a tool to forecast ATCO staffing needs in RTCs based on weather forecasts.

To fill the research gap on classification of weather impact at different airports, we interviewed experienced ATCOs working at five (small) Swedish airports on measurement, incidence, classification and resulting additional ATCO tasks for various weather phenomena (snow, low visibility, precipitation, wind, and convective weather). In particular, we are interested in thresholds for significantly increased taskload induced by the phenomena. We concentrate on taskload (rather than workload), which measures the objective demand of a task rather than the subjective stress experienced during that task (see, e.g., Suárez et al., 2014; Josefsson et al., 2018 for the study of objective measures correlating with workload for en-route traffic and multiple remote control).

We then aim to integrate the identified influence of weather on the ATCOs in our prior model for RTC staff scheduling (Josefsson et al., 2017), while also taking into account the uncertainty in the weather prediction. Previously, we limited the number of movements per hour that a single ATCO may handle, and suggested to resolve conflicts in terms of simultaneous movements at two airports within a 5-min-interval (Josefsson et al., 2017; Dahlberg et al., 2017). However, we know that ATCO workload is not a monotone, linear function of the number of movements: it might stay more or less constant with an increasing number of movements under normal conditions, but will rise suddenly in case of unexpected events. Here, we identify occurrence of a certain strength of a weather phenomenon as an unexpected event which needs to be taken into account: a conflict between airports appears not only because of simultaneous movements, but also when an impactful weather event at one airport demands the full attention of an ATCO, effectively switching the mode from multiple to single.

Weather conditions have a high impact on the performance of the air traffic management (ATM) not only in towers, but also in general (see, e.g., Borsky and Unterberger (2019)). Within SESAR,[1] new models for weather forecasts and their integration in planning problems, e.g., in trajectory planning, have been developed in several projects (e.g., Anon (2015, 2020-2022,a)). 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). In our prior work Josefsson et al. (2020), we used probability distributions of meteorological parameters from an ensemble weather product to yield the probability distribution of the number of necessary ATCOs. In this paper, we calculate a solution (the optimal number of ATCOs) for each member of the ensemble, from which we derive probability distributions of the number of necessary ATCOs . In particular, while in Josefsson et al. (2020) we assumed that weather events are independent, this is no longer a necessary assumption for our new approach, which might give more realistic results. In addition, in this paper we perform a sensitivity analysis on the strength of weather phenomena that are considered impactful.

[1] The Single European Sky ATM Research program

Roadmap. The rest of the paper is organized as follows. In Section 2, we review the related work. In Section 3, we outline our procedure for integrating weather impact in RTC staff scheduling and present its details in Sections Section 4 (ATCO interviews and deduction of taskload-driven impact factors), 5 (definition of numerical thresholds for different impactful weather phenomena for obtaining weather data), and 6 (integration of weather-related constraint into our previous optimization model and resulting distribution of the necessary number of ATCOs for RTC rostering). We present experimental results for five Swedish airports in Section 7 and conclude in Section 8.

2. Related work

In this section, we review state of the art on staff planning at RTC and the weather impact on air traffic services in general.

RTC staff scheduling. Van den Bergh et al. presented a literature review of modern techniques for personnel scheduling problems (Van den Bergh et al., 2013). 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.

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 et al. (2010) emphasized the role of radio communication for RTCs. Meyer et al. (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 and Schulz-Rueckert (2010) suggested sensor-based solutions that alleviate the dependency on visibility conditions and tower location. In addition, Friedrich et al. (2017), Möhlenbrink et al. (2012), Möhlenbrink and Papenfuss (2011), Manske and Schier (2015) and Papenfuss and 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 behavioral 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 et al., 2004), university course timetabling (Chiarandini et al., 2006), or multi-skilled staff planning (Li and 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. Stojadinović (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 et al. (2014) suggested an effective greedy heuristics to solve the problem.

The authors of all these studies aimed to provide rosters for ATCOs in a conventional tower. In prior work, we have developed a framework to compute rosters for ATCOs in an RTC (Andersson et al., June, 2016; Josefsson et al., 2017,?; Dahlberg et al., 2017; Josefsson et al., 2019).

Weather in ATM. Quantification of the impact of different weather phenomena on airport operation is reflected in many recent research activities. 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 et al. (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, 2021) and determined threshold values for meteorological metrics to distinguish between hazardous and non-hazardous situations, some of which we use in this paper.

The problem of analyzing and quantifying the effects of meteorological uncertainty in Trajectory-Based Operations was studied in Hernández et al. (2016) and Rivas et al. (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 et al. (2017) and Saltikoff et al. (2018). Impact of deep convection and thunderstorms is also subject of ongoing research, e.g., Steiner et al. (2010), Steiner (2015) and Song et al. (2009) investigated their implication both on en-route flow management and for terminal area applications. Klein et al. (2009) used a high-level airport model to quantify the impact of weather forecast uncertainty on delay costs. Recently, various authors Reitmann et al. (2019), Steinheimer et al. (2019) and Lemetti et al. (2020) confirmed the relevance and emphasized the importance of studying the weather impact on airport operation.

To the best of our knowledge, there were no published attempts to quantify the effect of different weather phenomena on controllers taskload or workload.

3. Strategy outline for integrating weather impact in RTC staff scheduling

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, see Section 4.
(2) Define threshold values for the impactful weather phenomena from (1), see Section 5.2.
(3) Obtain weather data in form of EPS, see Section 5.1.
(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), see Section 6.

4. Weather impact on ATCO taskload

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. We present the airports and ATCOs in Sections 4.1 and 4.2, respectively. In Section 4.3, we present the interviews and, in Section 4.4, we present our results on the impact of different weather phenomena at these five airports on ATCOs.

4.1. Airports

The five Swedish airports (APs) we consider can be characterized by a couple of criteria:

- *AP1*. Small AP with low traffic, few scheduled flights per hour. Inland location north of the Arctic Circle and continental subarctic climate (Köppen climate classification Dfc, see Britannica (2020)).
- *AP2*. Small regional AP with regular scheduled flights (usually open 24/7). Coastal location, Dfc, north of AP3-5.
- *AP3*. Small regional AP with regular scheduled flights. Coastal location, Dfc, north of AP5.
- *AP4*. Small regional AP with regular scheduled flights. Coastal location, Dfc, north of AP3 and AP5.
- *AP5*. Low to medium-sized AP, multiple scheduled flights per hour (usually open 24/7). Coastal location in the South of Sweden, Marine West Coast Climate.

4.2. ATCOs

We selected ATCOs with experience in working in a remote tower and/or with significant operational experience (as not all five airports are currently operated remotely); this way we ensured they are familiar with all weather phenomena at the selected airports.

The main goal with the interviews was to obtain the additional tasks appearing for different strengths of various weather phenomena. This mainly depends on the airport's specifics and its location and climate, but not on the subjective work assessment of specific ATCOs—that is, we target objective information. Hence, we did not aim to interview several ATCOs per airport, but to interview at least one ATCO per airport, who had long lasting experience there. One ATCO answered the interview questions for AP1–AP3; one for AP3, AP4; and one for AP5.

The three interviewed ATCOs had an average and median experience as ATCO of 17.7 and 21 years, respectively; and an average and median working time at the considered towers of 13 and 10 years, respectively. Two of the ATCOs have worked remotely. Since our goal is to map the additional weather-induced tasks at the five airports, experience of working remotely is not important (as several of the airports are only considered for future remote operation, but currently not operated remotely).

4.3. Structured interviews

The structured interviews were performed based on a questionnaire (see Schmidt and Polishchuk (2020)). Each ATCO was interviewed separately via Zoom; each interview lasted 2–3 h (each ATCO was interviewed on one airport, and we asked them to fill in the questionnaire for other airports).

We first asked for general information on the ATCO and the ATCO career. Then, we posed questions on the traffic density and its seasonal variations at the airport: how many movements they usually observe, how many Visual-Flight-Rules (VFR) and Instrumental-Flight-Rules (IFR) movements are present on a normal day without impact by weather phenomena, and during which seasons they observe highest traffic.

Table 1
Prose to numerical values.

Prose formulation	Numerical value
no	0
rarely, not too much	0.25
sometimes, maybe, can happen, several times	0.5
often, increased, more likely, higher	0.75
yes	1
much more; yes, significantly	1.25

After this background information on ATCO and airport, we moved to weather-related questions. This included questions relating to all weather phenomena: sources for weather information, person in charge for and frequency of weather updates, and influence of weather on staffing decisions when operating the airport from a conventional tower.

Thereafter, we treated different weather phenomena separately: snow, low visibility, precipitation (excluding snow), wind (strong low-level and surface winds), and convective weather. For each weather phenomenon we asked about its metric and usual values of this metric, and which additional ATCO or manager tasks appear in case of occurrence of that weather phenomenon. Additionally, we asked how the number of VFR and IFR movements changes for light, moderate and severe occurrence of the weather phenomenon. Finally, we queried the occurrence of additional ATCO tasks in case of a light, moderate or severe occurrence of the weather phenomenon (we derived the list of possible additional tasks associated with different weather phenomena from the hazard assessment cards suggested by EUROCONTROL (2013)). Examples for the additional tasks are:

- Anticipation and condition detection
- Visual observation
- Runway closing for inspection and re-opening
- Change of departure/arrival runway
- Clearing arrivals to holding areas
- Increased coordination with the ground traffic
- Provision of information on alternate aerodromes' conditions and availability

We completed the weather-phenomenon-specific questions for each weather phenomenon with an open question on potential additional ATCO tasks the ATCO would want to add to our list.

4.4. Interview results on weather impact

The ATCOs answered, in prose, our queries (presented in the tables in Sections 4–8 of Schmidt and Polishchuk (2020)) on the occurrence of additional ATCO tasks in case of a light, moderate or severe strength of the weather phenomena. We transfer these answers to numerical values according to Table 1. Taking the average of these values for all additional ATCO tasks associated with a weather phenomenon (and for AP3 over two ATCOs' answers), 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 Fig. 1(a), (b), (c), and (d), respectively.

Regarding convective activity, we could not find a strong definition from the interviewed ATCOs about the difference in tasks for different intensities of convective activity (only the ATCO interviewed on AP5 was at all able to identify a difference between light, moderate, and severe thunderstorm occurrence). As a consequence, we treat thunderstorms as a binary variable, i.e, we differentiate between only two states: no convective activity and convective activity.

From the impact-heat tables, we can clearly see that the ubiquitous weather phenomenon snow has highest impact on the northern airports AP1 and AP2, and has hardly any influence on AP5, located in the South, where it occurs rarely. Remember that we consider taskload (not workload). Hence, even though the ATCOs working at AP1 and AP2 are used to snow, its occurrence still yields additional tasks and, thus, an increased taskload. A particularly high impact of severe low visibility can be observed at AP2: a coastal airport in the North of Sweden.

These average taskload-driven impact factors allow us to differentiate the impact that different intensities of the weather phenomena have on the five airports. However, as a next step, we aim to integrate the varying impact into the staff scheduling for an RTC with AP1–AP5 in remote control. Hence, we need to decide what constitutes a threshold over which a weather phenomenon influences ATCO's work at an airport significantly. In our prior work Josefsson et al. (2020), taking Table 1 into account, we used a value of 0.5 as a cutoff for the taskload-driven impact factor (with the rationale being that an impact that happens at least sometimes is strong enough to necessitate integration in planning). In this paper, apart from introducing a new method for the integration of weather uncertainty, 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.

In operational staff scheduling, the cutoff value may be changed depending on the operator's estimate of what constitutes a strong enough impact to be accounted for. In Table 2, we summarize the strength of a weather phenomenon at each airport that has an average taskload-driven impact factor of at least 0.7, 0.6, 0.5, 0.4, 0.3, and 0.2, respectively, and which, hence, is considered strong enough that it must be accounted for in staff planning.

5. Weather input

In this section, we describe Steps (2) and (3) from Section 3, related to the definition of numerical thresholds for different impactful weather phenomena and to the retrieval of probabilistic weather information from EPS.

5.1. EPS

Weather forecasts inevitably involve some level of uncertainty, which is a consequence of the chaotic nature of the atmosphere and the limited capacity to measure and model meteorological conditions. Probabilistic weather forecasts include quantitative information about this uncertainty intrinsic to meteorological predictions. One popular probabilistic weather forecasting technique is ensemble weather forecasting (EWF), which consist of generating a range of future weather possibilities. Today's trend is to use EPS, which is based on running a deterministic Numerical Weather Prediction (NWP) model multiple times from slightly different initial conditions and with slightly perturbed weather models (World Meteorological Organization, 2012). Typically, an EPS is a collection of 10 to 50 forecasts, referred to as members; the uncertainty information is on the spread of the members.

Probabilistic weather information obtained from EPS can be integrated into aviation problems using two different approaches. In the first one, probability distributions of meteorological parameters of interest are obtained from the ensemble forecast, and these distributions are used later to obtain the probability distribution of the sought solution using a probabilistic methodology (transformation approach). In the second approach, a deterministic methodology is used for each member of the ensemble, leading to an ensemble of solutions from which probability distributions can be derived (ensemble approach). In

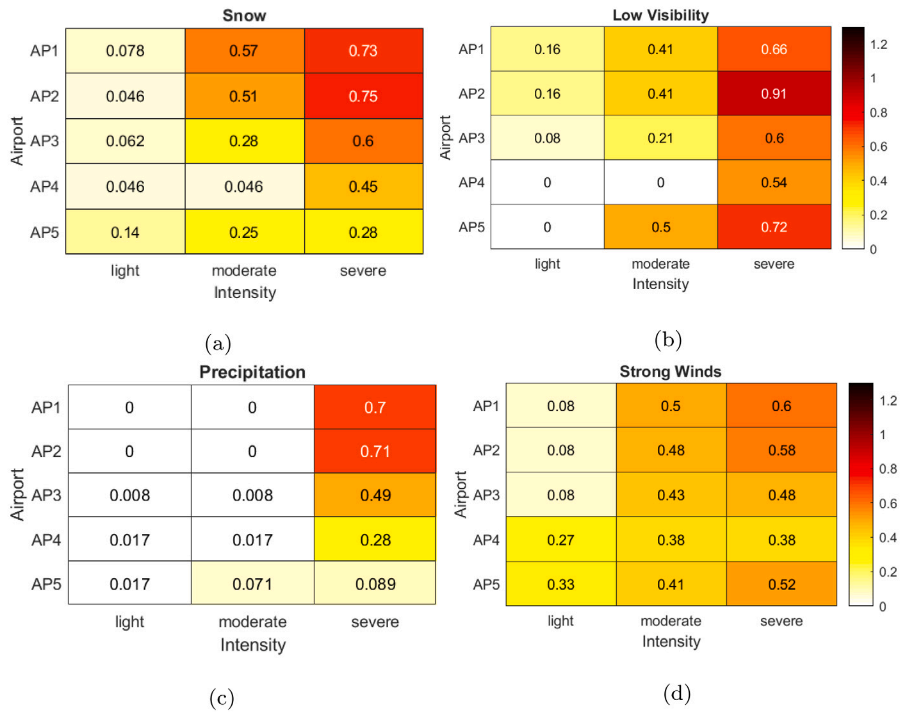

Fig. 1. Impact-heat tables for (a) snow, (b) low visibility, (c) precipitation, and (d) strong winds.

Table 2
Weather Intensity for different Average Taskload-Driven Impact Factors.

		Cutoff value for average taskload-driven impact factor					
Airport	Intensity	≥0.7	≥0.6	≥0.5	≥0.4	≥0.3	≥0.2
AP1	Snow	severe	severe	moderate	moderate	moderate	moderate
	Low visibility	–	severe	severe	moderate	moderate	moderate
	Precipitation	severe	severe	severe	severe	severe	severe
	Strong winds	–	severe	moderate	moderate	moderate	moderate
AP2	Snow	severe	severe	moderate	moderate	moderate	moderate
	Low visibility	severe	severe	severe	moderate	moderate	moderate
	Precipitation	severe	severe	severe	severe	severe	severe
	Strong winds	–	–	severe	moderate	moderate	moderate
AP3	Snow	–	severe	severe	severe	severe	moderate
	Low visibility	–	severe	severe	severe	severe	moderate
	Precipitation	–	–	–	severe	severe	severe
	Strong winds	–	–	–	moderate	moderate	moderate
AP4	Snow	–	–	–	severe	severe	severe
	Low visibility	–	–	severe	severe	severe	severe
	Precipitation	–	–	–	–	–	severe
	Strong winds	–	–	–	–	moderate	light
AP5	Snow	–	–	–	–	–	moderate
	Low visibility	severe	severe	moderate	moderate	moderate	moderate
	Precipitation	–	–	–	–	–	–
	Strong winds	–	–	severe	moderate	light	light

our prior work Josefsson et al. (2020), we followed the first approach. In this paper, the second approach is employed.

For the sake of illustration, the probabilistic weather information in this paper is obtained from the European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis dataset. 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 a spacial granularity of 30 km and 137 vertical levels from the surface up to a height of 80 km. The dataset includes an uncertainty estimation for ERA5 in the form of a 10-member ensemble (European Centre for Medium-Range Weather Forecasts, 2021), which has a temporal granularity of three hours. We use this last ensemble product to illustrate the capabilities of our methodology in this paper.

5.2. Numerical weather thresholds

Next, we define the parameters quantifying the weather phenomena and identify the thresholds corresponding to different intensities of the weather phenomena.

The selection of weather parameters and numerical weather thresholds in this paper is inspired by the work of Taszarek et al. (2020), where the authors use ERA5 reanalysis data to define proxies associated with hazardous weather conditions causing disruptions in European air traffic. Notice that, as mentioned in Taszarek et al. (2020), the defined thresholds are only proxies of a potential impactful weather occurrence, and they cannot be considered discriminators that will perfectly distinguish between particular hazardous and non-hazardous weather events.

Table 3
ERA5 parameters for impactful weather phenomena.

Weather phenomenon	ERA5 parameter	Variable
Strong winds	Instantaneous 10 meter wind gust	$i10fg$
Low visibility	Cloud base height Low cloud cover	cbh lcc
Snow	Snowfall	sf
Precipitation	Total precipitation	tp
Convective activity	Convective available potential energy Convective precipitation	$CAPE$ cp

The weather parameters and some of the thresholds herein described are tailored to the ECMWF ERA5 reanalysis ensemble product. Should any other ensemble weather product be used as a source for weather data, it may be necessary to revisit and adapt these parameters.

The chosen numerical values for the different impactful weather events of light, moderate and severe intensity for the different airports can be classified into two types: airport-specific threshold values obtained from the ATCO interviews, and general threshold values derived from literature. A summary of the used ERA5 weather parameters and the correspondent variables can be found in Table 3.

Airport-specific thresholds. We have identified two weather phenomena whose threshold values were described by ATCOs in the conducted interviews, and that vary from airport to airport: strong winds and low visibility.

The weather parameter of the ERA5 reanalysis ensemble product used to identify strong winds is the instantaneous maximum wind gust at a height of ten meters above the surface of the Earth ($i10fg$). The ATCO working at airports AP1, AP2, and AP3 defined moderate wind with values between 15 knots and 25 knots for all the three airports; with this information, moderate winds in these airports are identified in the range 15 knots$\leq i10fg<$25 knots, and severe winds for $i10fg\geq$25 knots. The ATCO working at AP5 defined light wind to be more than 15 knots, moderate wind to be between 25 and 35 knots, and severe wind to be above 35 knots; the thresholds for strong winds in airports AP4 and AP5 are based on this description.

Following the work of Taszarek et al. (2020), low visibility thresholds are based on the decision height defined by the Instrument Landing System (ILS). Two weather parameters in the ERA5 reanalysis data, cloud base height (cbh) and low cloud cover (lcc), are used to identify this decision height. We have approximated the decision height as the cbh, with the condition that the values of lcc describe a broken (BKN) sky (over five oktas, or, equivalently, $lcc\geq$0.625) (US Department of Transportation. Federal Aviation Administration, 2016). In the interviews, ATCOs at airports AP1, AP2, AP3, and AP4 identified severe low visibility at 550 m Runway Visual Range (RVR); which is the equivalent to ILS CAT I, with a decision height of 200 ft. They also described moderate low visibility as RVR values around 800 m. Taking this into account and using the decision height values for different RVRs described in European Commission (2007), the cbh threshold used as a proxy for severe low visibility in airports AP1 to AP4 is $cbh\leq$200 ft (RVR<550 m), while moderate low visibility sits in the range 200 ft$<cbh\leq$301 ft (550 m≤RVR<800 m). On the other hand, the ATCO in airport AP5 identified severe low visibility at 300 m (equivalent to ILS CAT II, with a decision height of 100 ft). For this last airport, we considered the described thresholds for ILS CAT I as the thresholds for light and moderate low visibility, and define a new value for severe low visibility as $cbh\leq$100 ft (RVR<300 m).

The values of the numerical thresholds at each airport for wind and low visibility are collected in Table 4.

Table 4
Airport-dependent numerical thresholds for impactful weather phenomena.

Airport	Intensity	Strong winds	Low visibility
AP1	Light Moderate Severe	– 15 knots$\leq i10fg<$25 knots $i10fg\geq$25 knots	– 200 ft$<cbh\leq$301 ft, $lcc\geq$0.625 $cbh\leq$200 ft, $lcc\geq$0.625
AP2	Light Moderate Severe	– 15 knots$\leq i10fg<$25 knots $i10fg\geq$25 knots	– 200 ft$<cbh\leq$301 ft, $lcc\geq$0.625 $cbh\leq$200 ft, $lcc\geq$0.625
AP3	Light Moderate Severe	– 15 knots$\leq i10fg<$25 knots $i10fg\geq$25 knots	– 200 ft$<cbh\leq$301 ft, $lcc\geq$0.625 $cbh\leq$200 ft, $lcc\geq$0.625
AP4	Light Moderate Severe	15 knots$\leq i10fg<$25 knots 25 knots$\leq i10fg<$35 knots $i10fg\geq$35 knots	– 200 ft$<cbh\leq$301 ft, $lcc\geq$0.625 $cbh\leq$200 ft, $lcc\geq$0.625
AP5	Light Moderate Severe	15 knots$\leq i10fg<$25 knots 25 knots$\leq i10fg<$35 knots $i10fg\geq$35 knots	200 ft$<cbh\leq$301 ft, $lcc\geq$0.625 100 ft$<cbh\leq$200 ft, $lcc\geq$0.625 $cbh\leq$100 ft, $lcc\geq$0.625

Table 5
General numerical thresholds for impactful weather phenomena.

Intensity	Snow	Precipitation
Light	$0<sf\leq1$ mmh^{-1}	$0<tp\leq2.5$ mmh^{-1}
Moderate	1 mmh^{-1} $<sf\leq2.5$ mmh^{-1}	2.5 mmh^{-1} $<tp\leq10$ mmh^{-1}
Severe	$sf>2.5$ mmh^{-1}	$tp>10$ mmh^{-1}

General thresholds. General thresholds are defined for snow, precipitation and convective activity events. The chosen parameter of the ERA5 ensemble product used to measure snow is the accumulated snowfall over the time interval of three hours, measured in meters of water equivalent; the snowfall rate (sf), measured in millimeters per hour, is obtained by evenly dividing the accumulated snowfall over these three hours. The thresholds for light, moderate and severe snowfall are obtained from the guidelines of the Society of Automotive Engineers' (SAE) Ground Deicing group, also accepted by the International Civil Aviation Organization (ICAO) (International Civil Aviation Organization, 2008): light snowfall falls in the range 0 to 1 mm per hour, moderate snowfall is considered to fall between 1 mm and 2.5 mm per hour, and severe snowfall is registered for values over 2.5 mm per hour.

To measure precipitation, we used the total precipitation accumulated over three hours. Similar to the case of snowfall, we divide the accumulated precipitation by the three-hour time interval to obtain the total precipitation rate (tp). The thresholds for light, moderate, and severe precipitation are based on the World Meteorological Organization guidelines, described by ICAO in Doc 9837 (International Civil Aviation Organization, 2011): light precipitation comprises values between 0 and 2.5 mm per hour, moderate precipitation falls between 2.5 mm and 10 mm per hour, and severe precipitation exceeds 10 mm per hour.

The numerical thresholds for snowfall and precipitation are summarized in Table 5. As previously mentioned in Section 4.4, we treat convective activity as a binary variable. Following the work of Taszarek et al. in (2020) and (2019), thresholds for two parameters in the ERA5 reanalysis model are used as a proxy for convective initiation: convective available potential energy ($CAPE$) and convective precipitation (cp). $CAPE$ is a measurement of the potential outbreak of a thunderstorm; in particular, it is a vertical integral of the thermal buoyancy of a hypothetical air parcel that is lifted from its original vertical position (Groenemeijer et al., 2019). For the ascending parcel considered for the calculation of $CAPE$ in the ECMWF Integrated Forecasting System (IFS), 1000 Jkg^{-1} can be considered a threshold for the potential outbreak of convective activity (European Centre for Medium-Range Weather Forecasts, 2021). An additional proxy for convective activity is the occurrence of convective precipitation. Following the definition of a thunderstorm day in Taszarek et al. (2019), we define a value of $cp\geq$0.075 mmh^{-1}. In summary, convective activity is identified when both conditions $CAPE\geq$1000 Jkg^{-1} and $cp\geq$0.075 mmh^{-1} are met.

Table 6
Notation: Parameters.

Parameter	Definition
A	Set of airports
A^+	Set of airports for breaks
C	Set of controllers
P	Set of time periods
p	Number of time periods
z	Max number of consecutive periods controller is in position
$Mov_{\max}$	Max number of movs per controller per period
$A_{\max}$	Max number of airports per controller per period
$C_{\max}$	Max number of controllers per airport per period
$Amov_{a,h}$	Number of movs at airport a during period h
$op_{a,h}$	=1 if airport a is open during period h, = 0 otherwise
$\ell_{i,a}$	=1 if controller i holds endorsement to control airport a
Γ	Set of airports which have conflicts in schedules
$\Gamma_{a,a'}$	Set of periods when airport a has conflicts with airport a'
$T_{\max}$	Upper bound on the length of controller shift
$T_{\min}$	Lower bound on the length of controller shift
$B_{\min}$	Minimum number of break periods per controller
$B_{\max}$	Maximum number of break periods per controller
$R_{\min}$	Minimum rest periods between the shifts
$R_{\max}$	Maximum rest periods between the shifts

Table 7
Notation: Variables.

Variable	Definition
q_i	binary, = 1 if controller i is used during some period
$y_{i,h}$	binary, = 1 if controller i is at work during period h
$v_{i,h}$	binary, = 1 if controller i starts his shift at period h
$period_{i,a,h}$	binary, = 1 if controller i is assigned to airport a during period h
$mov_{i,a,h}$	number of movs handled by controller i at airport a during period h
$w_{i,h}$	number of consecutive periods including h controller i is at work

6. Optimal RTC staff scheduling

Our MIP for RTC staff scheduling is based on our prior work (Josefsson et al., 2017). Hence, we start with recapitulating that MIP and present some changes to it, which refer solely to shift properties. Then, we introduce constraints to take care of periods during which impactful weather appears at an airport. Finally, we describe the computation of the probability distribution of the necessary number of ATCOs using EPS.

6.1. MIP for RTC staff scheduling

Tables 6 and 7 summarize the notation used in this section. Constraints of our original MIP are given in Eqs. (1)–(17) (we create a cyclic schedule, hence, we consider the periods, h, modulo the total number of periods,(mod p), whenever we do not consider a single period only).

$$\sum_{a\in A} mov_{i,a,h} \le Mov_{\max} \quad \forall i\in C, \forall h\in P \tag{1}$$

$$\sum_{a\in A\cup A^+} period_{i,a,h} \le y_{i,h}\cdot A_{\max} \quad \forall i\in C, \forall h\in P \tag{2}$$

$$mov_{i,a,h} \le period_{i,a,h}\cdot Mov_{\max} \quad \forall i\in C, \forall a\in A, \forall h\in P \tag{3}$$

$$\sum_{i\in C} mov_{i,a,h} = Amov_{a,h} \quad \forall a\in A, \forall h\in P \tag{4}$$

$$\sum_{i\in C} period_{i,a,h} \ge op_{a,h} \quad \forall a\in A, \forall h\in P \tag{5}$$

$$\sum_{i\in C} period_{i,a,h} \le C_{\max} \quad \forall a\in A, \forall h\in P \tag{6}$$

$$period_{i,a,h} + period_{i,a',h} \le 1 \quad \forall i\in C, \forall a,a'\in\Gamma, \forall h\in\Gamma_{a,a'} : a\ne a' \tag{7}$$

$$\sum_{h\in P} period_{i,a,h} = 0 \quad \forall i\in C, \forall a\in A\cup A^+ : \ell_{i,a}=0 \tag{8}$$

$$v_{i,h} \ge y_{i,h} - y_{i,(h-1)(\mathrm{mod}\ p)} \quad \forall i\in C, \forall h\in P \tag{9}$$

$$v_{i,h} \le y_{i,h} \quad \forall i\in C, \forall h\in P \tag{10}$$

$$\sum_{\eta=h+1-T_{\min}}^{h} v_{i,\eta(\mathrm{mod}\ p)} \le y_{i,h} \quad \forall i\in C, \forall h\in P \tag{11}$$

$$\sum_{\eta=h+1-T_{\max}}^{h} v_{i,\eta(\mathrm{mod}\ p)} \ge y_{i,h} \quad \forall i\in C, \forall h\in P \tag{12}$$

$$\sum_{h\in P} v_{i,h} \le 1 \quad \forall i\in C \tag{13}$$

$$period_{i,a,h} + period_{i,a',h} \le 1 \quad \forall i\in C, \forall a\in A, \forall a'\in A^+, \forall h\in P : \ell_{i,a}=\ell_{i,a'}=1 \tag{14}$$

$$y_{i,h} \le \sum_{\substack{a\in A:\\ \ell_{i,a}=1}} period_{i,a,h} + \sum_{\substack{a'\in A^+:\\ \ell_{i,a'}=1}} period_{i,a',h} \quad \forall i\in C, \forall h\in P \tag{15}$$

$$w_{i,h} = \sum_{\eta=h}^{h+z-1} (y_{i,\eta(\mathrm{mod}\ p)} - period_{i,a,\eta(\mathrm{mod}\ p)}) \quad \forall i\in C, \forall a\in A^+ : \ell_{i,a}=1, \forall h\in P \tag{16}$$

$$period_{i,a,(h+z)(\mathrm{mod}\ p)} \ge (1/z)\cdot w_{i,h} - (z-1)/z \quad \forall i\in C, \forall a\in A^+ : \ell_{i,a}=1, \forall h\in P \tag{17}$$

We introduce some changes to the MIP from (Josefsson et al., 2017):

$$\sum_{\eta=h+1}^{h+R_{\min}} v_{i,\eta(\mathrm{mod}\ p)} \le q_i - y_{i,h(\mathrm{mod}\ p)} \quad \forall i\in C, \forall h\in P \tag{18}$$

$$\sum_{\eta=h+1}^{h+R_{\max}} v_{i,\eta(\mathrm{mod}\ p)} \ge q_i - y_{i,h(\mathrm{mod}\ p)} \quad \forall i\in C, \forall h\in\{1\ldots p-R_{\max}\} \tag{19}$$

$$\sum_{h\in P} period_{i,a,h} \le B_{\max} \quad \forall i\in C, \forall a\in A^+ : \ell_{i,a}=1 \tag{20}$$

$$\sum_{h\in P} period_{i,a,h} \ge B_{\min}\cdot q_i \quad \forall i\in C, \forall a\in A^+ : \ell_{i,a}=1 \tag{21}$$

Eq. (1) enforces a maximum number of movements that any ATCO handles during any period; Eq. (2) enforces a maximum number of airports that any ATCO handles during any period. With Eq. (3), we ensure that an ATCO handles (at most $Mov_{\max}$) movements at an airport only if the ATCO is assigned to that airport during the same period. Eq. (4) guarantees that all movements (at all airports and during all periods) are assigned to some ATCO. Eq. (5) guarantees that all opening hours of all airports are covered. Eq. (6) yields a maximum number of ATCOs assigned to the same airport during any period. Eq. (7) makes sure that potential conflicts in airport schedules are avoided (that is, two airports with simultaneous movements during a 5-min interval are never assigned to the same ATCO during the period in which this interval falls). Eq. (8) enforces that no ATCO is assigned to an airport for which the ATCO does not hold an endorsement, that is, that ATCOs are assigned only to those airports, for which they hold endorsements.

The remaining constraints implement the operational controller shift requirements. Our formulation of ATCO shifts is based on the on/off sequences presented by Pochet and Wolsey (Pochet and Wolsey, 2006). We use auxiliary, artificial "break" airports: the set A^+. Each ATCO holds an endorsement for $A_{\max}$ individual such break airports (i.e., exactly one controller holds an endorsement for each of the airports in A^+). We consider the breaks as part of the working day, and controllers are assigned to airports in A^+ during their breaks. No opening hours at these airports need to be covered. After z continuous hours of work at "real" airports, the ATCO must be assigned to an airport in A^+.

Eqs. (9) and (10) ensure that an ATCO can start a shift during period h only if they do not work during period $h-1$ and do work at all during h. Eqs. (11) and (12) yield the lower and upper bound on the shift length (i.e., a minimum and a maximum ATCO shift length): when working during period h the ATCO cannot have started their shift during the last $T_{\min}-1$ periods, but must have started their shift during the last $T_{\max}-1$ periods. With Eq. (13), we yield that an ATCO only works at all, if the ATCO starts a shift at some point. Eq. (14) lets ATCOs work only at a real airport or on a "break" airport, but not on one of each simultaneously; Eq. (15) ensures that an ATCO is at work during period h only if the ATCO is assigned to work at some real or break airport during that period. Finally, we aim to enforce a maximum and a minimum number of consecutive periods during which an ATCO may work "in position" (a maximum and minimum continuous time "in position"). With Eq. (16), we look z periods ahead (including the currently considered period h) and count the number of periods among these z periods during which an ATCO worked in position (that is, was assigned to at least one airport from A). Eq. (17) then enforces an assignment to a break airport in period $h+z$, if the ATCO worked all z periods (period h until period $h+z-1$): if $w_{i,h}=z$ (i.e., if ATCO i worked all z periods from period h until $h+z-1$), the right-hand side of Eq. (17) equals $\frac{1}{z}$, which enforces the left-hand binary to be 1; if $w_{i,h}<z$, the right-hand side of Eq. (17) is less or equal to zero, and, hence, the left-hand side is not forced to a specific value.

Eqs. (18) and (19) enforce a minimum and maximum rest period (time off work) between two consecutive shifts for an ATCO. Eqs. (20) and (21) enforce that each controller takes at most $B_{\max}$ and at least $B_{\min}$ breaks.

As objective function we choose the minimization of the number of ATCOs (in addition, when we want to improve the resulting schedules, we can minimize airport-assignment switches or the average number of ATCOs per airport, as in Josefsson et al. (2017)):

$$\min \sum_{i\in C} q_i \tag{22}$$

6.2. Integrating impactful weather periods into the MIP

We introduce a final constraint that enforces an airport with impactful weather during an hour h to be handled in single mode during that time. We introduce a new binary parameter $s_{a,h}$, which is 1 if airport a must be operated in single mode in period h, and a new Constraint (23): If an airport a must be operated in single mode in period h (because of impactful weather at a during h, that is, if in the ensemble member we have a weather-phenomenon intensity at a during h for which the taskload-driven impact factor exceeds the cutoff value), an ATCO assigned to a in h may not be assigned to any other airport in h. This substitutes the old Constraint (2).

$$\sum_{\substack{a'\in\\ A\cup A^+}} period_{i,a',h (\mathrm{mod}\ p)} \le y_{i,h (\mathrm{mod}\ p)} \cdot A_{\max} - (A_{\max}-1)s_{a,h}\cdot period_{i,a,h (\mathrm{mod}\ p)}$$

$$\forall i\in C,\ \forall h\in P,\ \forall a\in A \tag{23}$$

We give an example for setting the parameter $s_{a,h}$: Assume that in the considered ensemble member, we have severe low visibility at AP1 during hour 5 (i.e., $cbh \le 200ft, lcc \ge 0.625$). The taskload-driven impact factor of severe low visibility at AP1 is 0.66 (Fig. 1b). If we use a cutoff value of 0.6 this yields that AP1 should be operated in single mode during hour 5, that is, $s_{\mathrm{AP1},5}=1$.

6.3. Distribution of necessary number of ATCOs

The probability distribution of the necessary number of ATCOs (Q) is obtained using the described MIP and EPSs as follows. For each of the M EPS ensemble members, we solve the MIP and obtain the number $Q_m, m=1\ldots M$ of ATCOs needed. Then the probability that at most k ATCOs are needed is:

$$P(Q\le k)=\frac{1}{M}\sum_{m=1}^{M} X_m(k), \tag{24}$$

where

$$X_m(k)=\begin{cases} 1 & \text{if} \quad Q_m\le k,\\ 0 & \text{otherwise.}\end{cases} \tag{25}$$

7. Experimental study: Sweden

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 AP1–AP5 in remote control. We follow Steps (1)-(5) from Section 3.

(1) Identify impactful weather phenomena for each considered airport: We considered AP1-5, and the impactful weather phenomena were identified as described in Section 4.4, Table 2.

(2) Define threshold values for the impactful weather phenomena: We deduced threshold values for the impactful weather phenomena from Table 2 in Section 4.4, and the chosen values are listed in Section 5.2.

(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:

- February 16, 2020: A winter day during which four out of the five considered weather phenomena occurred: snow, low visibility, strong wind and precipitation.
- 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 5.1, the ERA5 reanalysis ensemble presents weather data every three hours. The hourly weather variables used in this work are obtained 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. The movement data for February 16, 2020, and July 29, 2020, is shown in Fig. 2(a) and (b), respectively. 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.

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

The following parameters are set for the experiments to reflect the safety and efficiency requirements for RTC personnel operation typical for controller shifts (Josefsson et al., 2017):

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

(a)

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

(b)

Fig. 2. The number of flight movements for the five Swedish airports during nine hours of operation on (a) February 16, 2020, and (b) July 29, 2020.

(a) *Maximum number of airports assigned to one controller (A_{max})*: The default value of the maximum number of airports assigned to a controller is set to 2. From the experts we learned that there may be problems with visual representation, communication, and switching between the views when more than two airports are controlled by the same person within one remote tower module. But theoretically it is possible to control even more airports from one controller working position, e.g., three airports are considered in simulation studies by DLR (Friedrich et al., 2020).
(b) *Maximum number of movements per controller per period (Mov_{max})*: The maximum number of movements one controller handles at the remote tower during one hour is set to 10. This conservative assumption represents a manageable workload for the ATCO.
(c) *Maximum number of controllers per airport (C_{max})*: In this work we assume each airport is handled by one ATCO during each period of time. But in principle, for safety reasons it may be needed to assign two controllers to control one airport. Our model provides such a possibility.
(e) *Length of controller shift (T_{min} and T_{max})*: The total time a controller spends at work should be between 3 and 9 h.
(g) *Maximum continuous time without break (z)*: Controllers should not work "in position" for longer than 4 h without break.
(i) *Length of controller breaks (B_{min} and B_{max})*: The controller is restricted to have at least 1 but no more than 4 h for the breaks, which matches requirements for the lengths of controller shift and total hours "in position".
(j) *Time between the shifts (R_{min} and R_{max})*: In between two shifts an ATCO must rest for at least 2 but at most 10 h. These parameters are based on the considered time interval of 9 h: as we create a cyclic schedule, parameter values used for actual 24/7 operation would not create realistic solutions here. For daily or weekly schedules larger values should be used.
(k) *Period*: The length of the time period is one hour.

As described in Section 4.4, we use six different cutoff values (0.2, 0.3, 0.4, 0.5, 0.6, and 0.7) to perform a sensitivity analysis and study the impact on the number of ATCOs needed. We solve our MIP from Section 6 for each of six cutoff values for each of ten EPS members getting as a result 60 scenarios for each day. Additionally, we—using our MIP without Constraint (23)—compute the minimum number of ATCOs necessary when no weather influence is taken into account. We use Gurobi optimization software installed on a very powerful Tetralith server (Anon, 2020), utilizing the Intel HNS2600BPB computer nodes with 32 CPU cores, 384 GiB, provided by the Swedish National Infrastructure for Computing (SNIC). The computational time of each run of our optimization program on this powerful machine varied between 0.08 and 3.03 s with an average value of 0.38 s.

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. Taking weather into account, we obtain different distributions of the number of necessary ATCOs dependent on the cutoff value (see also Fig. 3 for bar diagrams):

- February 16, 2020
  - Cutoff 0.2: 8 ATCOs necessary with a probability of 100%
  - Cutoff 0.3: 8 ATCOs necessary with a probability of 100%
  - Cutoff 0.4: 8 ATCOs necessary with a probability of 100%
  - Cutoff 0.5: 7 and 8 ATCOs necessary with a probability of 30% and 70%, respectively
  - Cutoff 0.6: 6 ATCOs necessary with a probability of 100%
  - Cutoff 0.7: 5 ATCOs necessary with a probability of 100%
- July 29, 2020
  - Cutoff 0.2: 5 and 6 ATCOs necessary with a probability of 30% and 70%, respectively
  - Cutoff 0.3: 5 and 6 ATCOs necessary with a probability of 30% and 70%, respectively
  - Cutoff 0.4: 5 and 6 ATCOs necessary with a probability of 30% and 70%, respectively
  - Cutoff 0.5: 5 and 6 ATCOs necessary with a probability of 90% and 10%, respectively
  - Cutoff 0.6: 5 and 6 ATCOs necessary with a probability of 90% and 10%, respectively
  - Cutoff 0.7: 5 ATCOs necessary with a probability of 100%

The following additional metrics are summarized in Tables 8 and 9:

- Average number of ATCOs per airport: we count the number of controllers assigned to each particular airport during the day and calculate the average over the given number of airports.
- Average number of endorsements per ATCO: for each controller we count the number of airports he/she is assigned to during the day and calculate the average over the number of controllers.
- Average time at work: we count the total number of hours controllers spend at work (including breaks) and take the average over the number of controllers.
- Average time "in position": for each controller we count the number of hours each controller works "in position" and calculate the average over the number of controllers.
- Coefficient of performance (COP): for each controller we calculate the ratio of the time "in position" over the total time at work, and take the average over the number of controllers. This metric may be interpreted as an indicator of the controller's work intensity, and at the same time represents the quality of the resulting controller shift, as it shows the percentage of the time a controller is actually "in position" during his/her shift.

To calculate these metrics we fixed the number of controllers (to the minimum number we obtained) and ran the experiments with another objective, minimizing the number of active controllers per airport, using the approach developed in Josefsson et al. (2017). Additionally, we took an average over ensemble members statistics.

Discussion. We can clearly observe the impact of weather and the cutoff value on the resulting distribution of the number of necessary ATCOs. If we optimize the number of ATCOs without taking weather into account, we would plan to schedule 5 ATCOs for both days. For February 16, 2020, 8 ATCOs need to be scheduled when a low taskload-driven impact factor (with cutoff value 0.2) is taken into account, while

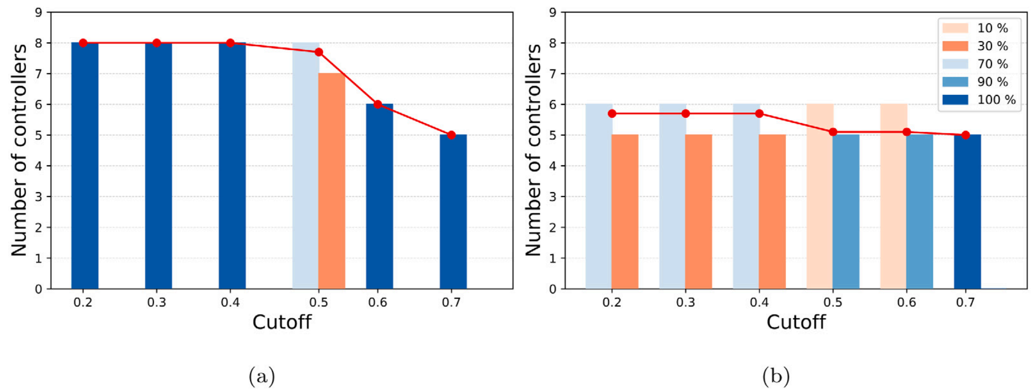

Fig. 3. Distribution of the necessary number of ATCOs with different cutoff values for (a) February 16, 2020, and (b) July 29, 2020. Red dots indicate the expected value for the necessary number of ATCOs (the red line indicates the trend of this expected value).

Table 8
Statistics for the roster for February 16, 2020.

Cutoff	Av. # of ATCOs per airport	Av. # of airports per ATCO	Av. time in position, hours	Av. time at work, hours	COP
0.2	2	1.25	5.63	6.75	0.83
0.3	2	1.25	5.63	6.75	0.83
0.4	2	1.25	5.63	6.75	0.83
0.5	2.04	1.33	5.73	6.85	0.84
0.6	2	1.67	6	7	0.86
0.7	2	2	5.68	6.98	0.81
No weather	2	2	5.8	7	0.83

Table 9
Statistics for the roster for July 29, 2020.

Cutoff	Av. # of ATCOs per airport	Av. # of airports per ATCO	Av. time in position, hours	Av. time at work, hours	COP
0.2	2	1.77	5.89	6.98	0.84
0.3	2	1.77	5.89	6.98	0.84
0.4	2	1.77	5.89	6.98	0.84
0.5	2	1.97	5.78	6.94	0.83
0.6	2	1.97	5.76	6.92	0.83
0.7	2	2	5.82	7	0.83
No weather	2	2	5.8	7	0.83

only 5 are needed for a cutoff value of 0.7. For July 29, 2020, 5 ATCOs will be sufficient only with 30% probability if we choose a low cutoff for the impact factor (0.2), but with 100% probability in case of a cutoff value of 0.7.

The choice of an appropriate cutoff value depends on the preferences of the operational manager: With a lower cutoff value a higher safety level can be achieved, as a larger set of potentially critical situations is avoided, however, this comes at the cost of using more staff members. That is, we see a clear trade-off between safety level (reflected in the chosen cutoff level) and staffing need, with the resulting higher HR cost.

From the roster statistics, we observe that the cutoff value does have hardly any impact on the average number of ATCOs that are assigned to work with an airport during the 9-h time intervals. However, with increasing cutoff value, the average number of served airports per ATCO increases—with a higher cutoff value airports are operated in single mode less frequently, thus, ATCOs are more often working in multiple position and, hence, need to be trained for more airports.

We used a weather product with ten ensemble members. Consequently, our probabilities come in a step size of 10%. Thus, the lowest non-zero probability for a number of necessary ATCOs is 10%, which—depending on the desire to include even less likely scenarios—might be a reasonable value to take into account. With weather products with more ensemble members, finer granularity in the resulting distribution can be achieved. Operations might then opt to ignore a probability of, e.g., 2% (possible with at least 50 ensemble members).

The probabilistic weather information used for this paper stems from the ERA5 data set, which was used to illustrate the capabilities of our staffing model. This is not a weather forecast, hence, the distribution of weather features less variability than a probabilistic forecast would. Consequently, while in our experiments several cutoff values led to a number of necessary ATCOs with 100% probability, this is less likely in the actual application scenario for forecasting in which we will have probabilistic weather information that will most likely present higher variability.

Finally, while we do consider taskload-driven impact factors and while the taskload does not vary between different ATCOs, the workload, that is, the subjective stress experienced during the same tasks can vary depending on, e.g., ATCO experience, ATCO age, etc. This could be taken into account when determining the appropriate cutoff value.

Practical application. 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 results in a higher safety level. The implementation of such a schedule, which may have significant variations in the number of ATCOs from day to day, can be challenging. However, we see clear benefits of being prepared instead of facing possible staff shortages on the day of operation. Moreover, the training unit could complement the new schedules by planning training events during days with fewer scheduled ATCOs: the ATCOs working not in position can be trained to sustain their competence, which contributes also to a higher overall safety level.

8. Conclusion

We proposed a method to account for weather impact on ATCO work in RTC staff 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. 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.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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