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Enhancing Air Traffic Management: Weather and Controller Workload Challenges

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Sammanfattning

Lufttrafikledning (ATM) står inför betydande utmaningar när det gäller att säkerställa effektivitet, säkerhet och hållbarhet. Väderförhållanden och flygtrafikledarnas (ATCO) arbetsbelastning spelar en avgörande roll för det övergripande systemets prestanda. Ogynnsamma väderförhållanden stör ofta verksamheten, vilket leder till ineffektiva flygvägar, ökad bränsleförbrukning och miljöpåverkan. Det medför även en ökad arbetsbelastning för ATCO, vilket försvårar deras förmåga att upprätthålla ett säkert och effektivt trafikflöde. Denna avhandling undersöker datadrivna och analytiska metoder för att hantera dessa utmaningar, med fokus på vädrets inverkan på flygeffektivitet, luftrumskapacitet och ATCO-planering i fjärrstyrda torncentraler. Dessutom analyseras ATCO-arbetsbelastningsprognoser baserade på beteendemässiga och fysiologiska data. Studien omfattar tillämpningar inom luftrumskapacitetshantering, personalplanering och bedömning av ATCO:s arbetsbelastning.

Studien analyserar historiska flyg- och väderdata från Stockholm Arlanda och Göteborg Landvetter flygplatser under en tvåårsperiod (2019–2020) och belyser kvarstående ineffektivitet trots minskad trafik under COVID-19-pandemin. Denna avhandling presenterar en metodik baserad på statistisk analys för att identifiera de viktigaste faktorerna som påverkar olika aspekter av ankomstprestanda, med särskilt fokus på effekterna av ogynnsamt väder och trafikintensitet. Den föreslagna metoden identifierar specifikt de mest betydande faktorerna som påverkar ankomstprestanda i både horisontella och vertikala dimensioner.

Ogynnsamma väderförhållanden, såsom konvektivt väder, kan leda till restriktioner för flygrörelser, minska tillgängliga rutter och kräva justeringar av ATM-strategier. Därför är det avgörande att förstå och förutsäga väderrelaterade effekter på luftrumskapaciteten för att optimera lufttrafikflödet och minimera förseningar. I denna avhandling utvecklar vi en metodik, baserad på den kontinuerliga maxflow/mincut-teorin, för att uppskatta minskningar i flygtrafikledningens (ATC) sektorkapacitet till följd av förutspådd konvektiv väderaktivitet. Osäkerheten i meteorologiska prognoser kvantifieras med hjälp av ensembleväderprognoser. Vi demonstrerar tillämpningen av denna metodik för att bedöma trängsel i ATC-sektorer, med exempel på en realistisk sektor och en fullständig sektorkonfiguration. Vi introducerar dessutom ett probabilistiskt ramverk för att presentera

trängselstatus, med syfte att stödja beslutsprocesser vid flödeshanteringspositionen.

Studien presenterar probabilistiska modeller som integrerar effekten av ogynnsamma väderförhållanden i ett blandat heltalslinjärt optimeringsramverk för ATCO-skift-schemaläggning i både fjärrstyrda och konventionella torn. Dessa modeller hanterar specifikt vädrets inverkan på ATCO:s arbete i fjärrstyrda torn genom att bygga vidare på tidigare projektutvecklingar. Probabilistiska väderprodukter används för att generera ensemblelösningar för bemanning, vilket möjliggör härledning av sannolikhetsfördelningar för det nödvändiga antalet ATCO:er. Denna modellansats utnyttjar nyligen utvecklade tekniker för att hantera utmaningar kopplade till väderosäkerhet. De föreslagna lösningarna valideras med hjälp av historiska flyg- och väderdata från fem svenska flygplatser som är utpekade för framtida fjärrstyrd drift.

Den sista delen av denna avhandling fokuserar på att utveckla diskreta metoder för att förutsäga ATCO:s arbetsbelastning genom att undersöka möjligheterna med icke-intrusiva datainsamlingstekniker i kombination med maskininlärningsalgoritmer. Ögonrörelsedata, som tidigare har identifierats som en lovande indikator för ATCO:s arbetsbelastning, samlades in från flygtrafikledare i simulerade miljöer och användes som prediktiva variabler. Subjektiva arbetsbelastningsbedömningar, baserade på självskattade Cooper-Harper-skattningar, användes som målvariabler. Flera maskininlärningsmodeller utvärderades för att förutsäga arbetsbelastning, och tekniker för variabelurval tillämpades för att identifiera en minimal men effektiv uppsättning av ögonrörelsevariabler. Denna metod möjliggör en sömlös och icke-intrusiv kontinuerlig bedömning av arbetsbelastning, vilket gör den till ett värdefullt verktyg både för forskning och operativa tillämpningar inom flygtrafikledning.

Denna avhandling bidrar till ett säkrare, mer effektivt och miljömässigt hållbart lufttransportsystem genom att hantera kritiska utmaningar inom ATM. Resultaten har stor betydelse för framtidens ATM, särskilt i en tid med ökande efterfrågan på lufttrafik och föränderliga väderutmaningar. Integrationen av datadrivna tekniker, optimering och probabilistisk modellering erbjuder ett kraftfullt ramverk för att förbättra beslutsfattandet inom ATM. De metoder som föreslås i denna avhandling kan fungera som en grund för framtida forskning och industriella tillämpningar, vilket möjliggör kontinuerliga förbättringar av ATM:s prestanda och motståndskraft mot externa störningar.

Abstract

Air Traffic Management (ATM) faces significant challenges in ensuring efficiency, safety, and sustainability. Among these, weather conditions and Air Traffic Controller (ATCO) workload play crucial roles in overall system performance. Adverse weather frequently disrupts operations, leading to inefficient flight trajectories, increased fuel consumption, and environmental impact. It also elevates ATCO workload, thereby complicating ATCOs' ability to maintain safe and efficient air traffic flow. This thesis explores data-driven and analytical approaches to address these challenges, focusing on the impact of weather on flight efficiency, airspace capacity, and ATCO scheduling in remote tower centers. Additionally, it examines ATCO workload prediction using behavioral and physiological data. The study covers applications in airspace capacity management, staff scheduling, and ATCO workload assessment.

The thesis examines historical flight and weather data from Stockholm Arlanda and Gothenburg Landvetter airports over a two-year period (2019–2020), revealing persistent inefficiencies in arrival operations despite the overall reduction in traffic during the COVID-19 pandemic. It presents a methodology grounded in statistical analysis to identify the key factors influencing arrival performance, with particular emphasis on the impact of adverse weather conditions and traffic intensity. The proposed approach systematically determines the most influential variables affecting arrival performance in both the horizontal and vertical flight dimensions.

Adverse weather conditions, such as convective weather, can lead to restrictions on aircraft movements, reduce available routes, and necessitate adjustments in ATM strategies. As a result, understanding and predicting weather-related impacts on airspace capacity is essential for optimizing air traffic flow and minimizing delays. In this thesis, we develop a methodology, based on the continuous maxflow/mincut theory, to estimate reductions in Air Traffic Control (ATC) sector capacity due to predicted convective weather activity. The uncertainty in meteorological forecasts is quantified using Ensemble Weather Forecasting. We demonstrate the application of this methodology for assessing congestion in ATC sectors, using a realistic sector and a full sector configuration as examples. Additionally, we introduce a probabilistic framework for presenting congestion status, aimed at supporting decision-making processes at the Flow Management Position.

The thesis presents probabilistic models that incorporate the impact of adverse weather conditions into a Mixed-Integer Linear Programming framework for ATCO shift scheduling in remote and conventional towers. Building on previous project developments, these models specifically address the influence of weather on ATCO operations in remote towers. Probabilistic weather products are used to generate ensembles of staffing solutions, enabling the derivation of probability distributions for the required number of ATCOs. The modeling approach leverages recently developed techniques to tackle challenges associated with weather uncertainty. The proposed solutions are validated using historical flight and weather data from five Swedish airports designated for future remote operation.

The final part of this thesis focuses on developing unobtrusive methods for predicting ATCO workload by exploring the feasibility of non-intrusive data collection techniques combined with machine learning algorithms. Eye-tracking data, previously identified as a promising indicator of ATCO workload, were collected from controllers in simulated environments and used as predictive features. Subjective workload assessments, based on self-reported Cooper-Harper scale ratings, serve as label variables. Multiple machine learning models are evaluated for workload prediction, and feature selection techniques are applied to identify a minimal yet effective set of eye-tracking features. This approach provides a seamless, non-intrusive means of continuously assessing workload, making it a valuable tool for both research and operational applications in ATC environments.

By addressing critical challenges in ATM, this thesis contributes to a safer, more efficient, and environmentally sustainable air transport system. The findings of this thesis have significant implications for the future of ATM, particularly in an era of increasing air traffic demand and evolving weather challenges. The integration of data-driven techniques, optimization, and probabilistic modeling offers a powerful framework for improving decision-making in ATM. The methodologies proposed in this thesis can serve as a foundation for future research and industry applications, enabling continuous improvements in ATM performance and resilience against external disruptions.

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Anastasia Lemetti

Contents

Abbreviations

ACC Area Control Centre

AFCR Available Flow Capacity Ratio

ASCR Available Sector Capacity Ratio

ASM Airspace Management

AIF Aggregated Impact Factor

ANSP Air Navigation Service Provider

ATC Air Traffic Control

ATCO Air Traffic Controller

ATFM Air Traffic Flow Management

ATM Air Traffic Management

ATS Air Traffic Services

CAPE Convective Available Potential Energy

CCOs Continuous Climb Operations

CDOs Continuous Descent Operations

CHS Cooper-Harper Scale

CTA Control Area

CTR Control Zone

ECMWF European Centre for Medium-Range Weather Forecasts

EEG Electroencephalography

EPS Ensemble Prediction System

EWF Ensemble Weather Forecasting

FAP Final Approach Point

FMP Flow Management Position

GFS Global Forecast System

GRIB Gridded binary

ICAO International Civil Aviation Organization

IFR Instrument-Flight-Rules

ISA Instantaneous Self Assessment

kNN k-Nearest Neighbors

LFV Luftfartsverket

LIU Linköping University

METAR Meteorological Terminal Aviation Routine Weather Reports

MILP Mixed-Integer Linear Program

MV Monitoring Value

NM Nautical Mile

NOAA National Oceanic and Atmospheric Administration

NOMADS National Operational Model Archive and Distribution System

NWP Numerical Weather Prediction

OPERA Operational Programme for the Exchange of Weather Radar Information

PCA Principal Component Analysis

PI Performance Indicator

PRU Performance Review Unit

RTC Remote Tower Center

RTO Remote Tower Operation

SAF Satellite Application Facilities

SESAR Single European Sky ATM Research

SID Standard Instrument Departure Route

STAR Standard Arrival Route

TIF Traffic Impact Factor

TMA Terminal Manoeuvring Area

TOD Top of Descent

VFE Vertical Flight Efficiency

VFR Visual-Flight-Rules

WIF Weather Impact Factor

Chapter 1

Introduction

1.1 Motivation

The rising demand for air travel requires continuous enhancements in efficiency and safety. However, several factors, particularly adverse weather and increasing traffic density, pose significant challenges. Severe weather can drastically reduce airspace capacity and elevate Air Traffic Controller (ATCO)s' workload. Evaluating the impact of weather conditions on flight efficiency and airspace capacity is essential for maintaining high standards of safety and performance in Air Traffic Management (ATM). This allows for better planning and resource allocation during adverse conditions. Integrating weather into ATCOs shift scheduling is crucial to prevent safety compromises caused by high workload during storms or other disruptions. Moreover, it is advantageous to implement objective methods for assessing ATCO workload, rather than relying solely on their subjective assessments. Such methods can provide more accurate and consistent evaluations, contributing to better management of ATCO performance and overall air traffic safety.

This thesis delves into four interrelated research areas that aim to tackle these challenges and contribute to a more sustainable and resilient ATM system:

1. Identifying Impact Factors on Flight Efficiency: Understanding the key factors influencing fuel consumption is crucial for optimizing flight trajectories and reducing emissions. This research investigates such parameters as weather conditions and traffic intensity to identify

their individual and combined contributions to flight efficiency.

2. Probabilistic Modeling of Airspace Capacity Reduction due to Weather Conditions: The impact of weather on airspace capacity is often unpredictable, leading to inefficiencies and disruptions. This research proposes a probabilistic model to quantify the potential reduction in airspace capacity under severe weather scenarios.

3. Integrating Weather Information into Optimization Framework for ATCO Scheduling: Weather disruptions pose a significant challenge for ATCOs, requiring dynamic adjustments to flight schedules. This research explores integrating forecasted weather information into an optimization framework for ATCOs staff scheduling in RTC to maintain safety.

4. Assessment of ATCO Workload Through Eye-Tracking Measurements Using Machine Learning Techniques: ATCO workload plays a crucial role in ensuring safety and efficiency. This research explores utilizing eye-tracking technology and machine learning techniques to objectively measure ATCO workload in real-time, paving the way for adaptive task allocation and workload management strategies.

These four research areas address critical yet interdependent challenges in ATM. By unraveling the impact factors on flight efficiency, accurately forecasting airspace capacity reduction, optimizing ATCOs scheduling based on weather information, and objectively assessing ATCOs workload, this thesis aims to contribute towards a more efficient, safe, and sustainable air transport system.

1.2 Thesis Outline

The thesis is a compilation of five scientific papers and the remaining chapters are organized as follows. Chapter 2 lays the groundwork for our research by defining the core concepts of the field, reviewing the current state of the art, and identifying the key challenges that researchers are currently facing. Chapter 3 presents the research questions and describes the methods used in the thesis, followed by the delimitations and the data description. It then delves into the individual papers that form the foundation of this thesis and summarizes the overall contribution of our research. Chapter 4 presents our conclusions and explores potential avenues for future research. Finally, the papers comprising the thesis are reprinted.

Chapter 2

Background and State-of-the-art Research

2.1 ATM Structure

According to SKYbrary [1]—an electronic repository of safety knowledge related to flight operations, ATM and aviation safety initiated by EUROCONTROL—ATM encompasses a complex system designed to ensure the safe and efficient flow of air traffic. This system relies on three distinct, yet interconnected, services:

1. Air Traffic Services

Air Traffic Services (ATS) aim to ensure the safe and orderly flow of air traffic. This is achieved through Air Traffic Control (ATC), which manages traffic flow, and the flight information service, which provides essential information to flight crews. In emergencies, the alerting service coordinates with appropriate bodies, such as search and rescue teams. ATS are primarily carried out by ATCOs whose key roles include preventing collisions by applying separation standards and issuing clearances and instructions for orderly traffic flow. These instructions accommodate crew requests for flight levels and paths, facilitate continuous climb and descent operations, and minimize holding times both in the air and on the ground. ATS involve tactical interventions by controllers and direct communication with flight crews, usually throughout the entire flight.

2. Air Traffic Flow Management

Air Traffic Flow Management (ATFM) adopts a broader perspec-

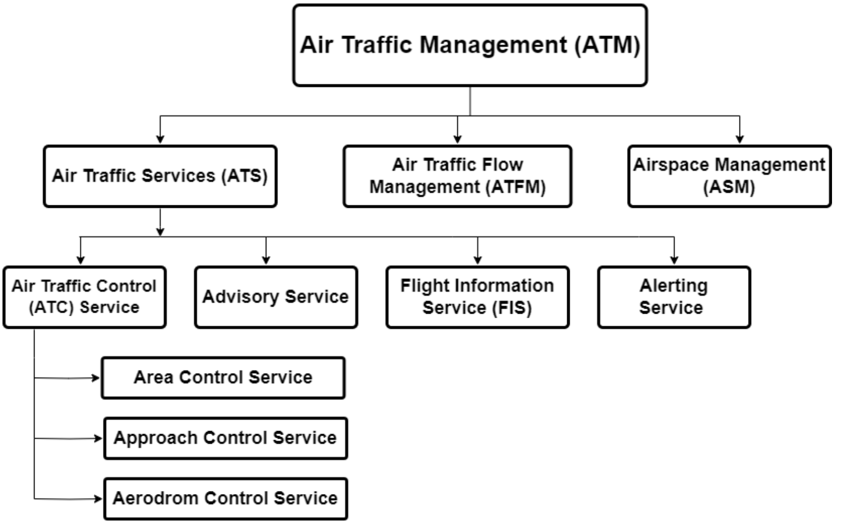


Figure 2.1: The structure of ATM (Source: SKYbrary [1]).

tive, focusing on strategic measures to prevent congestion and optimize overall traffic flow. Its primary objective is to achieve a balance between supply and demand of air traffic. Demand is managed by implementing measures such as adjusting flight schedules, specifying arrival times, and advising on route selection to distribute traffic more uniformly. Supply management involves aligning staffing levels in control sectors with forecasted demand. Acting proactively, ATFM influences the near future to prevent potential bottlenecks and maintain efficient traffic flow across larger regions.

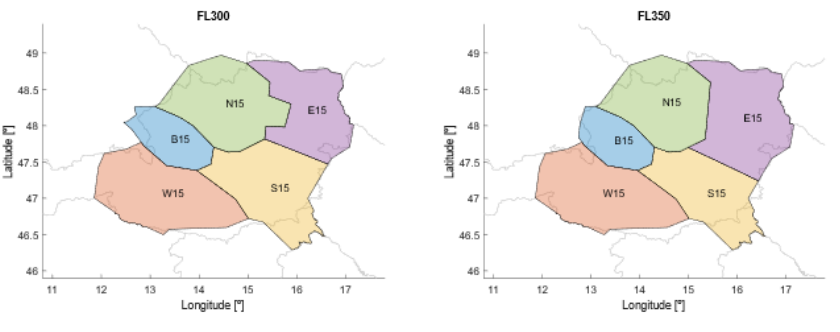


Figure 2.2: Figure 3 from paper 3—example of ATC sectors in the Austrian airspace for flight levels FL300 and FL350.

3. Airspace Management

Airspace Management (ASM) deals with the long-term planning and organization of the "highway" itself—the airspace. It aims to maximize the efficiency of this limited resource by focusing on two main areas: airspace allocation and airspace structuring. Airspace allocation involves designing and assigning routes, zones, and flight levels for various users (civil and military) to ensure safe and efficient separation. Airspace structuring refers to defining the overall layout and infrastructure of the airspace to support the effective provision of ATS. Operating on a strategic level, ASM shapes the framework within which the tactical operations of ATS and ATFM can function smoothly.

Therefore, the success of ATM hinges on the seamless interplay of these three services. ATS ensure the immediate safety and order of each flight, ATFM prevents congestion and optimizes overall flow, and ASM creates the efficient infrastructure for both. Their combined efforts ensure the safe, efficient, and accessible skies we rely on today.

Figure 2.1 illustrates the structure of ATM, in particular explains the relations between ATM, ATS and ATC. The present thesis focuses on two key components within this structure: the provision of ATC services, which manage the flow of air traffic, and ATFM, which aims to optimize traffic demand and capacity across the airspace system.

ATC is responsible for the safe, orderly, and efficient movement of aircraft both in the airspace and at airports, and its primary function is to prevent collisions between aircraft. ATC services are provided by ground-based ATCOs, who monitor aircraft positions and issue guidance and instructions to pilots to ensure they can operate safely and efficiently. These services are typically delivered by a designated organization known as an Air Navigation Service Provider (ANSP).

An Area Control Centre (ACC) is a facility responsible for providing ATC services for a designated region of controlled airspace. ACCs primarily manage the en-route phase of flight, overseeing aircraft operations at higher altitudes—typically above 10,000 feet—between departure and arrival phases. En-route controllers, also referred to as ACC controllers, are responsible for maintaining safe separation between aircraft cruising at high altitudes over long distances. They monitor and guide aircraft through extensive ATM sectors, coordinate handovers between adjacent sectors, and provide navigational support using radar, communication systems, and flight data processing tools. These sectors are organized to balance workload and ensure

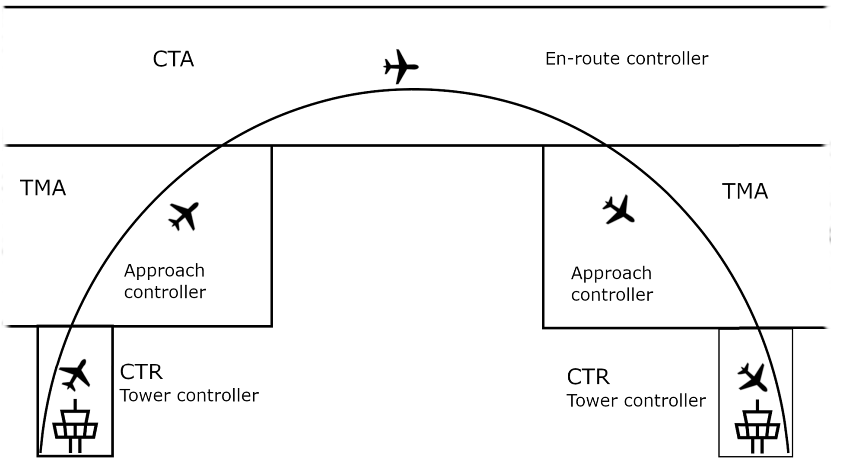


Figure 2.3: Airspace and ATC scheme.

coverage across the controlled airspace. En-route controllers operate within Control Area (CTA)s—controlled airspace regions at higher altitudes—where they facilitate the efficient and safe flow of air traffic outside of terminal areas (see Figure 2.2 for an example of sectorization).

A Terminal Manoeuvring Area (TMA) is a designated area of controlled airspace surrounding a major airport where arriving and departing aircraft are managed. It serves as a transition zone between en-route airspace and the airport itself. Aircraft enter the TMA during descent and exit it when climbing after takeoff.

Approach controllers are ATCOs responsible for managing aircraft within the TMA. They ensure safe sequencing and spacing of arriving and departing aircraft, guiding them during descent and climb-out while coordinating with both en-route and tower controllers. Approach controllers typically work in dedicated facilities near or at airports, which can be standalone buildings or a part of larger ATC centers. These facilities enable seamless communication and coordination with both en-route and tower controllers. Approach controllers rely on radar displays, communication systems, and navigation aids to monitor and direct aircraft movements within the TMA.

A Control Zone (CTR) is a controlled airspace extending from the surface up to a defined altitude, typically protecting aircraft operating near an airport. It encompasses the immediate airspace around an airport where takeoffs, landings, and ground movements are actively managed.

Control towers at airports, also known as ATC towers, house controllers responsible for managing aircraft movements on the ground and in the immediate airspace surrounding the airport, known as the CTR. ATCOs working in control towers are referred to as Control Tower ATCOs. In addition to radar systems and communication tools, tower controllers use visual observation techniques to ensure safe and efficient operations within their jurisdiction, which includes managing aircraft within the CTR and coordinating movements with approach controllers operating in the TMA. An overview of the airspace structure and corresponding ATC responsibilities is illustrated in Figure 2.3.

A **Remote Tower Center (RTC)** is a type of ATC facility that allows ATCOs to remotely manage the movements of aircraft at one or more airports from a centralized location. Remote tower centers use advanced camera and sensor technology, along with high-speed data links, to provide controllers with a real-time view of the airport and surrounding airspace.

Instead of being physically located in a tower at the airport, controllers in a RTC monitor and manage aircraft movements using digital displays and other advanced technologies. The cameras and sensors used by remote tower centers provide a 360-degree view of the airport, which allows controllers to detect potential safety hazards such as runway incursions and ground conflicts.

RTCs can provide a range of benefits over traditional tower facilities, including increased safety, greater flexibility, and cost savings. By centralizing ATC operations, RTCs can reduce the need for physical infrastructure and support a more efficient and scalable ATC system.

In recent years, several countries, including Sweden, Germany, and Norway, have begun implementing RTCs as a way to modernize their ATC systems and improve safety and efficiency.

In a RTC, ATCOs can work in a “multiple” position or mode where they monitor traffic at more than one airport. Currently, all ATC services are provided in a single mode, with one controller responsible for each airport. However, some countries, including Sweden, are planning to implement multiple operations as a cost-saving measure. This would involve having one controller monitor two or three airports from a single location.

2.2 ATM Impactful Weather

Among all the elements affecting flights safety, efficiency, and scheduling, weather is the most uncertain and influencial. It can directly impact the aircraft or indirectly affect pilot decisions. The following weather phenomena can have significant effect on aircraft operations and are counted in the current thesis [1].

Wind. Wind direction and speed alter the ground speed of aircraft, thereby impacting flight time and fuel consumption. Besides, turbulence caused by jet streams, wind shear, or gusty conditions can impact aircraft stability and passenger comfort, prompting pilots to request altitude changes.

Convective Weather (Thunderstorm). The hazards associated with thunderstorms include phenomena such as wind shear, turbulence, lightning, and icing. Additionally, hailstones can cause damage to the airframe, and strong updrafts and downdrafts can affect aircraft control and performance. Thus, thunderstorms often force aircraft to deviate from planned routes in order to avoid hazardous conditions.

Snow. Heavy snow reduces visibility and obscure the runway markings and lights, which can make it difficult for pilots to see where they are going. Snow removal operations may temporarily close runways, causing delays, holding patterns, or, in more severe cases, airport closures and flight diversions to alternate destinations.

Clouds. Different types of clouds influence commercial aviation in various ways, affecting visibility, turbulence, flight routing, and fuel efficiency. Low clouds, such as stratus and cumulus, form below 6,500 feet (2,000 meters) and can significantly impact flight operations. A critical factor in aviation is the cloud base, which is the lowest altitude at which clouds begin to form. It determines whether aircraft can fly under Visual-Flight-Rules (VFR) or must rely on Instrument-Flight-Rules (IFR). A low ceiling (a low cloud base of broken or overcast clouds) can reduce visibility, leading to flight delays, diversions, or cancellations. Stratus clouds are commonly associated with fog, drizzle, and widespread low visibility, which can severely impact takeoff and landing operations. Cumulus clouds, while typically harmless in their fair-weather form, can develop into towering cumulus or cumulonimbus clouds. These formations can produce turbulence, wind shear, and localized downpours, while also generating sudden updrafts and downdrafts that pose risks during takeoff and landing. Additionally, icing can occur in both stratiform and cumuliform clouds under specific temperature and humidity conditions. Aircraft flying through these clouds may experience ice buildup on wings and control surfaces, which can degrade performance and require de-icing measures.

Medium clouds, including altocumulus and altostratus, typically form between 6,500 and 20,000 feet (2,000–6,000 meters). Altocumulus clouds, often appearing as small, white patches or waves, can indicate atmospheric instability. When these clouds develop into altocumulus castellanus–characterized by turret-like structures–they signal the potential for thunderstorm formation, requiring pilots to monitor weather conditions closely. Altostratus clouds, on the other hand, often precede warm fronts and bring steady precipitation, which can reduce visibility and create icing conditions, particularly if aircraft pass through supercooled water droplets. Icing at these altitudes is a significant concern for aviation, as it can affect lift and aircraft control surfaces, necessitating anti-icing or de-icing measures.

High clouds, such as cirrus and cirrostratus, form above 20,000 feet (6,000 meters) and generally have minimal direct impact on aviation safety. However, they provide valuable meteorological information. Cirrus clouds, composed of ice crystals, often indicate the presence of upper-level jet streams, which can affect flight routes and fuel efficiency. Tailwinds from these strong winds can shorten flight times, while headwinds can increase fuel consumption. Cirrostratus clouds may also signal the approach of a warm front, allowing pilots and meteorologists to anticipate deteriorating weather conditions. Additionally, thick cirrus layers may obscure satellite-based navigation signals or affect pilot visibility under certain lighting conditions.

The most hazardous cloud type for aviation is the cumulonimbus cloud, which can form across different altitude levels. These towering storm clouds produce severe turbulence, lightning, wind shear, hail, and even tornadoes. Aircraft must avoid cumulonimbus clouds, as flying through them can be extremely dangerous due to sudden updrafts and downdrafts that exceed the structural limits of commercial aircraft.

Precipitation. Precipitation is important to aviation as it reduces **visibility**, it often appears in connection with low clouds, and, in the case of heavy precipitation, it can be accompanied by downdraughts. All flights depend on visual conditions, or visibility, at some stage. Air traffic operating under VFR depends on visual contact with the terrain and other aircraft during the entire flight. Even aircraft operating under IFR depend on visual references when on the ground, and to a certain extent, during the take-off and landing phases. Increased distances are needed between landings and/or departures in low visibility conditions, which causes delays and increased ATS workload.

Phenomena such as sandstorms, volcanic ash, tornadoes, and space weather are not included in the scope of this thesis. These events, while potentially impactful to aviation operations, fall outside the primary focus and data coverage of the current study.

Each weather phenomenon can be characterized by a set of associated variables. In the context of this thesis, the following weather variables are utilized—note that the categorization is not rigid, as some variables may pertain to multiple phenomena—[2, 3, 4].

- Wind
  - *u-component of the wind:* Represents the east-west component of the wind, influencing horizontal motion.
  - *v-component of the wind:* Represents the north-south component of the wind, influencing horizontal motion.
  - *Wind gust:* Measures rapid increases in wind speed, indicating turbulent wind conditions.
- Snow
  - *Convective snowfall:* Indicates snowfall resulting from convective activity, often leading to localized heavy snow.
  - *Convective snowfall rate (water equivalent):* Represents the intensity of snowfall due to convection, indicating potential for rapid accumulation.
  - *Large-scale snowfall:* Refers to snow associated with broader weather systems (e.g., frontal systems).
  - *Large-scale snowfall rate (water equivalent):* Measures the intensity of snowfall from large-scale systems.
  - *Total snowfall:* The cumulative amount of snow that has fallen, impacting accumulation.
  - *Snow density:* The mass of snow per unit volume of snowpack.
  - *Snow reports:* The count of snow observations per day.

- Clouds
  - *Total column cloud ice water:* Represents the amount of ice in clouds, which can indicate the potential for severe weather.
  - *Total column cloud liquid water:* Indicates the total liquid water present in clouds, affecting cloud density and precipitation potential.
  - *Total column rain water:* Measures the amount of water that can fall as rain, impacting precipitation forecasts.
  - *Total column snow water:* Indicates the water equivalent of snow in the clouds, impacting snow forecasts.
  - *Total column water:* Represents all forms of water (liquid and solid) in the atmosphere, crucial for understanding humidity and precipitation.
  - *Total cloud cover:* Measures the extent of clouds in the sky, affecting solar radiation and precipitation potential.
  - *Low cloud cover:* Indicates clouds at low altitudes, impacting visibility and weather conditions.
  - *Medium cloud cover:* Indicates clouds at intermediate altitudes, affecting weather conditions.
  - *High cloud cover:* Indicates clouds at high altitudes, influencing overall weather patterns.
  - *Cloud base height:* The height of the lowest part of a cloud, important for understanding cloud structure and potential weather impacts.
- Convective Weather (Thunderstorm)
  - *Convective Available Potential Energy (CAPE):* Indicates the energy available for convection, crucial for assessing the potential for thunderstorms.
  - *K index:* A measure that combines temperature and moisture profiles to assess thunderstorm likelihood.
- Precipitation
  - *Convective precipitation:* Refers to precipitation resulting from convective processes, often associated with thunderstorms and heavy rain.

– *Total precipitation:* Represents all forms of precipitation, including rain and snow, affecting overall moisture input into the environment.
– *Visibility:* The greatest horizontal distance at which selected objects can be seen and identified.

2.3 Flight Efficiency

Flight efficiency refers to the optimal use of resources, such as time and fuel, during a flight. In our research we focus on flight efficiency within TMA.

Horizontal inefficiency during the climb and descent phases arises from deviations of flights from Standard Instrument Departure Route (SID) and Standard Arrival Route (STAR) procedures. SIDs and STARs are pre-defined routes that guide aircraft during the departure and arrival phases of flight, respectively. SIDs assist aircraft in transitioning from the airport to en-route airspace by providing a structured path to follow after takeoff. STARs guide aircraft from en-route airspace to the airport during the arrival phase. Both SIDs and STARs include specific waypoints, altitudes, and speeds, ensuring safe and efficient navigation in busy airspace while minimizing potential conflicts between flights.

Vertical inefficiency is produced by the inability of departure flights to keep up Continuous Climb Operations (CCOs) and of arrival flights to keep up Continuous Descent Operations (CDOs) [5], [6].

CDOs refer to a flight profile where an aircraft descends continuously from cruising altitude to the airport without leveling off or making intermediate climbs during the approach phase. CDOs enable a flight profile optimized to the aircraft's operating capability, resulting in optimal continuous engine-idle descents (without using speed brakes). Consequently, CDOs reduce fuel consumption, CO_2 emissions, and noise pollution. CDOs are typically flown from the Top of Descent (TOD) to the Final Approach Point (FAP), minimizing level flight segments during descent (see Figure 2.4).

CCOs refer to a flight profile in which an aircraft maintains a continuous climb from takeoff to its cruising altitude without leveling off or descending during the climb phase.

International Civil Aviation Organization (ICAO) proposed a set of Performance Indicator (PI)s to analyse the performance of arrivals

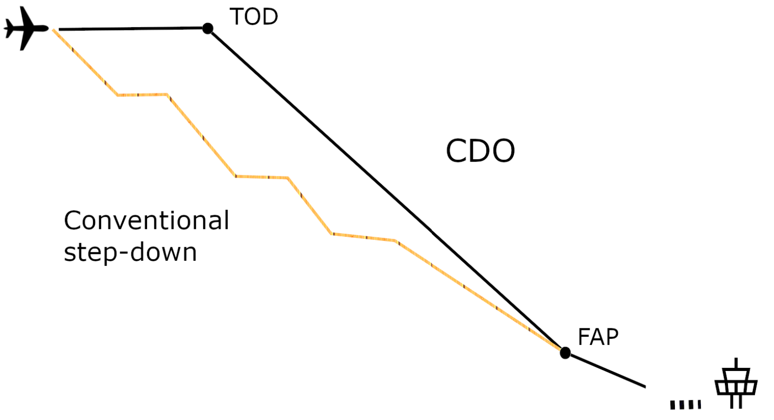


Figure 2.4: CDO and conventional descent.

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 [7]. EUROCONTROL Experimental Center developed new performance indicators targeting to capture different aspects of flight inefficiencies in TMA [8]. EUROCONTROL also proposed the techniques to calculate Vertical Flight Efficiency (VFE) PIs [9].

EUROCONTROL developed the methodology which was applied by its Performance Review Unit (PRU) for the analysis of VFE during climb and descent [9]. Performance Review Commission of EUROCONTROL conducted an assessment of the ATM system in Europe in 2019 using various indicators and examined flight inefficiency within the TMA at the top 30 airports in Europe, including Stockholm Arlanda airport. In [10] Pasutto et al. investigated the factors that affect vertical efficiency during descent at the top 30 European airports. Their analysis revealed a correlation between the vertical deviation and horizontal deviation, as well as a dispersion of the vertical deviation for the same horizontal deviation. The study also found a significant variation among airports, with some indicators differing by a factor of 5 or more. Zanin [11] conducted a study using large-scale datasets of aircraft trajectories to evaluate the efficiency of flights landing at an airport. The author's main focus was to understand the efficiency of different airspaces and compare them.

APACHE project [12], [13], an exploratory research project within Single European Sky ATM Research (SESAR) 2020, considered the estimation of flight inefficiencies in terms of extra fuel burn, based on the algorithm proposed in [14], primarily for the en-route flight phase. In a later study, Prats et al. [15] proposed a range of PIs to measure fuel inefficiency. In [16] Ryerson et al. evaluated fuel consumption in terminal areas using a Terminal Inefficiency metric, which measures the variation in terminal area fuel consumed across flights, as reported by a major U.S. airline. This metric allowed the authors to quantify the additional fuel burn caused by ATM delays and terminal inefficiencies. Additionally, [5] and [6] analyzed fuel savings resulting from the use of CDOs in comparison to conventional procedures. The studies reported a reduction in fuel consumption of approximately 25-40 % when flying CDOs.

Many recent research activities have focused on quantifying the impact of different weather phenomena on airport operation. Schultz et al. [17] utilized the ATMAP algorithm, provided by EUROCONTROL's PRU, to transform Meteorological Terminal Aviation Routine Weather Reports (METAR) data into a weather score that weighs various weather factors. They analyzed the correlation between flight operations' on-time performance and the ATMAP score at major European airports. Several SESAR projects, e.g., [18], [19], [20], have developed new models for weather forecasts and integrated them into planning problems, such as trajectory planning. To capture the uncertainty in weather predictions, the authors retrieve probabilistic weather data from an Ensemble Prediction System (EPS). EPS generate a range of weather forecasts called members, which represent potential states of the actual weather outcome [21].

Ongoing research is examining the impact of deep convection and thunderstorms. For example, studies such as [22], [23] and [24] investigated the implications of these weather phenomena on en-route flow management and terminal area operations. Using a high-level airport model, Klein et al. [25] quantified the impact of weather forecast uncertainty on delay costs. Steiner [26] emphasized the crucial effect of accurate forecasts of high-impact winter weather for efficient airport and airline capacity management, highlighting the need for data sharing and integrated decision-making between stakeholders. Recent works, such as [27] and [28], confirmed the relevance of weather impact quantification and analysis for airport operation.

In this work, we propose a methodology that allows to distinguish which factors have the highest impact on which aspects of arrival performance in horizontal and vertical plane. In particular, we introduce

Weather Impact Factor (WIF) and Traffic Impact Factor (TIF), a unified condition metrics representing the current weather and traffic situations, which we apply in regression analysis in order to determine what factor influence the chosen PI most and also to decouple the influencing factors.

2.4 Airspace Capacity

ICAO defines airspace capacity as: “The maximum number of aircraft that can be accommodated in a given time period by the system or one of its components (throughput)” [29]. In this context, the system refers to the entire ATM framework, while its components include specific airspace sectors, airports, and control units. Sector capacity, as a key component, represents the maximum number of aircraft that can be safely managed within a defined airspace sector, considering factors such as air traffic control workload, airspace structure, surveillance capabilities, and operational constraints, all of which contribute to determining overall airspace capacity.

Flow Management Position (FMP) is responsible for monitoring and balancing air traffic demand with available airspace capacity, taking into account various factors such as weather, aircraft performance, equipment failures, airspace restrictions, staffing levels, and other factors. If the FMP observes that traffic exceeds capacity, they coordinate traffic flow measures at both the ACC and Network Manager levels.

Adverse weather conditions such as thunderstorms, snowstorms, strong winds, and low visibility can limit the number of aircraft that can safely operate in a given airspace, reducing the overall airspace capacity. It is generally recommended for aircraft to avoid flying through adverse weather zones, especially severe convective weather zones. Thunderstorms can produce severe turbulence, lightning, hail, and strong winds, which can all pose a significant risk to aircraft and passengers (see Figure 2.5 for examples of weather-impacted regions).

Nowadays, the FMP monitors the traffic load of each ATC sector via the Collaboration Human Machine Interface, a standalone application which provides a graphical interface to display data [30]. The traffic load is usually measured as the rate of flights predicted to enter the sector in a 1-hour rolling interval, i.e. the entry count, and it is compared with the Monitoring Value (MV) [31]. The MV is the agreed number of flights accepted to enter into a reference location per rolling hour beyond which coordinated actions may be considered. The MV is not the capacity itself, but normally close to 90% of real capacity; thus, if the capacity is reduced, the MV should be reduced in the same proportion. An overload of 3% over MV is not considered as an overload, it starts to be an overload once the load reaches 10% over MV.

The efforts made in the past to predict the congestion of a particular airspace can be grouped into two different approaches: the separate prediction of traffic load and capacity values and then its comparison, or the direct prediction of the congestion status. The first approach is the one followed by the Network Manager, and the one proposed in [32] for a probabilistic methodology. The work presented in [33] follows the second approach to directly predict the activation of ATFM regulations, by using machine learning and historical data.

In this work, we follow the first approach, where probabilistic traffic loads and probabilistic MVs are predicted, using the same weather forecasts, and then compared. This allows for a direct assessment of how predicted weather conditions may impact sector capacity by examining the alignment or divergence between traffic demand and capacity constraints.

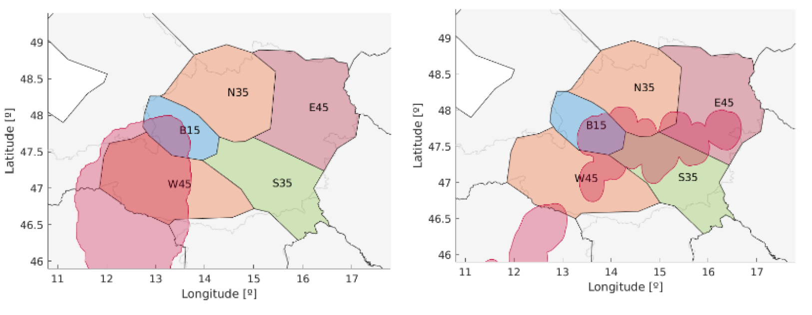


Figure 2.5: Figure 4 from paper 3—Examples of weather-impacted regions in the Austrian airspace from two different weather forecast products.

2.5 ATCOs Scheduling

In [34], Van den Bergh et al. conducted a literature review of modern techniques for personnel scheduling problems. They analyzed 291 articles published since 2004 and classified optimization tasks and their solution methods from various perspectives. The authors made several recommendations, some of which are adopted in our work, e.g. applying several objective functions that reflect the interests of different stakeholders, each with their own priorities.

The RTC concept aims to provide ATC service simultaneously to multiple airports with ATCOs at a remote location [35]. Different aspects of this concept are investigated in the recent works. The authors of [36] and [37] focused on usability within the new remote-control environment. Wittbrodt et al. [38] emphasized the role of radio communication in RTCs. Meyer et al. [39] provided a safety assessment of the RTC concept and suggested conducting functional hazard analyses to identify potential risks, while also highlighting the challenge of obtaining reliable probability values for the models. Oehme and Schulz-Rueckert [40] proposed sensor-based solutions to reduce the dependency on visibility conditions and tower location. In addition, several studies (e.g., [37, 41, 42, 43, 44]) examined work organization and human performance issues related to remote towers. These studies proposed various methods for controlling two airports from a single RTC and investigated how monitoring performance could affect system design and behavioral strategies. In particular, they presented results on the design of novel RTC workplaces.

Rostering of ATCOs naturally inherits some features from other related staff scheduling problems, e.g., from nurse scheduling [45], optimization of university course planning [46] or multi-skilled staff rostering [47]. Optimization of scheduling for ATCOs should take into account even stricter constraints. In [48] the authors surveyed the state of the art for ATC staff scheduling, reflecting also the European regulations and policies connected to ATCO work organization. Several techniques have been applied for scheduling ATCOs. In a survey, Conniss [49] lists several methods, including Linear Programming, Tabu Search, Simulated Annealing, Constraint Programming, and Case-Based Reasoning. Stojadinovic [50] proposed using various exact methods, such as CSP, SAT, Partial MaxSAT, SMT, ILP, and PB. The results show that SAT-related approaches outperform other methods for the described problem. Conniss et al. [51] suggested a greedy heuristic as an effective solution. While these studies aimed to provide schedules for ATCOs in conventional towers, their problem descriptions are similar to the one we have formulated, but they lack constraints related to Remote Tower Operation (RTO).

Creating an optimal assignment of remote controllers to the airports is an optimization problem which has to take into account at least the following constraints:

1. Restrict the number of airports assigned to one controller.
2. Limit the number of movements one controller can handle.
3. Avoid the potential conflicts in schedules.
4. Enforce upper and lower bounds on the controller shift length.
5. Limit the maximum total time "in position".
6. Limit the maximum continuous time "in position" without a break.
7. Ensure that controller has an endorsement for the airport he/she is assigned to.

Several alternative objective functions can be used in the model, such as the number of controllers at the RTC or the average number of controllers per airport. The choice of objective function depends on the specific operational priorities—such as minimizing the number of ATCOs required, balancing controller workload across sectors, or optimizing the allocation of ATCOs to match traffic demand patterns.

An optimization framework for scheduling ATCOs at the RTC was developed in Linköping University (LIU)–Luftfartsverket (LFV) project KODIK and it is summarized in [52]. The framework is designed to produce efficient and balanced rosters that satisfy operational requirements, taking into account constraints such as sector staffing demands, duty time regulations, and individual controller endorsements. However, the framework does not take into account the potential impact of weather-related factors on overall ATCOs scheduling requirements.

Adverse weather conditions significantly affect flight safety and increase ATC service workload. Phenomena such as thunderstorms, heavy rain, snow, fog, and strong winds can impair aircraft performance, reduce visibility, and complicate navigation and control. Thunderstorms present serious hazards—including lightning, hail, turbulence, and wind shear—that may render the aircraft unstable and force pilots to deviate from planned routes, increasing ATC complexity. Heavy rain and snow can degrade runway conditions and aircraft performance, while snow accumulation necessitates runway closures and elevates ATC service workload. Fog reduces visibility during critical phases of flight, increasing collision risk. Strong winds, especially crosswinds, can disrupt takeoff, landing, and in-flight control. In response to these conditions, pilots often request altitude changes, requiring controllers to coordinate vertical separation, adjust sequencing, and resolve potential conflicts—further intensifying their workload.

Gultepe et al [53] provided suggestions for improving the measurement and prediction of weather-related parameters to ensure safe aviation operations. They noted that weather events such as fog, precipitation, turbulence, wind shear and icing may be linked to changing climate conditions and stressed the importance of considering aircraft flying conditions to enhance future aviation operations. Taszarek et al. [54] investigated the spatial and temporal variability of situations that cause disruptions in airline traffic and airport operations, such as limited visibility, thunderstorms, low-level wind shear, and snowfall. They used environmental parameters derived from the ERA5 database [2] and established threshold values for meteorological metrics to distinguish between hazardous and non-hazardous situations, some of which are used in our study. The effects of meteorological uncertainty on Trajectory-Based Operations were examined in [55, 56], where the authors considered two types of meteorological uncertainty: wind uncertainty and convective zones. In [57, 58], new probabilistic radar-based nowcasting methods were proposed to support ATM systems challenged by winter weather.

To the best of our knowledge, there has been no published research conducted on quantifying the impact of different weather phenomena on ATCO workload or task load. In this study, we introduce a method to consider the effect of weather on ATCO work in RTC staff scheduling. We establish various sources for numerical thresholds related to impactful weather events and use probabilistic weather products to generate a set of staffing solutions, which enables us to calculate probability distributions for the required number of ATCOs. To generate the set of staffing solutions, we modify our previous Mixed-Integer Linear Program (MILP) for RTC staff scheduling, adding a constraint, which forces the airport to operate in a single mode if impactful weather is present. Additionally, we provide a comprehensive sensitivity analysis for the taskload-driven impact factor cutoff value, highlighting the trade-off between safety and staffing needs.

2.6 ATCO Workload

The mental workload of operators in socio-technical systems has long been recognized as a critical factor for both safety and capacity. Hart and Staveland [59] define workload as “a hypothetical construct that represents the cost incurred by a human operator to achieve a particular level of performance”. To maintain optimal working conditions and performance commitment in ATC, ATCO workload should remain at a moderate level, as supported by the inverted-U theory of Yerkes and Dodson [60]. Workload is a non-linear, multi-dimensional function where traffic load is only one of many influencing factors, see Josefsson et al. [61] and Meyer et al. [62]. The workload of ATCOs depends on various factors, such as the number of aircraft under their control, the complexity of the airspace, weather conditions, the level of automation available, and also the personality traits of individual controllers such as experience, age, and training.

The workload of ATCOs is typically highest during peak hours when air traffic reaches its maximum. However, additional factors such as weather-related delays, unexpected events, and emergencies—such as medical diversions or security incidents—can further increase their workload.

Beyond managing aircraft, ATCOs must also coordinate with pilots, fellow controllers, and ground service staff using radios, telephones, and other communication tools. Their role demands exceptional multitasking abilities, quick decision-making, and the capacity to work effectively under pressure.

Given these demands, workload monitoring should be regarded as a critical safety barrier. Consequently, ATCOs have a mandated duty to cease operations when their task-performance abilities are compromised [63]. However, self-assessment of workload is inherently uncertain. As noted by Gopher and Donchin [64, pp. 14–2], “... an operator is often an unreliable and invalid measuring instrument.” This limitation arises from challenges in self-awareness and individuals’ difficulty in accurately assessing their own workload due to subjective perceptions of their capacity [65, 66].

Efforts to predict workload can be effective in the simplest cases by employing explanatory models that define specific causes and their effects. For instance, Cañas et al. [67] present a psychological model that describes workload as a dynamic allocation of cognitive resources, influenced by factors such as engagement and effort. This approach extends beyond traditional models that focus solely on task demands by incorporating variations in arousal levels and resource dedication, offering a more comprehensive perspective on workload prediction. This model also helps predict the effects of automation on ATCO performance and supports the development of strategies to mitigate potential negative outcomes.

Another model-based approach, the Cognitive Complexity computerized model—the Cognitive ModEl for ATCO Workload Assessment (COMETA)—was developed by Frutos et al. [68]. This model integrates ATC events with an ATCO task model, which consists of ATC actions, to estimate the cognitive demand and mental workload associated with task performance. Cooper-Harper Scale (CHS) values were used for its calibration and validation. Expanding on this work, Ibáñez-Gijón et al. [69] validated an enhanced COMETA model by incorporating the real-time effects of controllers' actions on the state of the airspace. Their study included the recording of Instantaneous Self Assessment (ISA) and the NASA Task Load Index (NASA-TLX) values, along with physiological indicators such as electrodermal activity and heart rate.

Recent research emphasizes evidence-based workload assessment, leveraging physiological and behavioral indicators to refine self-assessments and guide sector management decisions while ensuring non-intrusive monitoring that maintains safety and avoids disruptions to ATCOs' tasks. To advance workload assessment while addressing these challenges, researchers have focused on identifying reliable workload metrics. Zamarreño Suárez et al. [70] contributed to this effort by identifying parameters that serve as references for defining workload thresholds. They designed a series of scenarios in which ATCOs were subjected to overload conditions and used Electroencephalography (EEG) and eye-tracking data to objectively measure workload. Their findings highlighted the number of blinks as the most significant eye-tracking parameter and confirmed correlations between scenario difficulty and EEG metrics related to engagement, stress, and focus. They suggested using these variables to define brain activity thresholds. Building on this work, Zamarreño Suárez et al. [71] conducted simulations with six ATCO students, applying a slightly modified version of the original method as a case study.

Charles and Nixon [72] reviewed 58 journal articles across various domains, including but not limited to air traffic, that explored the measurement and prediction of mental workload using electrocardiographic, respiratory, dermal, blood pressure, and ocular metrics. They concluded that no single measure can fully discriminate mental workload but identified key indicators, such as pupil diameter and blink rate, that effectively differentiate between low and high task loads. Additionally, they outlined the sensitivity of these measures to various influencing factors. More recently, Das Chakladar and Roy [73] conducted a review on estimating cognitive workload levels using physiological measures, further advancing the understanding of workload assessment.

Pagnotta et al. (2022) conducted a review of 39 studies examining physiological indicators of mental workload in ATC, with brain activity and heart rate emerging as the most commonly analyzed measures. Their findings highlighted a consistent positive relationship between these physiological metrics and task difficulty, supporting their effectiveness in assessing mental workload.

While cognitive and physiological models provide explanatory insights into workload arousal by defining relationships between task demands, cognitive resources, and physiological responses, machine learning takes a different approach. It shifts the focus entirely to predictive modeling, leveraging data-driven techniques to identify patterns and trends that may not be explicitly defined by traditional models.

As early as 1999, Chatterji and Sridhar [74] applied a multilayer neural network to model the relationship between statistical measures from traffic data and ATCOs' self-assessed workload, categorizing it into three levels: low, medium, and high. Gianazza [75] sought to infer ATCO workload based on historical sector operations. He assumed that sector collapses indicated low workload, sector maintenance reflected medium workload, and sector splits signaled high workload. Using this approach, he achieved an accuracy of approximately 82% in workload prediction.

Sciaraffa et al. [76] conducted a study where 35 ATCOs completed 45-minute scenarios designed by experts, with equal segments of low, medium, and high workload. Using 16 EEG channels, they extracted features and tested multiple classifiers, with k-nearest neighbor achieving the highest accuracy (84% for 28 features). Accuracy declined as features were reduced, confirming the potential of machine learning for classifying workload solely from EEG data.

Zhou et al. [77] applied unsupervised domain adaptation to develop an EEG-based cross-task workload recognition model, leveraging various machine-learning techniques. Zhou et al. [78] recently extended their analysis to cross-subject workload recognition.

Safari et al. [79] utilized an open-access EEG dataset from 48 users, applying feature selection on 150 features followed by seven-fold cross-validation across four machine-learning models. Their approach achieved an 80.53% accuracy in workload classification using a support vector machine algorithm.

Demirezen et al. [80] recently tackled the challenge of reproducibility in workload estimation research using EEG and machine learning. They reviewed existing efforts on reproducibility, conducted a systematic literature review on mental workload prediction with EEG data, and formulated guidelines to enhance research reliability. Additionally, they assessed studies from their systematic review to evaluate machine-learning-based approaches for workload estimation.

In this work, we employ a machine learning approach by validating a set of classical models for workload prediction. Eye-tracking features are used as input variables, labeled with Cooper–Harper self-reported workload ratings. Moreover, feature selection techniques are applied to identify a reduced and informative subset of features.

Chapter 3

Conducted Research

In this chapter, we describe the conducted research. We begin by outlining the overall goals and the specific research questions that guide this thesis. We then delve into the methodology employed to address these questions. This includes a detailed description of the chosen research methods and the data sources utilized. Following that, we provide a brief overview of each paper included in the thesis, highlighting how each paper contributes to answering the research questions.

3.1 Research Goals

This thesis pursues the following scientific goals.

1. Investigate how various weather phenomena affect different aspects of airspace operations. Develop a methodology to assess the impact of various weather phenomena on the flight efficiency.

2. Investigate the impact of weather on airspace capacity. Suggest the solution to evaluate reductions in airspace capacity caused by convective and other disruptive weather events. This goal seeks to provide tools for better traffic flow management in weather-impacted airspace.

3. Integrate the effects of adverse weather into the optimization framework for ATCOs scheduling at RTC. Refine the developed optimization framework, making it more robust with respect to weather uncertainties.

4. Explore and evaluate techniques for assessing ATCO workload, with the goal of proposing a reliable method for identifying workload levels. The focus is on unobtrusive behavioral and physiological indicators that can be used for real-time workload monitoring and prediction, improving ATCO performance management.

3.2 Research Questions

The following research questions should be answered to reach the goals.

- Q1: How do different weather phenomena impact various aspects of ATM?
- Q2: What specific weather phenomena have the most significant impact on flight efficiency in terms of additional time, fuel consumption, and route deviations?
- Q3: Which flight efficiency performance indicators are most impacted by the weather conditions?
- Q4: What methods can be used to accurately predict reductions in airspace capacity due to adverse weather phenomena?
- Q5: How can the impact of adverse weather conditions be effectively integrated into an optimization framework for Air Traffic Controller scheduling at Remote Tower Centers, and how can we account for uncertainties associated with these weather conditions?
- Q6: What techniques are available for evaluating Air Traffic Controllers' workload, and how can we assess controller workload in an unobtrusive manner using behavioral or physiological metrics as indicators of high workload?

3.3 Methods

The papers in this thesis employ quantitative methods to analyze data and address the research questions.

Data-Driven Methods

Statistical Analysis is a process of collecting, examining, and interpreting data to uncover patterns, relationships, and insights. It involves applying various statistical methods and techniques, such as descriptive statistics, correlation analysis, regression analysis, and hypothesis testing, to summarize and analyze quantitative or categorical data.

Descriptive statistics is a branch of statistics that focuses on summarizing and organizing data to provide a clear and concise representation of its main features [81]. It involves using various measures and visualizations to describe the characteristics of a dataset, including measures of central tendency, such as the mean (average), median (middle value), and mode (most frequent value), which indicate the center of the data. Additionally, it encompasses measures of dispersion, like the range (difference between the maximum and minimum values), variance (average of the squared differences from the mean), and standard deviation (the square root of variance), which describe the variability or spread of the data. Descriptive statistics also includes frequency distributions that organize data into categories or intervals to show how often each value occurs, as well as visualizations, such as histograms, bar charts, and box plots, to represent data distribution and trends.

Correlation analysis is a statistical method for evaluating the strength and direction of the relationship between two variables [82, 83]. Common measures include Pearson's correlation coefficient, which assesses linear relationships, and Spearman's rank correlation coefficient, which evaluates monotonic relationships based on ranked data. Both coefficients range from -1 to 1, where -1 indicates a perfect negative correlation, 1 a perfect positive correlation, and 0 no correlation. While Pearson captures linear associations, Spearman is more suitable for non-parametric or non-linear data. Correlation analysis helps identify patterns and dependencies in data but does not imply causation between the variables.

Regression analysis is a branch of statistical analysis that examines the relationship between a dependent variable and one or more independent variables [84, 85]. It encompasses both parametric models, which assume a specific form for the relationship, and non-parametric models, which do not require a predetermined functional form. Non-parametric approaches such as kernel regression and Loess are employed when the relationship is not well-defined or when parametric assumptions may not hold.

Parametric regression methods can be broadly classified into three categories: linear regression, nonlinear regression, and other specialized regression techniques. Linear regression is the most fundamental type, where the relationship between the dependent variable and one or more independent variables is modeled as a linear equation. This includes simple linear regression for one predictor and multiple linear regression for multiple predictors.

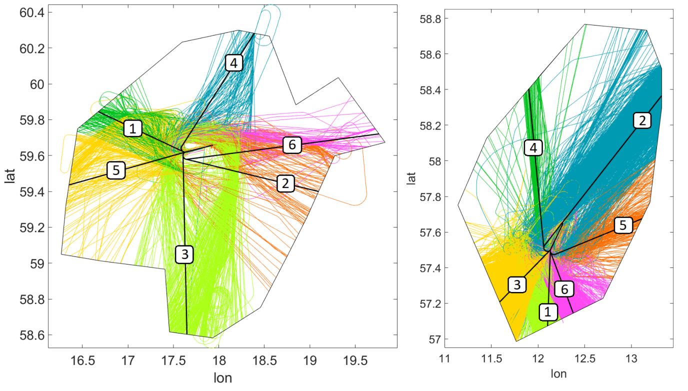
Nonlinear regression employs continuous functions that are not linear and can take various forms, such as polynomial regression, exponential regression, and logistic regression. Other specialized regression techniques include methods such as ridge regression and lasso regression, used for regularization and addressing multicollinearity; robust regression, designed to be less sensitive to outliers; regression techniques for categorical data, such as ordinal regression and multinomial regression; and mixed-effect models, which account for hierarchical or nested data structures [84].

We incorporate elements of statistical analysis, such as descriptive statistics or correlation analysis, in all of our papers. We apply simple and multiple linear regression methods in Papers 1 and 2 to analyze the dependence of flight efficiency performance indicators on weather conditions and traffic intensity. Additionally, in Paper 1, we utilize a backward selection algorithm, a technique for selecting the most significant features. This stepwise regression method begins with a model that includes all potential predictor variables and iteratively removes the least significant variable based on a specified criterion, such as the highest p-value, until only statistically significant variables remain. The significance of each variable during the removal process is typically assessed using statistical tests such as the F-statistic, which measures the overall significance of the model when a variable is removed [85, 86]. The statistical analysis was conducted using Python programming language, along with the scipy, statistics, and statsmodels libraries, to implement various aspects of the analysis.

Statistical learning, often referred to as **Machine Learning** in more practical contexts, extends the concepts of statistical analysis by focusing on prediction, classification, and the development of algorithms that can learn from and make decisions based on data. It encompasses various techniques and methodologies designed to handle different types of learning problems (supervised learning, unsupervised learning, reinforcement learning). Supervised learning uses labeled data to train algorithms that learn to map input features to output labels, enabling prediction on new data. It focuses on learning from known examples to make accurate predictions or classifications. In contrast, unsupervised learning works with unlabeled data, aiming to discover hidden patterns, structures, or relationships within the data without predefined outputs ([86, 87]).

In Paper 2, we utilize two algorithms of unsupervised machine learning—k-means clustering algorithm and Principal Component Analysis (PCA). The k-means clustering algorithm divides a dataset into k clusters by iteratively assigning each data point to the nearest cluster center and updating these centers based on the mean of the assigned points. We apply this algorithm to cluster the aircraft trajectories within TMAs. More precisely, we cluster the first points of the trajectories within the TMA (see the results in Figure 3.1). PCA is a dimensionality reduction technique used to transform high-dimensional data into a set of linearly uncorrelated variables called principal components. These components capture the maximum variance in the data, allowing for a simplified representation that retains essential information while reducing redundancy. We leverage PCA to transform our weather variable dataset into a set of independent components in Paper 2.

In Paper 5, we apply 10 algorithms of supervised machine learning: logistic regression, linear discriminant analysis, decision tree, AdaBoost classifier, bagging classifier, random forest, histogram-based gradient boosting classification tree, extra trees classifier, support vector classifier, and k-Nearest Neighbors (kNN). Linear regression predicts a continuous output by fitting a linear relationship between input variables and the target. Linear discriminant analysis projects input data onto a lower-dimensional space by maximizing class separability, finding a linear combination of features that best discriminates between classes. Decision tree recursively partitions data based on features to predict the target by navigating from root to leaf nodes. AdaBoost classifier combines multiple weak learners (we use decision



(a) (a) **(b)** (b)

Figure 3.1: Figure 1 from Paper 2—examples of the arrival trajectories colored by cluster, for Stockholm Arlanda runway 08 (a) and Gothenburg Landvetter runway 03 (b).

trees) by sequentially adjusting their weights to focus on misclassified samples, improving overall predictive performance through weighted majority voting. Bagging classifier trains multiple base estimators (decision trees in our model) on different random subsets of the training data and combines their predictions through averaging or majority voting to enhance accuracy and reduce variance. Random forest aggregates predictions from multiple decision trees to improve accuracy and reduce overfitting. Histogram-based gradient boosting classifier sequentially builds an ensemble of decision trees, iteratively improving prediction by minimizing errors using histograms of feature distributions. Support vector classifier separates classes in data by finding an optimal hyperplane that maximizes the margin between them. kNN classifies a data point by identifying the k closest points in the training set based on a distance metric and assigning the most frequent class among them. More detailed algorithms descriptions can be found, for instance, in [86] and [87].

We leverage these algorithms to classify ATCOs' workload into three classes (low, medium, high). Eye-tracking data serves as input features, while workload labels, derived from ATCOs' subjective assessments in the form of CHS scores, act as the target variables for classification. Python programming language and the scikit-learn library were utilized to implement the algorithms.

Mathematical Optimization

An optimization problem involves finding the best possible solution from a set of feasible solutions by maximizing or minimizing an objective function subject to a set of constraints. An optimization program, or mathematical program, is the formal representation of this problem, comprising the objective function, decision variables, and constraints. Mathematical optimization, also known as mathematical programming, is the broader field that encompasses these optimization programs, focusing on the development and application of algorithms and techniques to determine the optimal solution that meets all constraints while achieving the objective function optimum [88].

Optimization problems can be classified based on the form of the objective function and constraints (linear, nonlinear, convex, nonconvex), as well as the nature of the decision variables (continuous, discrete). When the objective and all constraint functions are linear and the variables are continuous, the problem is referred to as a Linear Program. If all decision variables are restricted to be integers, the problem is termed an Integer Program. When only some of the variables are required to be integers, the problem is called a Mixed-Integer Program. When the objective and all constraint functions are linear and some of the variables are required to be integers, the problem is called a **MILP**. Different solution techniques, including exact and heuristic algorithms, are available depending on the class of the optimization model. Algorithmic solutions of linear and integer problems can be found, for example, in [89] and [90].

In Paper 4, we formulate an MILP to optimize RTC staff scheduling by assigning ATCOs to airports while satisfying operational and regulatory constraints. The AMPL language with Gurobi solver was used for the numerical experiments with the model.

The notable branch of discrete optimization is combinatorial optimization, which refers to problems on graphs, matroids and other discrete structures. Network Flow Optimization is a branch of combinatorial optimization focused on efficiently routing resources through a network while adhering to capacity constraints [91, 92].

Network flow theory studies directed graphs where edges serve as capacity-limited channels for transporting commodities such as data, traffic, or fluids from a source (s) to a sink (t). The goal is to maximize total flow while respecting capacity constraints. A key result in this field, the **Maxflow Mincut Theorem**, states that the maximum achievable flow from s to t is equal to the total capacity of the smallest s-t cut (mincut) [91]. This theorem is instrumental in determining optimal flow values and identifying critical bottlenecks (mincuts), facilitating efficient resource allocation across various systems.

Extending these principles, the **Continuous Maxflow/Mincut Theory** generalizes classical discrete network flow results—including the maxflow mincut theorem, Menger's theorem (Maxflow Mincut Theorem for unweighted graphs), and the flow decomposition theorem—to continuous domains. Unlike discrete graphs, this approach represents flow optimization in a continuous space and is typically formulated as a convex optimization problem. The development of this continuous flow theory and its associated algorithms was initially driven by the demands of ATM. Applications of geometric flow results in ATM are discussed in [93], [94] and [95].

In Paper 3, we use the Continuous Maxflow/Mincut Theory as the starting point to assess the reduction in ATC sector capacity due to convective weather, supporting decision-making at the FMP. We implemented the framework for the numerical experiments using the MATLAB environment.

Probabilistic Modeling

We leverage a probabilistic approach to augment the methods used in Paper 3 and Paper 4. Both papers utilize weather forecasts, which inherently possess uncertainty due to the chaotic nature of the atmosphere and limitations in measurement and modeling. Probabilistic weather forecasts address this by providing quantitative information about the inherent uncertainty in meteorological predictions. One popular probabilistic technique is Ensemble Weather Forecasting (EWF), which generates a range of potential future weather scenarios. We employ an EPS, a popular implementation of EWF. The EPS framework involves running a deterministic Numerical Weather Prediction (NWP) model and creates a collection (ensemble) of forecasts by running the model multiple times with slightly different initial conditions and slightly perturbed weather models [21]. Typically, an EPS consists of 10-50 individual forecasts, called members, and the uncertainty information is derived from the spread of these members.

In Paper 3, we utilize EPS instead of fixed obstacle locations to enhance capacity estimation. The Available Sector Capacity Ratio (ASCR) is computed by averaging capacities across all altitude bands and flow paths, with its probability distribution enabling a probabilistic assessment of congestion. This distribution is derived by calculating ASCR for each ensemble member and analyzing the spread of capacity reductions across all forecasts, effectively quantifying the likelihood of different capacity constraints. Unlike previous approaches that relied solely on weather coverage, this method accounts for both spatial and temporal uncertainty, providing a more refined capacity estimation based on probabilistic weather inputs.

In Paper 4, we integrate EPS into the optimization model for RTC staff scheduling by introducing a new constraint into the MILP formulation to ensure that when impactful weather occurs at an airport, it must be operated in single mode, preventing an ATCO from simultaneously handling multiple airports. This is implemented through a binary parameter that enforces single-mode operation when weather conditions exceed a specified cutoff value. The MILP model is then solved separately for each ensemble member, generating an optimal staffing solution for each possible weather scenario. The probability distribution of the necessary number of ATCOs is computed by aggregating the solutions across all ensemble members. This approach enables probabilistic staffing assessment, enhancing workforce planning and mitigating understaffing risks in RTO.

3.4 Delimitations

- We limit the evaluation of flight efficiency to arrival flights within the TMA, focusing on the impact of weather conditions and traffic density, while acknowledging the potential influence of other factors. Inefficiencies are assessed using Stockholm Arlanda and Gothenburg Landvetter airports as case examples.

- The methodology of airspace capacity reduction evaluation is developed for the en-route airspace segment with numerical experiments conducted within Austrian airspace.

- In the ATCO scheduling optimization problem, we focus on the integration of weather conditions, while acknowledging that additional requirements and impact factors may be considered in future iterations. The numerical experiments with the model are limited to five small and medium-sized Swedish airports.

- The analysis of ATCO workload is confined to the en-route phase, with experiments conducted in a simulated environment for a single en-route sector within Swedish airspace.

3.5 Data

Aircraft Tracking Information

- Demand Data Repository (DDR2) hosted by EUROCONTROL

  EUROCONTROL provided data in SO6 format that is space separated values files which store flight trajectories (the lists of waypoints containing aircraft position 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 for both flight plans and actual trajectories of traffic within Stockholm Arlanda and Gothenburg Landvetter TMAs in Papers 1 and 2. We studied the benefits and drawbacks of DDR2 data in comparison to the OpenSky Network data in [96].

- EUROCONTROL R&D data archive

  We used flight plans (SO6 m1 files) of traffic crossing the Austrian airspace plus a surrounding area of 50 Nautical Mile (NM)s in Paper 3.

- Historical Database of the OpenSky Network

  OpenSky [97] is a crowd-sourced network of ground sensors which collect air traffic data from aircraft transponder signals. OpenSky provides an open access to the collected ATC data. We use aircraft state vectors (a summary of all tracking information) for every second of the trajectories inside TMA (Arlanda and Landvetter) in Papers 1 and 2.

  Our data preprocessing procedure for OpenSky data is described in [98].

- Flightradar24

  Flightradar24 [99] is an Internet-based service that provides real-time global air traffic data. It also offers historical flight data through a paid subscription. We utilize this data source for additional analysis of flight inefficiency on specific days in Paper 2.

Additionally, in Paper 4, we use Flightradar24 data to obtain the number of aircraft movements at the five selected airports during the days of consideration.

Aircraft Performance Data

BADA version 4.2 [100] is used for CDOs trajectory generation and fuel consumption calculation in Papers 1 and 2. Aircraft types operated by the studied flights not available in BADA are replaced by a type similar in performance and size.

Weather Data

- METAR

  METARs are reports that capture the present weather conditions at airports. These reports include details about the airport's location, date and UTC time, as well as weather information, such as wind speed and direction, visibility, precipitation, cloud cover, temperature, and pressure. This information is essential for air traffic management, especially for the smooth functioning of airport operations. We used METAR data in Paper 1.

- National Oceanic and Atmospheric Administration (NOAA)

  Gridded binary (GRIB) formatted files with 0.5 degrees granularity are provided by the Global Forecast System (GFS) through the National Operational Model Archive and Distribution System (NOMADS). These data were used to generate the longitudinal wind profiles as a function of the altitude (needed for the trajectory optimization), as well as for weather impact analysis in Paper 1.

- European Centre for Medium-Range Weather Forecasts (ECMWF) ERA5

  Reanalysis and ensemble datasets are provided via the C3S Data Store [101] in a 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 latitude-longitude 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 in Papers 1 and 2, as well as for fuel consumption calculation in Paper 2.

ECMWF ERA5 ensemble dataset includes an uncertainty estimation in the form of a 10-members 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 framework in Paper 4.

- Operational Programme for the Exchange of Weather Radar Information (OPERA), Satellite Application Facilities (SAF)

  The radar composites from OPERA and satellite products (convective rainfall rate and cloud top height) from SAF were used in combination to generate the nowcast data (short-term weather predictions with a lead time of up to 1 hour) in Paper 3.

- Germany's National Meteorological Service, the Deutscher Wetterdienst.

  The Deutscher Wetterdienst provided COSMO-D2-EPS - convection-permitting EPS weather product, which we used as the forecast data in Paper 3.

ATCOs' behavior-based/physiological data and self-reports

We conducted a controlled lab study in the ACC/radar simulation environment Topsky and collected the following data (used in Paper 5):

- Ocular and Head-Yaw Measures: We used the remote eye tracking system Smart Eye XO with two infrared cameras and 250 Hz sampling rate [102]. The system samples head position and movement, eyelid activity, and eye-gaze data, providing measures such as blink amplitude and speed, pupil diameter, saccades (rapid eye movements between fixation points), fixations, eyelid opening and closing amplitude and speed, and head rotation. It achieves up to 1.5 degrees of accuracy in head-rotation tracking and 0.5 degrees in gaze-tracking accuracy. Notably, it is compatible with eyeglasses wearers.

- Subjective workload Rating: We use an adapted CHS for workload—a ten-point numerical scale (see [103, 61]). The ten values of the scales are introduced by three questions: if the situation is solvable without major disturbance, it results in values 1-3; if the situation is solvable by capacity-reducing measures, it results in values 4-6; if the situation is solvable if the ATCO works with reduced situational awareness, it results in values 7-9; and a "no" to the last question results in value 10. We implemented an electronic self-assessment tool that utilizes this scale, enabling controllers to report their workload levels efficiently and systematically.

3.6 Publications Included in the Thesis

- **Paper 1** — A. Lemetti, T. Polishchuk, V. Polishchuk, R. Sáez, X. Prats. "Identification of Significant Impact Factors on Arrival Flight Efficiency within TMA." *Proceedings of the 9th International Conference for Research in Air Transportation (ICRAT)*, 2020.

- **Paper 2** — A. Lemetti, H. Hardell, T. Polishchuk. "Arrival Flight Efficiency in Pre- and Post-Covid-19 Pandemics." *Journal of Air Transport Management*, 2023.

- **Paper 3** — A. Lemetti, T. Polishchuk, V. Polishchuk, A. Valenzuela, A. Franco, J. Nunez-Portillo, D. Rivas. "Probabilistic Analysis of Airspace Capacity in Adverse Weather Scenarios." *Proceedings of the 12th SESAR Innovation Days (SIDs)*, 2022.

- **Paper 4** — E. Hernández-Romero, B. Josefsson, A. Lemetti, T. Polishchuk, V. Polishchuk, C. Schmidt. "Integrating Weather Impact in Air Traffic Controller Shift Scheduling in Remote and Conventional Towers." *EURO Journal of Transportation and Logistics*, 2022.

- **Paper 5** — A. Lemetti, L. Meyer, M. Peukert, T. Polishchuk, C. Schmidt, H. Alpfjord Wylde. "Predicting Air Traffic Controller Workload from Eye-Tracking Data with Machine Learning." *Journal of Open Aviation Science*, submitted February 2025.

3.7 Related Publications Not Included in the Thesis

- A. Lemetti, T. Polishchuk, R. Sáez, X. Prats. "Evaluation of Flight Efficiency for Stockholm Arlanda Airport Arrivals." *Proceedings of IEEE/AIAA 38th Digital Avionics Systems Conference (DASC)*, 2019.
- A. Lemetti, T. Polishchuk, R. Sáez, X. Prats. "Analysis of Weather Impact on Flight Efficiency for Stockholm Arlanda Airport Arrivals." *Proceedings of the 6th ENRI International Workshop on ATM/CNS (EIWAC)*, 2019.
- T. Polishchuk, A. Lemetti, R. Sáez. "Evaluation of Flight Efficiency for Stockholm Arlanda Airport using OpenSky Network Data." *Proceedings of the 7th OpenSky Workshop*, 2019.
- H. Hardell, A. Lemetti, T. Polishchuk, V. Polishchuk, V. Bulusu, E. Royo. "Morphing STARs vs Drones and Weather in TMA." *Proceedings of the 9th International Conference for Research in Air Transportation (ICRAT)*, 2020.
- A. Lemetti, T. Polishchuk, H. Hardell. "Arrival Flight Efficiency in Numbers: What New the Covid-19 Crisis is Bringing to the Picture?" *Proceedings of the 10th SESAR Innovation Days (SIDs)*, 2020.
- B. Josefsson, A. Lemetti, T. Polishchuk, V. Polishchuk, C. Schmidt. "Integrating Weather Impact in RTC Staff Scheduling." *Proceedings of the 10th SESAR Innovation Days (SIDs)*, 2020.
- H. Hardell, A. Lemetti, T. Polishchuk, L. Smetanova, K. Zeghal. "Towards a Comprehensive Characterization of the Arrival Operations in the Terminal Area." *Proceedings of the 11th SESAR Innovation Days (SIDs)*, 2021.
- H. Hardell, A. Lemetti, T. Polishchuk, L. Smetanova. "Evaluation of the Sequencing and Merging Procedures at Three European Airports Using Opensky Data." *MDPI Proceedings to OpenSky Symposium*, 2021.
- H. Hardell, A. Lemetti, T. Polishchuk. "Performance Evaluation of the Arrival Operations in the Terminal Area." *Proceedings of*

the 33rd Congress of the International Council of the Aeronautical Sciences (ICAS), 2022.

- H. Hardell, A. Lemetti, T. Polishchuk, L. Smetanova. "Performance Characterization of Arrival Operations with Point Merge at Oslo Gardermoen Airport." *Proceedings of the 15th USA/Europe Air Traffic Management R&D Seminar (ATM Seminar)*, 2023.

- A. Lemetti, L. Meyer, M. Peukert, T. Polishchuk, C. Schmidt. "Discrete-Fourier-Transform-Based Evaluation of Physiological Measures as Workload Indicators." *Proceedings of IEEE/AIAA 42nd Digital Avionics Systems Conference (DASC)*, 2023.

- G. Enea, T. Reynolds, J. Venuti, T. Polishchuk, V. Polishchuk, A. Lemetti, A. Lau, J. Solzer, T. Bölle. "Comparing Convective Weather Impacts on Air Traffic Management Operations in United States, Canada & Europe." *Proceedings of the 34th Congress of the International Council of the Aeronautical Sciences (ICAS)*, 2024.

- A. Lemetti, L. Meyer, M. Peukert, T. Polishchuk, C. Schmidt, H. Alpfjord Wylde. "Eye in the Sky: Predicting Air Traffic Controller Workload through Eye Tracking based Machine Learning." *Proceedings of IEEE/AIAA 43rd Digital Avionics Systems Conference (DASC)*, 2024.

- A. Lemetti, L. Meyer, M. Peukert, T. Polishchuk, C. Schmidt, H. Alpfjord Wylde. "Predicting Air Traffic Controller Workload using Machine Learning with a Reduced Set of Eye-Tracking Features." *Proceedings of the 35th European Association for Aviation Psychology Conference (EAAP)*, 2024.

3.8 Summary of the Included Papers

In this section we provide a summary for each paper included into the thesis.

3.8.1 Paper 1: Identification of Significant Impact Factors on Arrival Flight Efficiency within TMA

In this paper, we quantify flight efficiency using average Additional Time in TMA, average Time Flown Level, and Additional Fuel Consumption associated with inefficient flight profiles. We aim to identify key influencing factors, such as weather phenomena and traffic intensity, affecting the selected PIs. We leverage multiple data sources to obtain historical flight trajectories and weather measurements, enabling a comprehensive analysis of factors impacting TMA performance. First, we introduce the Aggregated Impact Factor (AIF), a unified condition metric representing current weather and traffic conditions. Regression of median values of Additional Time in TMA and Time Flown Level onto the AIF shows strong correlation for both PIs, confirming the significant effect of weather and traffic on flight efficiency. We then apply multiple linear regression with Backward Selection to identify statistically significant factors. Results indicate that wind gusts and snow had the greatest impact on arrivals at Stockholm Arlanda Airport in 2018.

The paper is co-authored with Tatiana Polishchuk, Valentin Polishchuk, Raúl Sáez and Xavier Prats. The author of this thesis contributed to conceptualization, the methodology development, collection and processing of the data, formal analysis (Additional time in TMA and Time flown level PIs, AIF, regression analysis, Backward Selection Algorithm), and writing of the manuscript.

3.8.2 Paper 2: Arrival Flight Efficiency in Pre- and Post-Covid-19 Pandemics

In this paper, we analyze the impact of weather and traffic intensity on arrival efficiency by examining two isolated scenarios: one with low traffic and one with favorable weather conditions. We introduce WIF, a unified metric representing current weather conditions, constructed using the PCA method, and apply it in the low-traffic scenario. Similarly, we define TIF, representing traffic conditions, and use it to study performance under good weather, isolating the influence of traffic. Flight inefficiency is assessed separately in the horizontal and vertical dimensions. To evaluate horizontal efficiency, we introduce a new performance metric—Additional Distance in TMA—defined as the difference between the actual flown distance and the ideal trajectory distance, capturing both airspace and operational inefficiencies. Reference trajectories are derived by clustering actual trajectories for each runway in the two TMAs using the approach in [104] and constructed as described in [105]. We find that weather conditions significantly impact vertical flight efficiency, while traffic intensity primarily affects lateral efficiency within the TMA.

The paper is co-authored with Henrik Hardell and Tatiana Polishchuk. The author of this thesis contributed to conceptualization, the methodology development, collection and processing of the data, formal analysis (Additional distance in TMA and Time flown level PIs, trajectory clustering, PCA, WIF, TIF, regression analysis), and writing of the manuscript.

3.8.3 Paper 3: Probabilistic Analysis of Airspace Capacity in Adverse Weather Scenarios

In this paper, we develop a methodology to estimate ATC sector capacity reduction due to predicted convective weather activity. Our approach is based on continuous maxflow/mincut theory, where each ATC sector is modeled as a 2D polygonal domain, with hazardous weather zones acting as obstacles that restrict air traffic flow. Aircraft enter and exit the sector through designated source and sink boundaries, while the bottom and top boundaries define the sector's flow constraints.

The mincut, representing the bottleneck limiting capacity, is computed using a critical graph representation, where vertices correspond to obstacles (hazardous weather cells) and sector boundaries, while edges represent distances between them. The mincut is identified as the shortest path separating the source and sink, determining the most restrictive passage for traffic flow.

We illustrate congestion detection in ATC sectors using a realistic sector example and a complete sector configuration, while also proposing a method to present probabilistic overload and congestion status to support decision-making at the FMP. The meteorological forecast uncertainty is quantified using EWF, which provides a probabilistic representation of atmospheric conditions by generating multiple forecast scenarios. For each ensemble member, hazardous weather cells are mapped as flow constraints.

To quantify capacity reduction, we compute the ratio between the mincut under weather constraints and the mincut in unobstructed airspace, representing the fraction of available sector capacity under adverse conditions, following [106]. We first compute the Available Flow Capacity Ratio (AFCR) for each altitude band and flow path, representing the fraction of usable capacity under weather constraints relative to its maximum unobstructed capacity, ranging from 0 (completely blocked) to 1 (fully available). These AFCR values are then averaged across all altitude bands and flow paths to determine the ASCR, which provides a sector-wide measure of capacity reduction due to adverse weather. The probability distribution of ASCR is derived by computing ASCR for each ensemble member and analyzing the spread of capacity reductions across all forecasts, quantifying the likelihood of different capacity constraints.

The paper is co-authored with Tatiana Polishchuk, Valentin Polishchuk, Alfonso Valenzuela, Antonio Franco, Juan Nunez-Portillo and Damián Rivas. The author of this thesis contributed to the implementation of the model, processing of the data, and writing of the manuscript.

3.8.4 Paper 4: Integrating Weather Impact in Air Traffic Controller Shift Scheduling in Remote and Conventional Towers

In this paper, we integrate weather impact into ATCO shift scheduling for RTCs. To achieve our goal, 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).

Weather-induced restrictions on the airport assignments are incorporated into the staff scheduling optimization framework as an additional constraint of the developed MILP. Then, the probability distribution of the necessary number of ATCOs is obtained using the developed MILP and EPSs.

Our experiments for five Swedish airports and two days with three to four weather phenomena occurring show the possible impact of weather. In most cases weather-induced additional restrictions cause the increased number of necessary ATCOs.

The paper is co-authored with Eulalia Hernández-Romero, Billy Josefsson, Tatiana Polishchuk and Christiane Schmidt. The author of this thesis contributed to the implementation of the model, collection and processing of the data, and writing of the manuscript.

3.8.5 Paper 5: Predicting Air Traffic Controller Workload from Eye-Tracking Data with Machine Learning

In this paper, we investigate feasibility of assessing ATCO workload using non-intrusive eye-tracking metrics in conjunction with machine learning algorithms. Subjective workload evaluations are concurrently obtained through self-reported CHS workload-rating scores, which serve as label variables. A sample of 18 ATCOs participate in simulated work sessions comprising tasks designed to elicit three distinct task-load levels: light, moderate, and heavy.

We assess the classification performance of ten conventional machine learning models. Focusing on the top-performing models, we employ feature selection techniques to derive reduced sets of eye-tracking features. Beginning with 42 features, we utilize a recursive elimination method based on permutation importance to identify the smallest feature subset that maintains or improves predictive performance. The findings demonstrate promising results in workload-level estimation, attaining an F1 score of 0.870 using 28 features for binary low/high workload classification, and an F1 score of 0.788 with 36 features for three-level workload prediction.

The feature sets may be further reduced to 7–13 features for different classification tasks with minimal degradation in performance. We identify a “knee point” that represents an optimal trade-off between model accuracy and feature dimensionality. Beyond this point, the inclusion of additional features yields negligible performance gains while increasing model complexity. These findings suggest that even a relatively small subset of around 10 features can suffice for effective workload prediction.

The paper is co-authored with Lothar Meyer, Maximilian Peukert, Tatiana Polishchuk, Christiane Schmidt and Helene Alpfjord Wylde. The author of this thesis contributed to conceptualization, the methodology development, collection and processing of the data, implementation of the models, formal analysis, and writing of the manuscript.

3.9 Research Contributions

In this section, we repeat the research questions formulated in Section 3.2 and for each question we explain in which papers and how it was addressed.

- Q1:
  - *How do different weather phenomena impact various aspects of ATM?*

    In Papers 1 and 2, we assess the impact of various weather phenomena on arrival flight efficiency, analyzing it in terms of horizontal, vertical, and fuel consumption efficiency, and proposing the methodology to determine which PIs are affected the most. In Paper 3, we examine how adverse weather affects en-route sector capacity, proposing a methodology to evaluate the resulting capacity reduction. In Paper 4, we analyze the impact of weather conditions on ATCO performance in an RTC operating in multiple mode. We establish thresholds for different weather phenomena that are critical for ATCOs and introduce a MILP constraint that limits ATCOs to managing a single airport under such weather conditions.
- Q2:
  - *What specific weather phenomena have the most significant impact on flight efficiency in terms of additional time, fuel consumption, and route deviations?*

In Paper 1, we apply statistical analysis to evaluate the impact of various weather phenomena on arrival flight efficiency, accounting for the current traffic situation, using Stockholm Arlanda Airport as a case study. We introduce the AIF, a unified condition metric that encapsulates current weather and traffic conditions, and conduct regression analysis of our PIs against the AIF. A strong correlation is found between the medians of the PIs and the AIF—particularly for Additional Time in TMA and Time Flown Level—demonstrating the influence of the components included in the AIF on these TMA performance indicators. Subsequently, we apply multiple linear regression combined with the Backward Selection algorithm to identify the statistically significant factors affecting the PIs. Among the considered variables—traffic intensity, snow, wind gusts, wind speed, total cloud cover, visibility, and CAPE—wind gusts and snow are identified as having the most substantial impact on arrival operations at Stockholm Arlanda during 2018.

- Q3:
  - *Which flight efficiency performance indicators are most impacted by the weather conditions?*

    In Paper 2, we use the opportunity given by Covid-19 pandemic traffic reduction to study the arrival performance in TMA in non-congested scenarios. We analyze the impact of weather and traffic intensity on arrival efficiency in isolated scenarios dominated by a single factor, such as low traffic or good weather. In the isolated scenario with low traffic flight performance, we use WIF developed in [107] (a unified weather condition metric), but enhance it by including more weather metrics and performing the classical tool of PCA. In the isolated scenario with good weather conditions we take TIF [107] as a factor that might influence the PIs. Regression analysis of the PIs onto WIF and TIF reveals that weather has a stronger influence than traffic intensity on the vertical efficiency, while traffic intensity has stronger effect on the lateral efficiency in both considered airports, Stockholm Arlanda and Gothenburg Landvetter. Additional Fuel Burn in the TMA shows moderate correlation with weather at both airports and strong correlation with traffic at Stockholm Arlanda, but no traffic correlation at Gothenburg Landvetter.

- Q4:

  - *What methods can be used to accurately predict reductions in airspace capacity due to adverse weather phenomena?* In Paper 3, we develop a methodology based on continuous maxflow/mincut theory to estimate sector capacity reductions caused by convective weather. This approach takes into account meteorological forecast uncertainty, quantified through EWF, which allows for the probabilistic prediction of both the spatial extent of weather hazards and their impact on air traffic flow.

    By applying this methodology to a realistic case study, the paper demonstrates how sector capacity reductions are forecasted and how probabilistic overloads are determined for specific airspace sectors. The integration of probabilistic weather forecasts with traffic flow modeling provides a tool for predicting congestion in air traffic sectors, thus supporting decision-making processes for FMPs.

- Q5:

  - *How can the impact of adverse weather conditions be effectively integrated into an optimization framework for Air Traffic Controller scheduling at Remote Tower Centers, and how can we account for uncertainties associated with these weather conditions?*?

    In Paper 4, we adjust the previously developed MILP model for RTC staff scheduling to account for uncertain impactful weather occurrence. For that we add a constraint that enforces an airport with impactful weather during a certain hour to be handled in single mode during that time. Whether the weather phenomenon can be considered as an impactful one, can differ for different airports and also depends on operator's estimate of what constitutes a strong enough impact to be accounted for. We use the literature and the ATCOs' interview answers to determine the thresholds for light, moderate and severe levels of five weather phenomena at five considered airports. We also deduce a taskload-driven impact factor for each weather phenomenon at each airport from ATCOs' answers. We perform a sensitivity analysis using a set of cutoff values for the taskload-driven impact factor. To take into account weather uncertainty, we use a probabilistic weather forecast in form of EPS, solve our MILP for each EPS ensemble member and deduce a probabilistic result from the solutions.

- Q6:

  – *What techniques are available for evaluating Air Traffic Controllers' workload, and how can we assess controller workload in an unobtrusive manner using behavioral or physiological metrics as indicators of high workload?*

    In Paper 5, we investigate the use of non-intrusive eye-tracking measures combined with machine learning algorithms for assessing ATCO workload. To achieve this, we collect data from ATCOs performing simulated tasks under light, moderate, and heavy task load conditions. In addition to eye-tracking data, we incorporate subjective self-assessments using the CHS, which serve as labels for workload prediction.

    The paper evaluates several machine learning models and identifies the most effective one for predicting ATCO workload levels based on the eye-tracking data. By applying feature selection techniques, the study reduces the number of features used in the models without compromising performance, demonstrating that a small, optimized set of eye-tracking features can predict workload levels with high confidence.

    The results indicate that these techniques are highly effective for evaluating workload, achieving F1 score=0.87 for predicting high workload. Moreover, the identification of a "knee point" in feature selection suggests that even a minimal set of features (7-13) can provide sufficient accuracy for workload prediction. This finding demonstrates that accurate and efficient workload evaluation is possible without overly complex models, providing valuable insights into how these techniques can be applied in operational settings.

Chapter 4

Conclusions and Future Work

Our studies have identified key areas for improvement within the ATM system, proposing novel methodologies with the potential to enhance both flight safety and operational efficiency. We investigated the impact of weather on air traffic operations, introducing innovative approaches for integrating weather conditions into ATCO shift scheduling and Flow Traffic Management practices. In pursuit of enhanced flight safety, we analyzed potential methodologies for objectively evaluating ATCO workload and proposed a novel, non-intrusive approach for detecting ATCO overload conditions.

Flight Efficiency. Our analysis of two Swedish airports—Stockholm Arlanda and Gothenburg Landvetter—shows that weather conditions have a significant impact on vertical flight efficiency, while traffic intensity is the primary factor affecting lateral efficiency within the TMA.

Since convective weather events are relatively rare in Sweden, we suspect that the weaker correlation observed between horizontal flight efficiency and weather conditions may be country-specific. In contrast, the strong correlation between horizontal flight efficiency and traffic intensity can be explained by the fact that, in congested scenarios, horizontal trajectories are often extended due to holdings or vectoring.

Our results indicate that wind gusts and snow have the most significant impact on our PIs at Stockholm Arlanda Airport. However, given the infrequency of convective weather events in our study area, our conclusion that such weather does not strongly affect flight performance within the TMA may have limited applicability. Future work could expand this analysis to airports where thunderstorms occur more frequently, such as Vienna International Airport, and explore more comprehensive descriptors of convective weather intensity that incorporate additional environmental variables.

The developed methodology can be applied to any airport and environmental variable, providing a valuable foundation for further research. This could include developing strategies to optimize arrival sequencing and mitigate delays caused by adverse weather. Additionally, insights from this approach may contribute to preemptive holding and diversion planning, enhancing operational resilience during challenging weather conditions. Improved coordination of ground operations, informed by these findings, could further enhance ATM efficiency and safety in adverse weather scenarios.

Airspace Capacity Reduction. We developed a methodology to forecast sector capacity reductions caused by convective weather, incorporating a probabilistic approach to account for meteorological forecast uncertainty, which is quantified using EWF. This approach, based on continuous maxflow/mincut theory, considers both the spatial extent and topology of weather hazards, as well as the direction of traffic flow. Applied to a realistic case study, the methodology estimates capacity reductions and determines the probabilistic overload of a given sector configuration.

A key advantage of this methodology is its potential to support timely and informed tactical flow management decisions under adverse weather conditions. By enabling better decision-making for FMPs, it enhances ATM efficiency, reduces flight delays, and improves the overall passenger experience.

Future research could extend this approach to identify and avoid airspace regions where specific atmospheric conditions impact flight efficiency or environmental sustainability. One example is the avoidance of areas with a high probability of persistent contrail formation, which could help reduce aviation's climate impact. By integrating this information into flight planning, it could help mitigate such effects, supporting environmentally conscious operations while maintaining efficiency.

ATCOs Scheduling. For RTC staff planning, we proposed a method to account for the impact of weather on ATCO work scheduling. To address uncertainty in weather predictions, we applied the EWF technique and obtained probabilistic weather data from EPS.

We tested this approach at five Swedish airports over two days with three to four different weather phenomena. The results suggest that the five ATCOs planned for these days may not be sufficient for the RTC without potentially compromising safety. The exception is a cutoff value of 0.7, where five ATCOs appear adequate to prevent what is considered a critical situation. The sensitivity analysis of the cutoff value clearly illustrates the trade-off between safety levels and staffing needs.

We emphasized the importance of developing higher-quality meteorological products with longer look-ahead horizons, tailored to the needs of airport staff planning—an aspect particularly crucial for remote towers. Given the inherent inaccuracy of weather predictions, additional staff buffers may be necessary to enhance roster robustness. Further analysis of historical data could help refine this technique. Expanding the study to include a broader range of airports with diverse climatic conditions would provide further validation and generalizability of the approach. Airports in regions with frequent convective weather, extreme temperatures, or high seasonal variability may present unique challenges for ATCO scheduling. Analyzing how different weather patterns influence staffing needs across various operational settings could help to refine the methodology and ensure its applicability to a wider range of ATM environments. In addition, considering the long-term impact of rapid climate changes and adjusting for their effects will be a crucial aspect of future work.

ATCO Workload. We demonstrated the significant potential of machine learning techniques for predicting ATCO workload using physiological data. Our findings highlight the efficacy of eye-tracking features, such as pupil diameter and blink metrics, either independently or in combination with head-movement data, in distinguishing varying levels of workload. By leveraging statistical summaries of eye-tracking measurements over time intervals, we effectively captured workload dynamics.

The results underscore feasibility of developing a non-intrusive workload monitoring system based on real-time eye-tracking and head-movement analysis. Such a system could serve as a valuable tool in operational environments by providing objective workload assessments to complement subjective self-reports and traditional performance metrics. Beyond detecting overload conditions that may compromise situational awareness and decision-making, the system could also identify underload situations, where low levels of engagement may lead to a false sense of security and reduced vigilance, ultimately diminishing operational performance.

Future research could incorporate additional physiological or behavioral signals (e.g., voice, visual scan patterns, and heart measurement variables) to refine workload estimation and improve model robustness. Another relevant research focus is investigating the tradeoffs between subject-independent and subject-specific strategies for workload prediction. While subject-independent models offer broader applicability, subject-specific approaches can provide higher accuracy by accounting for individual differences. Understanding these dynamics could help to refine workload assessment methods and inform potential applications in operational ATC environments.

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Papers

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