Data-Driven Occupancy Prediction in Adverse Weather Conditions using Thunderstorm and Traffic Observations

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***Abstract*—In recent years, convective weather has been the cause of significant delays in the European airspace. With climate experts anticipating the frequency and intensity of convective weather to increase in the future, it is necessary to find solutions to mitigate the impact of convective weather events on the airspace system. Analysis of historical air traffic and weather data will provide valuable insight on how to deal with disruptive convective events in the future. We propose a methodology for processing and integrating historic traffic and weather data to enable the use of data-driven algorithms to predict network performance during adverse weather. In this paper we process aircraft trajectory and storm observation data to test preliminary algorithms for predicting airspace capacity. Data sources include Demand Data Repository from EUROCONTROL and the Rapid Developing Thunderstorm product from EUMETSAT.**

***Keywords*—Thunderstorms, Air Traffic Flow Management, Data Science, Machine Learning, Aircraft Trajectories, Capacity Prediction**

I. Introduction

Proper execution of Air Traffic Flow Management (ATFM) requires well organised collaboration between stakeholders, including aircraft operators, Air Navigation Service Providers, MET service providers and the Network Manager [1]. On days with strong thunderstorm activity, the airspace system conditions can be highly volatile making it difficult to balance aircraft operator demand with airspace capacity. Thunderstorms can move quickly and exhibit lifecycles that can develop and dissipate within 2 hours, making them difficult to anticipate over longer time horizons. As a result, convective weather must be tactically managed during the execution of a flight, having significant impact on the the efficiency of the ATM system. In 2018, 4.8 million minutes of en route ATFM delay were due to adverse weather in the European airspace, a 124 percent increase vs 2017 [2]. In the top 10 days of convective activity over Europe in 2018, more than 1 million minutes of en route delay were accumulated due to adverse weather, with the cost of ATFM delay estimated at €100 per minute [3], weather has a significant financial impact on the system.

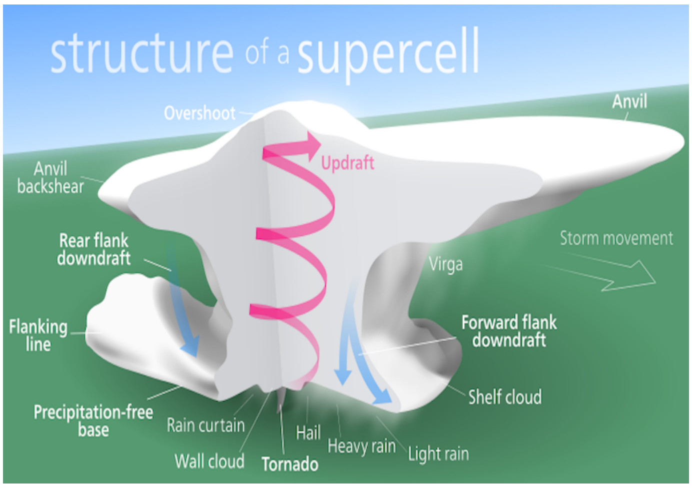
The motivation behind this research is to improve the ATFM process around convective weather events. By collecting historical data related to traffic demand, ATFM regulations, traffic trajectories, weather forecast, and storm observations we ambition to build machine learning algorithms to better predict demand and capacity of the system. Our goal is to improve the ATFM process through better integration of weather information during the tactical and pre-tactical phases.

II. Background

Convection is a well known aviation hazard; turbulence, wind shear, lighting and hail are elements within thunderstorms that can be catastrophic for aircraft. Aviation research related to thunderstorms and convection has typically focused on flight specific solutions, such as trajectory optimisation during the flight planning stage [see 4, and references therein]. Also, in the United States where convective weather is more prevalent, decision support tools have been developed to analyse active flights in the en route environment and find simple and efficient route corrections around convective weather [5]. Despite these developments, a network wide perspective focused on reducing the impact of adverse weather on the air traffic flow management process is lacking. Most research on air traffic flow management has focused on dealing with en route sector capacity constraints using integer programming techniques [6, 7], while effective, the formulation of these methods rely on predefined capacity values making it difficult to incorporate a dynamic weather environment.

Performing ATFM operations in a convective weather environment is particularly complex due to the dynamic nature of thunderstorms and their effect on air traffic demand and airspace capacity. At different time horizons, the weather information available widely varies. For longer time horizons, weather information is limited to numerical weather prediction (NWP) products with varying accuracy, these have proven to be very useful and research has been done on translating probabilistic information from ensemble NWP into air traffic capacity forecasts [8]. However, the large computational effort required to run NWP tools results in limitations in spatiotemporal granularity and the refresh rate of the forecast, typically around 12 hours.

For shorter time horizons, the weather information relies heavily on observations and extrapolation of radar and satellite,



(a) Convective cell schematic.[1]

(b) Rapidly Developing Thunderstorm (RDT) product visualisation.

Figure 1: Convective cell schematic (1a) and RDT visualisation (1b). Figure 1b shows data from June 7th, 2018 at 15:30. Hatch pattern contours indicate shelf clouds, colors represent storm severity, while an "X" indicates the location of overshoots.

data can be provided every 15 minutes proving to be fairly accurate but limited by the forecast time horizon, typically less than one hour. Detecting capacity-demand imbalances in the airspace network due to weather should be done on a continuous basis over varying time horizons. Indeed, one of our future research objectives will be to integrate weather data from various sources and multiple time horizons.

Our research will involve applying data science techniques on historical traffic and weather data. We intend to develop machine learning algorithms capable of predicting and quantifying the capacity and demand imbalances in the network due to weather over multiple time horizons.

The analysis will be performed in two steps. Step 1 will focus on relating storms and traffic. By analysing historical data of storm observations and air traffic patterns we hope to understand how convective weather impacts the air traffic flow management process. In this step, we focus on the research question: *"If we had access to a perfect weather forecast, how would we implement ATFM solutions?"* Applying machine learning and data science techniques to ATM is an extremely active area of research, and has proved to useful in predicting elements such as predicting controller workload [9] and flight trajectories [10, 11]. We are confident these techniques will also be viable for capturing the relation between weather and traffic patterns.

Once we understand how storms impact the air traffic system, Step 2 will focus on improving our ability of predicting storms over longer time horizons. By analysing historical numerical weather prediction forecast and storm observations we hope to enhance our capability of anticipating storms that are likely to impact the network. In this step, we acknowledge that having a perfect weather forecast is not possible, and consider the followup question: *"How can we still implement ATFM solutions based on a probabilistic weather forecast?"*. The concept of using machine learning methods to enhance weather prediction is also an active area of research. Convolution LSTM networks and support vector machines have proven successful for nowcasting applications [12, 13], as well as forecasting techniques that combine NWP and observations as input [14].

For this paper we will limit the scope to Step 1, relating storm observations and air traffic patterns. We will assume that we have a "perfect weather forecast" composed of data from storm observations, and use it to make predictions about the air traffic patterns. We will present a methodology to process historical storm and traffic data, as well as preliminary algorithms to predict capacity.

III. Data Sources

A. Weather Observations

The Rapidly Developing Thunderstorm (RDT) product is a satellite based software by EUMETSAT capable of tracking and identifying convective cloud cells i.e. storms. The RDT product covers the geographical region of Europe, and outputs storm data on a 15 minute interval. Furthermore, besides the storm observations, the RDT product can also extrapolate the cloud cell parameters to provide a nowcast of where the storm will be in 15 minute steps up to the hour. For each cloud cell, the RDT product defines a series of parameters capturing the location, shape, movement, severity, and lifecycle phase. In our research we focus on parameters defining the altitude of the cloud top, the contour coordinates of the top cloud and shelf cloud, the location of the overshoot, and severity of the storm. Figure 1 shows a thunderstorm schematic identifying the various storm features and a sample of the RDT product.

B. Air Traffic

We will use Demand Data Repository (DDR) from EUROCONTROL to analyse historical air traffic patterns during convective weather. DDR provides data describing the airspace

[1]Source: https://commons.wikimedia.org/wiki/File:Supercell.svg

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environment and the traffic in the network. Our research will focus on the historical ALLFT files provided by DDR. More specifically we will use the data from the Current Tactical Flight Model (CTFM) trajectories of historical flights. The CTFM uses a combination of the last filed flight plan and available radar data to compute the closest estimate of the flight trajectories handled by controllers on the date of operations. Previous studies comparing CTFM trajectories to other products such as ADS-B or FlightRadar 24, show that CTFM trajectories may not to be as accurate [15], however, the advantage of using the DDR is that it also provides the Filed Tactical Flight Model (FTFM); an initial trajectory based on the aircraft's last filed flight plan, and the Regulated Tactical Flight Model (RTFM) which is the same as the FTFM model, with a change in the time component of the trajectory to reflect the most penalising ATFM delay. Having data on the intentions and restrictions of aircraft through the FTFM and CTFM will be useful information to incorporate in our models. Nevertheless, using trajectory data from ADS-B or FlightRadar24 as input could easily be implemented in our methodology.

IV. Data Processing

Given the spatiotemporal nature of the problem, it is necessary to relate the air traffic data and storm observations in both time and space. The idea is to integrate the various data types onto a 4 dimensional grid. One can imagine splitting the airspace into discrete volumes of airspace defined by longitude, latitude and altitude, additionally we can also define time intervals thus creating the spatiotemporal domain. In pre-processing each data type it is important to consider the granular scale of the grid, as the choice in granularity may impact the degree to which our algorithm will be able to detect imbalances.

In the vertical axis we decided to choose a non-uniform altitude distribution that would give us more granularity in the upper airspace, but also capture data close to airports. In defining the vertical axis for our grid it was necessary to reconcile between trajectory height information provided in Flight Level and the storm cloud top information provided in pressure. Since aircraft flying above the transition altitude fly using Flight Levels defined by surfaces of constant pressure measured from the ISA conditions, it is possible to convert the trajectory Flight Levels to a pressure. As a result we ended up with 6 altitude levels, these are defined in Table I.

TABLE I: Altitude Level Definition

Altitude Level	Pressure Range (hPa)	Altitude Range FL
5	≤ 200	$\geq$390
4	200-250	390-340
3	250-300	340-300
2	300-400	300-240
1	400 - 700	240 -100
0	700-Surface	100 - Surface

With a spatiotemporal grid fully defined, the next step is to use the various data sources to create traffic and weather related features for each air-block.

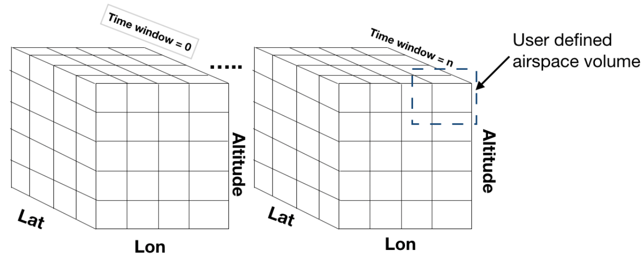


Figure 2: User defined grid will determine the scale at which traffic and weather features are extracted.

A. Weather Observations

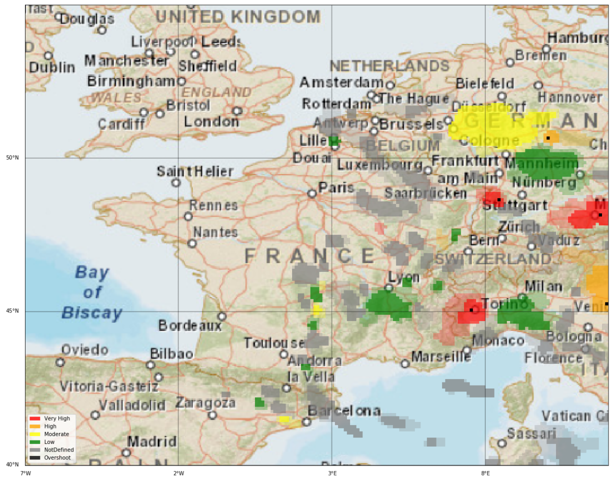
Using the location information of the storm cell, including shelf cloud contour, overshoot coordinates, the cloud top altitude, and severity type (Not Defined, Low, Moderate, High, Very High) from the RDT product we can relate the storm information onto our spatiotemporal grid as binary features. Figure 3 shows a sample of the RDT weather after it is fully processed. In mapping the RDT data onto our grid we make the simplifying assumption that the storm projection is constant from the cloud top altitude down to the ground, this column like representation of convection is a common way of modelling the weather phenomenon and has been used in other aviation applications [16]. Figure 4 shows a visualisation of the gridded RDT data on a map, as well as a three dimensional rendering of our storm data, from the image we can appreciate the vertical resolution provided by the cloud top altitude RDT parameter.

Time	Lon	Lat	Alt Level	Overshoot	Storm Cell	Shelf Cloud	Not Defined	Low	Moderate	High	Very High
2018-05-29 16:45:00	10.6	49.9	2	0	1	1	0	0	1	0	0
2018-05-29 13:15:00	1.9	41.7	3	0	1	0	0	1	0	0	0
2018-05-29 11:00:00	13.1	46.5	0	0	1	0	0	0	0	0	1
2018-05-29 22:15:00	17.2	45.7	1	0	1	1	1	0	0	0	0
2018-05-29 13:00:00	4.2	51.6	0	0	1	1	1	0	0	0	0

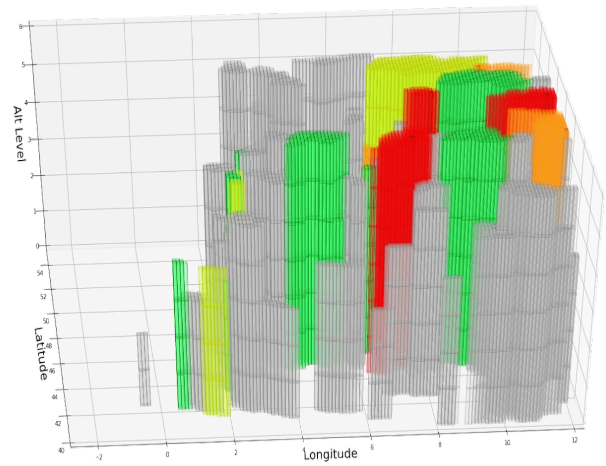
Figure 3: Sample of processed RDT data showing storm elements that were present at each point in our grid. The data sample shows a granularity of 0.1 x 0.1 degrees lat-lon and 15 minute time intervals. The five rightmost columns relate to storm severity.

B. Air Traffic

The current tactical flight model trajectories from the Eurocontrol DDR provides the 4D trajectory (latitude, longitude, altitude and time) for historic flights. The data sampling rate of these trajectories is not constant, often providing more data points during the departure and arrival phases of a flight than at cruise. By making the assumption of constant speed between data points, we are able to interpolate the CTFM trajectories to obtain points within each crossing air-block, the sampling rate we chose to interpolate the trajectories will provide the granularity of the spatiotemporal grid. Figure 5 shows a visual representation of the interpolation process.



(a) Processed RDT data in 2D (Lat x Lon)



(b) 3D rendering of RDT data with altitude.

Figure 4: Visual representation of processed RDT data for June 7th, 2018 at 15:30.

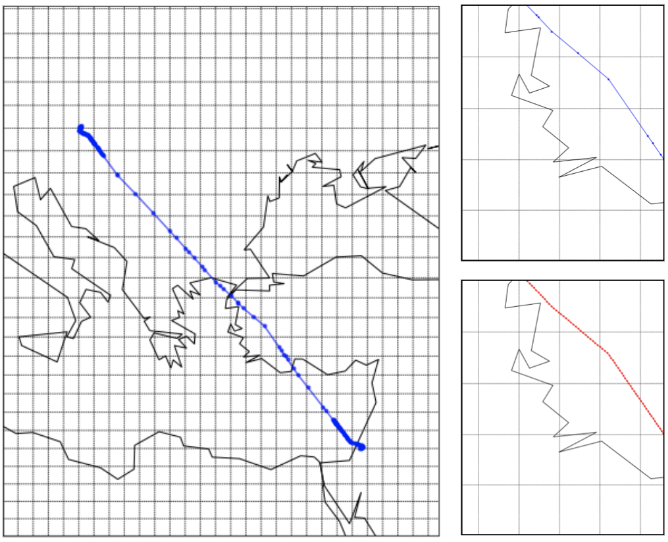


Figure 5: The box on the left shows the raw CTFM trajectory for a particular flight. The boxes on the right show a zoomed in view on a portion of the trajectory. The blue line represents the raw CTFM trajectory, the red line represents a resampled trajectory with interpolated points.

By working with the fully interpolated trajectories we can filter on latitude, longitude, altitude and time to identify the trajectory points within a given air-block in a given time window. Since each trajectory is uniquely identified by the Initial Flight Plan Processing System (IFPS), the number of unique IFPS IDs provide us with the occupancy count. Figure 6 shows a sample of traffic data once fully processed. The columns labeled 'Time, 'Lon', 'Lat' and 'AltLevel', define the spatiotemporal location of each air-block. Since time in our data is actually an interval, the value 'Time' represents the start of the time window. The column 'FlightIDs' lists which flights were in each air-block, and 'Count' provides the number of flights.

A visual representation of the traffic data is also provided in Figure 7 showing traffic at various altitude levels and spatiotemporal grid sizes. At lower levels we can see the traffic is concentrated near airports, while air routes begin to emerge at higher levels. From the image we can also appreciate the differences in granularity of the spatiotemporal grid.

Time	Lon	Lat	AltLevel	FlightIDs	Count
2018-06-27 08:00:00	10.0	44.0	5	[AA02918295]	1.0
2018-05-18 09:00:00	2.0	46.0	1	[AA01469354, AA01470024, AA01474501, AA01470387]	4.0
2018-05-25 16:00:00	-6.0	51.0	3	[AA01704145, AA01736414]	2.0
2018-06-19 17:00:00	8.0	42.0	1	[AA02634936, AA02626809, AA02623041, AA02623042]	4.0
2018-06-22 10:00:00	9.0	46.0	1	[AA02742016, AA02741969, AA02739767, AA02753810]	4.0

Figure 6: Sample of processed air traffic data showing the flights that were present at each point in our grid. Sample data shows granularity of 1 x 1 degrees lat-lon and hourly time intervals.

V. Case Study

In this section we will present a preliminary case study using 65 days of historical traffic and weather data from May 4th to July 7th of 2018.

As an initial objective we would like to understand how weather impacts the capacity in an airspace. Defining baseline capacity values for our spatiotemporal airspace airspace is not a trivial task. In practice defining capacity values of an airspace during the ATFM process is also complicated, as the real capacity value depends on many other variables including sector configuration, traffic complexity, and controller experience. In this case study we will build models to estimate the aircraft occupancy count in a volume of airspace for a given time window. We will assume that the historical aircraft count in a volume of airspace is a proxy for capacity. The goal will be to build a model that estimates the number of aircraft in a volume of airspace given the weather conditions.

A. Spatiotemporal Definition

In our analysis we have decided to process the data using a grid of 0.1 x 0.1 degrees latitudinal-longitudinal, the altitude

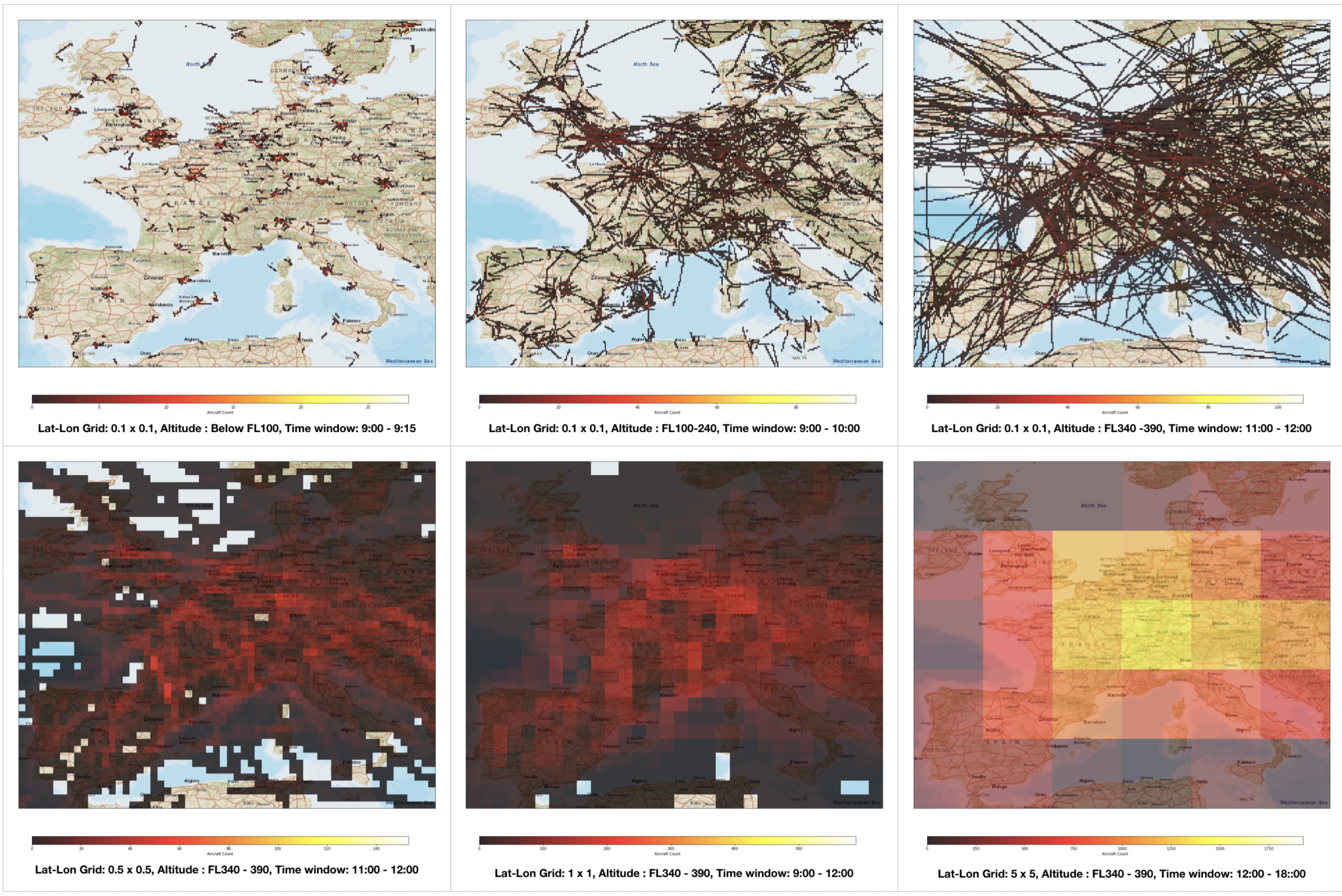


Figure 7: Traffic data for June 7th, 2018 at varying altitude levels, time windows and grid granularity.

levels described in Table I, and a one hour time step window.

B. Airspace Selection

For this example we have decided to focus on the airspace covering Maastricht Upper Area Control Centre (MUAC). Using the coordinates provided from the EUROCONTROL environment files we can select the air-blocks that fall within the MUAC airspace. Figure 8 shows the MUAC airspace represented on our grid. Since MUAC extends vertically from FL 245 to FL660, we can estimate the volume by only considering the air-blocks in altitude levels 2 - 5, as described in Table I.

C. Data Features

By aggregating the data for the air-blocks that make up the MUAC airspace, we can obtain the following parameters representative of the traffic and weather situation in the sector.

- FlightIDs - IFPS ID of flights in sector
- CTFM Occupancy - Aircraft occupancy based on CTFM (proxy for capacity)
- Overshoots - Number of air-blocks containing overshoot of storm
- Storm Cell - Number of air-blocks containing a storm cell

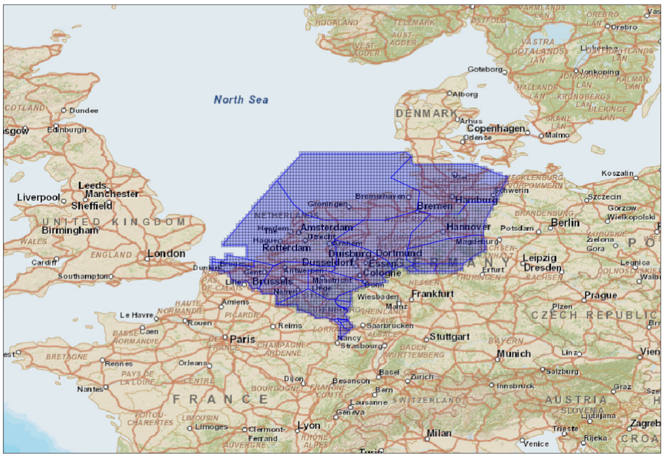


Figure 8: Maastricht Upper Area Control Centre represented using air-blocks. Image shows a 2D representation, but there is a similar layer of air-blocks for each altitude level.

- Shelf Cloud - Number of air-blocks containing the shelf cloud of storm cell
- Not Defined - Number of air-blocks with storm severity ”not defined”
- Low - Number of air-blocks with low storm severity

- Moderate - Number of air-blocks with moderate storm severity
- High - Number of air-blocks with high storm severity
- Very High - Number of air-blocks with very high storm severity

This list shows an initial set of parameters based on the data processing shown in the previous section, but we could also express other weather parameters for each air-block such as prevalent winds, the jet stream, visibility, etc. As for additional traffic parameters, we can create similar count parameters based on the filed and regulated flight tactical models (FTFM, RTFM). Additionally we can imagine using the flight IFPS IDs to cross reference other databases to formulate additional features that reflect traffic characteristics such as arrivals/departures aerodromes, traffic volumes, delays, etc.

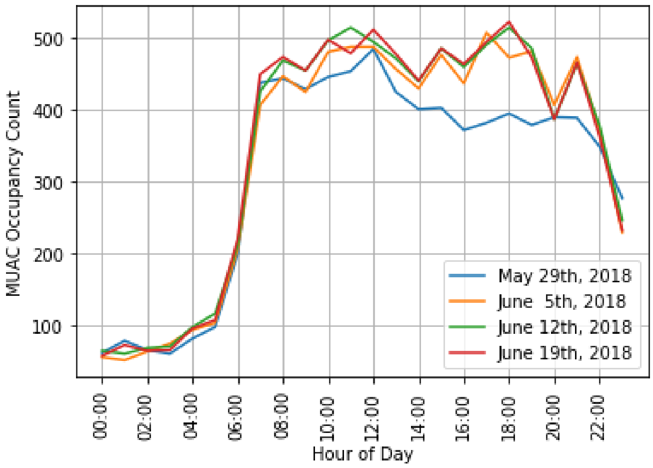


Figure 10: Comparison of occupancy count in MUAC on Tuesday May, 29th and the following three Tuesdays. Lower occupancy on the 29th can be attributed to afternoon thunderstorms in the sector.

D. Modeling

In this example we will predict the occupancy count based on a subset of weather parameters; overshoots, high, and very high storm severity. These three parameters were chosen since these are likely to have the largest impact on air traffic. Figure 9 shows a time series representation of traffic and the selected weather features from May 21st through June 13th, a period with thunderstorm activity in the MUAC airspace. From the figure we can see some decreases in the occupancy count corresponding to times with peak values of overshoots, high, and very high storm severity. The effect of weather can be better appreciated in Figure 10, it compares the occupancy count for Tuesday May 29th, 2018, the day with the most storms in our dataset, with the occupancy of the following three Tuesdays.

In formulating our models, we treated the occupancy count as our dependent variable, and the weather parameters as independent. We also created binary independent variables based on the day of the week and hour of the day. Our final input data consisted of 34 features, 3 related to weather, and 31 related to time (7 days of the week plus 24 hours of the day). Next, we split the data into two sets for training and testing, we chose to train on the data from May 4th - June 5th and test on the data for June 6th - July 7th. The intention was to have thunderstorms show up in both sets, from the data we see that there were two episodes with strong convection; the week of May 28th, and the days following June 6th, our attempt was to train the models with data from the first episode of storms to predict the second. We fit the data using multiple data science techniques using existing python libraries. From the data we created four different models based on multiple linear regression, decision tree regression, neural network, and a long short-term memory recurrent neural network (LSTM) method-

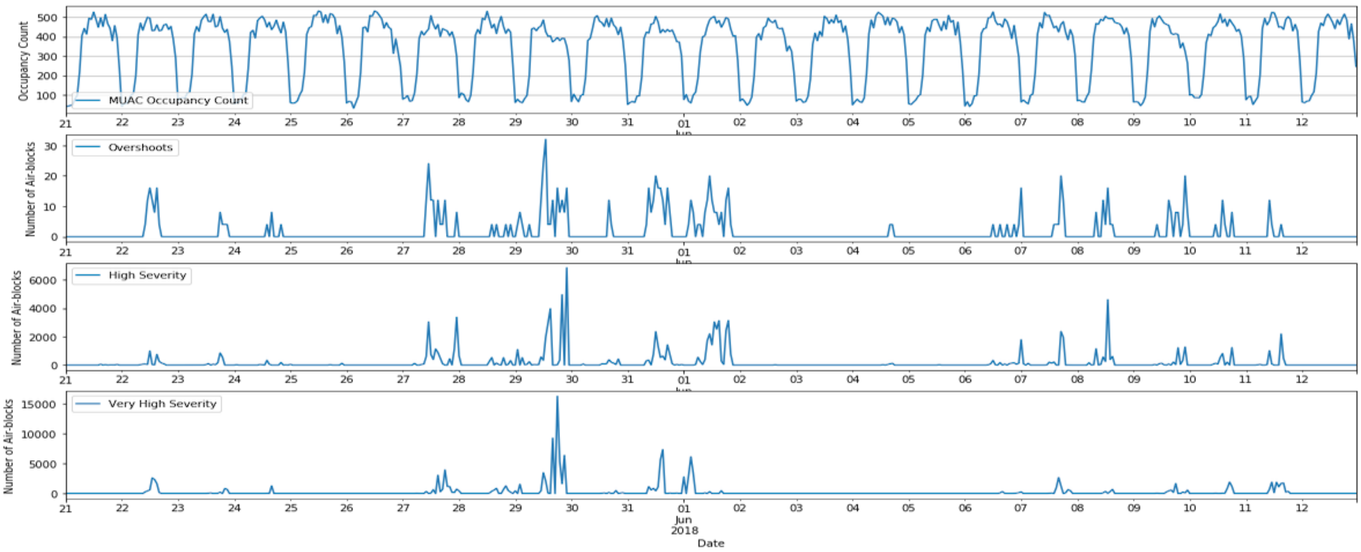


Figure 9: Time series representation of features occupancy count, overshoots, high and very high for MUAC airspace from May 21st - June 12th.

ologies. Further processing was performed to normalised the data using the "MinMaxScaler" function before fitting the data into the neural network and LSTM models.

1) Multiple Linear Regression: Model based on ordinary least squares regression using the python "statsmodels" library

2) Decision Tree Regression: A decision tree regressor using the python "sklearn" library. The decision tree was created with a max depth parameter of 30.

3) Neural Network: Neural network model using the "keras" library. Network architecture use was 34 input nodes, 3 hidden layers of sizes 40 ,80, 20, and 1 output node.

4) LSTM Neural Network: LSTM formulation using information from the previous 4 time steps. LSTM model was built using the "keras" library. The input dimension for model was 174 parameters, made up of (34 independent + 1 dependent variables) at the 4 previous time steps + 34 independent variables at current time step.

VI. Results

Figure 11 shows the outputs of the four models for the time period June 6th through June 12th, 2018, days in which there was also thunderstorm activity in the network. Table II shows the root mean square error and R^2 correlation coefficient for the multiple models over the entire validation set (June 6th through July 7th). The results show that the data can be modelled fairly accurately by simply using linear regression, this is likely due to the highly cyclical behaviour of aircraft occupancy in the MUAC sector. The neural network and LSTM model offer slightly better performance, however whether these models are capable of capturing sensitivity due to the weather parameters needs to be further analysed. Additional data containing more episodes of convection would allow us to further validate our models.

While our models may accurately predict the occupancy count in a sector, further development is needed to capture the relationship between storms and traffic. Deviations in traffic patterns due to aircraft flying around or over convective weather are likely to exist in the data, however these variations are lost by aggregating the data into a one dimensional vector. In future versions we intend to feed our models with multi-dimensional arrays rather than a one dimensional time series, the use of arrays will allow us to better capture the spatial relationships and location specific behaviour between storms and traffic.

TABLE II: Comparison of model performance for June 6th - July 7th data

Model Type	Root Mean Square Error	R^2
Multiple Linear Regression	25.565	0.978
Decision Tree Regression	24.410	0.980
Neural Network	19.626	0.987
LSTM NN	17.728	0.990

VII. Conclusion and Future Work

In this paper we set out to demonstrate a methodology for integrating historical weather and traffic data. We have also demonstrated a preliminary implementation of multiple machine learning algorithms to predict the occupancy count in the MUAC sector given the day of the week, time of day, and weather parameters. Initial results of a time series representation of the problem seem promising, however models need to be refined and tested with additional datasets to validate they are able to capture the effects of weather. We will also explore extracting additional features from DDR such as regulations and delays, allowing us to find correlations between these parameters and weather.

In the next steps of our research, we will move from the assumption of having a "perfect weather forecast" and use actual storm forecast as inputs to our traffic models. These storm forecasts will be the output of ongoing parallel work, in which

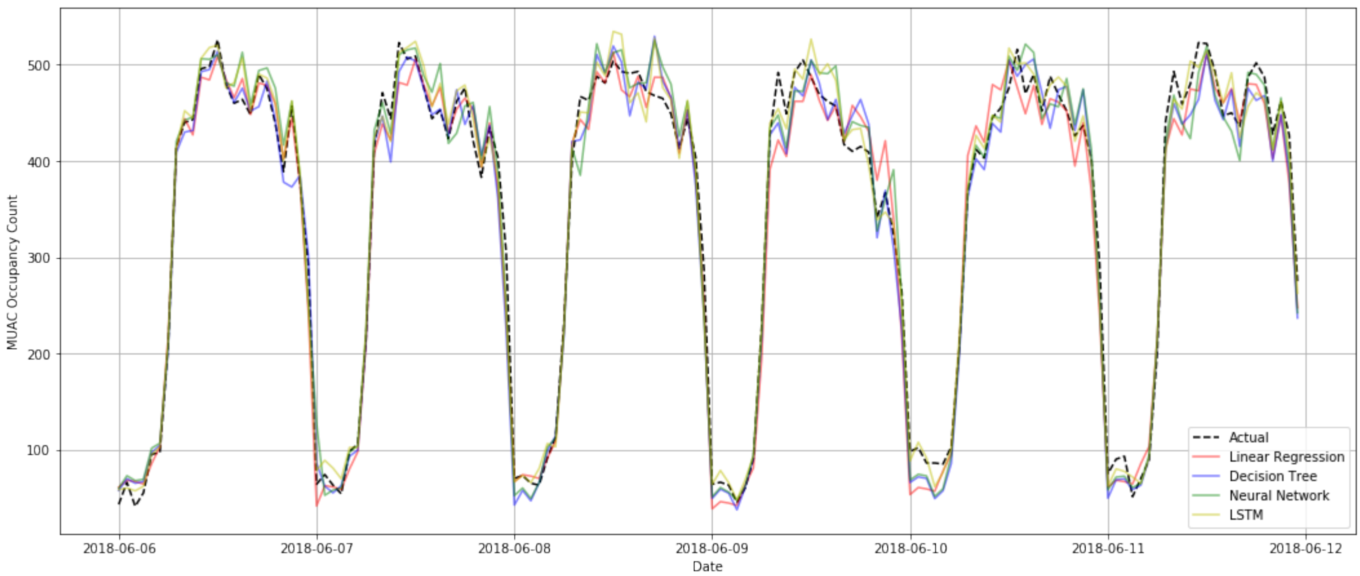


Figure 11: Comparison of models estimating MUAC occupancy for June 6th - June 12th, 2018

we integrate data from numerical weather prediction tools and storm observations to develop machine learning algorithms for weather prediction. The operational goal of this research will be to accurately assess the future characteristics of the network based on weather forecasts. Machine learning has already started making advances in the area of meteorology to improve the accuracy of weather forecasts, we aim to leverage these knowledge gains to improve the ATFM process.

VIII. Acknowledgements

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References

[1] EUROCONTROL, *ATFCM Operations Manual*, EUROCONTROL, https://www.eurocontrol.int/publication/atfcm-operations-manual, March 2019.

[2] ——, *2018 Performance Review Report, "An Assessment of Air Traffic Management in Europe during the Calendar Year 2018"*, EUROCONTROL, https://www.eurocontrol.int/air-navigation-services-performance-review, May 2019.

[3] A. Cook and G. Tanner, "European airline delay cost reference values: Updated and extended values," 2015.

[4] D. González-Arribas, M. Soler, M. Sanjurjo-Rivo, M. Kamgarpour, and J. Simarro, "Robust aircraft trajectory planning under uncertain convective environments with optimal control and rapidly developing thunderstorms," *Aerospace Science and Technology*, vol. 89, pp. 445–459, 2019.

[5] D. McNally, K. Sheth, C. Gong, M. Sterenchuk, S. Sahlman, S. Hinton, C. H. Lee, and F.-T. Shih, "Dynamic weather routes: two years of operational testing at american airlines," *Air Traffic Control Quarterly*, vol. 23, no. 1, pp. 55–81, 2015.

[6] G. Lulli and A. Odoni, "The european air traffic flow management problem," *Transportation science*, vol. 41, no. 4, pp. 431–443, 2007.

[7] S. Gupta and D. J. Bertsimas, "Multistage air traffic flow management under capacity uncertainty: a robust and adaptive optimization approach," *Proceedings of the 51st AGIFORS Annual Symposium and Study Group Meeting*, 2011.

[8] M. Steiner, R. Bateman, D. Megenhardt, Y. Liu, M. Xu, M. Pocernich, and J. Krozel, "Translation of ensemble weather forecasts into probabilistic air traffic capacity impact," *Air Traffic Control Quarterly*, vol. 18, no. 3, pp. 229–254, 2010.

[9] D. Gianazza, "Analysis of a workload model learned from past sector operations," 2017.

[10] R. Marcos, O. C. Ros, and R. Herranz, "Combining visual analytics and machine learning for route choice prediction. application to pre-tactical traffic forecast," *Seventh SESAR Innovation Days, Belgrade, Serbia, 28th–30th November*, 2017.

[11] E. C. Fernández, J. Cordero, G. Vouros, N. Pelekis, T. Kravaris, H. Georgiou, G. Fuchs, N. Andrienko, G. Andrienko, and E. Casado, "Dart: A machine-learning approach to trajectory prediction and demand-capacity balancing," *Seventh SESAR Innovation Days, Belgrade, Serbia, 28th–30th November*, 2017.

[12] S. Xingjian, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo, "Convolutional LSTM network: A machine learning approach for precipitation nowcasting," *Advances in Neural Information Processing Systems*, pp. 802–810, 2015.

[13] L. Han, J. Sun, W. Zhang, Y. Xiu, H. Feng, and Y. Lin, "A machine learning nowcasting method based on real-time reanalysis data," *Journal of Geophysical Research: Atmospheres*, vol. 122, no. 7, pp. 4038–4051, 2017.

[14] J. R. Mecikalski, D. Rosenfeld, and A. Manzato, "Evaluation of geostationary satellite observations and the development of a 1–2 h prediction model for future storm intensity," *Journal of Geophysical Research: Atmospheres*, vol. 121, no. 11, pp. 6374–6392, 2016.

[15] E. Spinielli, R. Koelle, M. Zanin, and S. Belkoura, "Initial implementation of reference trajectories for performance review," *Seventh SESAR Innovation Days, Belgrade, Serbia, 28th–30th November*, 2017.

[16] M. Sauer, M. Steiner, R. D. Sharman, J. O. Pinto, and D. R. Adriaansen, "Flight planning and execution with multiple weather hazards," *The Journal of Air Traffic Control*, vol. 58, no. 4, pp. 16–23, 2016.