Neural Network based Convection Indicator for Pre-Tactical Air Traffic Flow Management

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***Abstract*—A main objective of Air Traffic Flow Management is matching airspace and airport capacity with demand. Being able to accurately predict unexpected disruptions to the air traffic network, such as convective weather is essential in order to make better informed decisions and improve performance of the system. In this paper we demonstrate how machine learning can improve prediction of convective areas at time horizons necessary for the pre-tactical phase of ATFM. Data from numerical weather prediction forecast are merged with storm cell observations from satellite and used to train a neural network model to identify convective areas at time horizons up to 45 hours. Results show the neural network model outperforms an existing convection indicator in predicting thunderstorms.**

***Keywords*—Convection, Thunderstorms, Machine Learning, Numerical Weather Prediction, Ensemble Prediction System, Satellite Observations**

I. Introduction

Weather is a major disrupter to the air traffic system. In 2018, 4.8 million minutes of en route ATFM delay were attributed to adverse weather in the European airspace [1]. Convective weather is a main source of disruption, causing the majority of delays to occur during the summer months. Despite advances in weather forecasting techniques, aviation weather products used during pre-tactical ATFM operations are limited. In Europe, EUROCONTROL's Network Operations Portal (NOP) provides a Daily Network Weather Assessment [2]. The assessment is a document containing a brief written description of the general weather outlook for the Network, and severe weather alerts for en route airspaces and airports. The weather assessment also contains a series of static maps providing forecasts of temperature, winds and precipitation for the day. While this daily product is useful in providing some awareness of the meteorological conditions for the day, it fails to capture evolving weather phenomena such as convection. As a result, convective weather is typically managed tactically leading to inefficiencies in ATFM measures.

In the US, Federal Aviation Administration traffic managers must obtain high confident forecast with 2 - 8 hours lead time in order to effectively minimise disruptions in the network due to weather. In the case of a large scale weather impact, a Severe Weather Avoidance Plan (SWAP) may be put in place to completely relocate demand to another part of the country [3]. Having insight on where in the network thunderstorms are likely to develop could allow for re routing of en-route air traffic and improve ATFM efficiency.

In this paper we develop a methodology to train a neural network (NN) model to predict convective weather with the precision required to improve pre-tactical ATFM decisions for the en route environment. Our research makes use of observational and forecast weather data to formulate a binary classification supervised learning algorithm for identifying convective areas.

II. Weather Information

Weather information can be grouped into two categories; observation and forecasts. Weather observations can be made via radiosondes, radar, satellite or any other observing system to provide the current state of the atmosphere. In our research we use satellite observations from the Rapidly Developing Thunderstorm (RDT) product provided by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT).

Weather forecasts typically rely on numerical weather prediction (NWP) which use fluid dynamic and thermodynamic mathematical models to predict the state of the atmosphere up to multiple days into the future. In our research we use the Ensemble Prediction System (EPS) product from the European Centre for Medium-Range Weather Forecast (ECMWF).

A. Rapidly Developing Thunderstoms - Observation

The Rapidly Developing Thunderstorm (RDT) product is a satellite based software by EUMETSAT capable of tracking and identifying convective cloud cells i.e. thunderstorms. The RDT product covers the geographical region of Europe, and outputs storm data on a 15 minute interval. For each cloud cell, the RDT product can define a series of parameters including the location, shape, movement, severity, and lifecycle phase.

B. Ensemble Prediction System - Forecast

Ensemble forecasting is a technique based on numeric weather prediction models where small perturbation are made to model initial conditions producing multiple forecasts. Given that each forecast or member began from similar initial conditions, they have a tendency to behave similarly in the short-term but deviate over longer time horizons defining a domain of possible weather outcomes. Using the pool of members, it is possible to predict the probability that a particular weather event of interest might occur. The EPS product is comprised of one control member, using the most accurate estimate of the initial conditions plus 50 perturbed members. Furthermore, an additional member at a higher spatial resolution (HRES) is also produced. The 52 members are created twice a day at times 00:00 and 12:00 and provide a forecast up to 15 days ahead [4]. For this research we focus on the data solely from the 50 perturbed members, we make use of forecast provisions for the next 45 hours in 3 hour steps. The spatial resolution of the EPS grid is a quarter of a degree in latitude and longitude, assuming the rule of thumb of 60 nautical miles per degree, this equates to roughly 15 nautical miles between grid points.

III. Baseline Convection Indicator

It is possible to define an indicator for convection to anticipate where thunderstorms will develop using two parameters from the EPS; Total Totals Index and Convective Precipitation [5]. Total Totals Index (TT) is a representation for the temperature gradient and moisture in the lower levels atmosphere. Convective Precipitation (CP) is the accumulated water that falls to the Earth's surface and is generated by convection. Convection can be defined as an area where there is precipitation and the total totals index value is above a certain threshold. Thus we can evaluate each point of the numerical weather prediction model for convection using the following logistic expression:

$$Convection = (TT > TT_{TH}) \wedge (CP > 0)$$

Where TT_{TH} is defined as the TotalsTotals Index threshold value based on the level of convection of interest.

- 44-45 isolated moderate thunderstorms
- 46-47 scattered moderate / few heavy thunderstorms
- 48-49 scattered moderate / few heavy / isolated severe thunderstorms
- 50-51 scattered heavy / few severe thunderstorms and isolated tornadoes
- 52-55 scattered to numerous heavy / few to scattered severe thunderstorm / few tornadoes
- 55+ numerous heavy / scattered severe thunderstorms and scattered tornadoes

We are able to obtain the probability of certain level convection by calculating how many members out of 50 meet the convection criteria.

Figure 1 shows a graphical representation of the convection indicator, throughout our analysis this indicator will be used as a baseline to provide a comparison with our algorithm.

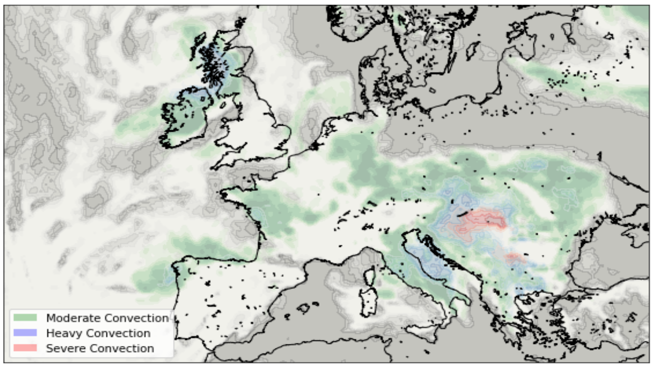


Figure 1: Baseline convection indicator for multiple levels of convection. Data taken from the 12:00 release EPS forecast for June 8th, 2018 at 15:00.

IV. Machine Learning Architecture

The learning task was to correctly identify where thunderstorms will develop (convective areas) based on the EPS forecast. We formulated the task as a supervised learning binary classification problem. A neural network model was trained with historical forecast parameters (i.e. EPS data) as the independent variables and the corresponding storm observations (i.e. RDT data) as the dependent variable.

A. Dataset

Our dataset consisted of 14 days from the summer season of 2018, these days were selected due to their strong convective activity. For each day, the thunderstorm observational data from RDT and the corresponding forecasts from the previous 45 hours were used. Our 14 day dataset was split randomly to provide 8 day for training, 3 days for validation and 3 days for testing the model.

B. RDT Data Processing

A series of preprocessing steps were needed to transform the RDT data to match the spatiotemporal resolution of the EPS parameters. First, to merge the data in the spatial domain, the RDT convective cell polygons needed to be represented on a grid matching the EPS resolution, see Figure 2a. A grid pattern was projected onto the RDT polygons so that center of each square corresponded with EPS latitude-longitude points. A point was considered to contain to a thunderstorm if a storm polygon was present in the square surrounding the EPS point.

Second, given that EPS forecast has a 3 hour time step and the RDT satellite observations are provided every 15 minutes, it was necessary to reconcile this time difference in order to integrate the data. We decided to aggregate the storm data in time, by counting how many instances of thunderstorm were present at a point within a 3 hour period, see Figure 2b. The aggregated values ranged from 0, where no thunderstorms were present, to 12 where thunderstorms were present for the entire 3 hour window.

Lastly, the aggregated RDT data was converted into a binary representation, with 0 representing non-convective areas and 1 representing convective areas, see Figure 2c. In this way our machine learning classifier will answer the question: *Will there be a storm at a location in a three hour time window?*

Due to the fact that the EPS forecast is released every 12 hours it is important to note that each thunderstorm observation will corresponds with multiple forecasts. For example, the storm observations from June 6 2018 at 15:00 were associated with the 00:00 forecast from June 5, 2018 with time horizon 39 hours, the 12:00 forecast from June 5, 2018 with time horizon 27 hours, the 00:00 forecast from June 6, 2018 with time horizon 15 hours, and also the 12:00 forecast from June 6, 2018 with time horizon 3 hours .Furthermore, given the ensemble characteristics of EPS data, each observation-forecast pair consisted of the 50 perturbed members of the forecast.

C. EPS Parameter Selection - Physics of thunderstorms

Thunderstorms are most likely to occur under the following conditions [6]:

- Sufficient moisture in the atmosphere to form and maintain the cloud.
- Atmospheric instability determined by the vertical temperature profile or lapse rate.
- Lifting force or trigger mechanism to produce early saturation of air. In convective storms, this trigger action is typically caused by heat from the earth's surface causing moist air to rise.

With these conditions in mind 17 EPS parameters were selected to train the NN model. The list of parameters and their short name notation [1] is provided below.

- **2 metre dewpoint (2d)**
- **2 metre temperature (2t)**
- **Boundary layer height (blh)**
- **Boundary layer dissipation (bld)**
- **Convective available potential energy (cape)**
- **Convective available potential energy shear (capes)**
- **Convective inhibition (cin)**
- **Convective precipitation (cp)**[2]
- **Geopotential (z)**
- **K index (kx)**
- **Mean sea level pressure (msl)**
- **Surface latent heat flux (slhf)**
- **Surface pressure (sp)**
- **Surface sensible heat flux (sshf)**
- **Total column water (tcw)**
- **Total column water vapor (tcwv)**
- **Total totals index (totalx)**

Besides the EPS parameters, the model was also trained using the hour of the day and the range of the forecast as parameters, for a grand total of 19 parameters.

D. Model Architecture

The NN classifier was formulated using a multilayer perceptron model for binary classification using the python keras library. Our model consisted of four layers; a 19 node input layer, a 16 node hidden layer, a 16 node hidden layer, and a single node output. The artificial neural network was trained with the training and validation data sets using a binary cross-entropy loss function. A class weight function was applied to account for the unbalanced classes. Lastly, in our experiment each individual grid point was considered as an independent sample. The neural network did not take into account the coordinates of the grid point, instead it was trained to provide the likelihood of convection given only the EPS parameters.

V. Results

The test dataset was comprised of 3 days worth of data; June 6th. June 7th, and June 11th. Our dataset proved to be unbalanced with roughly 14% of data points belonging to the "convective area" class.

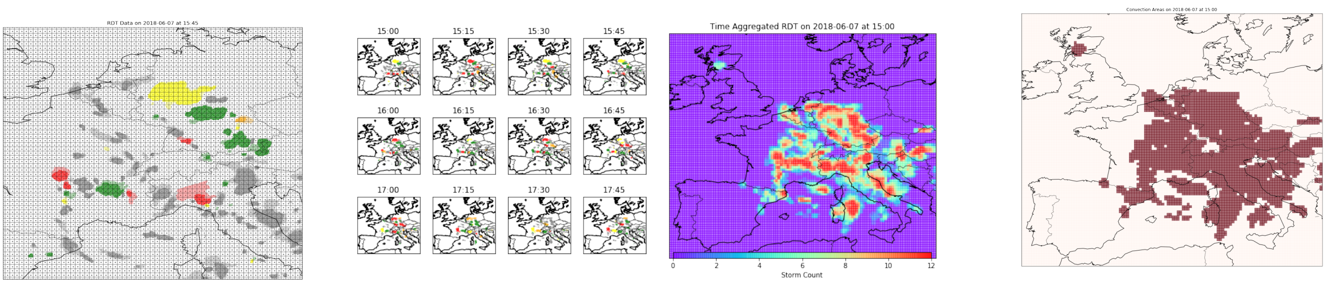
A. Indicator Performance

The baseline convection classifier was evaluated using a "low" Total Totals Index threshold value of 44 to account for moderate, heavy and severe thunderstorms.

The skills of the baseline and neural network convection classifiers were evaluated using a Receiver Operating Characteristic (ROC) curve. Threshold values for the baseline and NN classifier were chosen based on points closest to the top left corner of the ROC space and a normalised confusion matrix was obtained for each. Figure 3 shows the ROC curve and confusion matrix for each classifier, from the figure it is clear that NN indicator performs better than the baseline. While the specific values pertaining to the AUC and threshold of both the baseline and neural network indicator are dependent on the specific days being evaluated, we expect similar results for other days.

[1]ECMWF Parameter Database: https://apps.ecmwf.int/codes/grib/param-db

[2]While the Convective precipitation (cp) parameter is provided as precipitation accumulated since the release of the forecast, the model was trained using the difference in cp between the next and current step.



(a) Grid overlay on storm polygon.

(b) 12 RDT images in one 3 hour EPS time step.

(c) Binary representation of convection

Figure 2: Processing steps for RDT data.

A graphical representation of the convection indicators can be seen in figure 4. The left two images are based on the actual storm data (aggregated and binary) from June 11th 15:00 - 18:00, while the right two are the baseline and neural network predictions made 27 hours in advance. Compared to the baseline, the NN seems to make better predictions in the UK, Spain, southern France, and the Balkans, but underperforms in regions such as central Italy and Scandinavia.

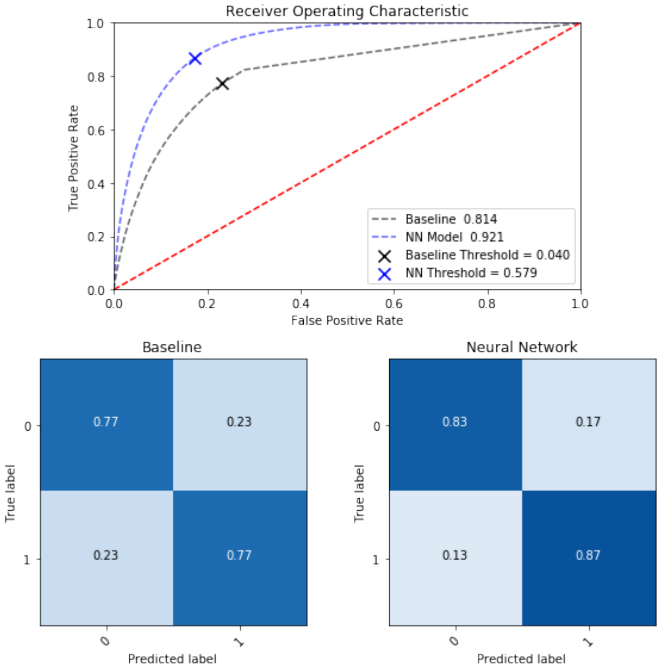


Figure 3: Comparison of baseline and neural network classifiers based on ROC curve and confusion matrix.

VI. Conclusion and Future Work

A neural network model to classify convective areas within a 3 hour period was developed, the model showed improved skill over a convection indicator found in the literature. In the next phase of our research we will continue developing our algorithm using hourly EPS forecast, thus refining the predictive time window and enable better decision making during ATFM operations. We also intend to expand our dataset to cover a full year worth of data to improve the model's ability to identify thunderstorms during other seasons apart from summer. Lastly, in this analysis we handled the most generic case of predicting whether there will be a storm of any kind, however, in the future we hope to train our model based on a filtered set of storms that match a certain criteria. A model could be developed to allow prediction of storms with a certain severity, or storms that extend beyond a certain altitude level as these would be most impactful for ATFM operations.

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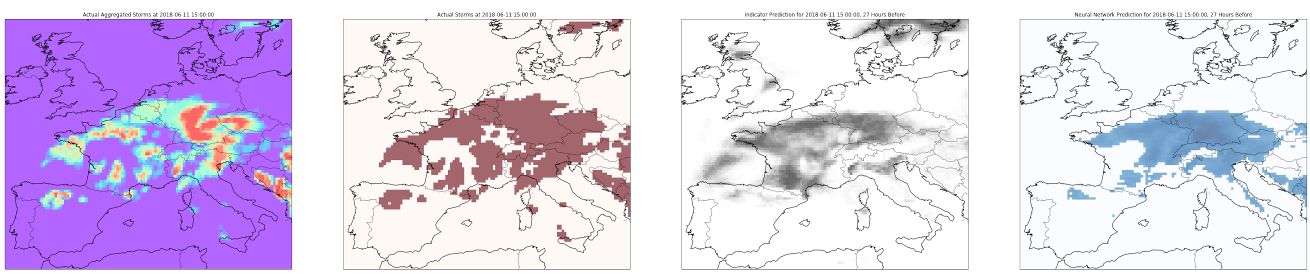

(a) Aggregated Storms (b) Binary Storms (c) Baseline Convection Indicator (d) NN Convection Indicator

Figure 4: Graphical representation of thunderstorm observations and convection predictions made 27 hours in advance.