

A solid blue triangle pointing to the right, located on the left side of the slide.

# Automated DCB Hotspot detection



Author: Sergi Mas-Pujol  
Advisor: Esther Salamí  
Co-advisor: Enric Pastor

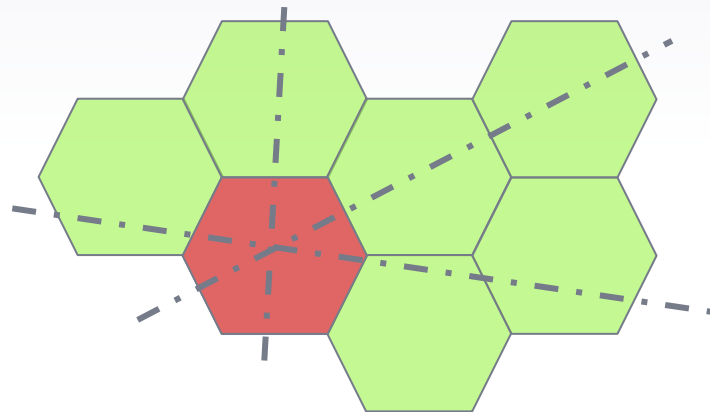
August 30th, 2021

# Content

- ▶ Introduction
  - ▷ Demand-Capacity balancing
  - ▷ ATFCM regulations detection
- ▶ Methodology
  - ▷ C-ATC Capacity ATFCM regulations
    - ▷ RNN, CNN, RNN-CNN hybrid model
  - ▷ W-Weather ATFCM regulations
    - ▷ RNN-base model
- ▶ Results
  - ▷ Performance
  - ▷ Model explainability
- ▶ Conclusions
- ▶ Future work

# Demand-Capacity Balancing

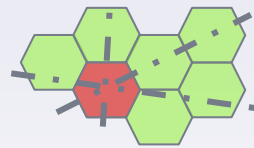
- DCB **protects** the ATC sectors in order to expedite safe and manageable traffic,
- This protection is ensured by two keys:
  - **Detect future problems;**
  - Resolve identified problems.



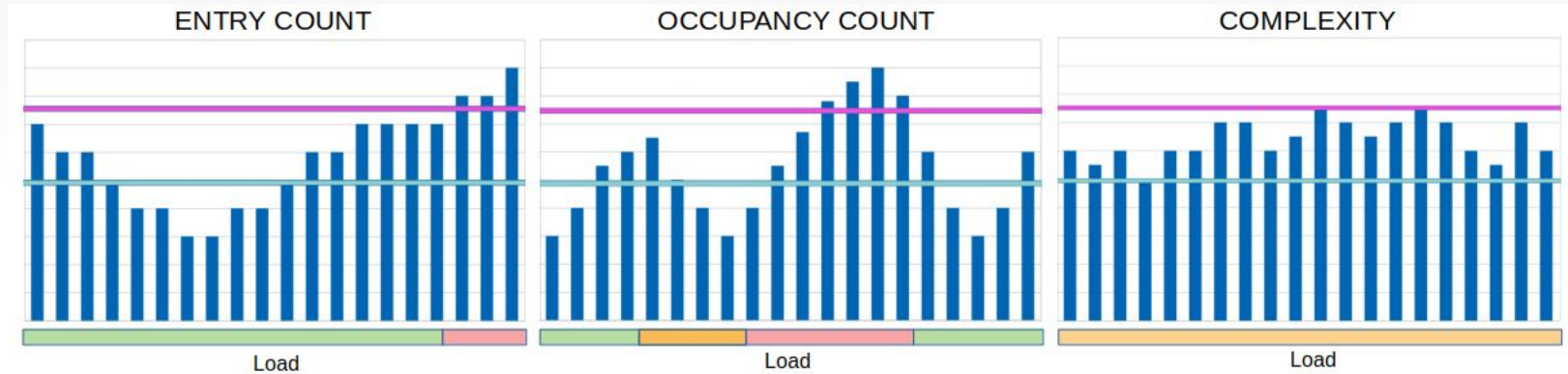
# ATFCM regulations detection



- **Cyclic process,**
- **Identification of required operational constraints** to ensure that the available declared capacity meets the traffic demand,
- It is based on pure **human know-how**.
- **Supervised deep learning techniques** to automatically detect required ATFCM regulations

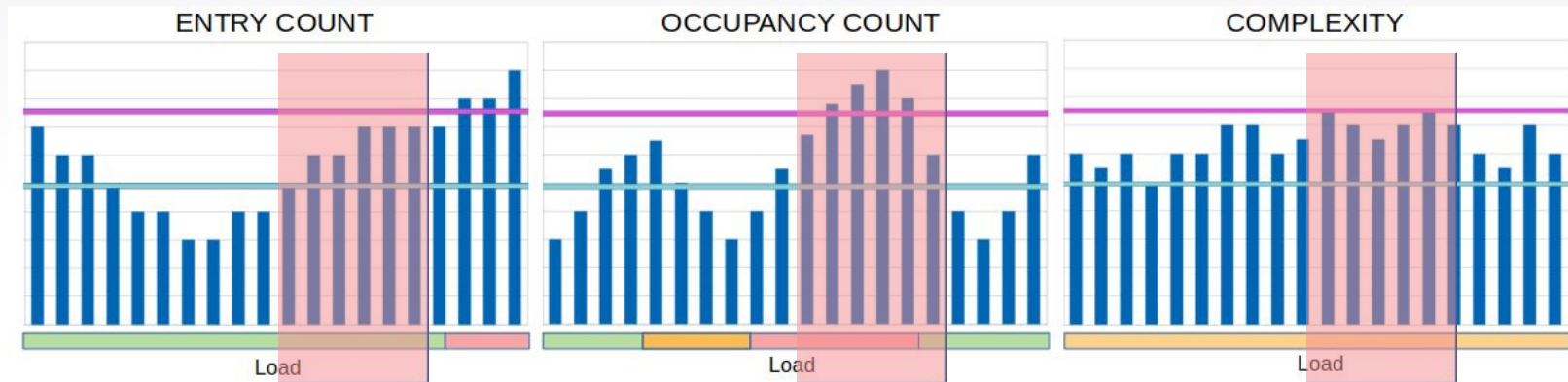


# ATFCM regulations detection



Many metrics need to be analyzed → A **Huge amount of information** needs to be **manually processed**.

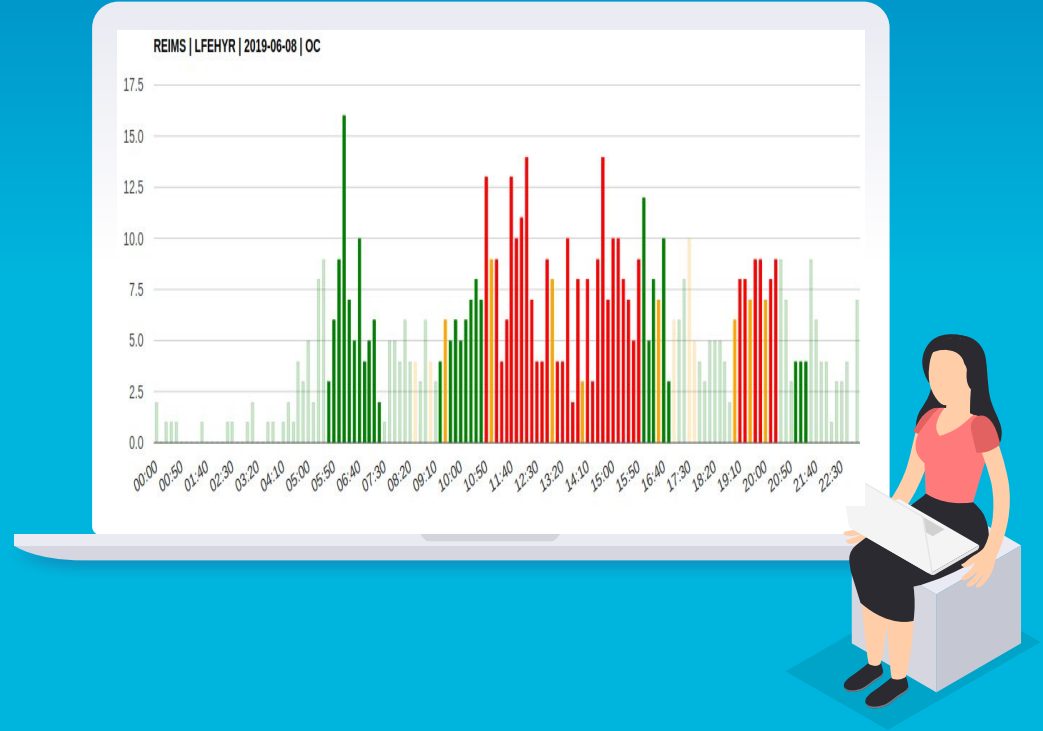
# ATFCM regulations detection



**Machine learning** could be really beneficial → It **can process** huge **amounts of information** really **fast** and **efficiently**.

# Web application?

- User friendly
- Visual
- Interactive





# Methodology



# C-ATC Capacity regulations

## RNN-base model

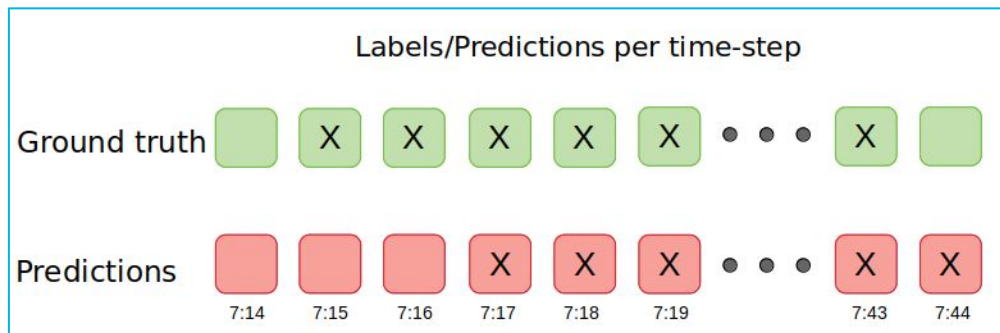
- Scalar variables
- Time-distributed LSTM

## CNN-base model

- Artificial Images
- Time-distributed CNN

## RNN-CNN hybrid model

- Cascade architecture



# RNN-base model (C-ATC)

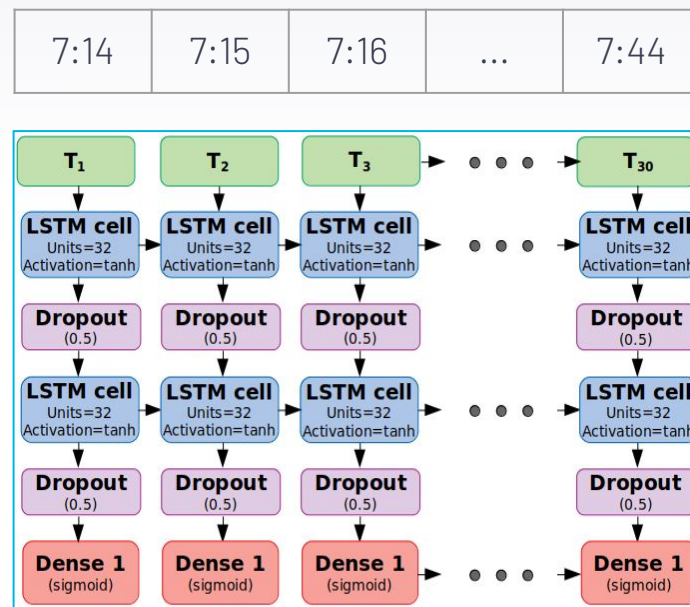
- RNNs are able to process **scalar variables** that evolve on time,
- Input features:
  - Timestamp,
  - Capacity,
  - Occupancy count
  - Entry count (20 and 60 minutes)
  - Workload
  - Climbing, cruising and descending

|      |      |      |     |      |
|------|------|------|-----|------|
| 7:14 | 7:15 | 7:16 | ... | 7:44 |
|------|------|------|-----|------|

|       |       |       |       |       |
|-------|-------|-------|-------|-------|
| Time. | Time. | Time. | Time. | Time. |
| Cap.  | Cap.  | Cap.  | Cap.  | Cap.  |
| OC.   | OC.   | OC.   | OC.   | OC.   |
| ...   | ...   | ...   | ...   | ...   |
| Desc. | Desc. | Desc. | Desc. | Desc. |

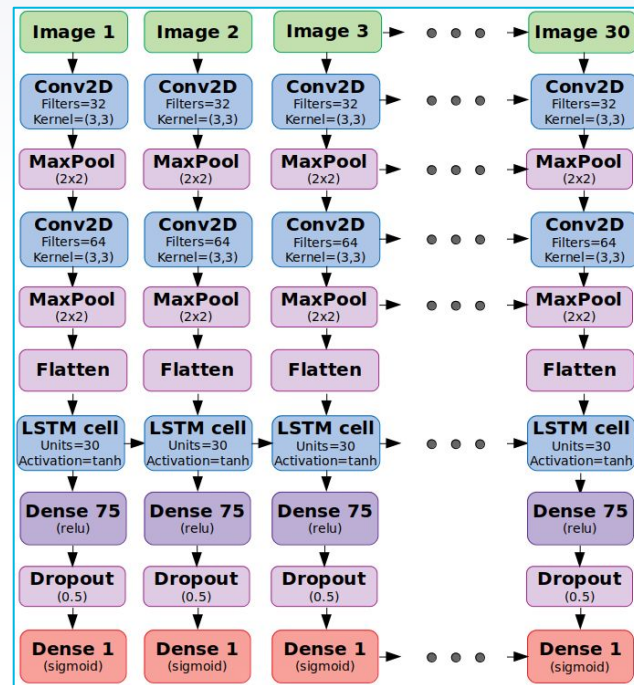
# RNN-base model (C-ATC)

- RNNs are able to process **scalar variables** that evolve on time,
- Input features:
  - Timestamp,
  - Capacity,
  - Occupancy count
  - Entry count (20 and 60 minutes)
  - Workload
  - Climbing, cruising and descending

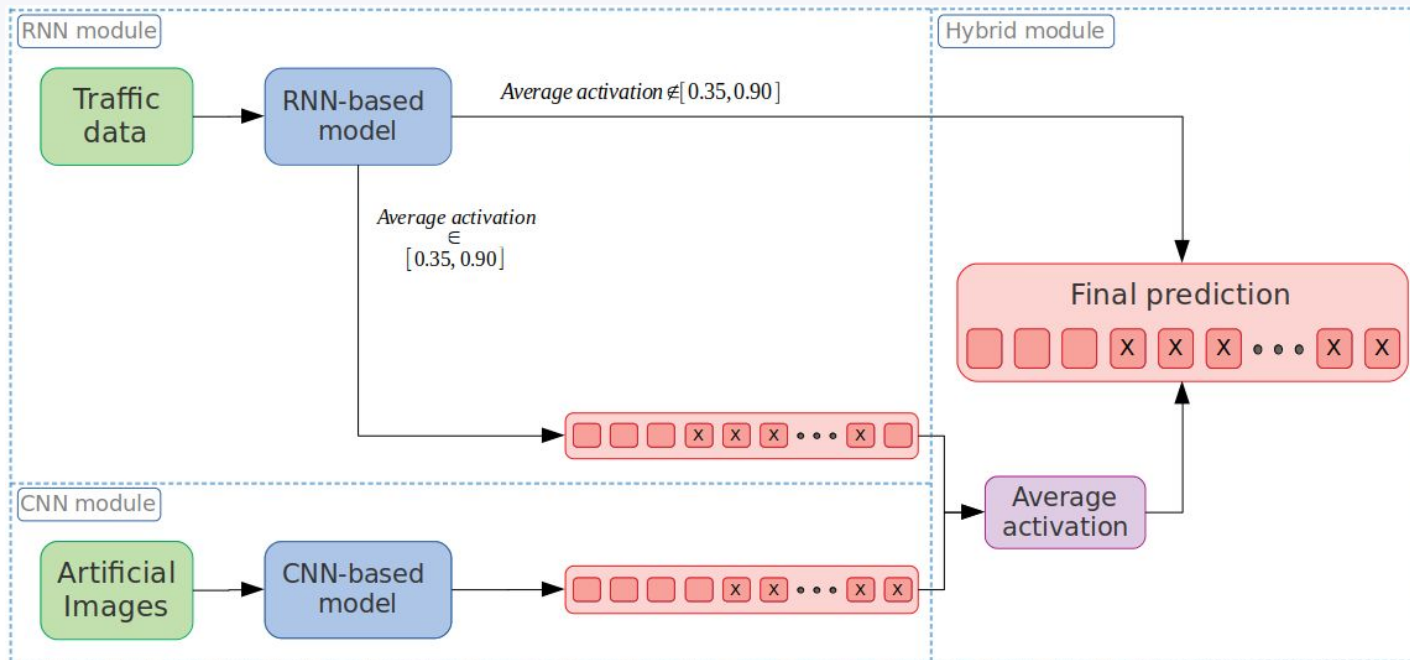


# CNN-base model (C-ATC)

- CNNs are most commonly applied to analyze **static visual imagery**
- Input images:
  - From trajectory file (interpolation)
  - TV's shape from Newmaxo ASCII Region file



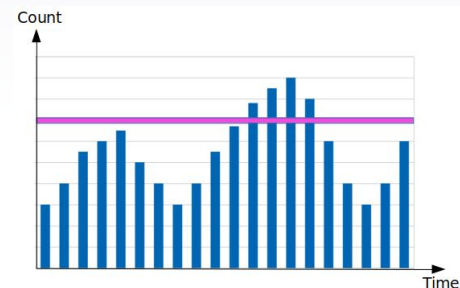
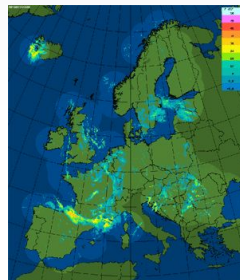
# RNN-CNN hybrid model (C-ATC)



# ► W-Weather regulations

## RNN-base model

- **Scalar variables**
- Time-distributed LSTM



# RNN-base model (W-Weather)

- Traffic input features:
  - Timestamp,
  - Capacity,
  - Occupancy count
  - Entry count (20 and 60 minutes)
  - Workload
  - Climbing, cruising and descending
- Weather input features:
  - Cloud cover
  - Vorticity
  - Humidity
  - Cloud ice / water content
  - Cloud rain / snow content
  - Temperature
  - Wind

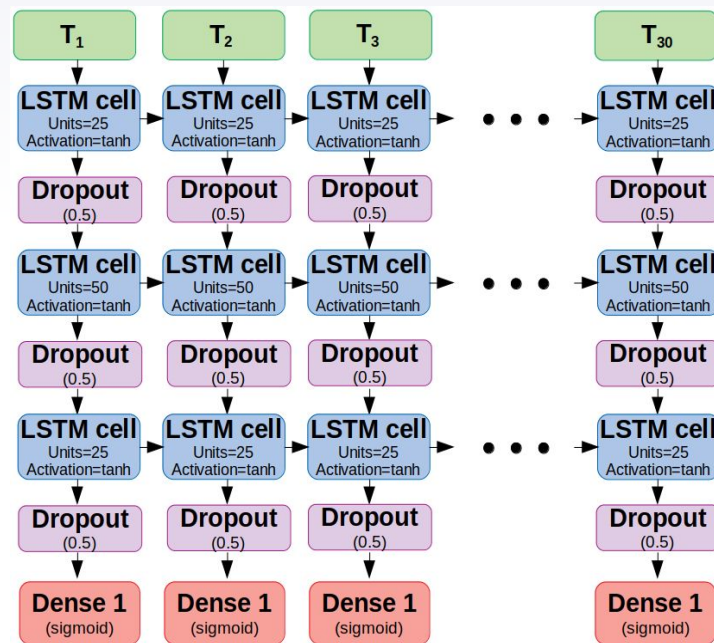
|      |      |      |     |      |
|------|------|------|-----|------|
| 7:14 | 7:15 | 7:16 | ... | 7:44 |
|------|------|------|-----|------|

|       |       |       |       |       |
|-------|-------|-------|-------|-------|
| Time. | Time. | Time. | Time. | Time. |
| Cap.  | Cap.  | Cap.  | Cap.  | Cap.  |
| OC.   | OC.   | OC.   | OC.   | OC.   |
| ...   | ...   | ...   | ...   | ...   |
| Desc. | Desc. | Desc. | Desc. | Desc. |

|        |        |        |        |        |
|--------|--------|--------|--------|--------|
| Cloud. | Cloud. | Cloud. | Cloud. | Cloud. |
| Wind.  | Wind.  | Wind.  | Wind.  | Wind.  |
| Humid. | Humid. | Humid. | Humid. | Humid. |
| ...    | ...    | ...    | ...    | ...    |
| Water. | Water. | Water. | Water. | Water. |

# RNN-base model (W-Weather)

- Traffic input features:
  - Timestamp,
  - Capacity,
  - Occupancy count
  - Entry count (20 and 60 minutes)
  - Workload
  - Climbing, cruising and descending
- Weather input features:
  - Cloud cover
  - Vorticity
  - Humidity
  - Cloud ice / water content
  - Cloud rain / snow content
  - Temperature
  - Wind





# Evaluation of the models

## Accuracy

Fraction of predictions the model got right

## Recall

Proportion of positive samples correctly identified

## Precision

Proportion of positive identifications correctly identified

## F1-Score

Harmonic mean of the precision and the recall



How many regulations are detected?



How many predicted regulations are right?



# Results

# Regions

- **Two different regions** have been studied to **predict ATFCM regulations** using **4 AIRACs**:

## MUAC

- 359 C-ATC Capacity regulations
- 151 W-Weather regulations.

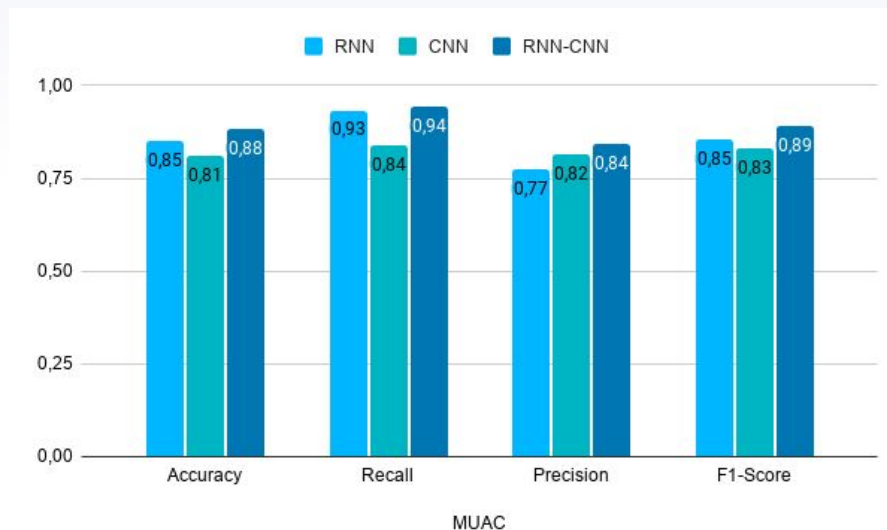
## REIMS

- 764 C-ATC Capacity regulations;
- 582 W-Weather regulations.

- In both cases, around **1200 different 30-minutes intervals** have been used
- We have used a **balance dataset**. More or less, we have used the same number of positive and negative time-steps for the training/testing.

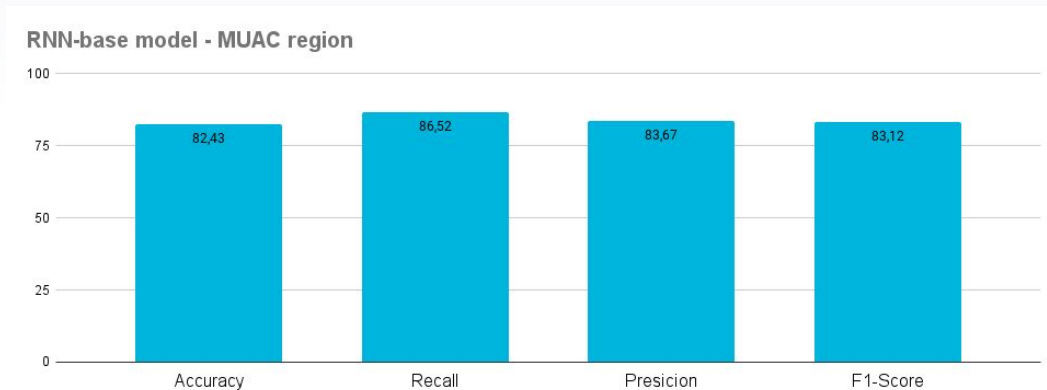
# MUAC C-ATC regulations

- Average results given the region
- Individual TV:
  - MASBOLN
  - MASB3EH
  - MASD6WH
- Model for the entire region with slightly worse performance



# ► MUAC W-Weather regulations

- Average results given the region
- Individual TV:
  - MASHRHR
  - MASHSOL
  - MASB3LL
- Model for the entire region with slightly worse performance



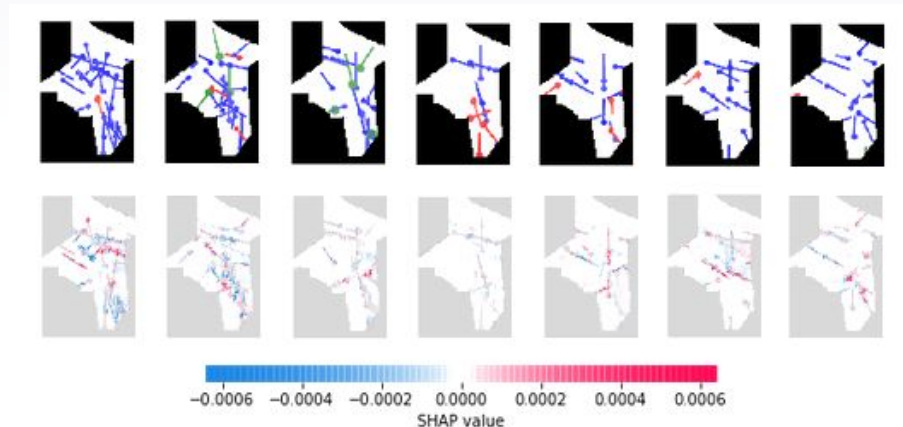
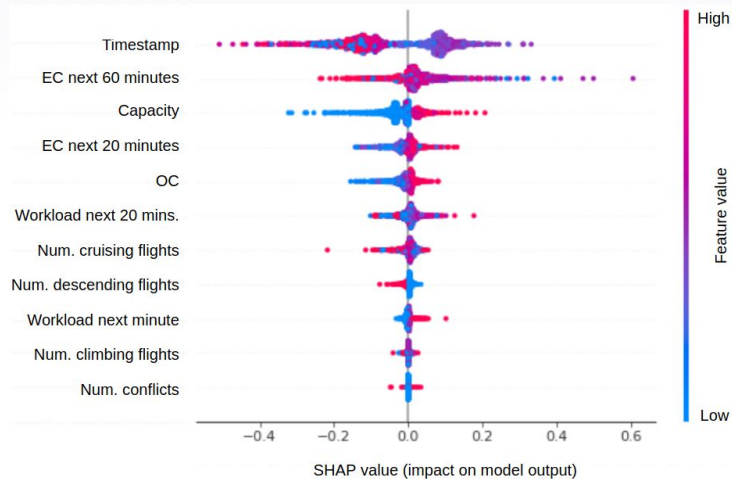
# ► Model explainability – SHAP

- **Understand the accuracy of the findings**, providing the ability to **explain the model** to possible stakeholders,
- Moreover, **understanding the reason behind the predictions** is crucial to ensure compliance to industry standards and gain trust,
- **SHapley Additive exPlanations (SHAP)**[2] is a game theory approach, to explain the output of any model,
  - It aims to identify which input features are more relevant for the trained model



SHAP

# C-ATC regulations – MAUC



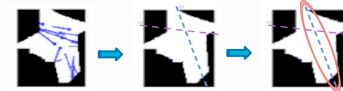
# Conclusions

- **Deep learning models** can be used to **predict ATFCM regulations** across **different regions** of the European airspace:
  - MUAC and REIMS
- For **specific ATC sectors**, the model exhibits an **accuracy higher than 82%**, a **recall of higher than 84%**, and a **precision around 85%** when predicting specific time-steps,
  - Despite the small dataset used,
- The SHAP analysis has proved that the models have a **behavior close to the current methodology**,
  - Important to gain trust on the predictions and ensure compliance with industry standards,
- There is **room for improvement**.



# Future work

django



...

**Integrate** the models for **W-Weather** regulations into the Web application

**Uncertainty study**

Study other tools for **model explainability**

**Integration** of the models in **R-NEST**

Model-based simulation tool dedicated to research

Improve **advise capabilities** of the framework

Improve how we show the information to the FMPs

# THANKS!

You can find me at:

- ▶ [sergi.mas.pujol@upc.edu](mailto:sergi.mas.pujol@upc.edu)

