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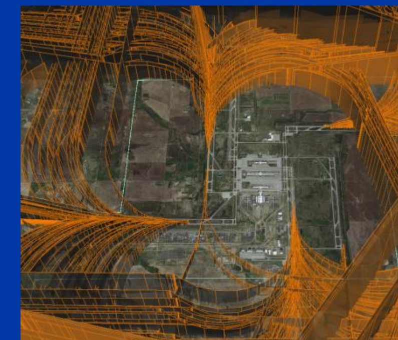


NOWcasting

Proof-of-Concept of TAAM Nowcast

Jeppesen / BR&T-Europe

XVII Brazilian Air Transportation Symposium (SITRAER)

São Paulo, October 22nd-24th, 2018

Overview

- Introduction to TAAM
- TAAM Nowcast: Concept and architecture
- TAAM Nowcast applied to arrival time prediction
  - Machine Learning applied to arrival time prediction
  - Model-based vs data-driven predictions: initial comparison
- Conclusions

TAAM® Total Airspace and Airport Modeller

A sophisticated fast-time 4-dimensional gate-to-gate simulation model for decision support, planning, design and analysis

- Comprehensive simulation model – *functionality*
  - Gate to gate
  - Current paradigm and future concepts
  - Integrated Jeppesen Nav Database
  - Very high detail
  - Complete build / edit / sim/ analysis suite
  - Fast time discrete-event engine

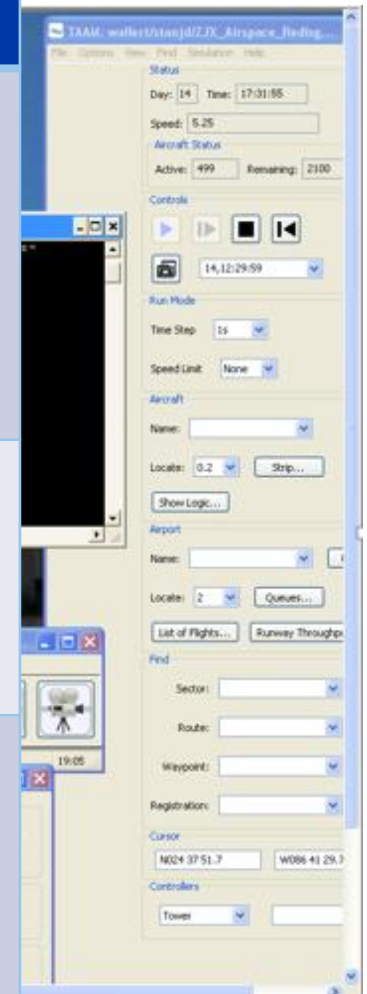
TAAM may be used to simulate aircraft

- departing from an airport
  - pushback, taxi, takeoff roll and SID
- transitioning airspace
  - utilizing appropriate climb rates, flight levels, speeds, and separation criteria
- landing at a destination airport
  - including STAR, landing, taxi, and arrival at gate

Models can be end-to end or can focus on any phase of flight

How Does TAAM Work and How is it used?

Customer	Problem/Question
Airline	-When we open a new city-pair, how should the schedule be modified? -Can we achieve time and cost savings by using different taxi patterns at airport X? -How do we plan for disruptive airport events (construction / cleaning?) -How do modifying flight plans reduce / increase emissions? -What is the best way to plan next season's schedule to minimize disruptions?
ANSP	-How do we maximize usage of current infrastructure? -We want to restructure a TMA –what is the impact? -If we close Airspace X; what is the impact on capacity? -How efficient is the ATM system? -How will a new airport impact the ATM System?
Airport	-Should we invest in new infrastructure? -What is the impact of runway closure for repairs / construction / cleaning? -What is the overall efficiency impact of Procedure Redesign? -For a "greenfield" airport, what is the most efficient design? -What is the impact of additional infrastructure at an existing airport?



TAAM Nowcast Concept

TAAM Nowcast consists of predicting the evolution of an airspace system using TAAM simulation engine driven by real-time data

- Potential tool to predict and conduct “what-if” analysis for airline operations

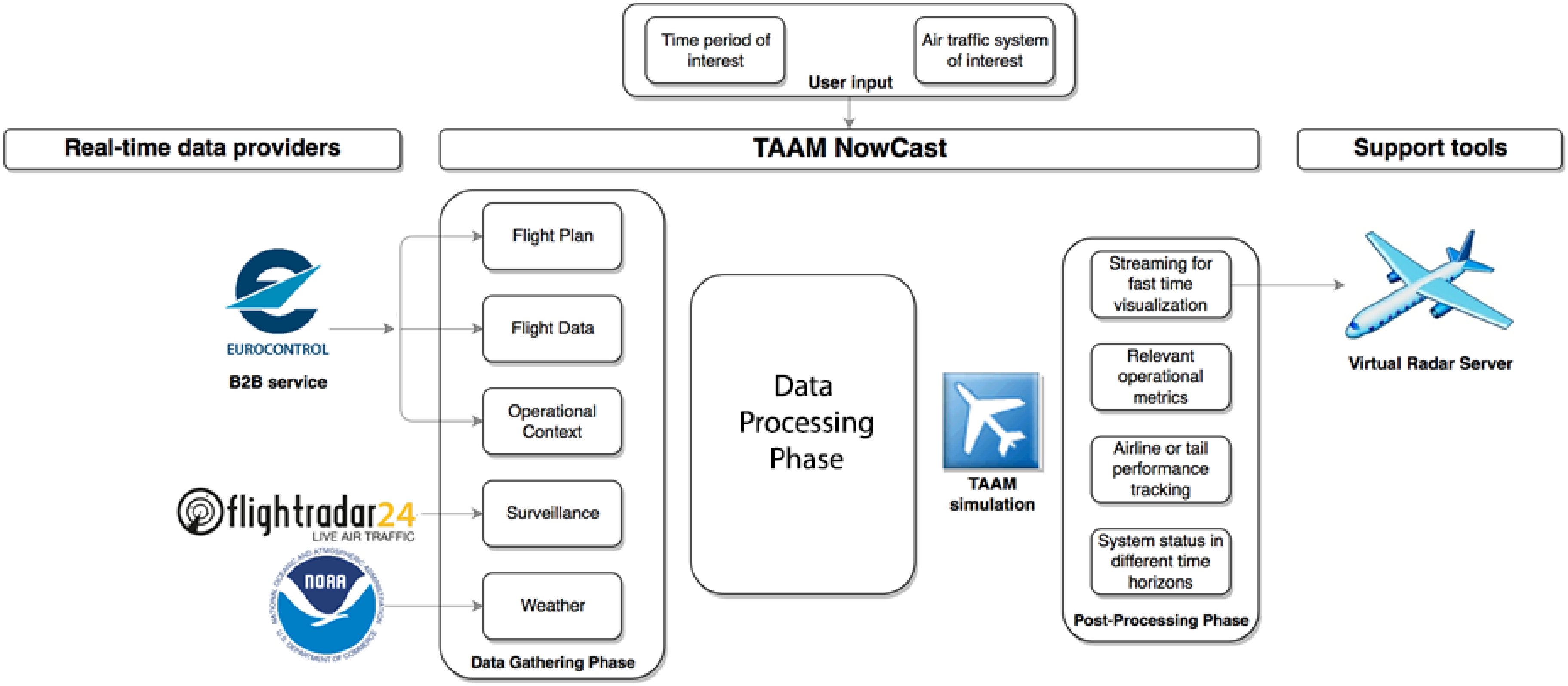
- **TAAM Nowcast comprises of the following steps:**

    - *Create the inputs for the TAAM simulation engine*
        - Gather data from different sources (SWIM, third party providers, weather providers, etc) representing the current state of the traffic
        - Process data to create TAAM input data

    - *Run TAAM simulation engine*
        - Launch simulation and collect results

    - *Analyze results*
        - Depending on the use case different metrics can be studied and used for decision making: delay, airspace congestion, airport utilization, etc.

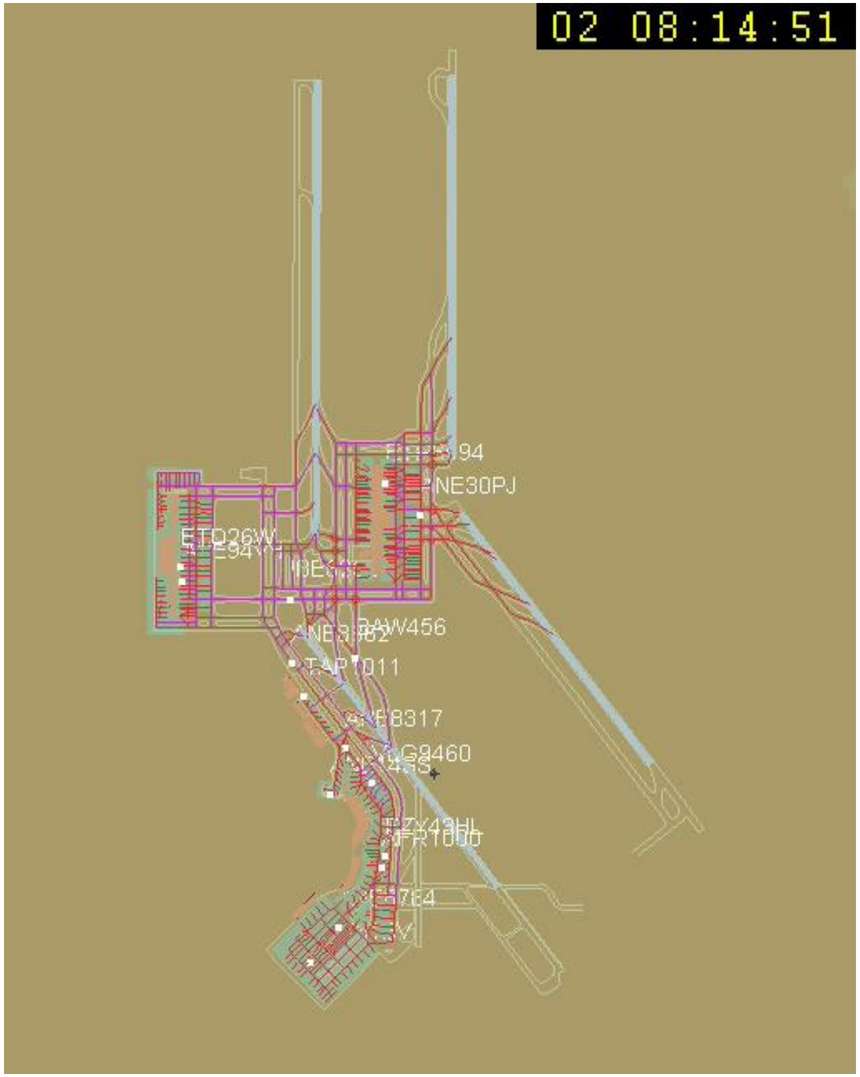
TAAM Nowcast Proof-of-Concept Architecture



TAAM Nowcast in Action

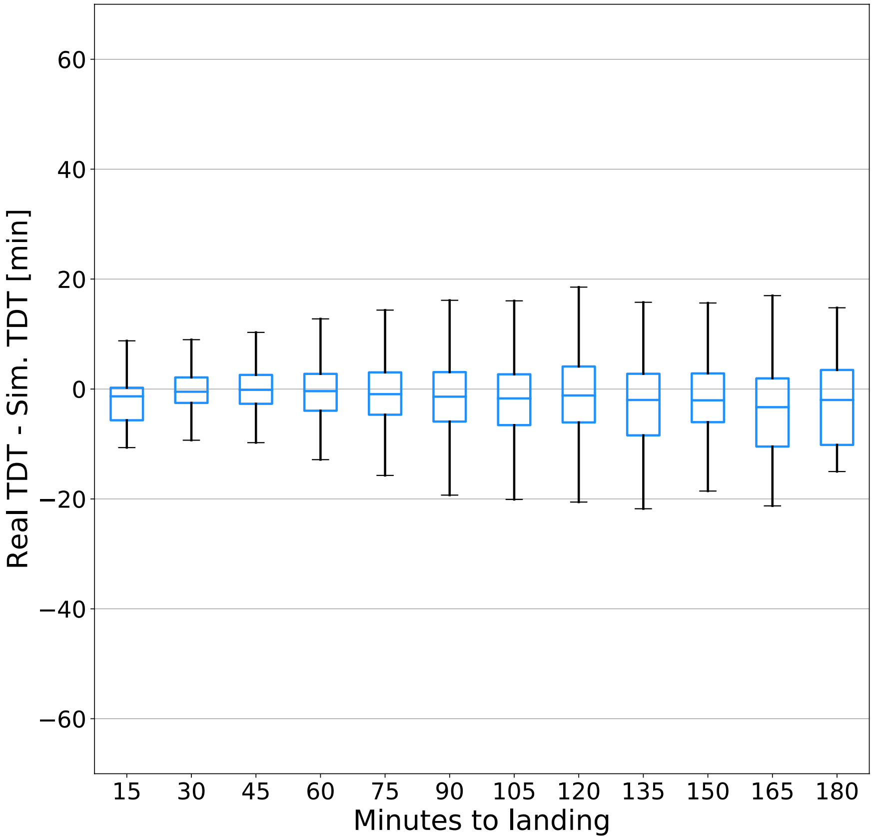
Example Use Case: Arrival Time Prediction at Madrid Airport

- The use case study focuses on **arrival operations at Madrid airport** (LEMD)
- The objective is to predict the **touchdown time** for all flights bound for the airport during a specific time interval
- TAAM Nowcast was run every **30 mins** for **5** different days (**2018/02/01 to 2018/02/05**). In total, **2,054** arrival operations were simulated, amounting to **235** TAAM Nowcast runs and more than **6,123** arrival time predictions
- Prediction results were compared with recorded actuals for different prediction look ahead times



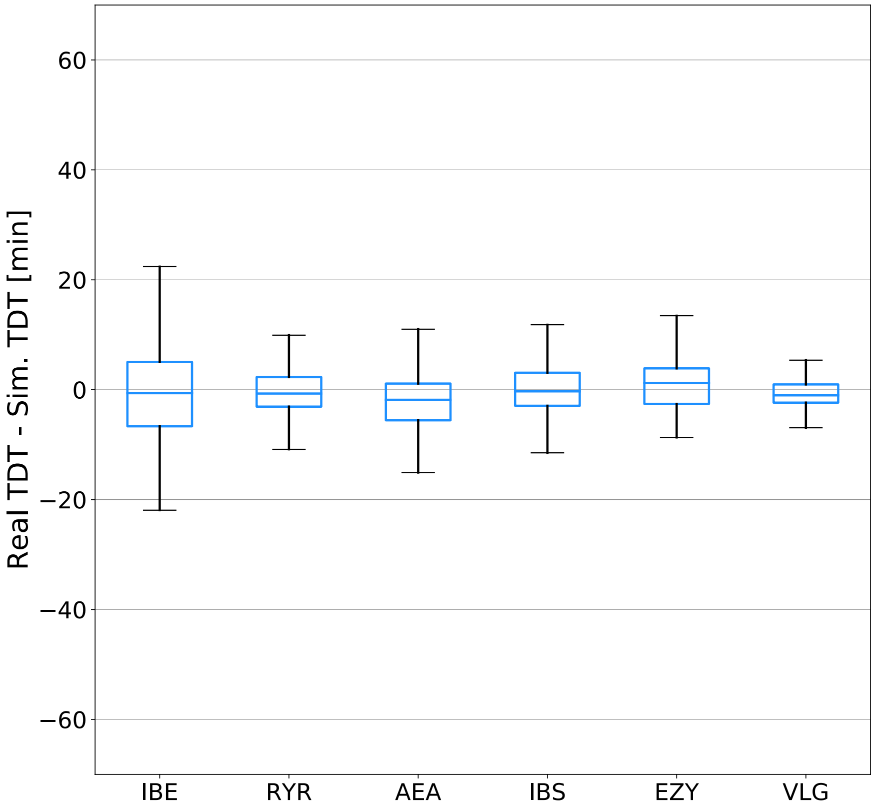
Arrival time prediction: Initial Results

Prediction accuracy results classified according to look ahead time



Accuracy degrades for look ahead times of 2 hours or more. Max errors of . ±15 min with look ahead times of less tan 2 hours

Prediction accuracy results for the main airlines operating at the airport

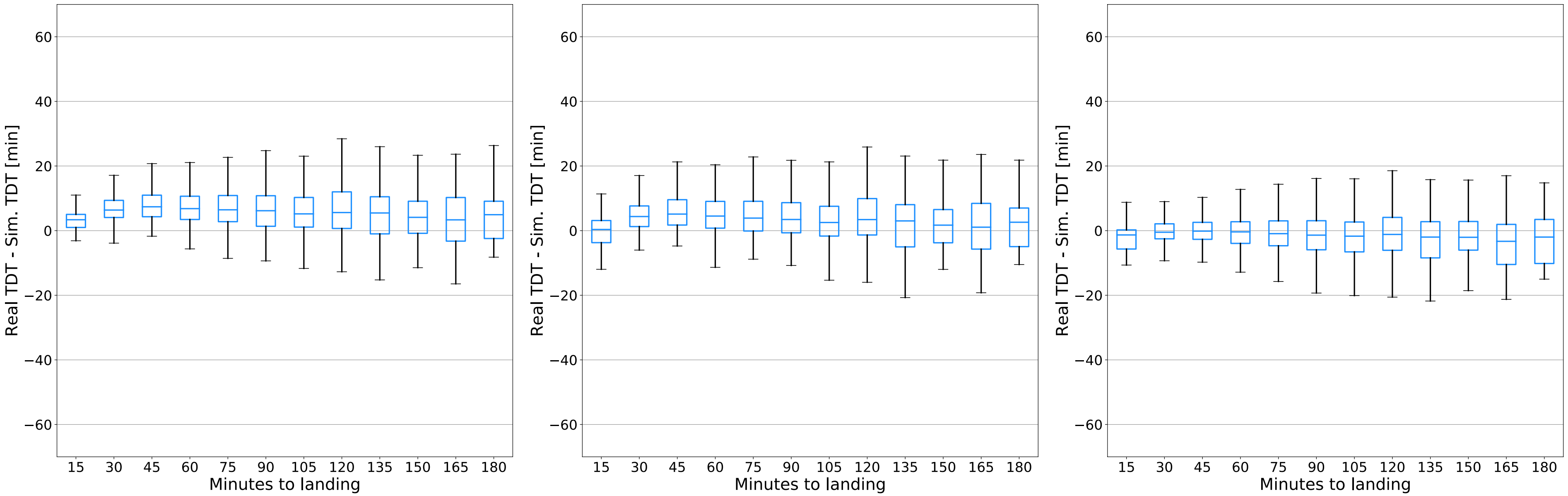


Aggregated results ordered by number of movements at the airport (larger to the left)

Arrival time prediction: Sensitivity Analysis

Results shown were obtained by including the full LEMD airport model within the TAAM simulation. A sensitivity analysis was executed to understand how the level of detail of the airport model affects prediction accuracy. Three frameworks were considered:

1. Airport as a point: Only the airport location.
2. Simple airport model: Only airport runways & STARs
3. Full airport model: Full airport layout, STARs, basic sequencing and usage rules



Data-driven approach: Machine Learning

Feature	Units	Type	Example
Airline	-	string	*IBE*
Aircraft Type	-	string	*B737*
Operation Type	-	string	*International*
Origin country code	-	string	*USA*
Latitude	*deg*	float	*45.43616*
Longitude	*deg*	float	*9.28201*
Distance to departure airport	*nm*	float	*424.87*
Distance to arrival airport	*nm*	float	*93.23*
Altitude	*ft*	int	*38000*
Declared Cruise altitude	*ft*	int	*40000*
Vertical speed	*ft/s*	int	*11*
Groundspeed	*kn*	int	*453*
Declared cruise velocity	*kn*	int	*475*
Heading	*deg*	int	*158*
Estimated flight time	*s*	int	*7360*
Temperature at arrival airport	*K*	float	*273.15*
Dew point at arrival airport	*K*	float	*272.15*
Relative humidity at arrival airport	*%*	float	*47.6*
Wind direction at arrival airport	*deg*	float	*15.6*
Wind velocity at arrival airport	*kn*	float	*11.2*
Weekday	-	int	*4*
Hour of the day	-	int	*22*
Month	-	int	*12*

Variable to be predicted	Units	Type	Example
Time left to touchdown	*s*	int	*3478*

To benchmark the accuracy of the arrival time predictions obtained with TAAM Nowcast, a machine learning-based approach was implemented and applied to the same scenario

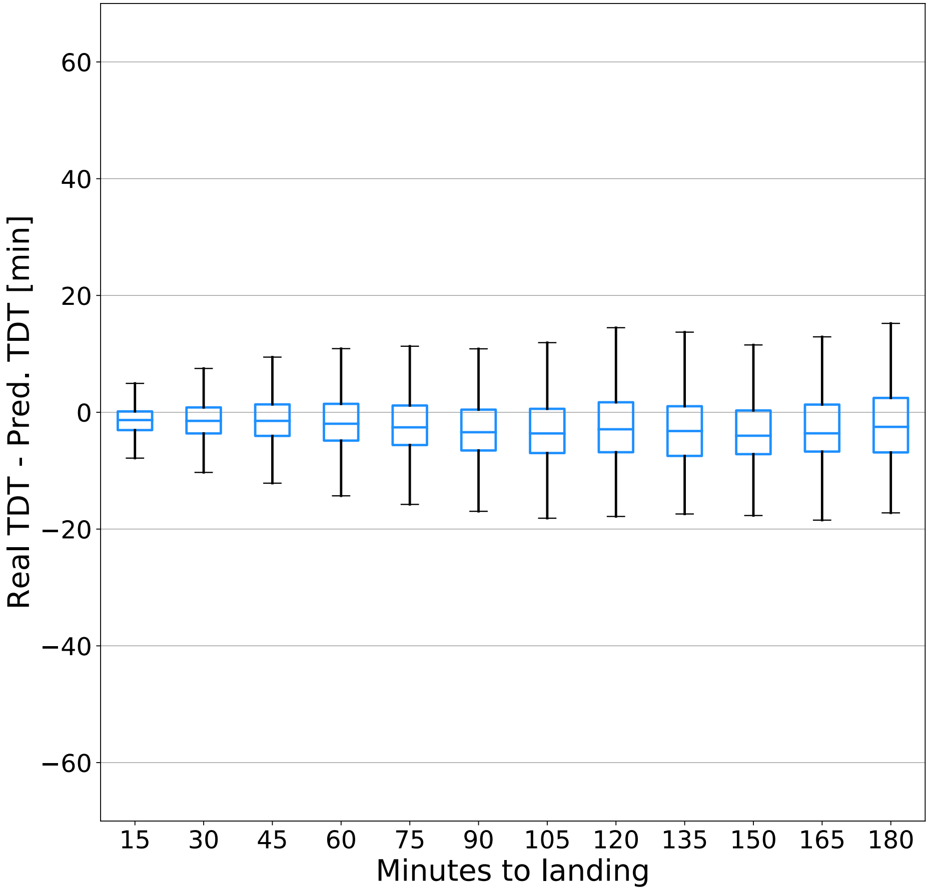
The selected ML algorithm was the **Gradient Boost Machine** (GBM) and the development framework selected is Python + H2O over a 8 node-344 cores cluster

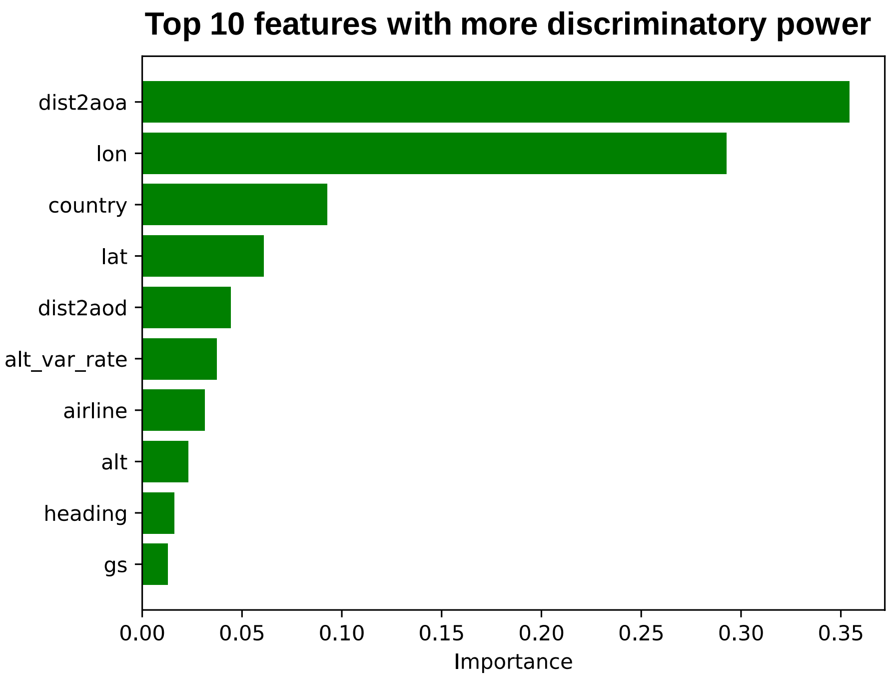
Data for a full year (2017) was used. The training set included **45,623,875** observations, for which a **70-15-15** % train-validation-test split was chosen

The evaluation of the model is performed over the same period defined for TAAM Nowcast (**5** days, from **2018/02/01** to **2018/02/05**).

Data-driven approach: Results

Arrival time prediction results for all flights bound to LEMD between 2018/02/01 and 2018/02/05



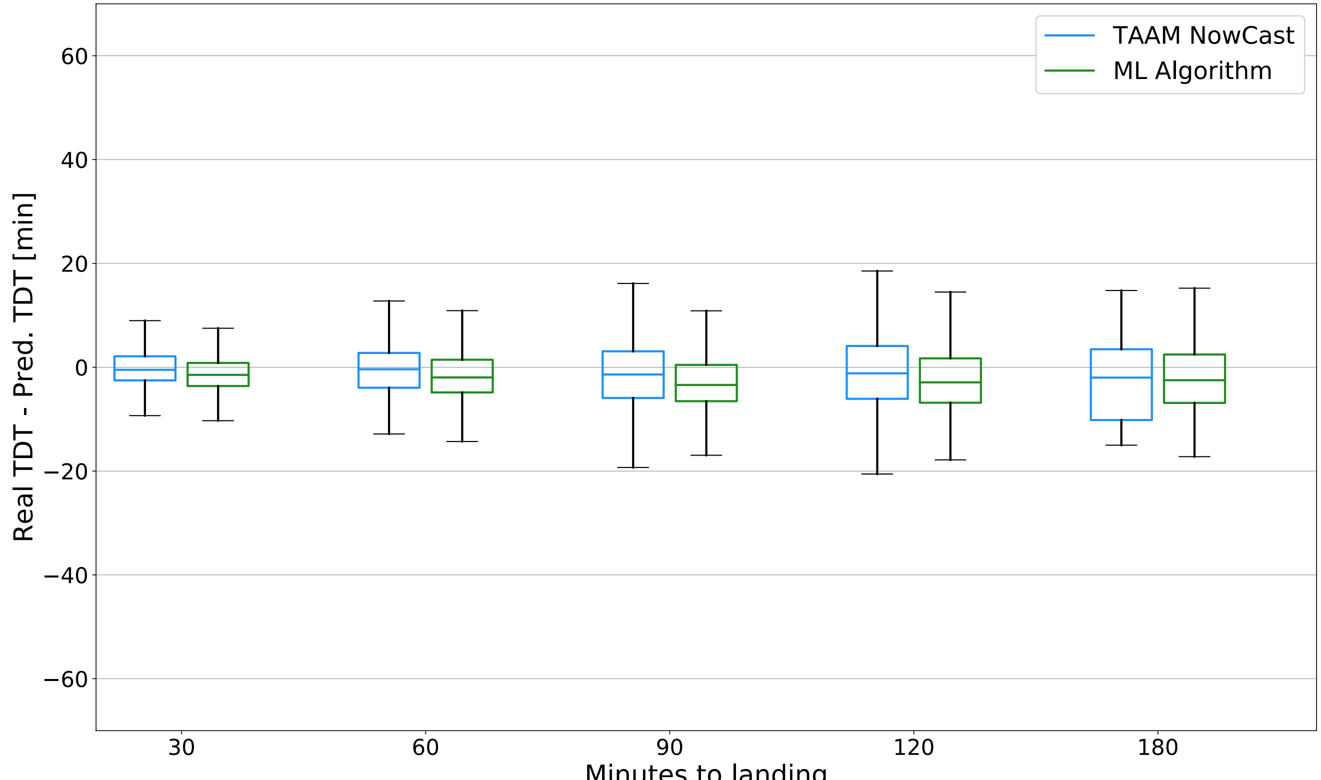


Deviation bias observed in the results may be removed in further iterations of the machine learning model.

TAAM NowCast vs Machine Learning: pros and cons

Comparison of the results obtained with both methods (in their current development stage) for different look-ahead times

- TAAM Nowcast generally produces more accurate results with less bias for shorter look ahead times
- ML performs marginally better for longer look ahead times



TAAM NowCast vs Machine Learning: pros and cons

TAAM NowCast

+ Can provide predictions of **full flight trajectory** as well as other **airspace and airline metrics**, not only flight arrival times.
+ **Does not need historical data to run**, so it is easily applicable in different scenarios.
+ **Traceability and understanding** of the operational reasons behind the predictions.
− **Frequency** of predictions may be limited due to computational requirements (each TAAM Nowcast run took around 5-10 minutes in the current setting).
− **Airspace/airport system data and knowledge** required for accurate predictions.
− **Simulation errors** correlated to lack of forecasts for some flights (only a partial model of the World used)

Machine Learning

+ **Predictions** can be obtained **as frequently as required** (very fast model once trained).
+ **Accuracy and precision can be further enhanced** with more data, considering additional features and/or different algorithms.
+ **Does not required operational knowledge** about the scenario, aircraft performance characteristics, etc
− **Limited understanding** of the reasons behind **predictions results**
− **Requires large amount of historical data** for the scenario of interest
− **Specific models** have to be trained **for each variable to be predicted** and **scenario** for which predictions are required.

Conclusions

- **Successful Proof-of-concept of TAAM Nowcast**
  - Demonstrated the use of TAAM in a real time context
  - Initial validation in a delay prediction use case

- **Initial comparison with data-driven approach**
  - State of the art machine learning algorithms applied to delay prediction
  - Historical data used for training
  - Common scenario used for cross-validation

- **Comparable performance with limited TAAM parameter tuning**
  - TAAM Nowcast predicts not only delay but other airline and airspace metrics
  - ML will require specific training for each scenario and target variable, TAAM produces satisfactory results with limited tuning

- **Potential to explore hybrid approaches to refine (“learn”) TAAM model rules based on historical data**

Thanks for your attention