

Supporting
European
Aviation



Using machine learning to predict the evolution and propagation of delays

Ramon Dalmau-Codina
EUROCONTROL



Outline

1. Air traffic flow management (ATFM) delay evolution

- Introduction
- Model
- Experiment
- Results

Members of the team:

- Brice GENESTIER
- Camille ANORAUD
- Peter CHOROBA
- Darren SMITH

2. Delay propagation

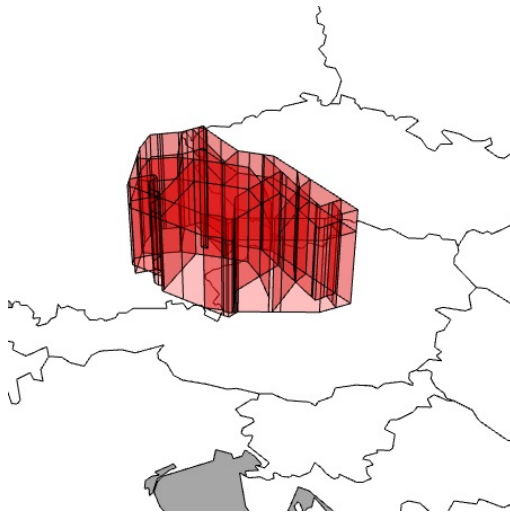
- Introduction
- Model
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Members of the team:

- Giuseppe MURGESE
- Yves de WANDELER
- Ricardo CORREIA
- Alan MARSDEN

ATFM delay evolution - Introduction

- The airspace is divided in sectors
- Each sector has a given capacity (in entries per hour)
- When the demand exceeds the capacity, ATFM measures are applied to delay flights on ground and smooth the demand
- Flights are delayed in a *first-come-first-served* basis by CASA



Example:

Regulation applied at LOVW12 sector from 13:00 to 18:00 affected 62 flights and generated 348 min of delay

ATFM: Air Traffic Flow Management
CASA: Computer Assisted Slot Allocation

ATFM delay evolution - Introduction

- Airlines only know the current ATFM delay
- The ATFM delay assigned to a flight may change with time
- The objective was to predict the evolution with machine learning

Flight Delay History @ 09:48:57

Fri 04 Mar
 ARCID:
 ADEP:
 ADES:
 EOBT:
 Auto Refresh:

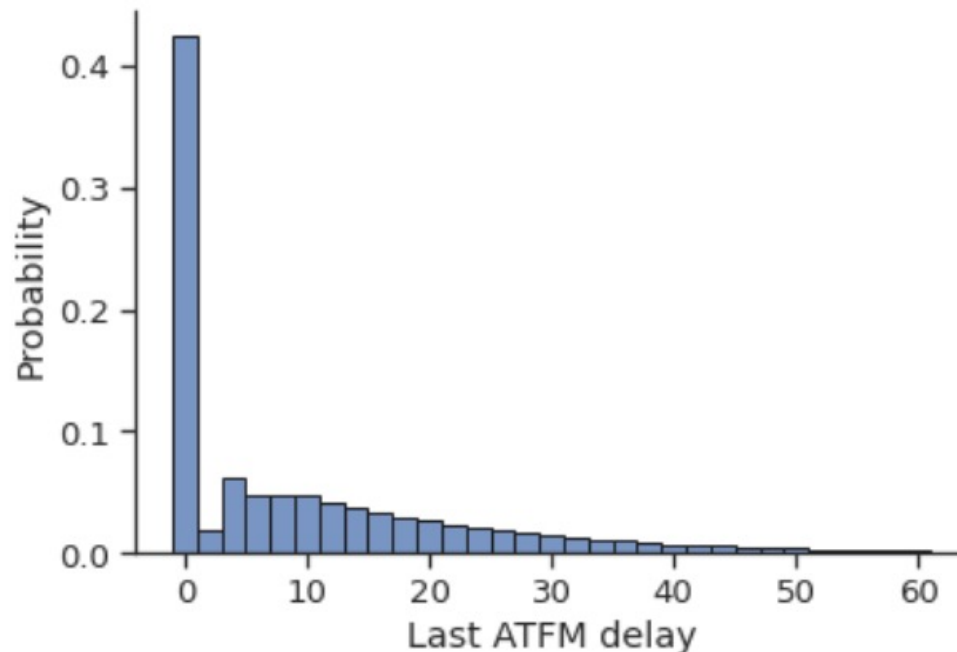
TIME	(REL)	EVENT	STATE	EOBT	COBT	AOBT	TOBT	TSAT	TAXI	DELAY	MPR
22:28:37	-11h36	IFP	FI	10:00					11		
04:28:36	-05h36	PTX	FI	10:00					11		
07:00:13	-03h04	EDI	FI	10:00					6		
08:00:15	-02h04	TDI	FI	10:00					6		
08:25:16	-01h39	SIT	SI	10:00	10:22				6	22	EDWMA04M

ATFM delay evolution - Model

- Two tasks
 1. Predict the trend (binary classification)
 2. Predict the last ATFM delay (*tweedie* regression)
- Two version:
 1. Recurrent Neural Network (RNN) – sequence of *messages*
 2. Gradient Boosted Decision Trees (GBDT) – single message
- One source of data
 1. Enhanced Tactical Flow Management System (ETFMS) flight data messages (EFD) collected by the Network Manager (NM) :
 - Departure and destination airports
 - Airline
 - List of ATFM regulations affecting the flight
 - Current ATFM delay (from CASA)
 - Estimated Off-Block Time (EOBT)

ATFM delay evolution - Model

- The last ATFM delay does not follow a Normal distribution
- The last ATFM delay follows a Poisson-Gamma distribution
- The regression models were trained to minimise the *tweedie* loss
- The classification models were trained to minimise the binary logloss



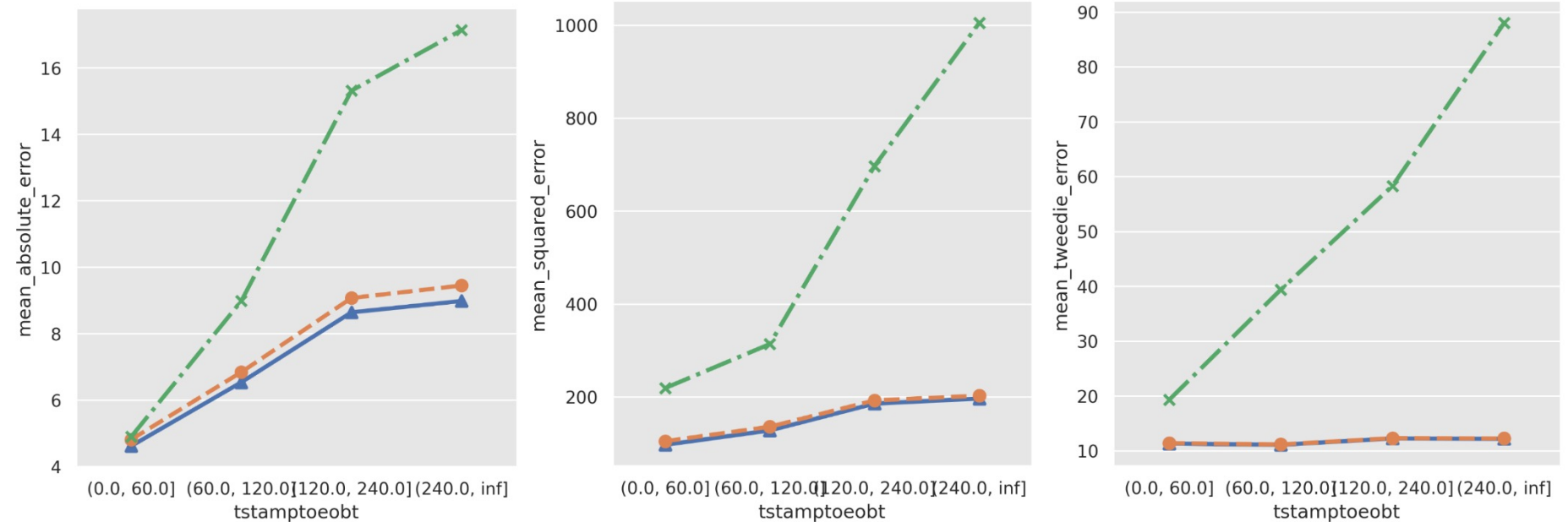
ATFM delay evolution - experiment

- April 2021: Assessment on the test set
 - The predictions of the model outperform the information that is available nowadays
- March 2021: Validation exercise in replay mode
 - Improvements were confirmed
 - Wish for further testing in live trial
- October 2021 – Present: Live trial
 - The models are connected to the Network Manager's operational system
 - Airlines access the predictions from their operational control centres (OCCs)



ATFM delay evolution - Results

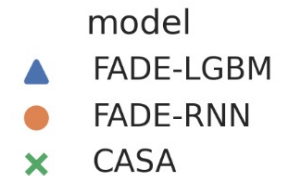
Low is better



FADE-LGBM: Model that does not consider sequential information

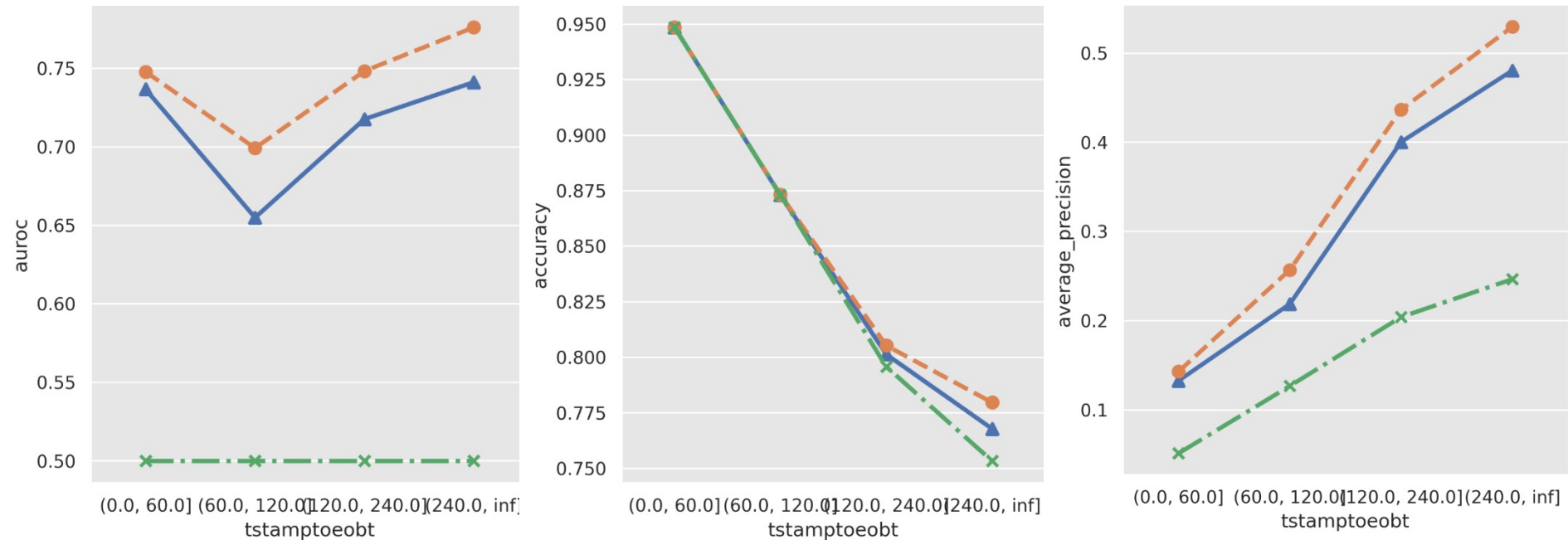
FADE-RNN: Model that considers sequential information

CASA: A dummy model that always predicts the current ATFM delay



ATFM delay evolution - Results

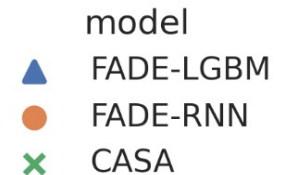
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FADE-LGBM: Model that does not consider sequential information

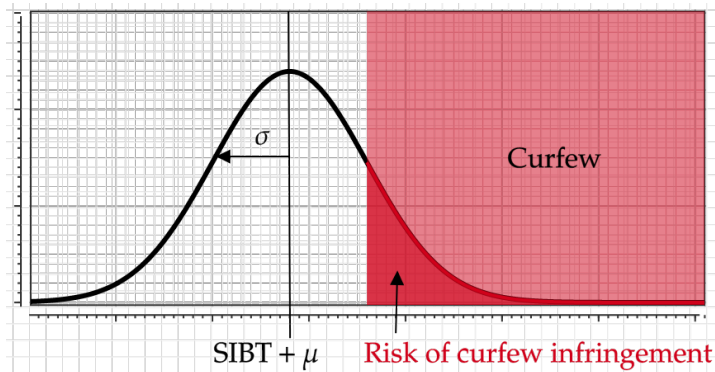
FADE-RNN: Model that considers sequential information

CASA: A dummy model that always predicts False (delay stable)

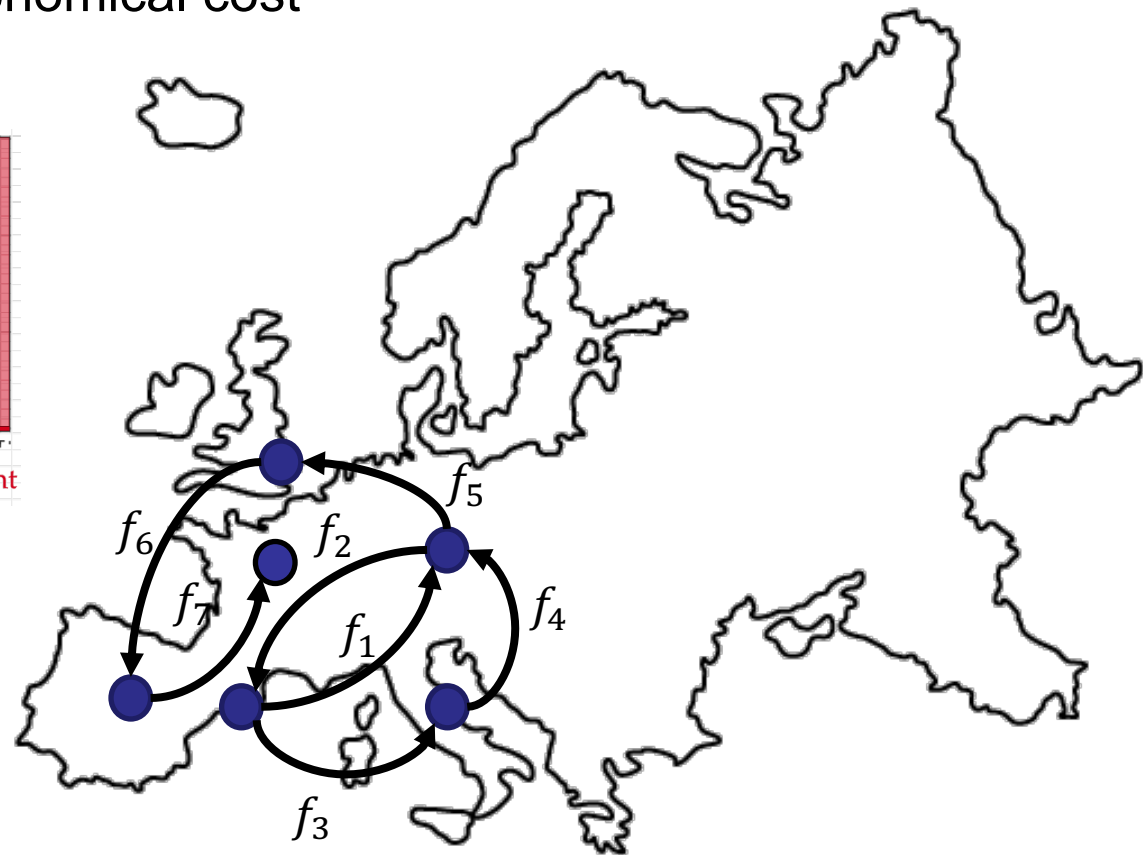


Delay propagation - Introduction

- Night curfews are environmental restrictions applied at some airports
- Delay propagation may lead to a night curfew infringement
- High operational and economical cost



SIBT: Scheduled In-Block Time



Delay propagation - Introduction

Date: 13/07/2019 11:00:00

Apply

Reset

Auto Refresh (5 min)



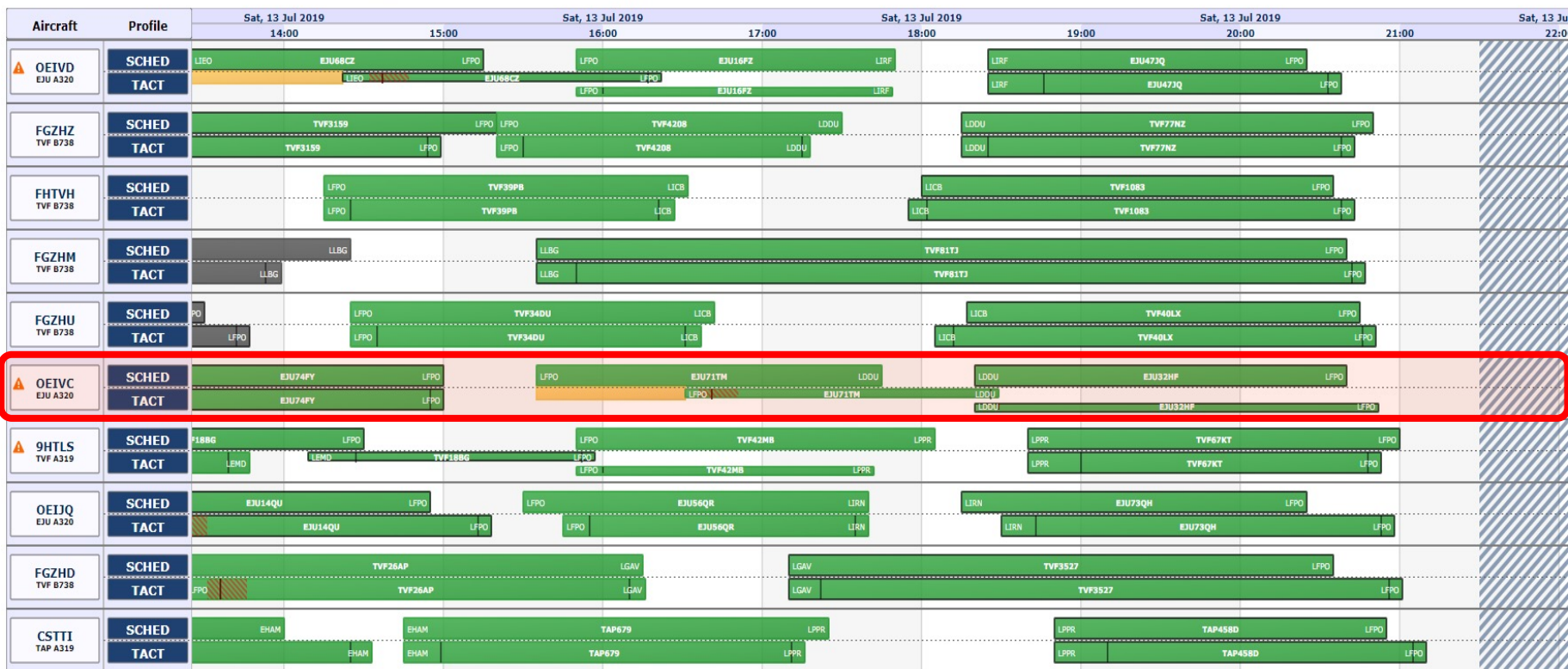
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Show Alt



Show KPIs



MIRROR HMI: TACT demand at 11:00utc for LFPO late evening arrivals on 13-07-2019 based on ETFMS (Enhanced Tactical Flow Management System) flight data (EFD)

Delay propagation - Introduction



Date: 13/07/2019 11:00:00

Apply

Reset

Auto Refresh (5 min)

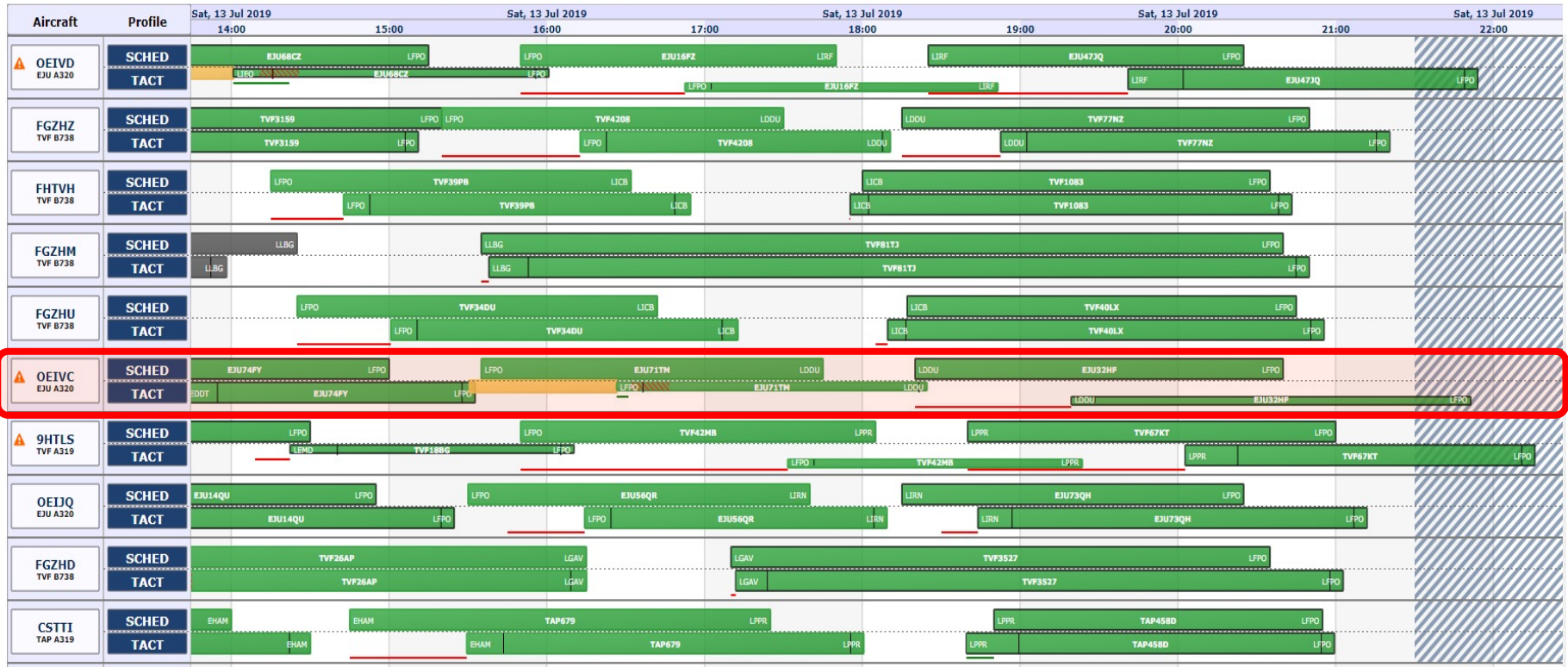


- 100% +



Show Alt.

Show KPIs



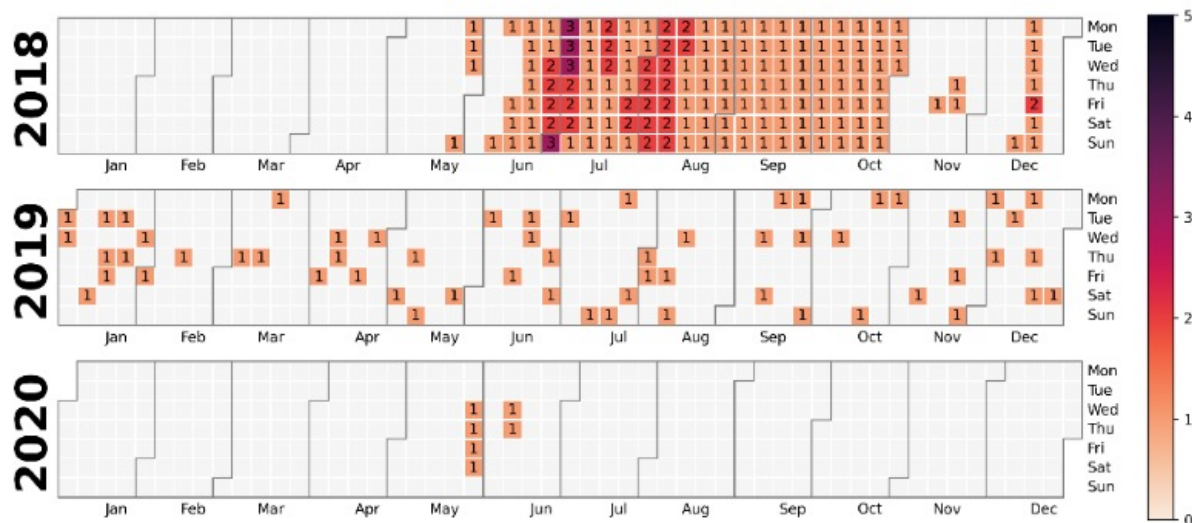
MIRROR HMI: TACT demand at 11:00utc for LFPO late evening arrivals on 13-07-2019 based on ETFMS (Enhanced Tactical Flow Management System) flight data (EFD) + predictions from machine learning model

Delay propagation - Model

- One tasks
 1. Predict the arrival delay *distribution* (mean and standard deviation), of each flight in the sequence, modelled as the difference between the Actual and the Scheduled In-Block Times (AOBT – SIBT)
Trained to minimise the negative log-likelihood
- One version:
 1. Bi-directional Recurrent Neural Network (BiRNN) – sequence of flights (for each light, the most up-to-date information)
- Two sources of data
 1. Enhanced Tactical Flow Management System (ETFMS) flight data messages (EFD) collected by the Network Manager (NM)
 2. Airline schedules
 - SIBT and scheduled off-block time (SOBT)

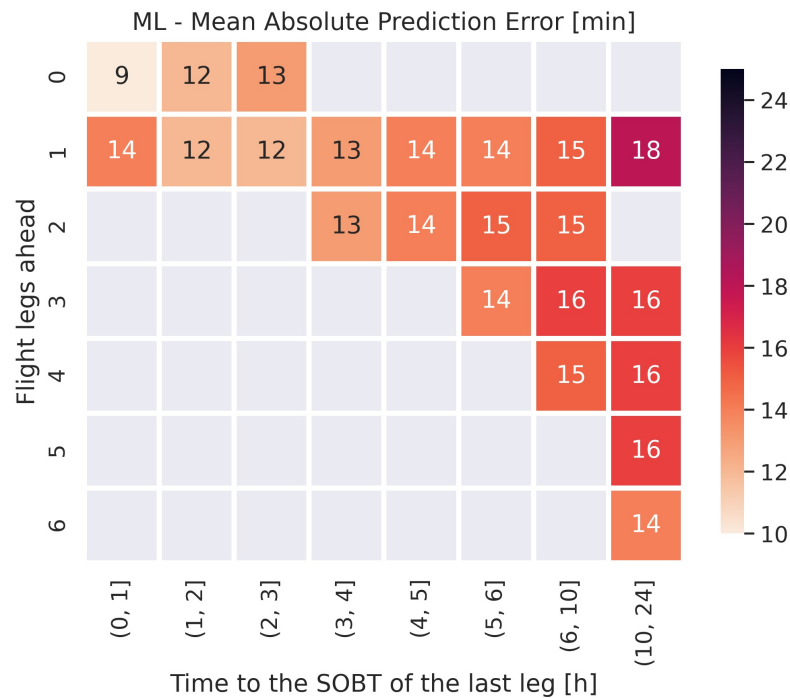
Delay propagation - Experiment

- Training
 - 300 days of 2019
- Testing:
 - 60 days of 2019
 - June to December 2018
 - COVID period (January to May 2020)

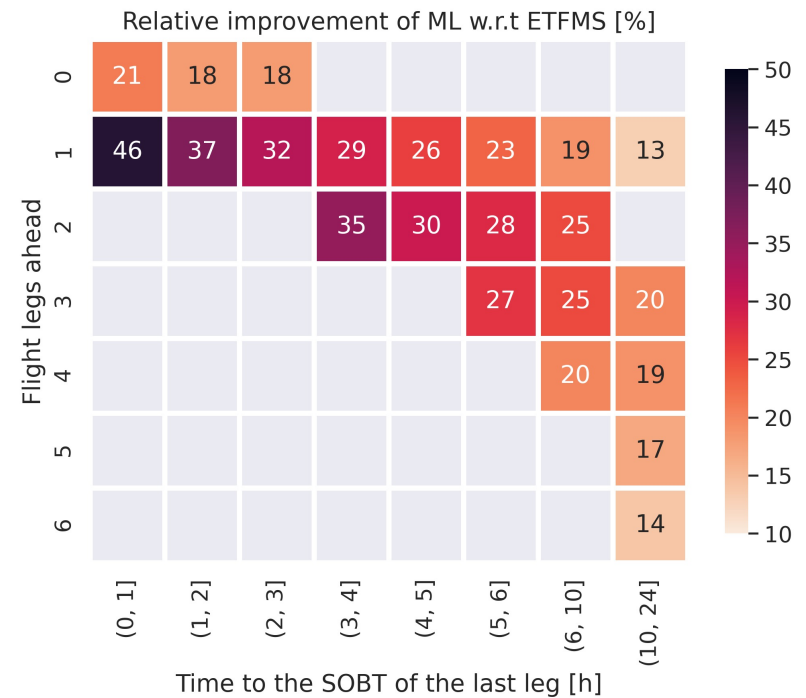


Delay propagation - Results

Results on 60 days of 2019



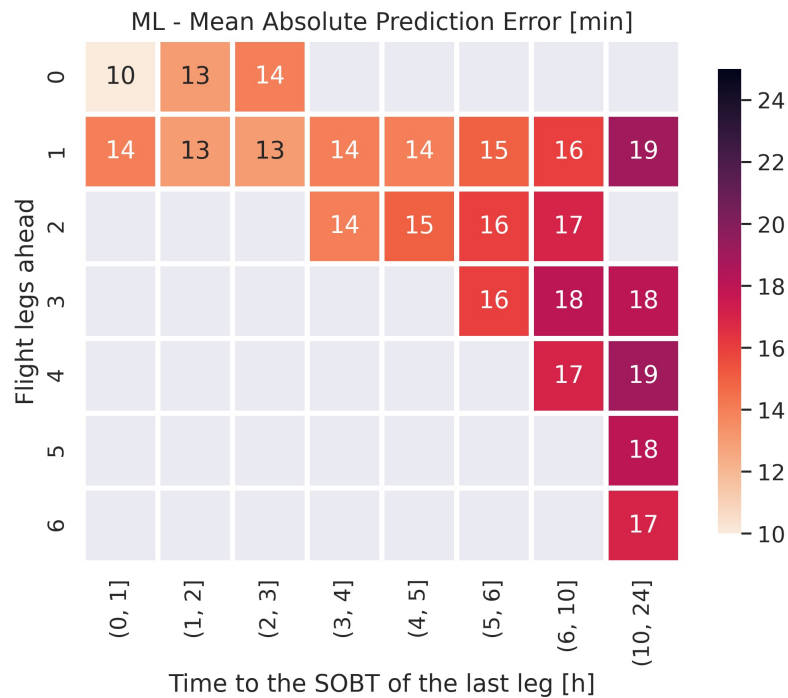
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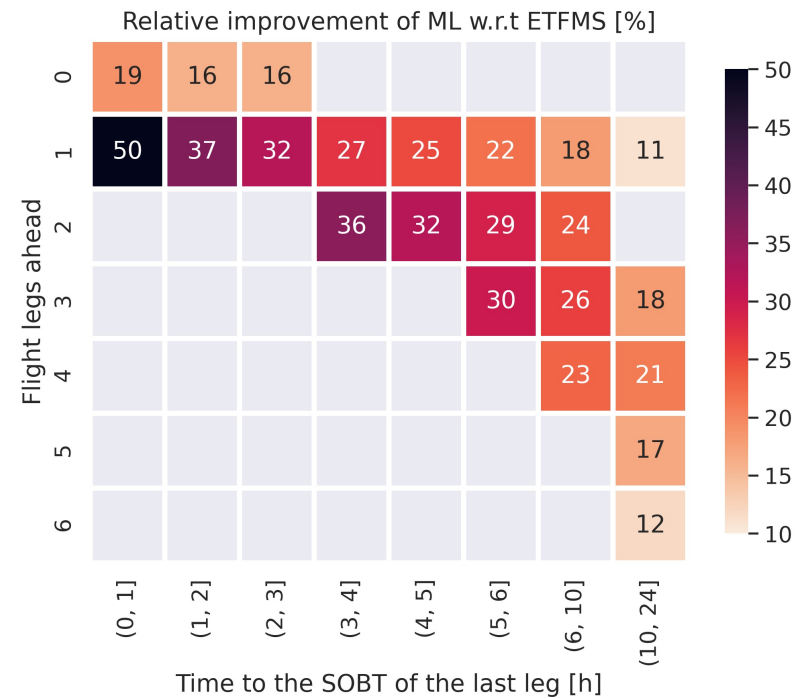
High is better

Delay propagation - Results

Results on past data (June to December 2018)



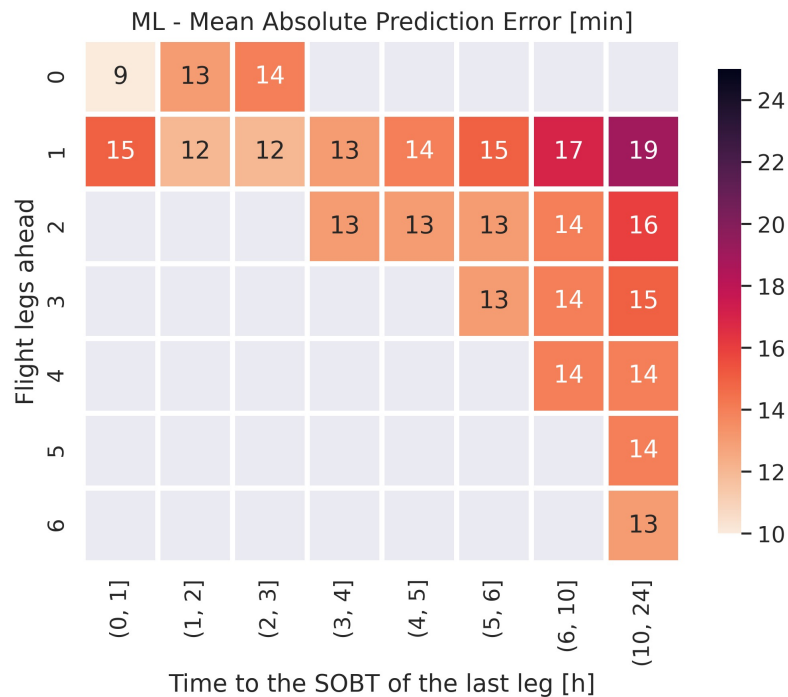
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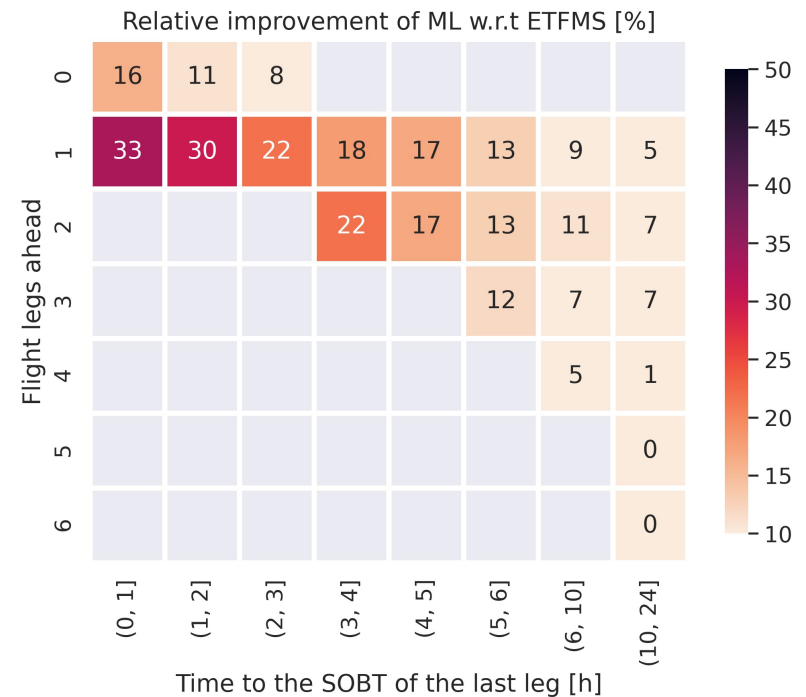
High is better

Delay propagation - Results

Results on COVID period (January to May 2020)



Low is better



High is better

More info:

Dalmau, R. et. al. Early Detection of Night Curfew Infringements by Delay Propagation with Neural Networks. 2021. 14th USA/Europe Air Traffic Management Research and Development Seminar (ATM2021)

Dalmau, R. et. al. A Machine Learning Approach to Predict the Evolution of Air Traffic Flow Management Delay. 2021. 14th USA/Europe Air Traffic Management Research and Development Seminar (ATM2021)

