Toward novel environmental impact assessment for ANSPs using machine learning

Gabriel Jarry (DSNA), Daniel Delahaye (ENAC)

ACROPOLE

InterFAB Research Workshop
Climate change and the role of air traffic control

Vilnius 23/09/21

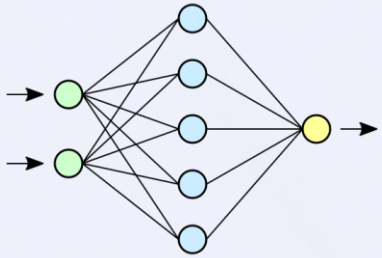
Philosophy

Radar Data
Position, speed, altitude …

Machine Learning

FDR Data Estimation
Fuel flow, aerodynamic configuration...

Neural Networks



- Accurate prediction
- Generalization property
- Good metric for extra fuel consumption

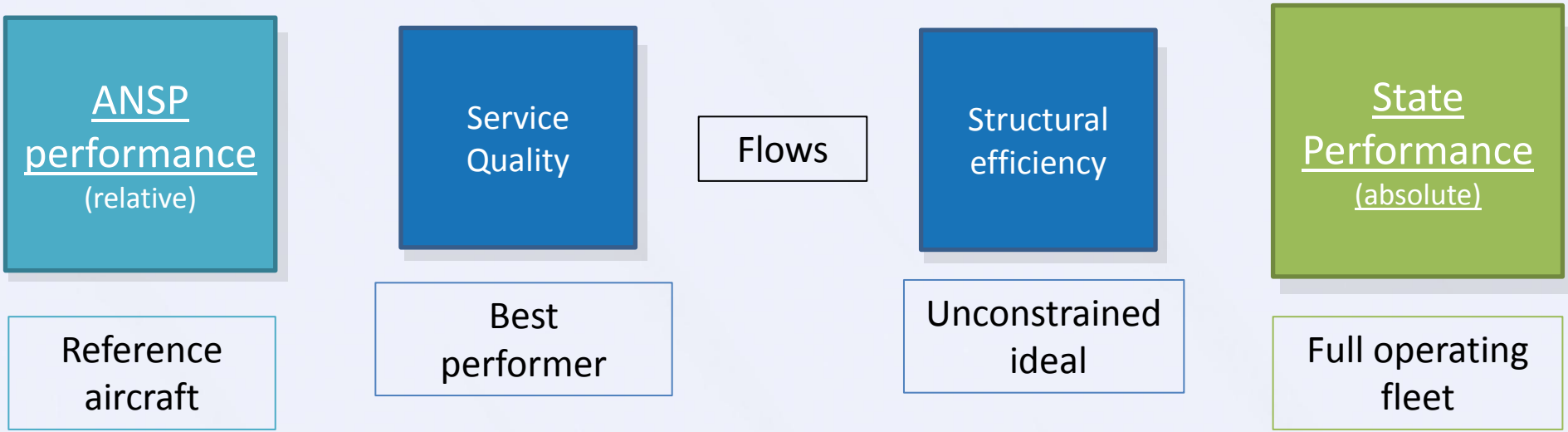
Models, metrics and indicators

Complementary metrics and indicators

Environmental impact and ANSP performance assessment

What do we want to measure and how ?

- Fuel efficiency
- Noise efficiency

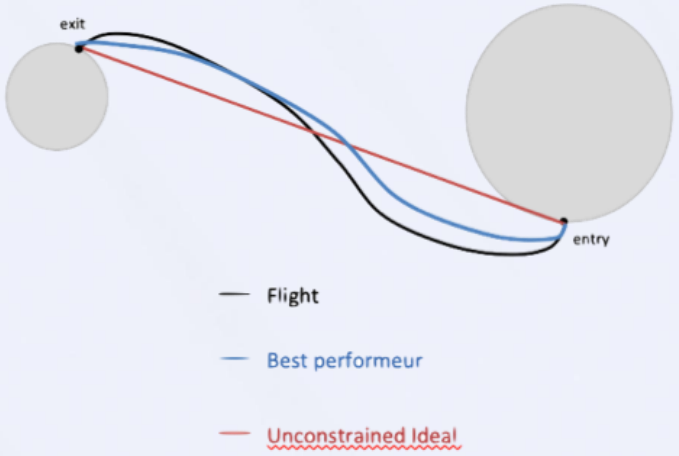


KPI/PI proposal

***KPI 1a: ANSP* service quality**

Ex: en-route, (other phases)

***KPI 1b: State* service quality**



PI 2a: ANSP lateral structural efficiency

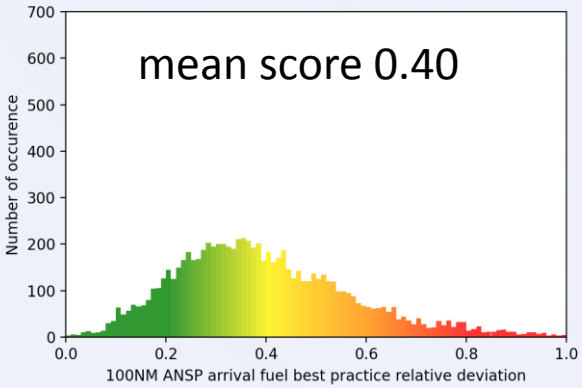
PI 2b: State lateral structural efficiency

PI 3a: ANSP profiles structural efficiency

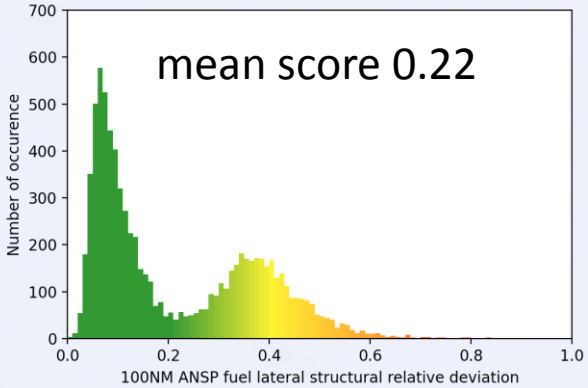
PI 3b: State profiles structural efficiency

Use case : focus on approach at CDG (100NM)

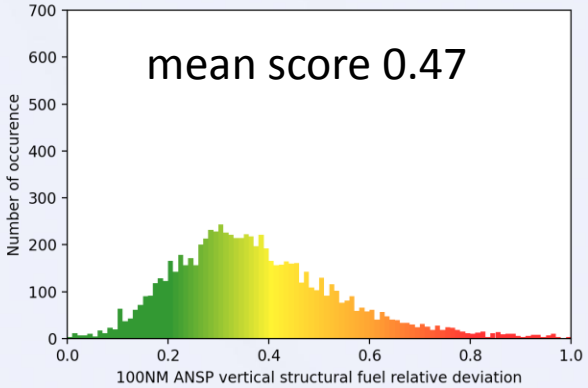
KPI 1a: 100NM arrival fuel ANSP service quality



PI 2a: 100NM arrival fuel ANSP lateral structural efficiency



PI 3a: 100NM arrival fuel ANSP profiles structural efficiency

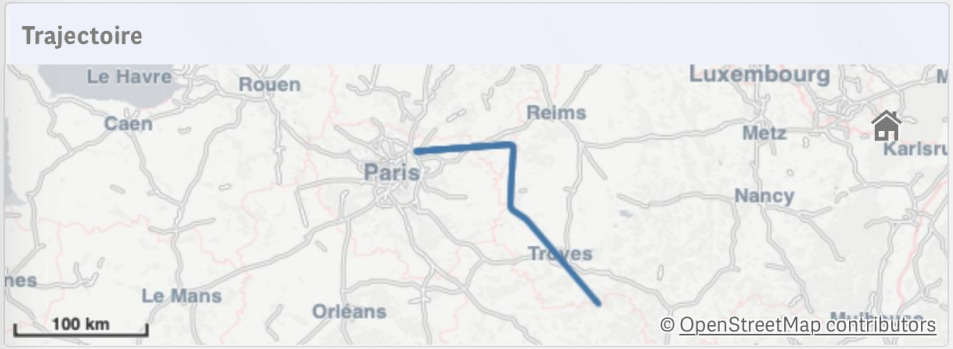


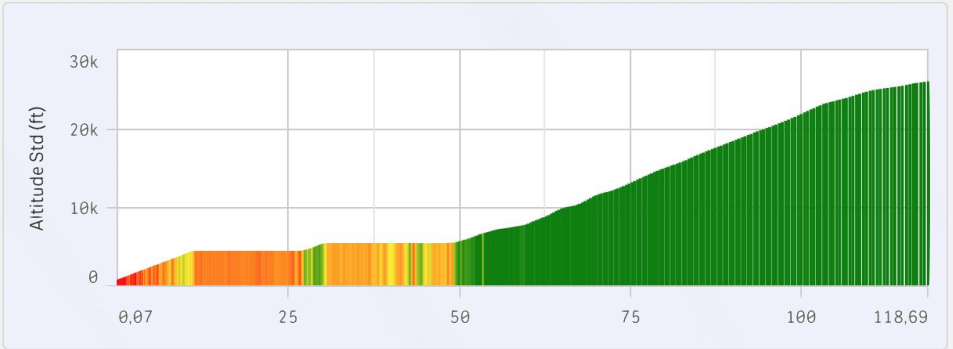
Example flight 1 – 26L South-East flow

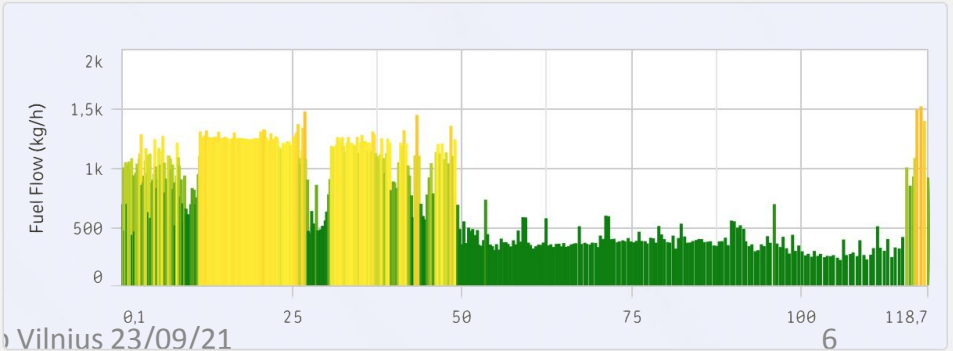
KPI 1a 1.12

PI 2a 0.35

PI 3a 1.09





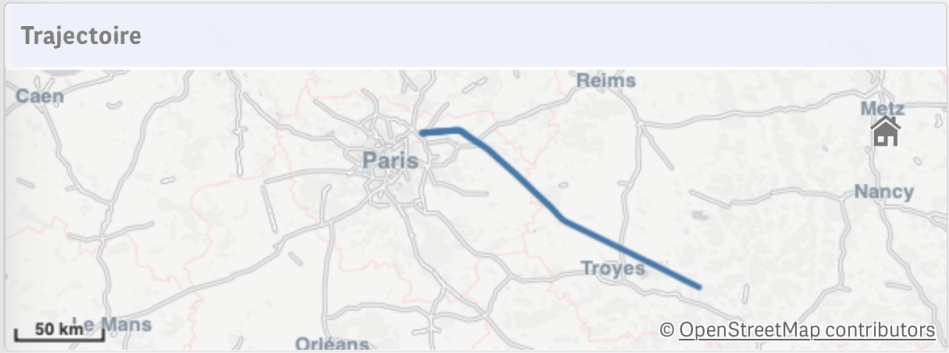


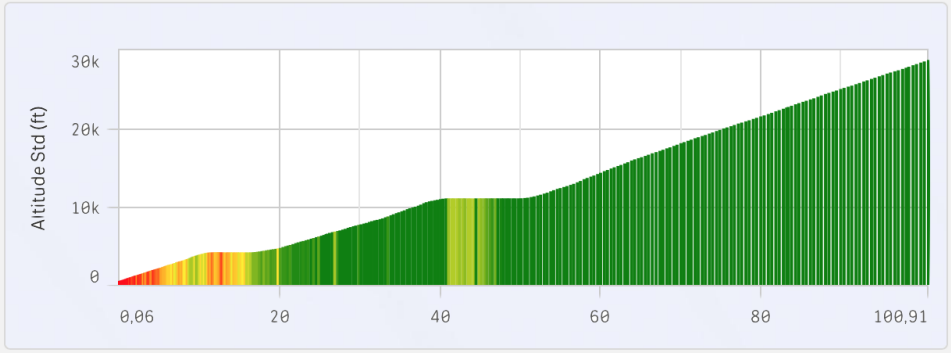
Example flight 2 – 26L South-East flow

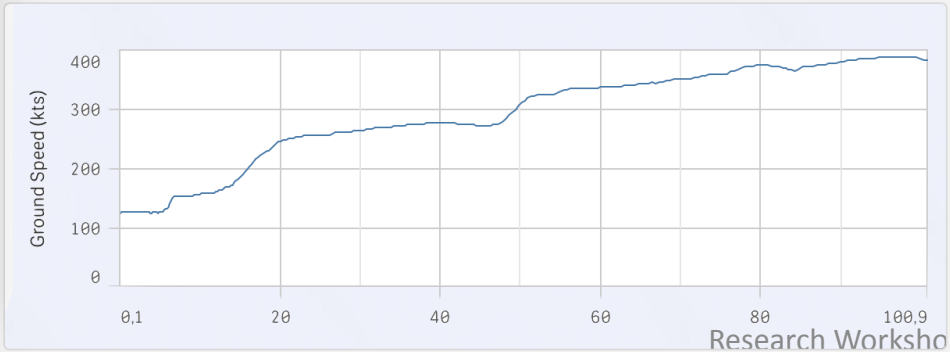
KPI 1a 0.20

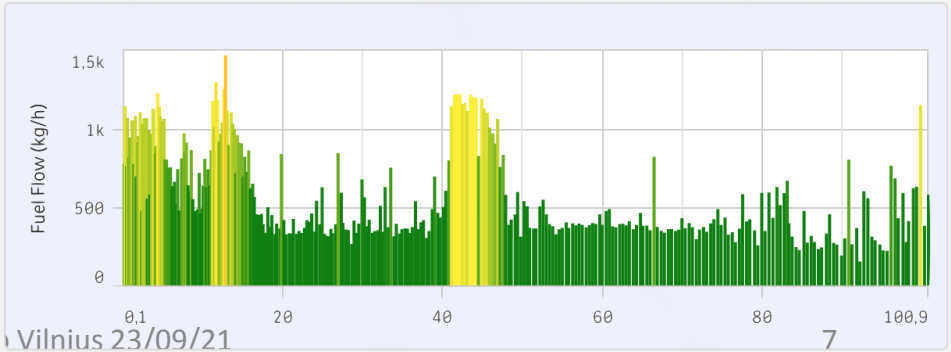
PI 2a 0.03

PI 3a 0.31







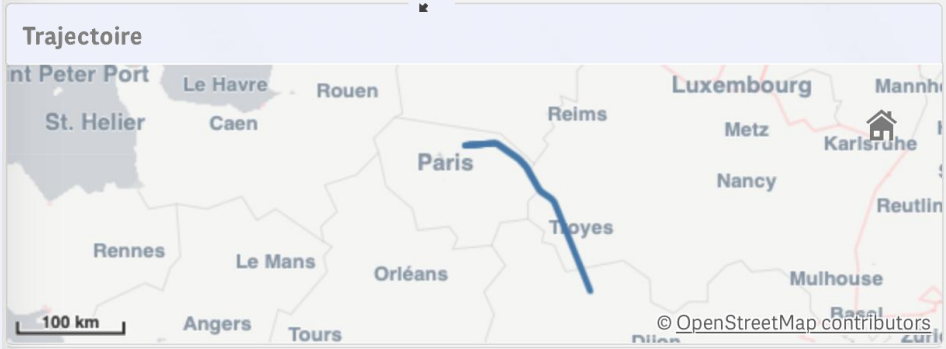


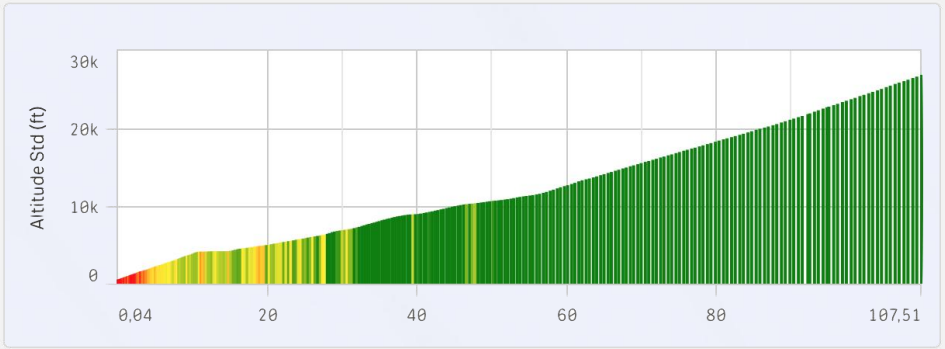
Example BP – 26L South-East flow

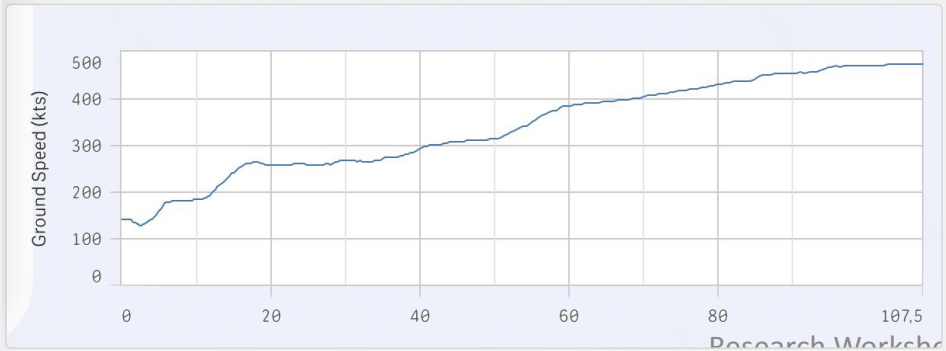
KPI 1a 0.10

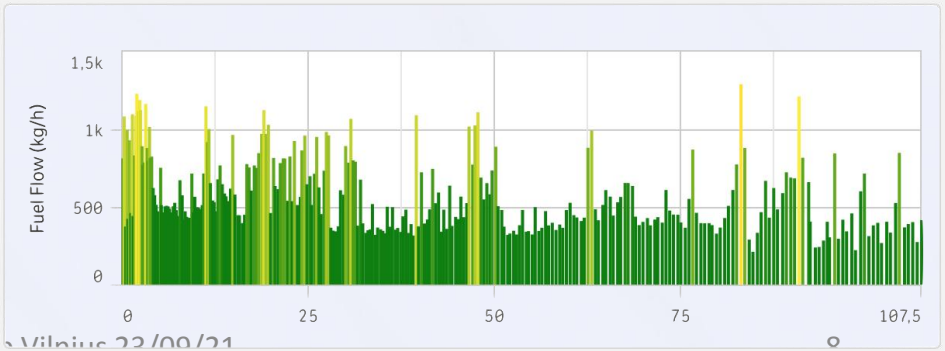
PI 2a 0.09

PI 3a 0.15







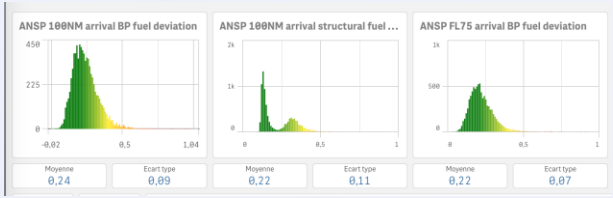


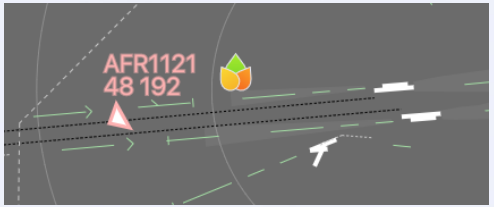
Perspectives

AI model improvements
+
weather / noise indicators

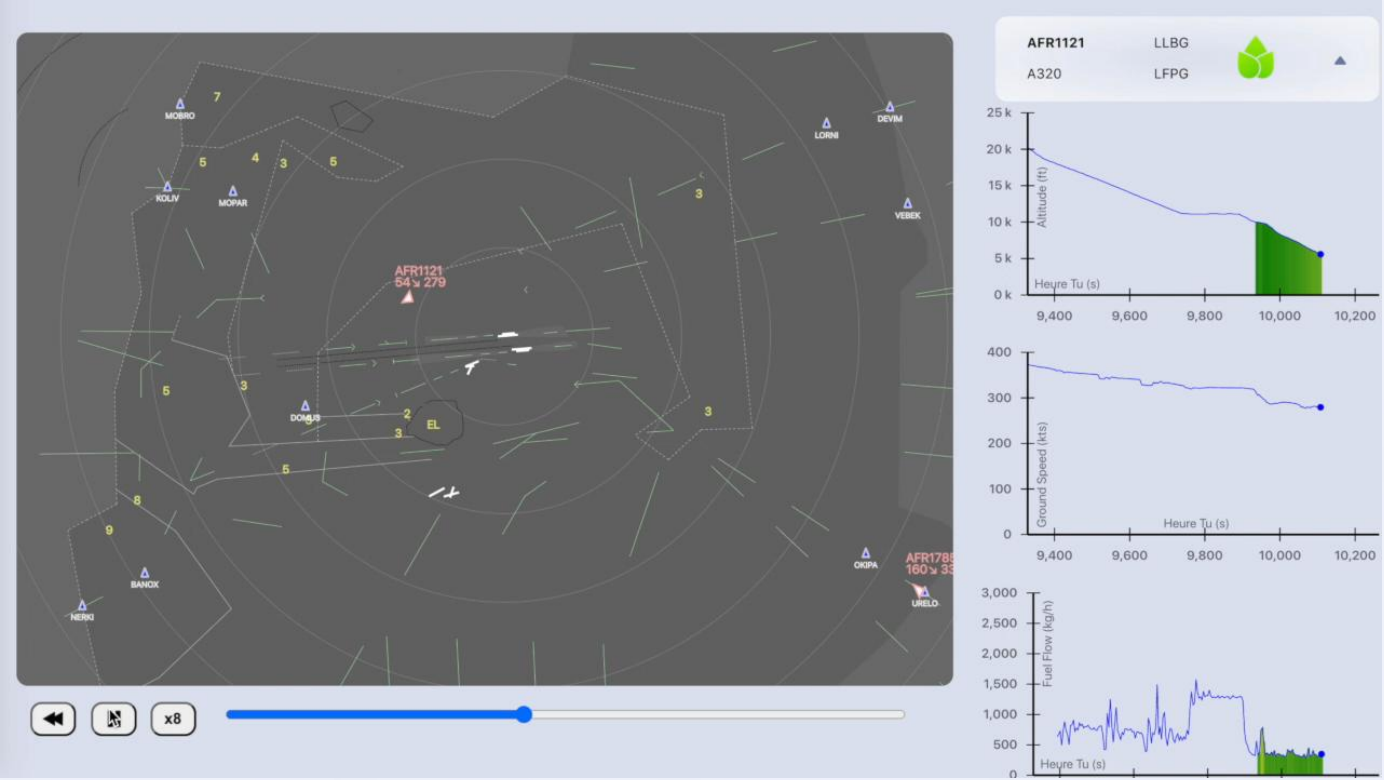
Large scale ANSP deployment for post-ops analysis
(CDG-NICE-ORY-LYO)

Real time experimentation with ATC center + safety tools





Perspectives



Thank you for your attention !

gabriel.jarry@aviation-civile.gouv.fr
alain.bourgin@aviaiton-civile.gouv.fr
DSNA/ME/AMO

ACROPOLE

Appendix

Modelization

Data Set

Ex : A320
15 000 FDR trajectories
(3 French airlines)

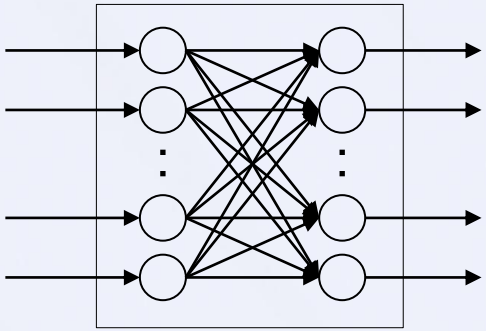
Model

Neural Networks

Inputs

Radar information

Altitude (ft),
Ground Speed (kts),
Vitesse vertical (ft/min)
True Air Speed (kts)



Outputs

Fuel flow (kg/h)
Aerodynamic configurations (Flaps, Gear)

Fuel model error quantification and model generalization

A320 – evaluation 1000 flights

Phase	$MAPE_{fuel}$ (%)	MAE_{fuel} (kg/h)	r_{fuel}	Samples #	$MAPE_{conso}$ (%)	MAE_{conso} (kg)	ME_{conso} (kg)	Flight #
ALL	5.95	50.5	99.1	7[illegible]88512	1.73	92.0	1.5	1000
TAXI	11.21	45.5	23.4	3[illegible]69704	4.92	3.4	0.4	1000
CLIMB	1.66	38.2	99.2	1[illegible]47940	1.19	20.3	4.0	1000
CRUISE	3.68	44.1	86.7	4[illegible]11650	2.8	72.5	-2.8	995
DESCENT	11.17	56.2	96.2	1[illegible]76614	2.88	10.4	2.0	999
APPROACH	16.9	115.0	86.7	2[illegible]24834	6.51	6.1	0.3	998

Low MAE

High correlation

Centered Error

B737 – generalization – ICAO Fuel coefficient ratio - 1000 flights

Phase	$MAPE_{fuel}$ (%)	MAE_{fuel} (kg/h)	r_{fuel}	Samples #	$MAPE_{conso}$ (%)	MAE_{conso} (kg)	ME_{conso} (kg)	Flight #
ALL	9.59	82.9	96.0	9[illegible]86056	2.71	153.7	-52.5	1000
TAXI	22.73	85.4	25.0	3[illegible]65444	8.78	6.8	-6.0	1000
CLIMB	4.26	103.0	97.1	1[illegible]61423	2.49	38.0	-18.3	1000
CRUISE	4.5	51.1	79.4	5[illegible]02375	3.3	102.6	-32.0	998
DESCENT	15.42	68.8	94.2	1[illegible]05903	4.01	15.5	-0.7	999
APPROACH	17.66	143.8	83.5	1[illegible]99789	7.96	7.7	2.0	1000

increased MAE

High correlation

Potential Bias

Summary of the approach

Performance	ANSP	Global
Reference	Best Performer, Direct	Best Performer, Direct
Metric	Reference model consumption	Real consumption
Indicator type	Relative deviation	Absolute deviation
Phases	Gate-to-gate, departure, en-route, approach	Gate-to-gate, departure, en-route, approach