Constraint Design of Experiments & Adaptive Sampling

OpenTURNS User Day

Ivo CURTIUS on behalf of
Peter EISENSCHMIDT, Max SAHLKE, Jasone GARAY GARCIA, Yann NIVET,
Hasier GOITIA HERNANDEZ, Jishnu SIVARAMAN, Eric WORLITZER

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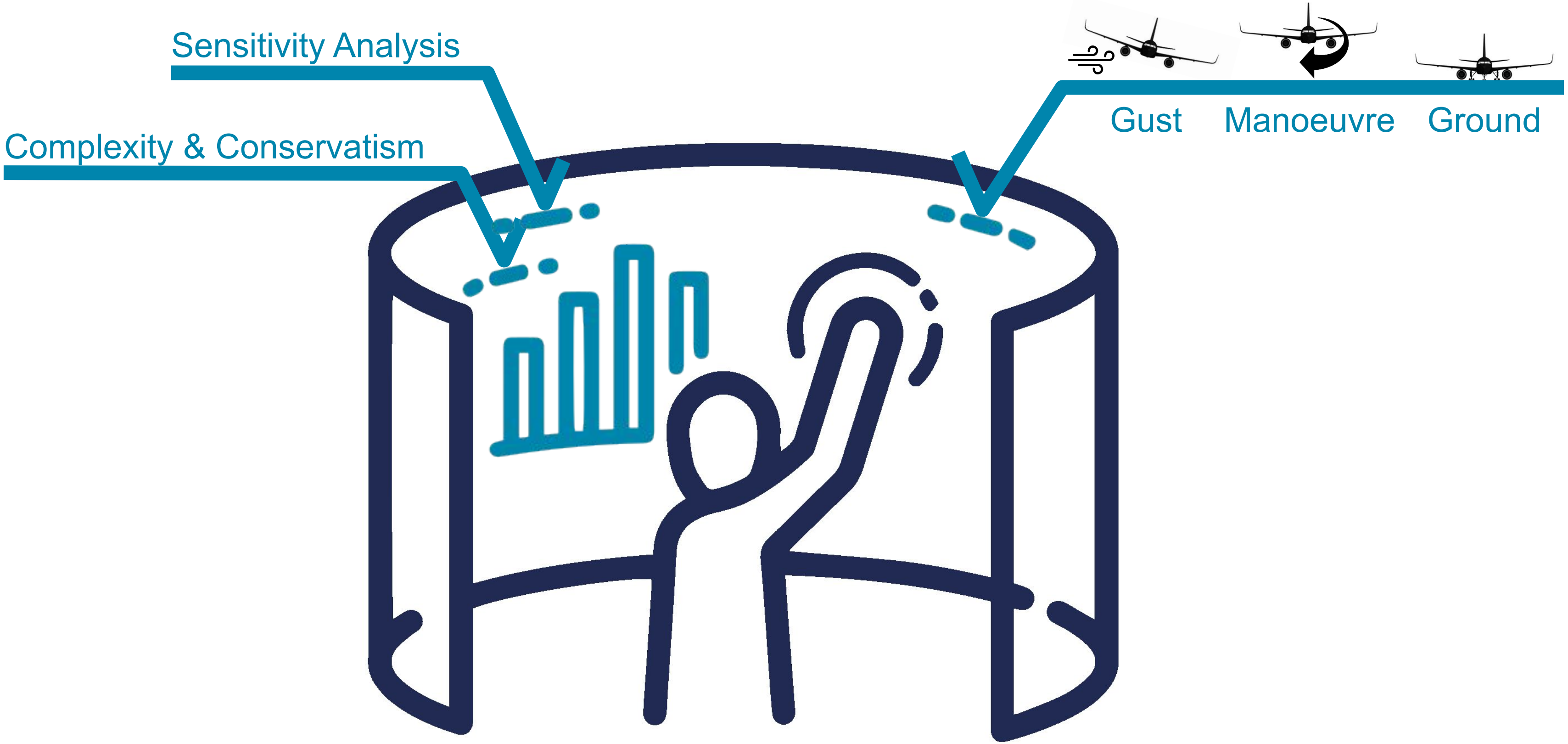
Introduction



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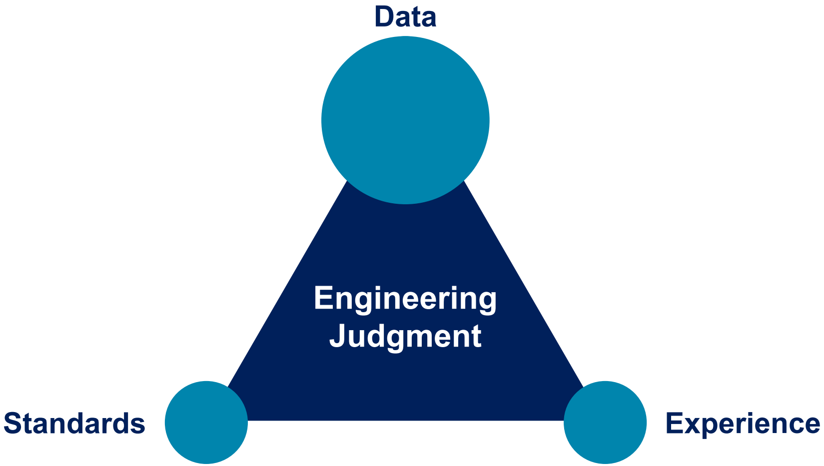
Introduction
Impact & Search for Solution



ICT 4% of global emission,
Data Centers 15% GHG emission, 24% Electricity

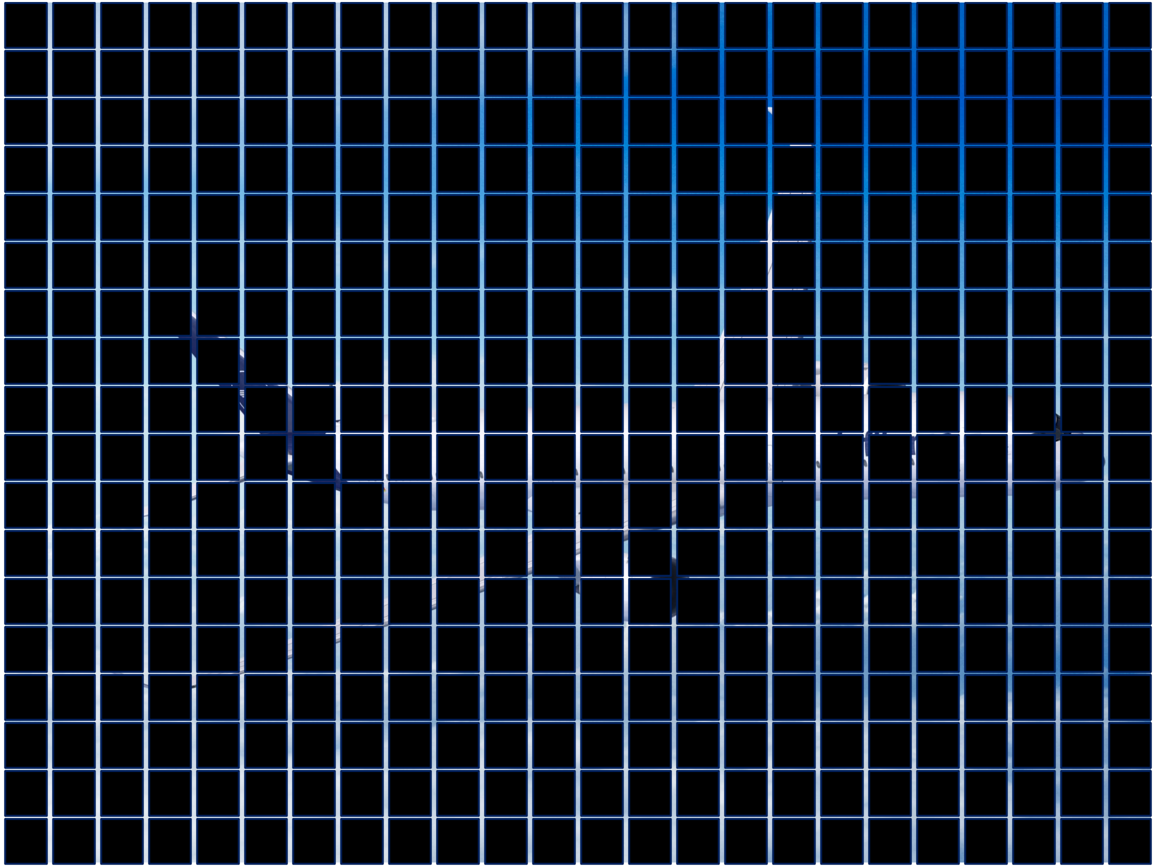
How do we select what data to produce?

How do we gain the most value from each data point?

How do we do this in a systematic way to be secure, economical, fast and sustainable?

ICT - Information and communication technology, GHG - Green House Gas | Source

Simplified Example - What Aircraft do you see?

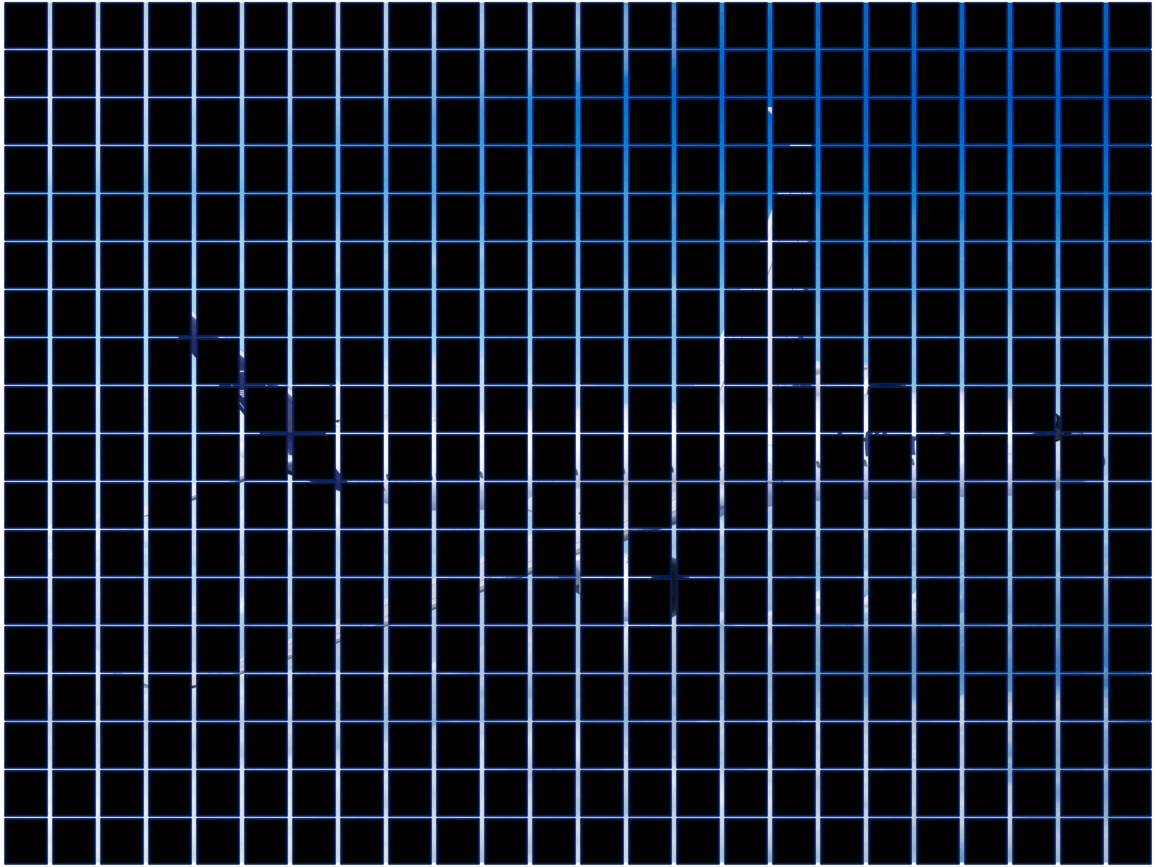


Let us take
20 sample
points using a
grid pattern

+5 additional
grid samples

25 samples

Simplified Example - What Aircraft do you see?



20 random
sample points

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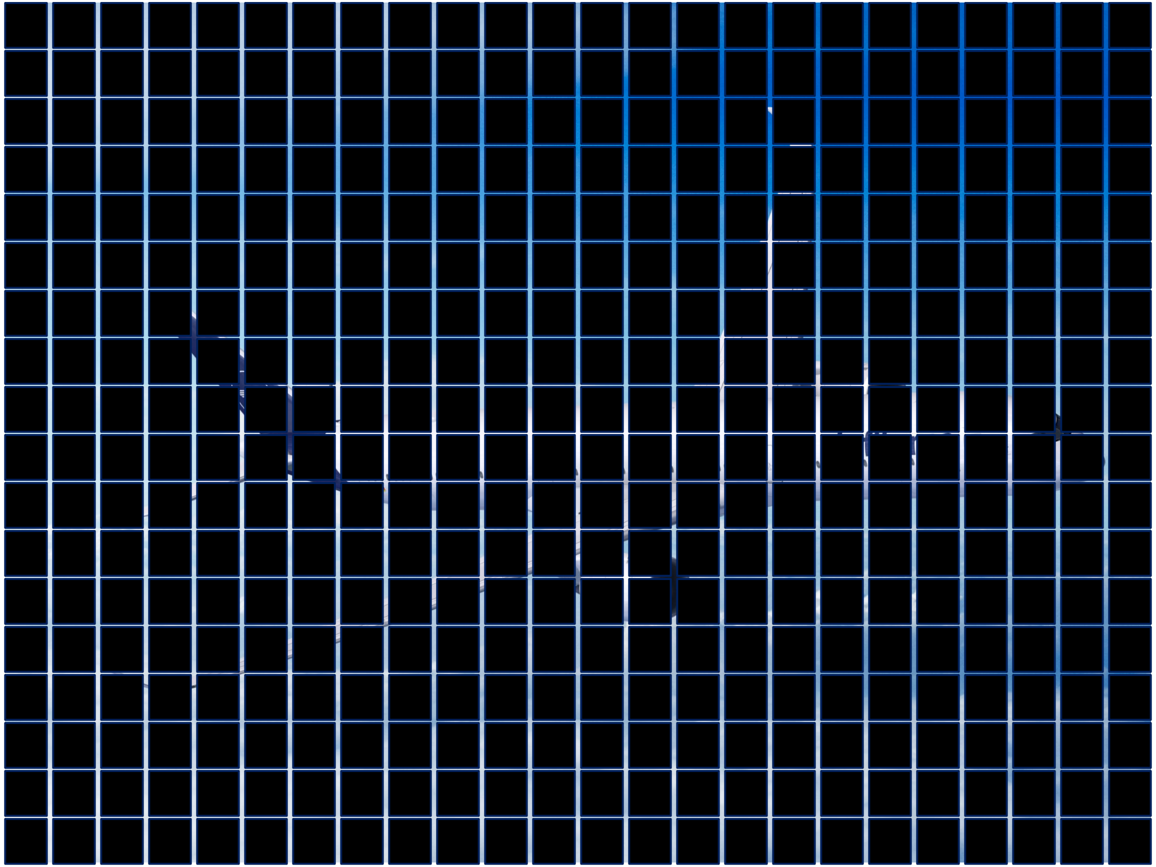
Simplified Example - What Aircraft do you see?



10 random samples

+ 5 adaptive samples

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15 samples

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Constraint Design of Experiment + Adaptive Sampling

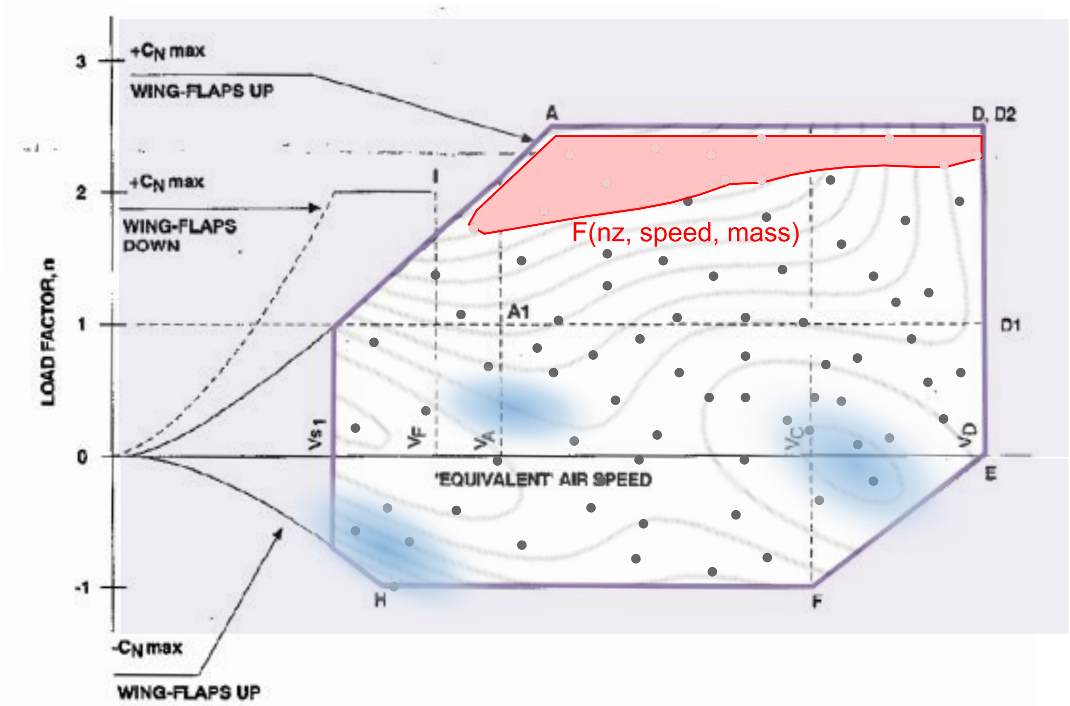
1st Level - Explicit - Identify areas of interest:

- Known constraints
  Example: CS25, …
- Constraints can be independent or correlated

2nd Level - Implicit - Identify areas that do not hold a physical solution:

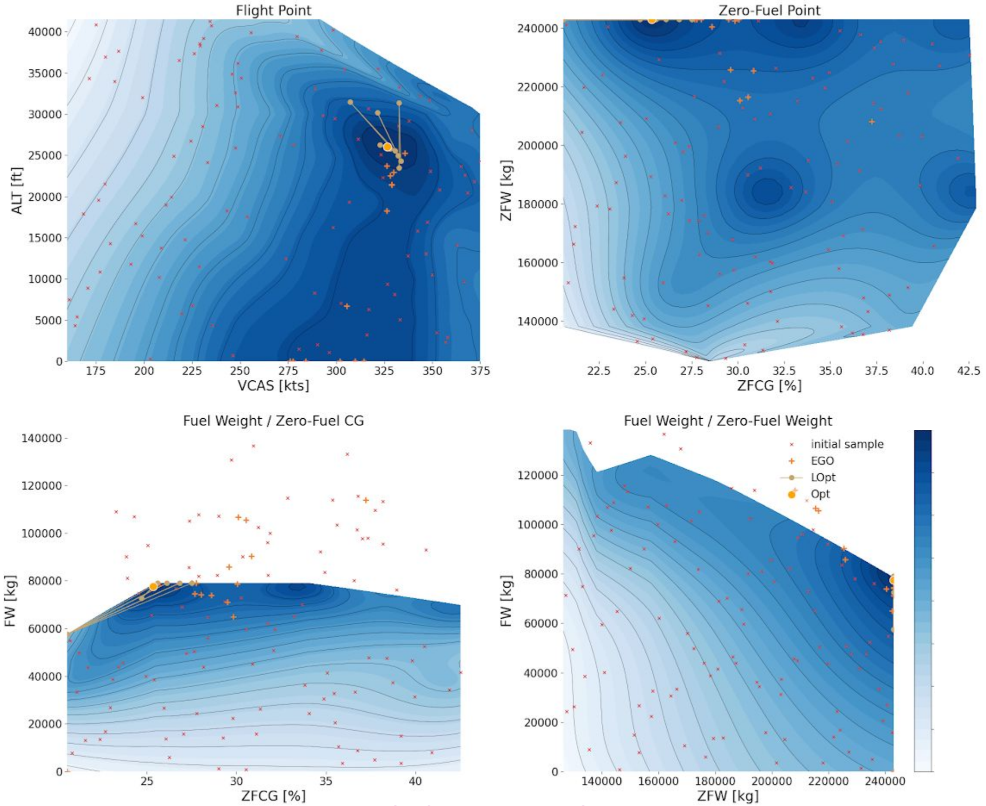
3rd Level - Implicit - Identify areas of increased Interest:

- **Optimization:** finding areas that lead to high loads (~Min/Max)
- **Active Learning:** finding areas of non-linear responses (~dense Isolines) or areas which are sparsely sampled in order to decrease the error of a surrogate model

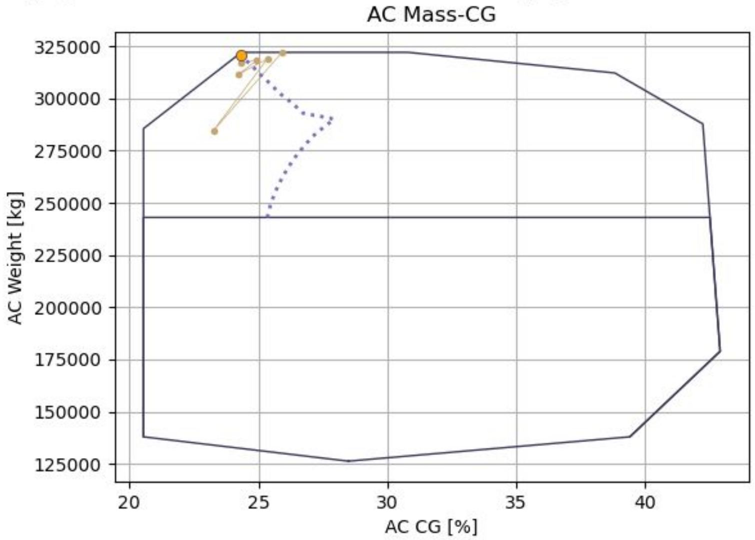


The solutions to these problems are developed in close collaboration with Central R&T at Airbus
And are continuously published in the public OpenTurns library

1. Optimization - Proof of Concept with 5 Input Dimensions



PoC of a 5D Design Space
(Altitude, Speed, Zero Fuel CG, Fuel Weight, Zero Fuel Weight)



Number of Samples:
- Initial: 75
- Global optimization: 45
- Local optimization: 10
- TOTAL: 130

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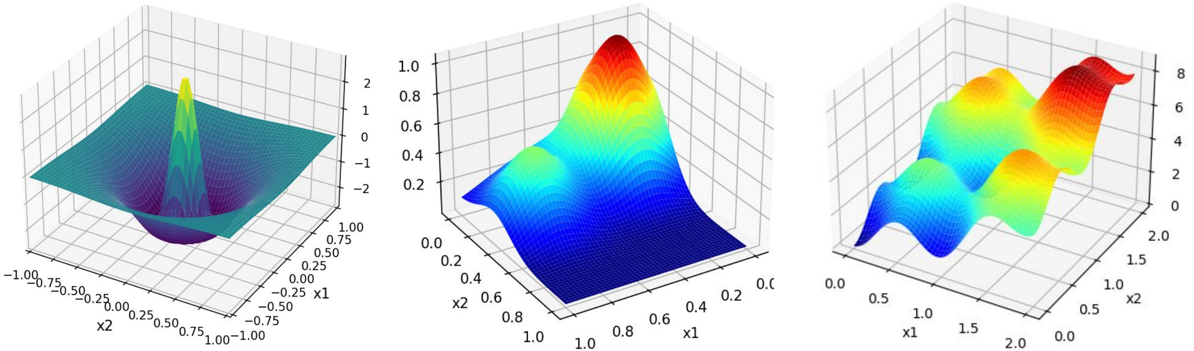
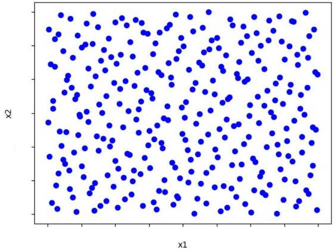
2. Active Learning - Proof of Concept on Benchmark Functions

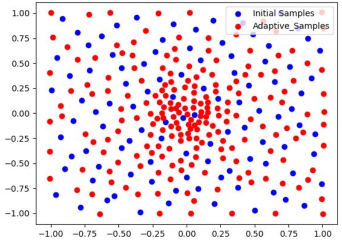
Benchmark functions

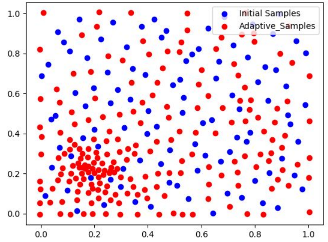


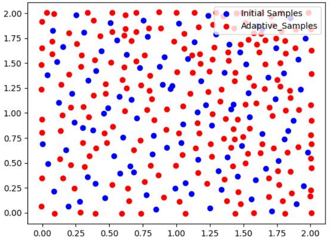
Dataset A:
300 random samples



3 Datasets B:
100 random initial samples + 200 adaptive samples (in a batch of 5 samples per iteration)







Improvement in Mean Squared Error for a surrogate model build with dataset A vs. dataset B	**58%**	**16%**	**6%**

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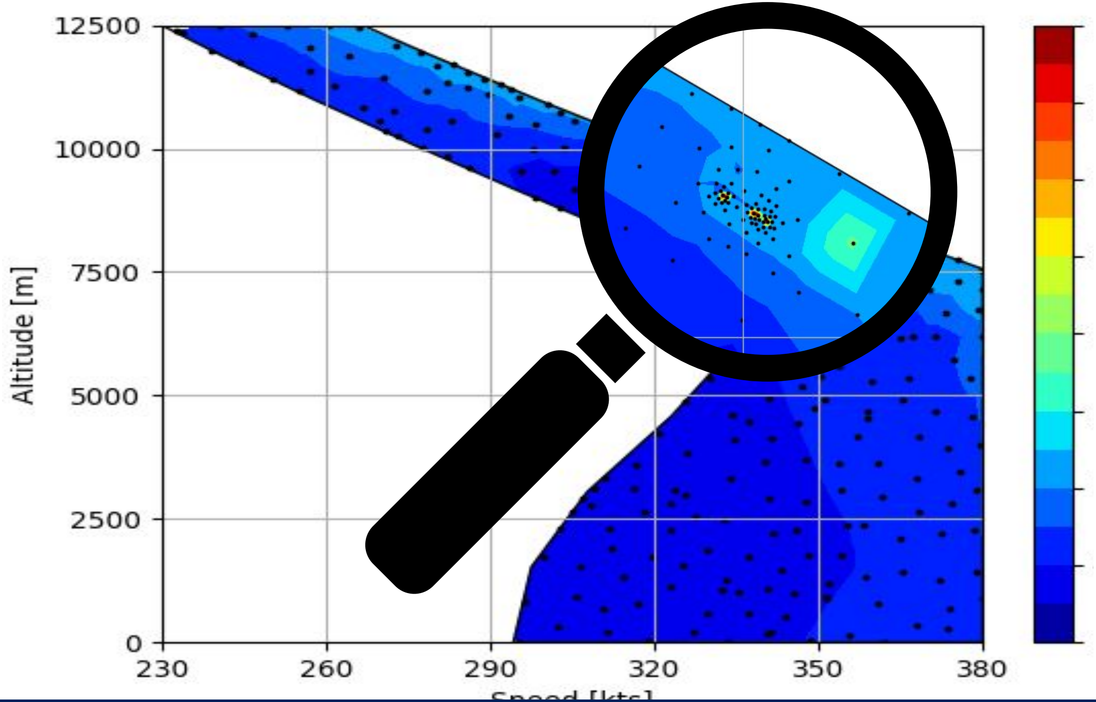
3. Active Learning - Positive Bycatch



- Clustering occurs in a very local region where the maximum output is doubled
- Such results are not physical
- They are caused by an error in the simulation model
- Such errors can easily be rectified if they are known

We are able to find modelling errors or insufficiencies in a more systematic way!

VTP - vertical tail plane

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Summary

Summary

Reduce the overall number of data points

Systematic and robust approach

Generic Code, Applicable to any engineer

Fosters engineering judgement

Increase value per generated data point

Find modelling errors or insufficiencies

Analyze constraint design space

Through good understanding of the design space

Questions?

Abbreviations

STA - Static
FAT - Fatigue
IQ - Interesting Quantity
DoE - Design of Experiment
DS - Design Space
OOC - Out of Cycle
LHS - Latin Hypercube Sampling
CEL - Confirmed Expert Leader
FPI - Flight Physics Integrator

Thank you

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