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Data-Driven Modeling of Aircraft Engine Performance

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Research Objectives

* ‘Hybrid’* models of aircraft engine performance
  * Physical principles + operational flight data (e.g. from FDR)
  * Aircraft engine performance + statistical data analysis/machine learning
* Intended intellectual outputs of the research
  * Methodology and techniques used to build the models
  * The models themselves

*Jaw, L. C., and Mattingly, J. D., *Aircraft Engine Controls: Design, System Analysis, and Health Monitoring*, AIAA, Inc., Reston, Virginia, 2009, Chap. 8.

Current Practice

* Gas turbine performance simulation softwares
  * Require knowledge of engine parameters – not easy to access
* Data-driven models of engine performance
  * Non-operational data from flight manuals, ground tests
  * Inability to quantify variability in performance for the same engine type (pilot behavior, operational and maintenance procedures, etc.)
* ICAO Engine Exhaust Emissions Databank
  * Fixed values of fuel flow rates for a particular engine type
  * Point estimates: no characterization of variability in fuel flow

Novelty in Our Approach

* Use of operational flight data from FDR to build models
  * Bypass need to know internal engine parameters
  * Capture variability in performance of the same engine type
* Combination of physical insights and data analysis techniques
  * Ensure data-based models conform to physical principles governing engine performance

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Foreseen Uses of Our Research

* Generation of fuel burn and emissions inventories
* Development of flight paths optimal on fuel burn
* Methodology behind model building can give insights into the application of data analysis techniques to aeronautical datasets
* Models built on operational flight data are abstractions of such data
    * Can be used by researchers as tools in the absence of raw operational data

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Risks and Payoffs

* Risks
  * Performance of models outside range of training data?
  * Scale of model applicability (aircraft types, O-D pairs)?
* Payoffs
  * Potential ‘proof of concept’
  * Merits of using operational data to model engine performance
  * Methods can be used to expand the models as more data are available

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Regression Methodology

* Conservation of energy:

$$\boxed{\dot{m}_{f_n} = \dot{m}_{f_n}(h, GS_n, W_{TO_n}, VS_n)}$$

* Predictor variables: pressure altitude (in m), normalized ground and vertical speeds, normalized takeoff mass
* Response variable: normalized fuel flow rate
* 65% data in training set, 35% in test set, 95% bootstrapped prediction intervals
* Method: Classification and Regression Trees (CART)

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Performance of CART Models
(fuel flow rates corrected to SLS uninstalled conditions)

* Sample mean prediction error:

Phase/Method	CART	ICAO Databank
Climb out (<= 3000' AGL)	1.03 – 4.78%	6.16 – 33.76%
Approach (<= 3000' AGL)	13.65 – 23.23%	34.95 – 97.59%

* 95% prediction interval coverage:

Phase/Method	CART	ICAO Databank
Climb out (<= 3000' AGL)	49.20 – 63.79%	0
Approach (<= 3000' AGL)	52.53 – 61.23%	0

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The Journey Ahead

* Study of more data analysis methods and choice of model variables and evaluation metrics
* Modeling of other engine performance parameters (thrust, pressure ratios, temperatures, spool speeds, …)
* Time – series analysis of a single flight
* Development of generalized models for different aircraft/engine types from trajectory data
  * Clustering into groups

THANK YOU

BACKUP SLIDES

Regression Methodology

- Conservation of energy:

$$\boxed{\dot{m}_f = \dot{m}_f(\rho, V, W, S, t)}$$

- Assuming ISA conditions, no winds aloft, VS = Δh/Δt:

$$\boxed{\dot{m}_f = \dot{m}_f(h, GS, W_{TO}, VS)}$$

- Normalizing fuel flow rate by ICAO databank values, speeds by cruise speed, and mass by MTOW:

$$\boxed{\dot{m}_{f_n} = \dot{m}_{f_n}(h, GS_n, W_{TO_n}, VS_n)}$$

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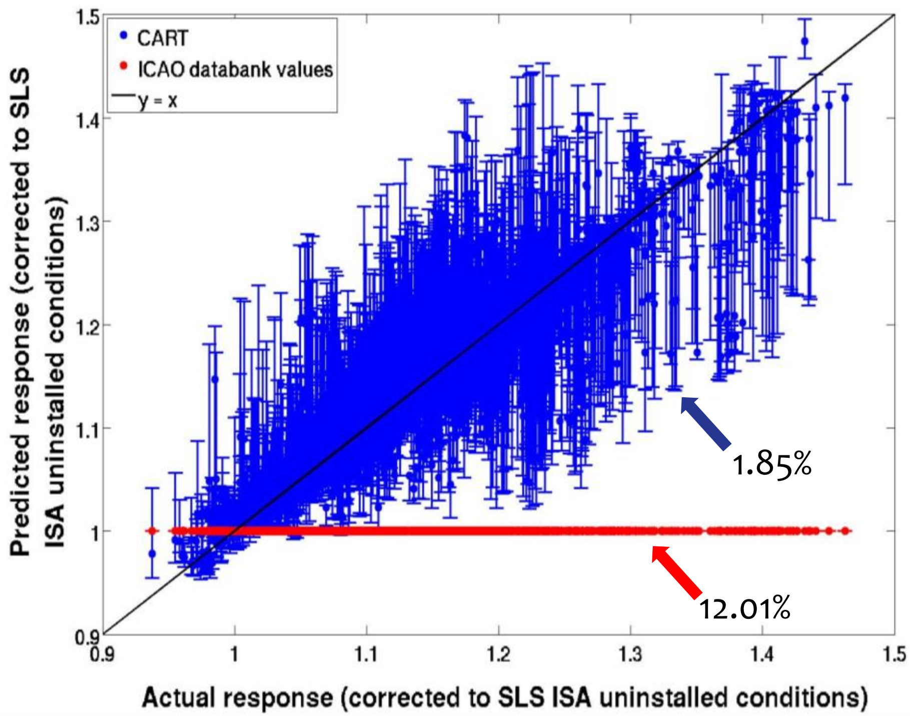
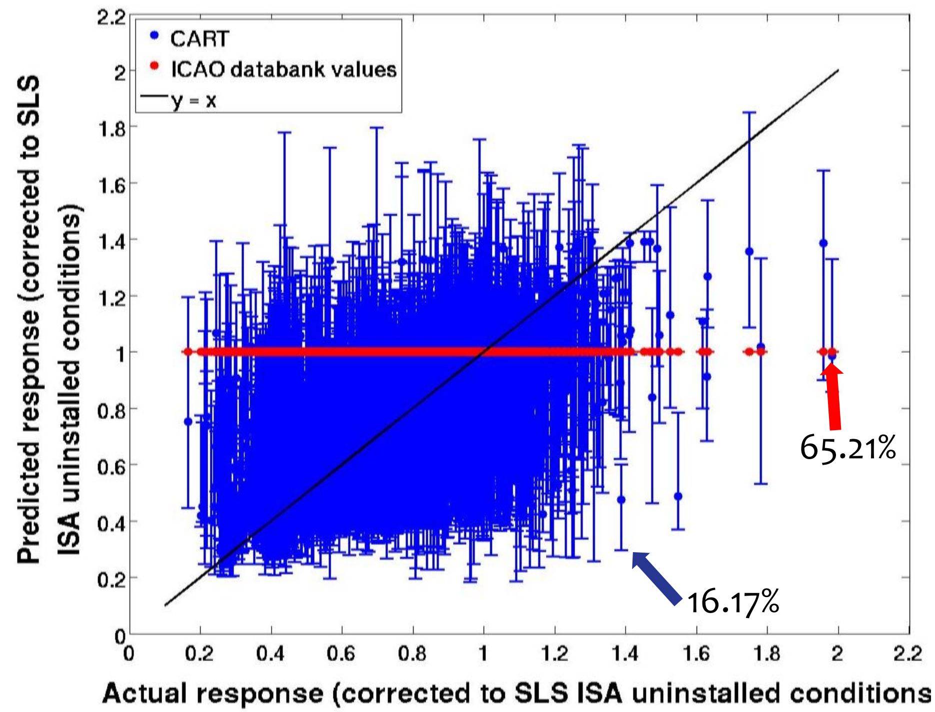


Climb out (<= 3000' AGL)



Approach (<= 3000' AGL)

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