Introduction Lecture

AE4320
System Identification of Aerospace Vehicles

Dr.ir. Coen de Visser, Dr.ir. Daan Pool
Department of Control & Simulation

Stall Model Identification

Air France Flight 447 (2009)

Pitot tubes blocked due to icing during cruise, normal law → alternate law → Pilot made abrupt nose-up input → plane stalls → all stall warning signs ignored, no attempt at recovery.
228 fatalities, no survivors

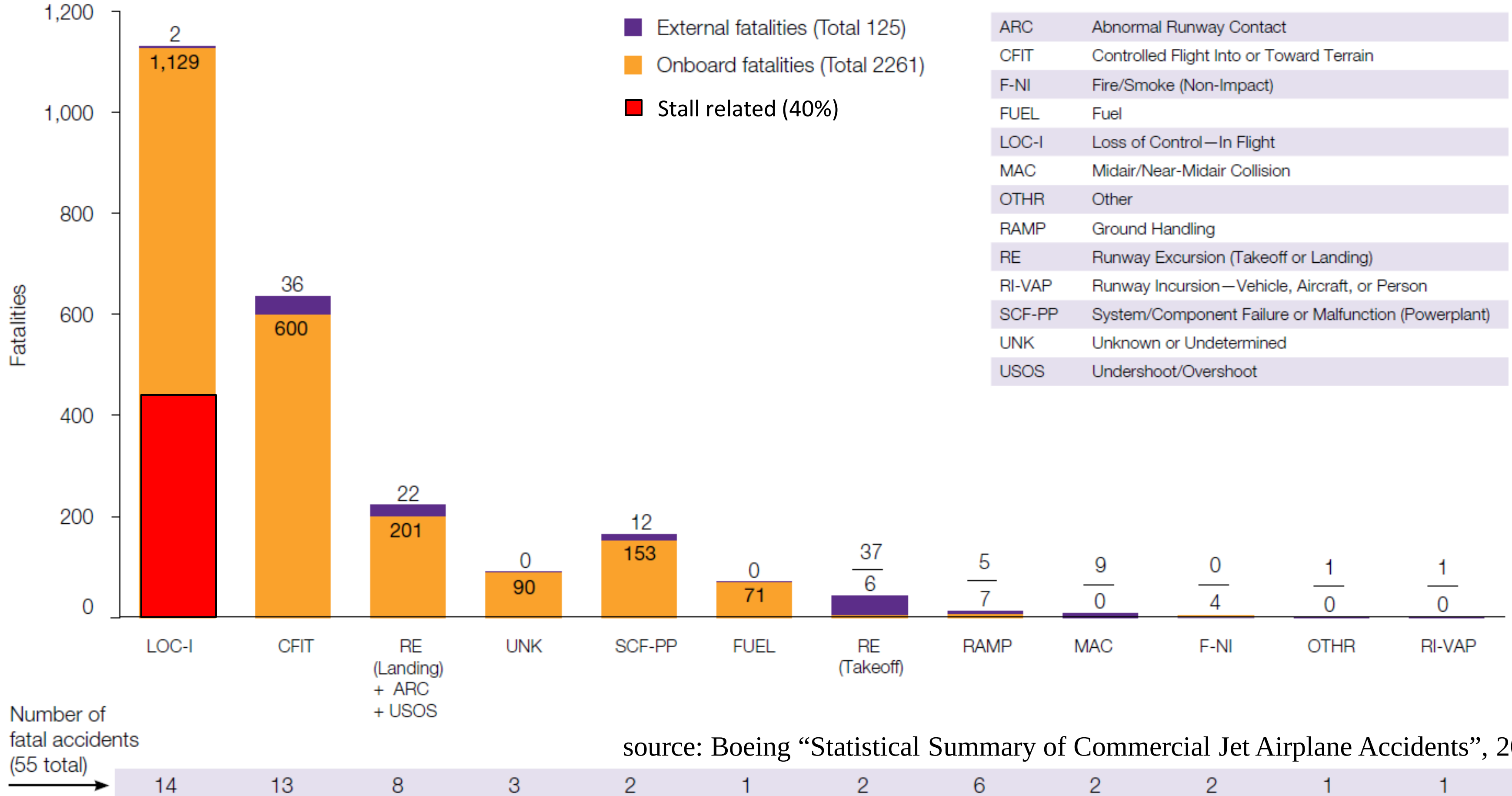
TransAsia Airways Flight 235 (2015)

Right engine flameout during takeof → pilots mistakenly cut power to left engine → aircraft stalls → stick pusher is ignored, ineffective crew response.
43 fatalities, 15 injuries

https://www.youtube.com/watch?v=a_DIAPfE8Fg

Stall Model Identification

Aviation fatalities 2008-2017



ARC	Abnormal Runway Contact
CFIT	Controlled Flight Into or Toward Terrain
F-NI	Fire/Smoke (Non-Impact)
FUEL	Fuel
LOC-I	Loss of Control—In Flight
MAC	Midair/Near-Midair Collision
OTHR	Other
RAMP	Ground Handling
RE	Runway Excursion (Takeoff or Landing)
RI-VAP	Runway Incursion—Vehicle, Aircraft, or Person
SCF-PP	System/Component Failure or Malfunction (Powerplant)
UNK	Unknown or Undetermined
USOS	Undershoot/Overshoot

source: Boeing "Statistical Summary of Commercial Jet Airplane Accidents", 2018

Stall Model Identification

- **Improved pilot training** is seen as best method to reduce stall-related LOC-I
- Flight simulator (FSTD) is preferred method (safety, cost)
- Current FSTDs are not fit for stall training
  → **research incentive!**

- **Timeline**

FAA AC 120-109A
Announcement of pilot stall training starting 2019

C&S Stall Modelling Task Force starts

FAA 14 CFR Pt. 60
New FSTD qualification requirements with details on how to model stalls.

C&S: First stall models (v. Horssen, v.d. Hoek)

C&S: Second generation stall models (v. Ingen)

C&S: current SMTF team has 8 members.
- 1st FSTD study complete (Smets)
- Hi-fi buffet model (Marschalk)
- integration of Fokker flight data

Required pilot training takes effect

2015 | 2016 | 2017 | 2018 | 2019 | 2020

Stall Model Identification

Aircraft

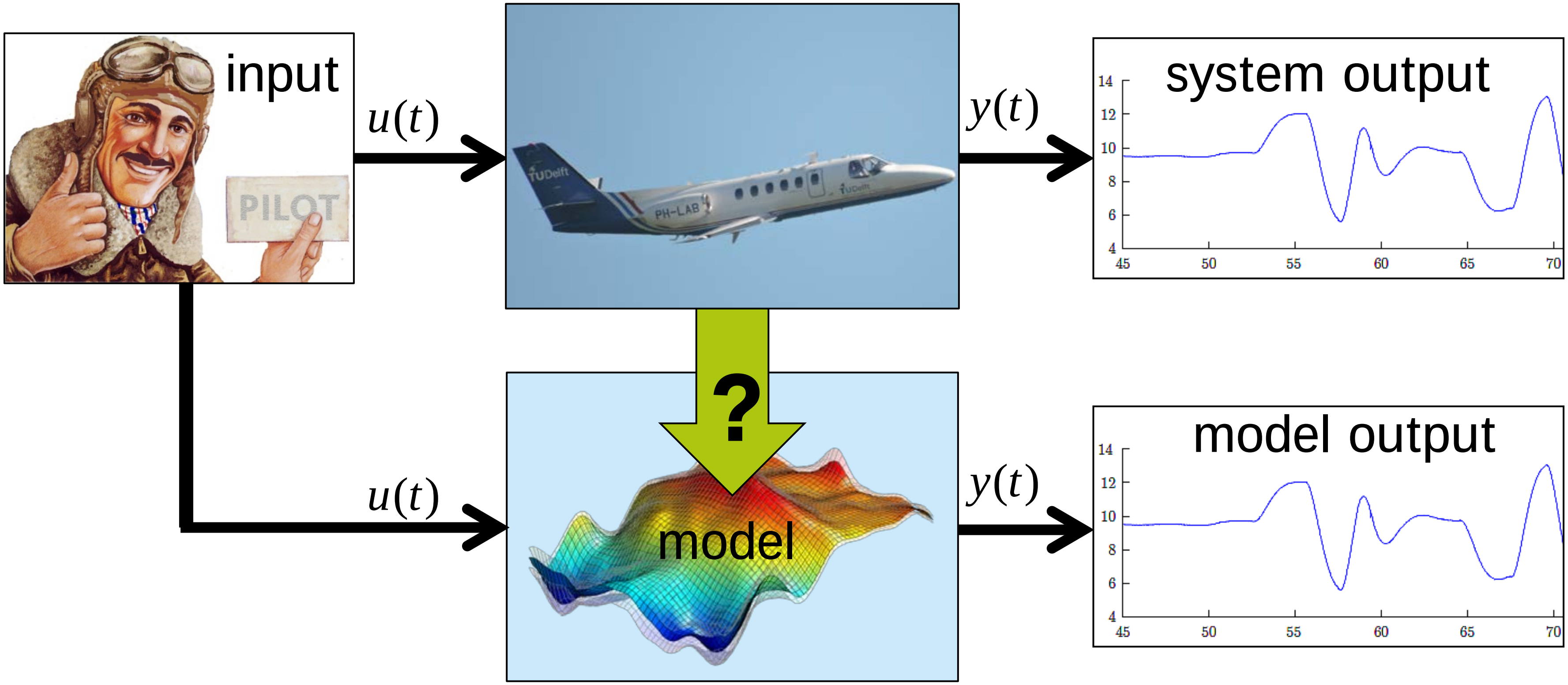
?

Stall-Model

Simulator

Course Goal

Main course goal:
To provide tools and theory for creating and validating models of dynamic systems in aerospace engineering.



Course Goal

Main course goal:

To provide tools and theory for creating and validating models of dynamic systems.

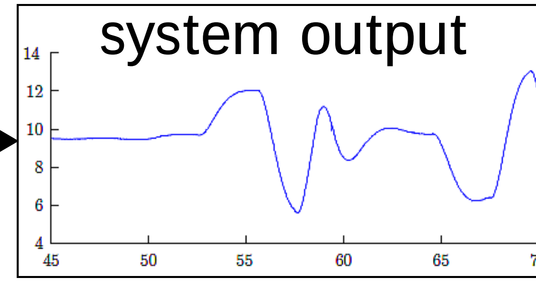
input

$u(t)$

system

$y(t)$

system output



? **System Identification**

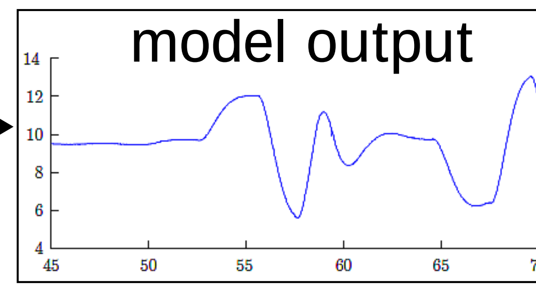
$u(t)$

$$Y(s) = H(s)U(s)$$

$$\dot{x}(t) = f(x,u,t)$$
$$y(t) = h(x,u,t)$$

$y(t)$

model output



Stall Model Identification

https://www.youtube.com/watch?v=71XjX0Vicu8

Course Objectives

What will you get out of this course:

1. How to use the principles of system identification to create models of dynamic systems.
2. How to design and execute a valid system identification experiment.
3. How to define and apply a Kalman filter for state estimation.
4. How to define and apply various parameter estimation techniques such as Ordinary Least Squares, Weighted Least Squares, Maximum Likelihood.
5. How to use advanced methods such as neural networks and multivariate splines.
6. How to assess the quality of your model using model validation techniques.

Course Objectives

AE4320 is recommended for the following courses:

- AE4311 Advanced Flight Control [0/0/0/4]
- AE4319 Manual Control Cybernetics [0/0/0/4]
- MSC graduation projects!

Relationship to comparable courses given at the TU-Delft:

- SC4040 Filtering and Identification 0/4/0/0
  - Focusses more on theory, Kalman filtering, least squares, sub-space identification, ARX, ARMA, ARMAX.

Lecturers

- **Dr.ir. Coen de Visser**
  - Aircraft system identification, multivariate splines, flight testing, nonlinear control.
  - Contact details:
    - Office: AE Room 0.24
    - email: c.c.devisser@tudelft.nl

- **Dr.ir. Daan Pool**
  - Pilot model identification, cybernetics, human-machine systems, flight testing.
  - Contact details:
    - Office: AE Room Sim 0.09
    - email: d.m.pool@tudelft.nl

Assessment

- Based on **individual** take-home assignment (**4 ECTS**)
  - Student individually chooses an assignment related to aircraft system identification (assignments will be posted on **BrightSpace**).
  - Student writes an **individual** report on the assignment (**<= 20 pages**).
  - Student hands in report and any used code using **BrightSpace**.
  - **Deadline for report: July 10 2020**

- Grading Criteria
  - Quality and completeness of report.
  - Quality and clarity of software code.
  - Originality of solution.

Course Outline

- **Lecture 1: (dr.ir. Coen de Visser)**
  - Course goals and objectives
  - Introduction to System Identification
- **Lecture 2,3: (dr.ir. Daan Pool)**
  - System Identification Experiments
- **Lecture 4,5,6: (dr.ir. Daan Pool)**
  - Kalman filters
  - State estimation & Sensor Fusion
- **Lecture 7,8: (dr.ir. Coen de Visser)**
  - Model structure selection
  - Model parameter estimation

Course Outline

- **Lecture 9: (dr.ir. Coen de Visser)**
  - Advanced identification approach: Neural networks
- **Lecture 10,11: (dr.ir. Coen de Visser)**
  - Advanced identification approach: Multivariate B-Splines
- **Lecture 12: (dr.ir. Coen de Visser)**
  - Model validation, course conclusion

Lecture Schedule

Week	#	Day	Hours	Room	Date	Topic	Lecturer
3.1	1	Tuesday	5+6	LR-CZ-K	11/2	Introduction	Coen de Visser
	2	Wednesday	7+8	LR-CZ-K	12/2	System Identification Experiments I	Daan Pool
3.2	3	Tuesday	5+6	LR-CZ-K	18/2	System Identification Experiments II	Daan Pool
	4	Wednesday	7+8	LR-CZ-K	19/2	State Estimation I	Daan Pool
3.3	-	Tuesday	-	-	25/2	No Lecture	-
	-	Wednesday	-	-	26/2	No Lecture	-
3.4	5	Tuesday	5+6	LR-CZ-K	3/3	State Estimation II	Daan Pool
	6	Wednesday	7+8	LR-CZ-K	4/3	State Estimation III	Daan Pool
3.5	7	Tuesday	7+8	LR-CZ-K	11/3	Parameter Estimation I	Coen de Visser
	8	Wednesday	7+8	LR-CZ-K	12/3	Parameter Estimation II	Coen de Visser
3.6	9	Tuesday	5+6	LR-CZ-K	17/3	Neural Networks	Coen de Visser
	10	Wednesday	7+8	LR-CZ-K	18/3	Multivariate Splines I	Coen de Visser
3.7	11	Tuesday	5+6	LR-CZ-K	24/3	Multivariate Splines II	Coen de Visser
	12	Wednesday	7+8	LR-CZ-K	25/3	Model Validation	Coen de Visser
3.8	13	Monday	3+4	LR-CZ-C	30/3	**Backup**	Coen de Visser

Course Material

Literature:

- V. Klein and E. A. Morelli, Aircraft System Identification, AIAA, 2006.
- L. Ljung, System Identification (2nd ed), Prentice Hall, 1999.
- Q.P. Chu, ‘Modern flight test technologies and system identification’, lecture slides, Faculty of Aerospace Engineering, Delft University of technology.
- D.M. Pool, ‘Objective Evaluation of Flight Simulator Motion Cueing Fidelity Through a Cybernetic Approach’, Ph.D. thesis, Delft University of technology, 2012.
- C.C. de Visser, ‘Global Nonlinear Model Identification with Multivariate Splines’, Ph.D. thesis, Delft University of technology, 2011.

Software:

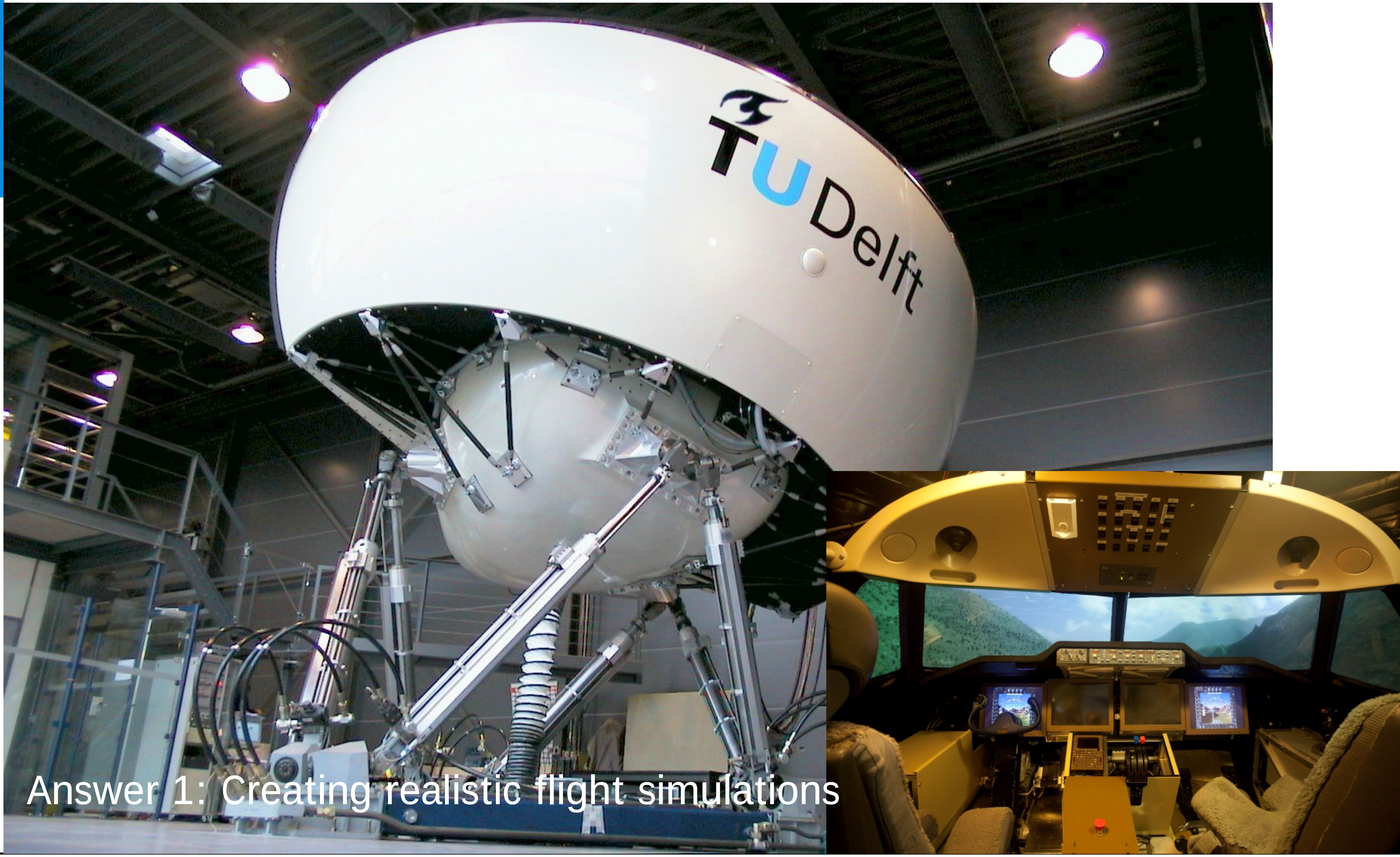
- Matlab/Python/C++
- Simulink

Aircraft System Identification at C&S

- Gerlach (1964, pioneer at TU-Delft)
- Mulder (1986, optimal dynamic manoeuvre design, two-step method)
- Chu (1994, theoretical proof of two-step method)
- Mulder (1999, pilot model identification)
- van Kampen (2010, interval analysis applied to system identification)
- de Visser (2011, aerodynamic model identification using multivariate splines)
- Pool (2012, pilot model identification from flight experiments)
- Venrooij (2014, measuring and modelling biodynamic feedthrough)
- Caetano (2016, flapping wing model identification)
- Van der El (2018, human preview information models)
- Armanini (2018, time-varying flapping wing model identification)

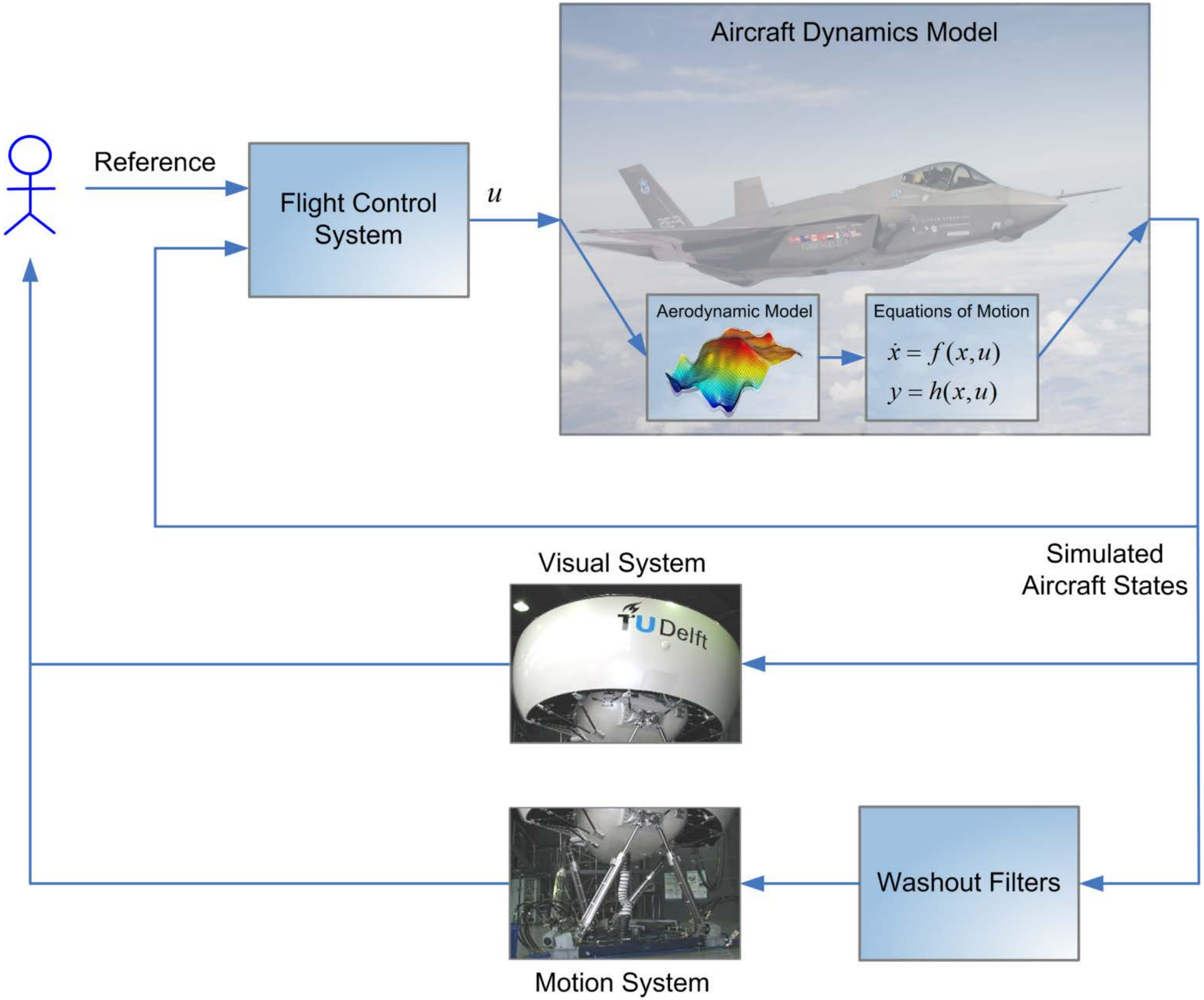
Aircraft System Identification at C&S

Introduction: Why do we need Models?

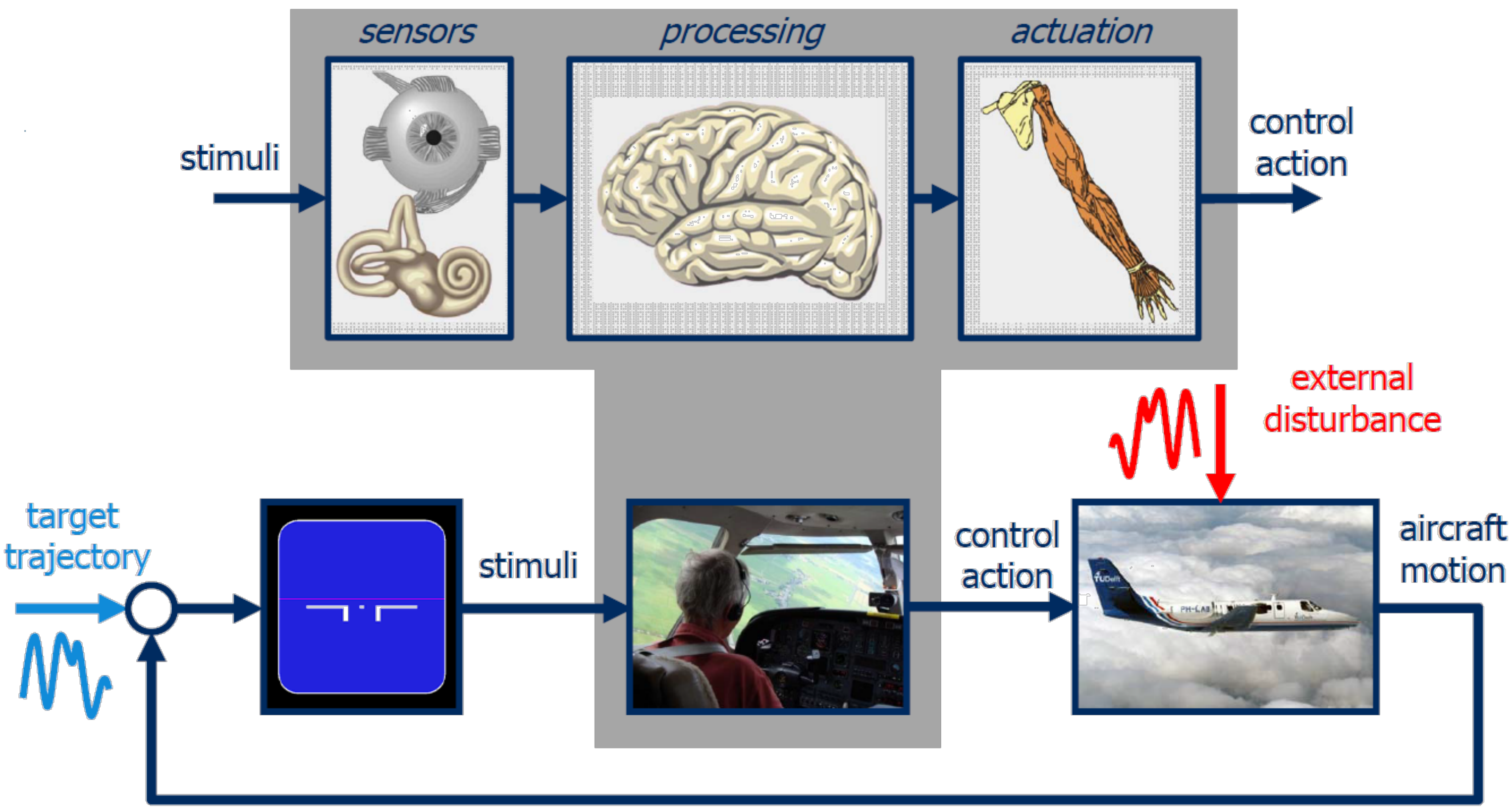


Answer 1: Creating realistic flight simulations

Introduction: Why do we need Models?

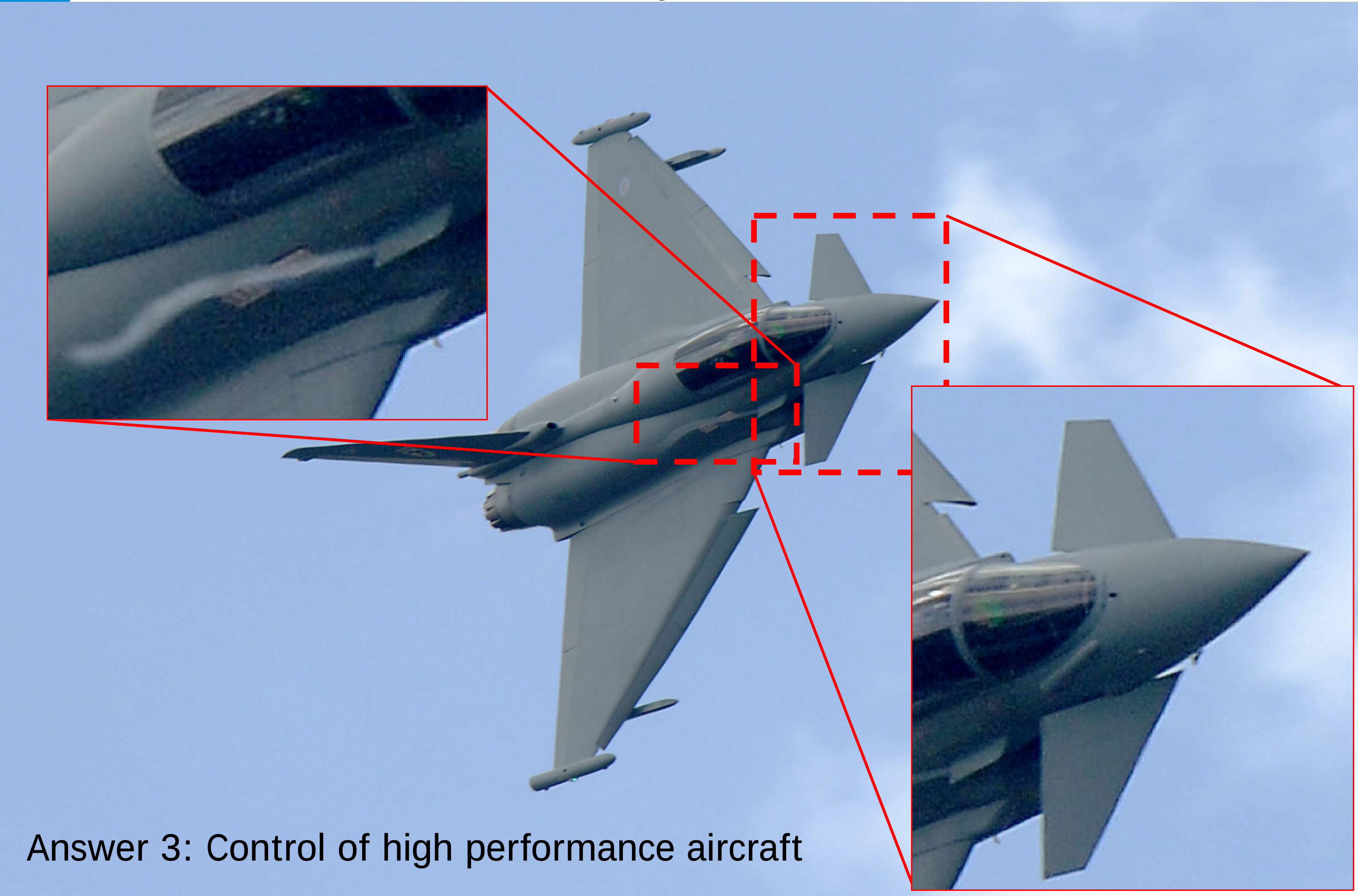


Introduction: Why do we need Models?



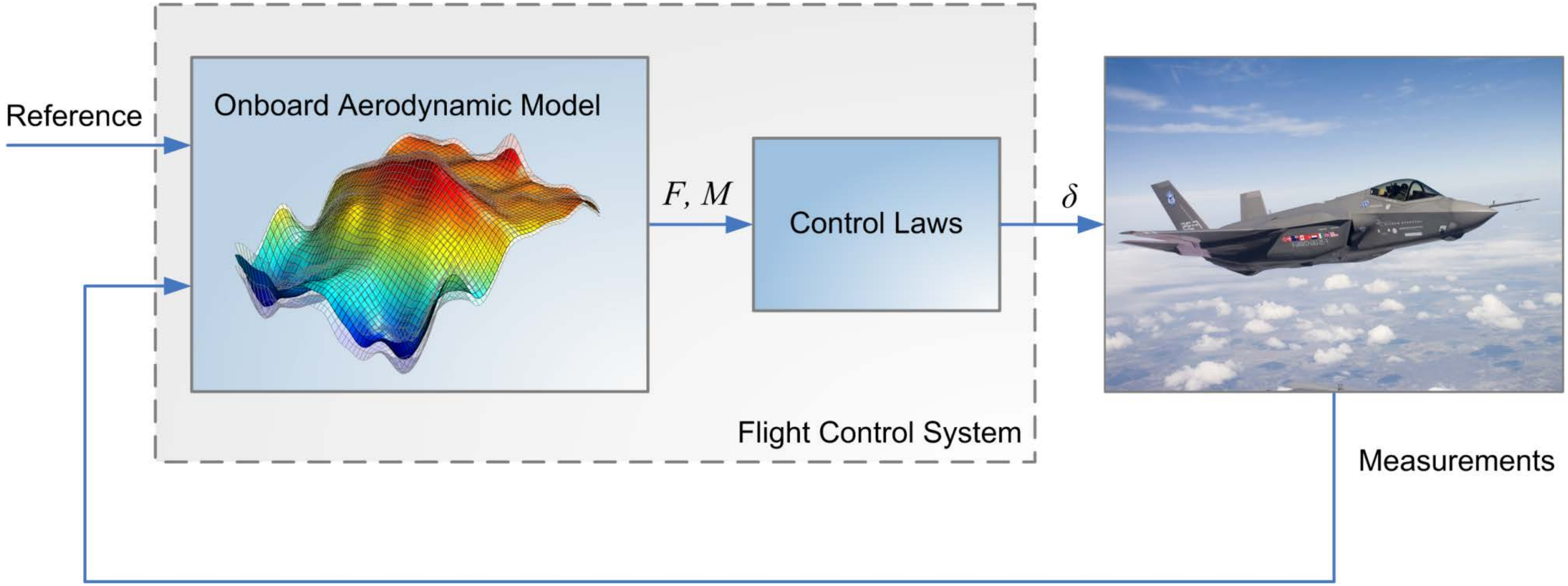
Answer 2: Understanding human information processing and integration, use in haptic feedback & pilot monitoring systems

Introduction: Why do we need Models?



Answer 3: Control of high performance aircraft

Introduction: Why do we need Models?



Introduction: Why do we need Models?

DHL Cargo Airbus A300

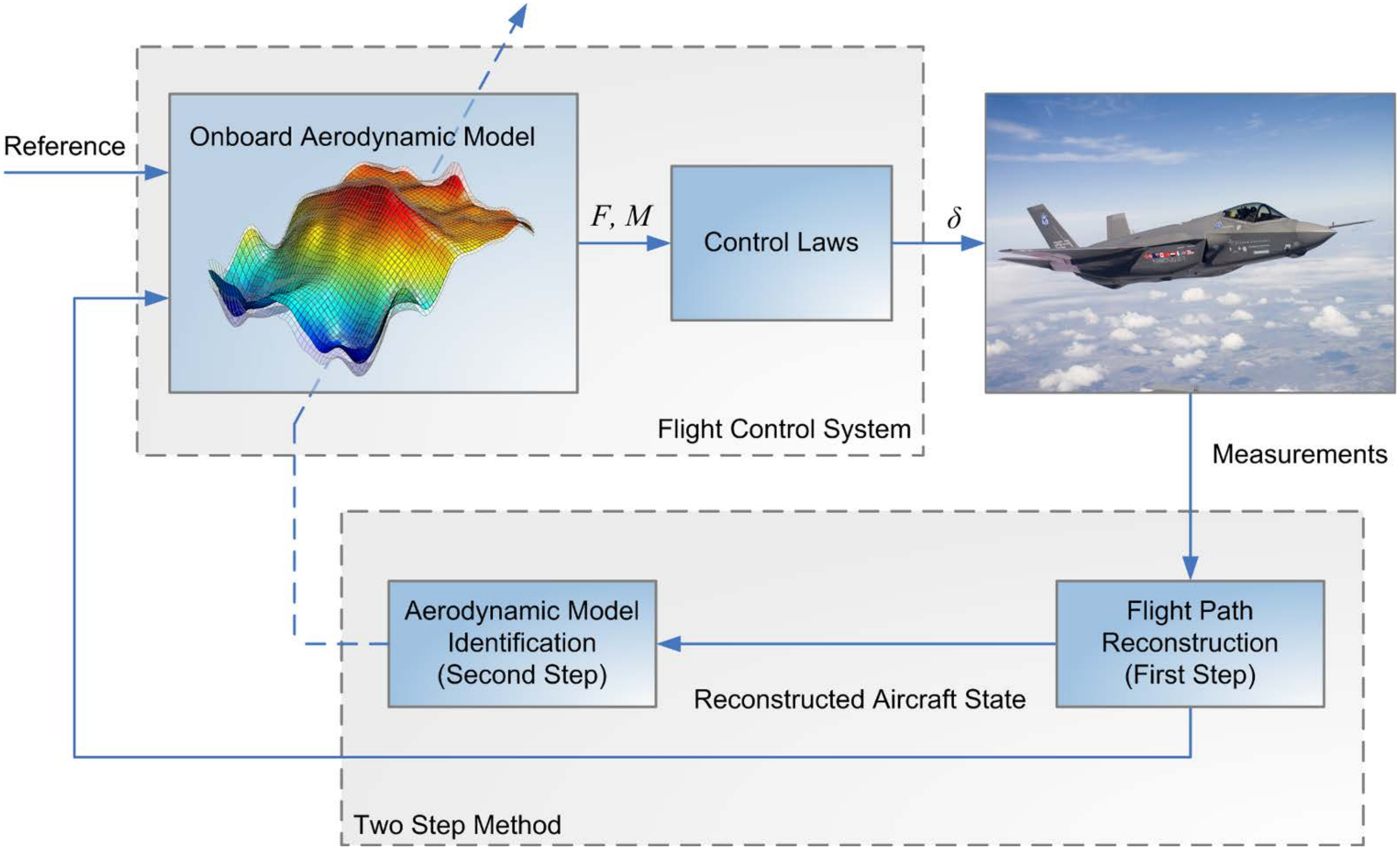
Accident description:

Impact by surface to air missile immediately after take off. Serious damage to wing and wing devices, all hydraulics lost. Aircraft control by engine thrust only.


Answer 4: fault tolerant control of damaged aircraft

Introduction: Why do we need Models?

Adaptive aerodynamic models for fault tolerant control



Introduction: Why do we need Models?

Enter the Drones...

Ehang 184

Google/Uber Cora

Airbus Vahana

Lilium

Introduction: Why do we need Models?

https://www.youtube.com/watch?v=ScYDOqFGOhk

S.Sun et al, *High-Speed Flight of Quadrotor despite Loss of Single Rotor, IEEE Robotics and Automation*, **2018**

Introduction: What is a model?

A model of a system is a **mathematical abstraction** of the system that aims to **capture** its **input-output behaviour** while at the same time **simplifying** and **conceptualizing** its inner workings.

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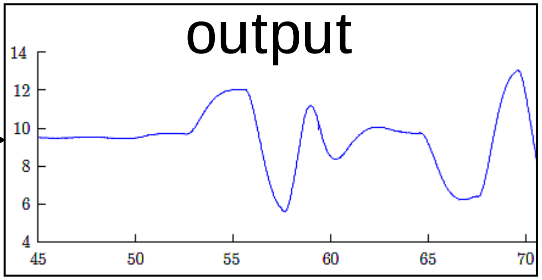

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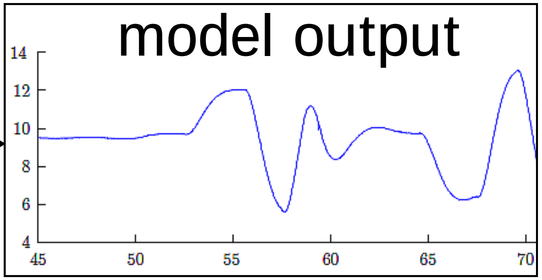
model

$$\dot{x}(t) = f(x, u, \theta, t)$$

$$y_{mod}(t) = h(x, u, \lambda, t)$$

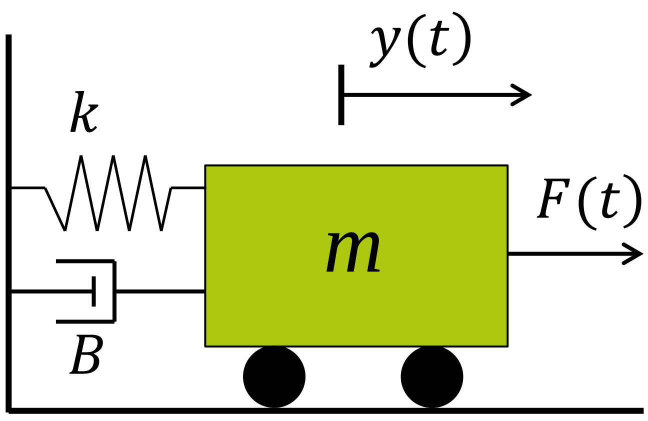
y_{mod}



Introduction: What is a model?

White-Box model

- Built on first principles, i.e. a physical model.
- Underlying physical principles are well understood.
- Have high prediction power.
- Examples:
  - Cart on rails...



EOM: $$m\frac{d^2y(t)}{dt^2} = F(t) - B\frac{dy(t)}{dt} - ky(t)$$

Laplace transform

$$ms^2Y(s) = F(s) - BsY(s) - kY(s)$$

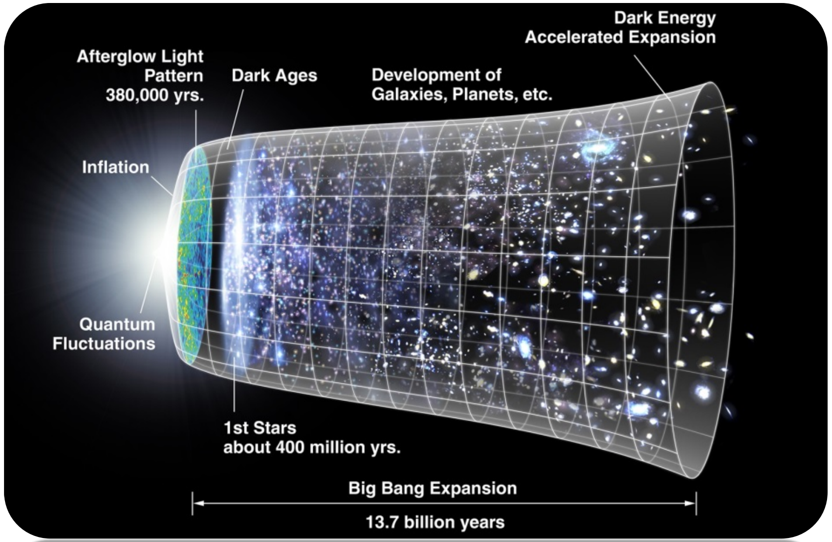
$$Y(s) = F(s)\underbrace{\frac{1}{ms^2 + Bs + k}}_{\text{system } \textbf{transfer function}}$$

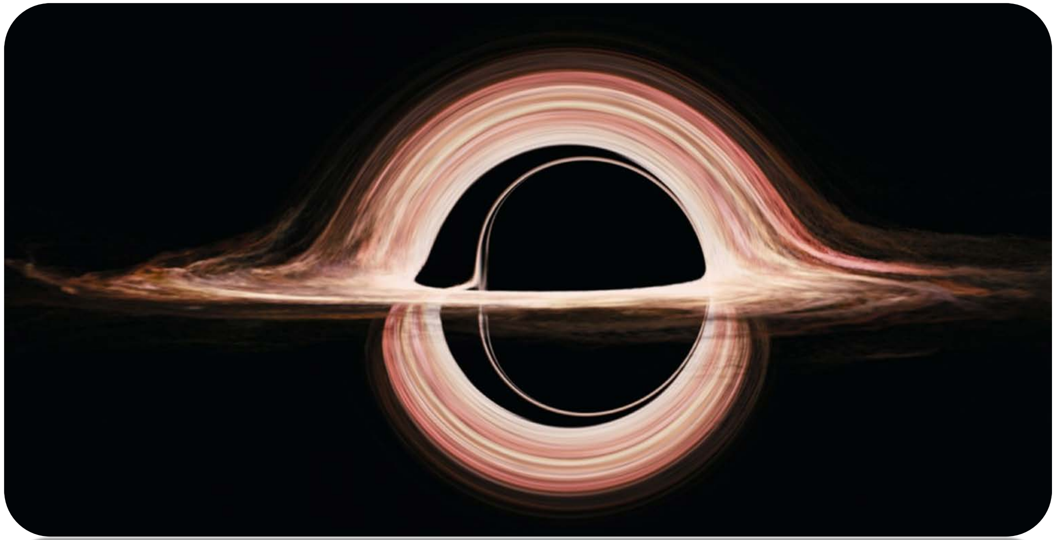
Introduction: What is a model?

White-Box model

- Built on first principles, i.e. a physical model.
- Underlying physical principles are well understood.
- Have high prediction power.
- Ultimate Example:
  - Einstein Field Equations of gravity: $G_{\mu\nu} + \Lambda g_{\mu\nu} = \dfrac{8\pi G}{c^4} T_{\mu\nu}$

"Spacetime tells matter how to move; matter tells spacetime how to curve" [Wheeler]



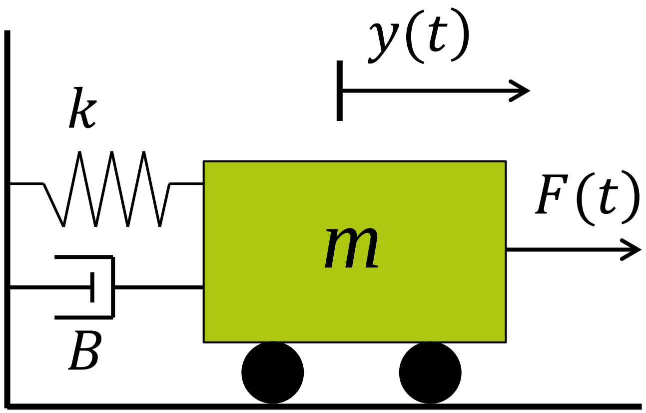


Introduction: What is a model?

White-Box model advantages & disadvantages

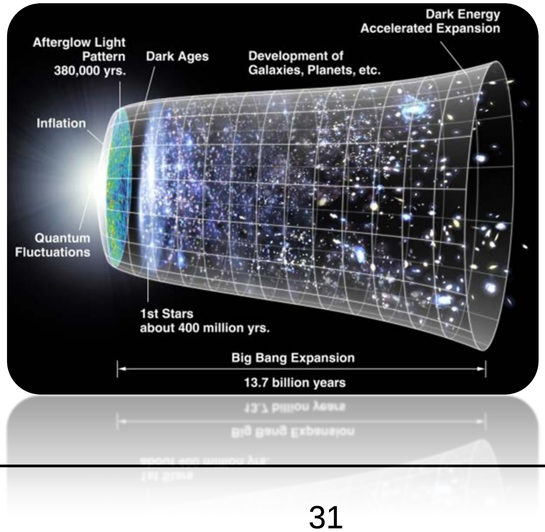
Advantages:

- Input-Output behavior is understood.
- Prediction time horizon is very high.
- Is valid for the entire system domain.



Disadvantages

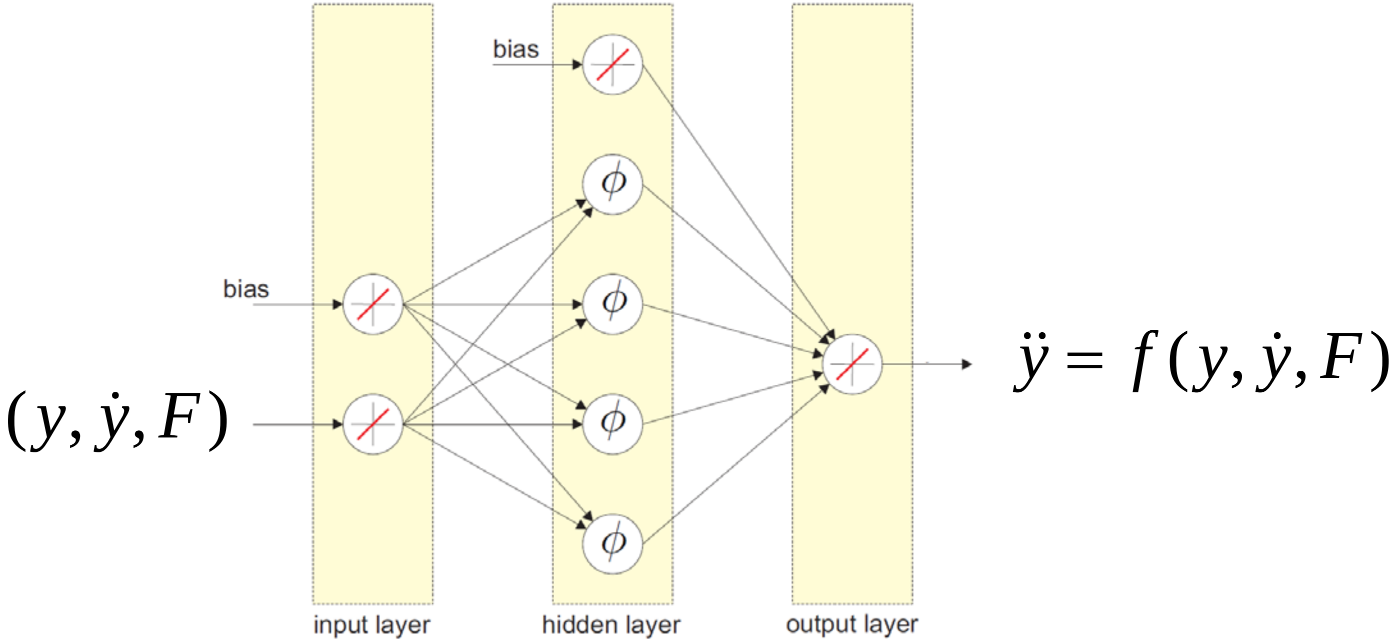
- Complete understanding of the physical principles of a system are required.
- "Fudge Factors" (e.g., Cosmological Constant) often remain.
- Even if differential equations are understood, exact solutions may be impossible to obtain using current mathematics.



Introduction: What is a model?

Black-Box model

- Based purely on input-output relationship of real system.
- Equations of motion of the system remain completely unknown.
- Prediction power is difficult or impossible to verify.
- Examples:
  - Neural network model of cart dynamics:

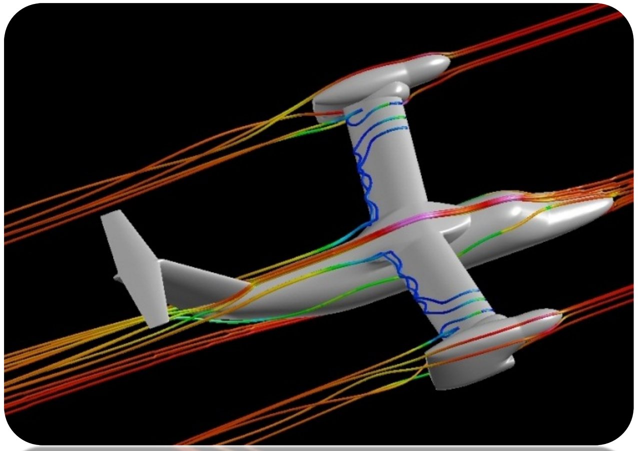


Introduction: What is a model?

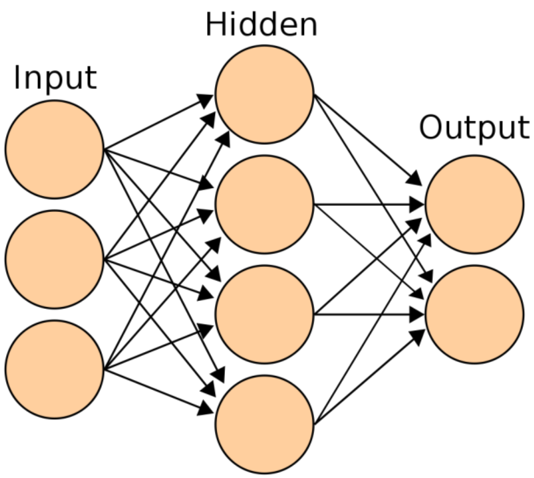
White-Box model

$$\rho\left(\frac{\partial v}{\partial t}+v\cdot\nabla v\right)=-\nabla p+\nabla T+f$$

Navier-Stokes equations



Black-Box Model



Neural network

Fundamentally different model structure, but same output!

Introduction: What is a model?

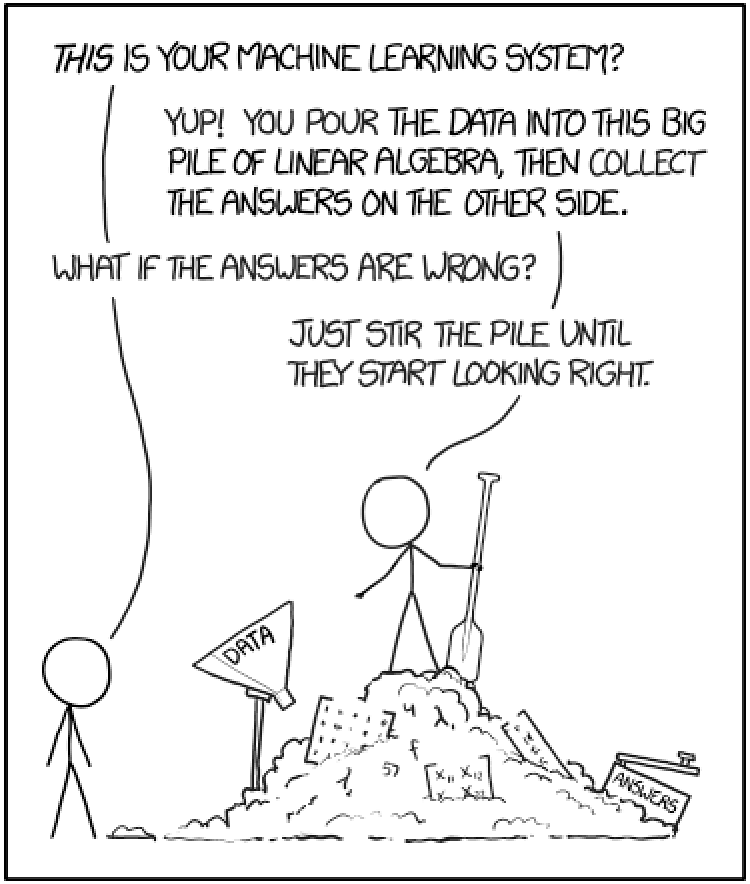
Black-Box model advantages & disadvantages

Advantages:

- No knowledge whatsoever of the actual physics (differential equations) of a system is required.
- Can be used to model any system given a set of input and output data.

Disadvantages

- Predictions are hard or impossible to verify.
- Is valid only inside the domain of the given input data.



Introduction: What is a model?

A third model class: Grey-Box models

Grey-Box model

- Based on physical principles where known, and where practical.
- Based on input-output behavior of system where not.
- Prediction power higher than black-box models.
- Examples:
  - rigid aircraft dynamics:

$$\ddot{x} = \frac{F}{m} - \omega \times \dot{x} + \begin{bmatrix} -g \sin\theta \\ g \sin\phi \cos\theta \\ g \cos\phi \cos\theta \end{bmatrix}$$

$$\dot{\omega} = J^{-1} M - J^{-1}\left(\omega \times J\omega\right)$$

Introduction: What is a model?

A third model class: Grey-Box models

Advantages:

- Combines the best of both worlds...
- Less knowledge of system dynamics required than for white-box models
- Easier to verify performance than black-box models
- Higher predictive power than black-box models

Disadvantages:

- Some knowledge of system physics required.
- More difficult to verify performance than with white-box models
- Lower predictive power than white-box models
- Often more difficult to create (identify!) than black-box models

Introduction: What is a model?

Example 1.1: grey-box pitching dynamics model of a symmetric, rigid aircraft

$$\dot{q} = \frac{1}{J_y}\left(\left(J_z - J_x\right) pr - J_{xz}\left(p^2 - r^2\right) + M\right)$$

pitching moment

Expert knowledge: we know that α and δ_e influence M.

Taylor's theorem tells us that any function can be approximated with arbitrary accuracy in the neighbourhood of a given α,δ_e using a Taylor series expansion:

$$M(\alpha,\delta_e) = M_0 + \frac{\partial M}{\partial \alpha}\Delta\alpha + \frac{\partial M}{\partial \delta_e}\Delta\delta_e + \frac{\partial^2 M}{2\partial \alpha^2}(\Delta\alpha)^2 + \frac{\partial^2 M}{2\partial \delta_e^2}(\Delta\delta_e)^2 + \frac{\partial^2 M}{\partial\alpha\partial\delta_e}\Delta\alpha\Delta\delta_e$$
$$+\cdots + R^k(\Delta\alpha,\Delta\delta_e)$$

Introduction: What is a model?

Example 1.1: grey-box pitching dynamics model of a symmetric, rigid aircraft

If we terminate the Taylor expansion after the linear terms, we end up with:

$$M(\alpha,\delta_e) = M_o + \frac{\partial M}{\partial \alpha}\alpha + \frac{\partial M}{\partial \delta_e}\delta_e + R^1(\alpha,\delta_e)$$

$$\approx M_0 + \frac{\partial M}{\partial \alpha}\alpha + \frac{\partial M}{\partial \delta_e}\delta_e$$

$$\frac{\partial M}{\partial \alpha} = M_\alpha \qquad \frac{\partial M}{\partial \delta_e} = M_{\delta e}$$

The 'parameters' M_α and $M_{\delta e}$ are unknown in general and must be *estimated* from measurement data...

Introduction: What is a model?

Example 1.1: grey-box pitching dynamics model of a symmetric, rigid aircraft

$$\dot{q} = \frac{1}{J_y}\left(\left(J_z - J_x\right)pr - J_{xz}\left(p^2 - r^2\right) + \left(M_0 + M_\alpha \alpha + M_{\delta_e}\delta_e\right)\right)$$

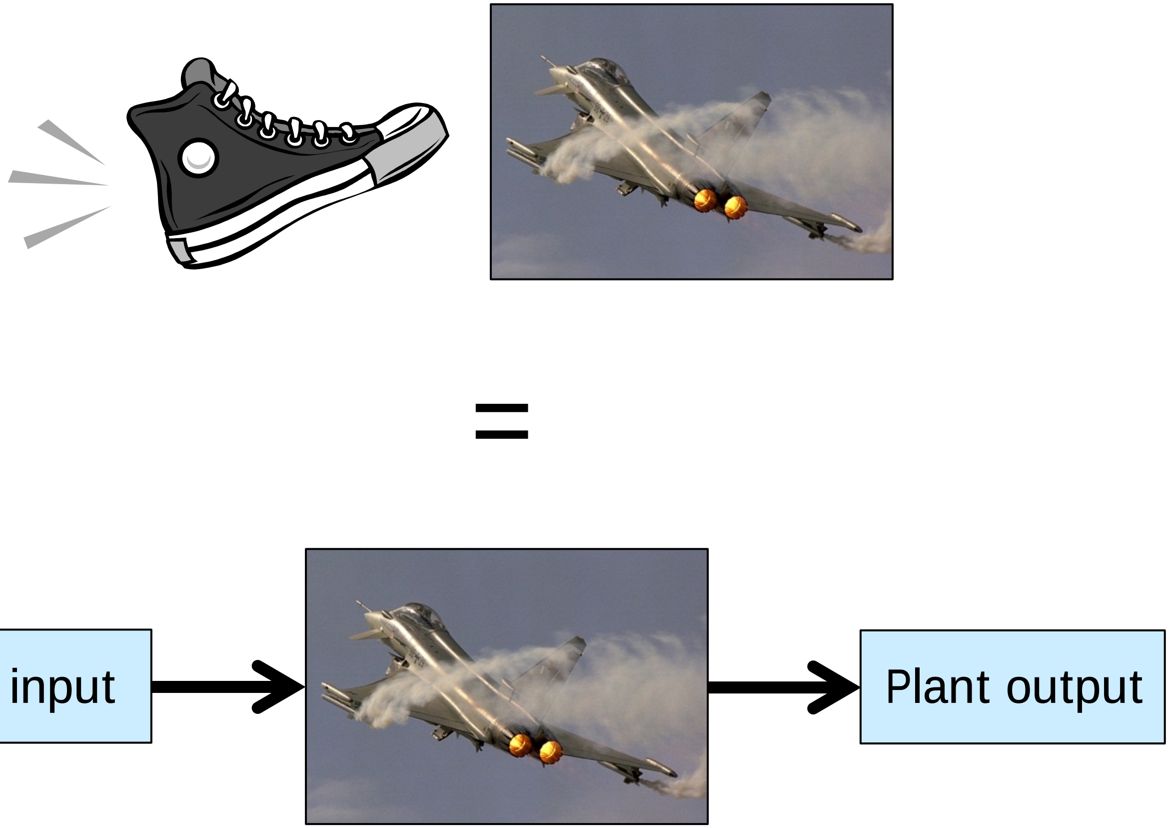
- **Parameter estimation** is concerned with estimating M_0, M_α and $M_{\delta e}$ from measurements on M, as well as on measurements on the states α, p, q, r, etc.

- **State estimation** is concerned with getting accurate estimates for the states α, p, q, r, (among others) given knowledge of the parameters M_α and $M_{\delta e}$.

- **Joint State-Parameter estimation** is concerned with estimating <u>both</u> the states α and δ_e , and the parameters M_α and $M_{\delta e}$ using measurements on M.

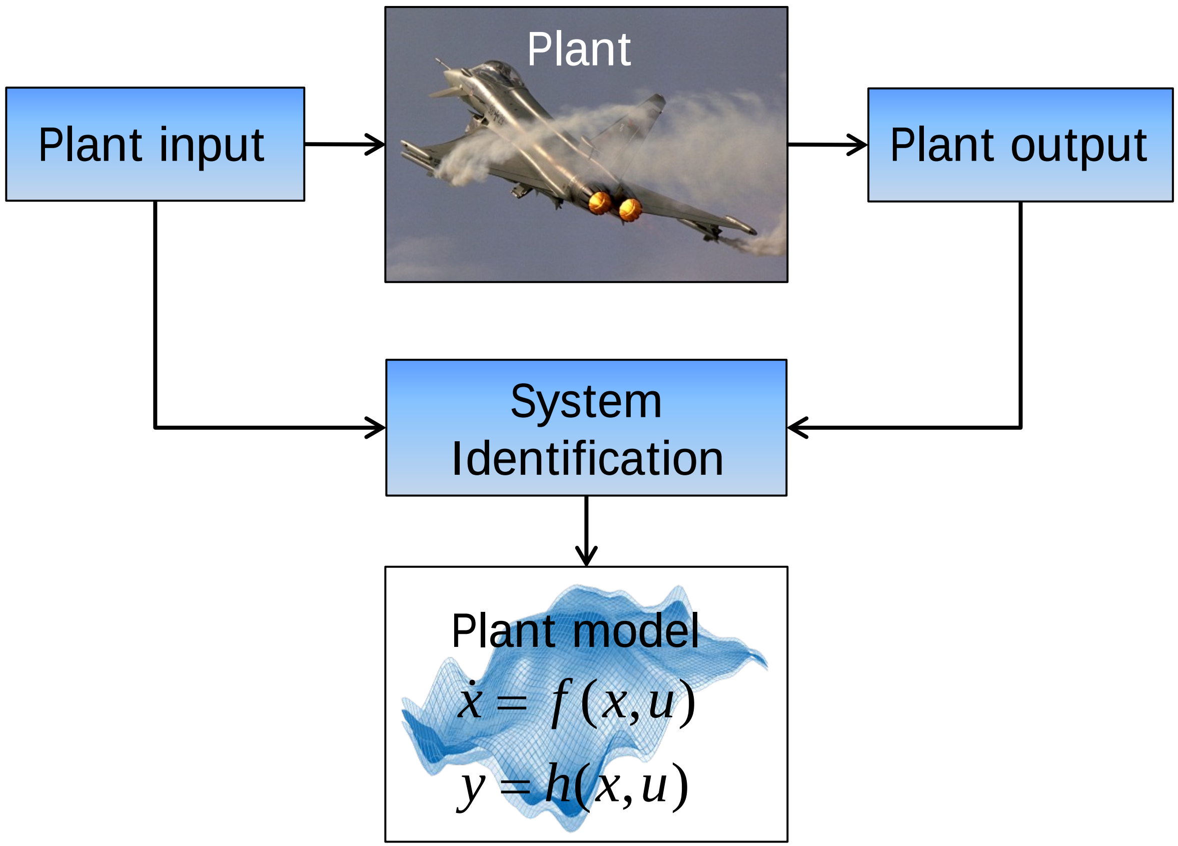
Introduction: How do we create models?

System Identification is the process of creating a model of a system based on its input/output behaviour.



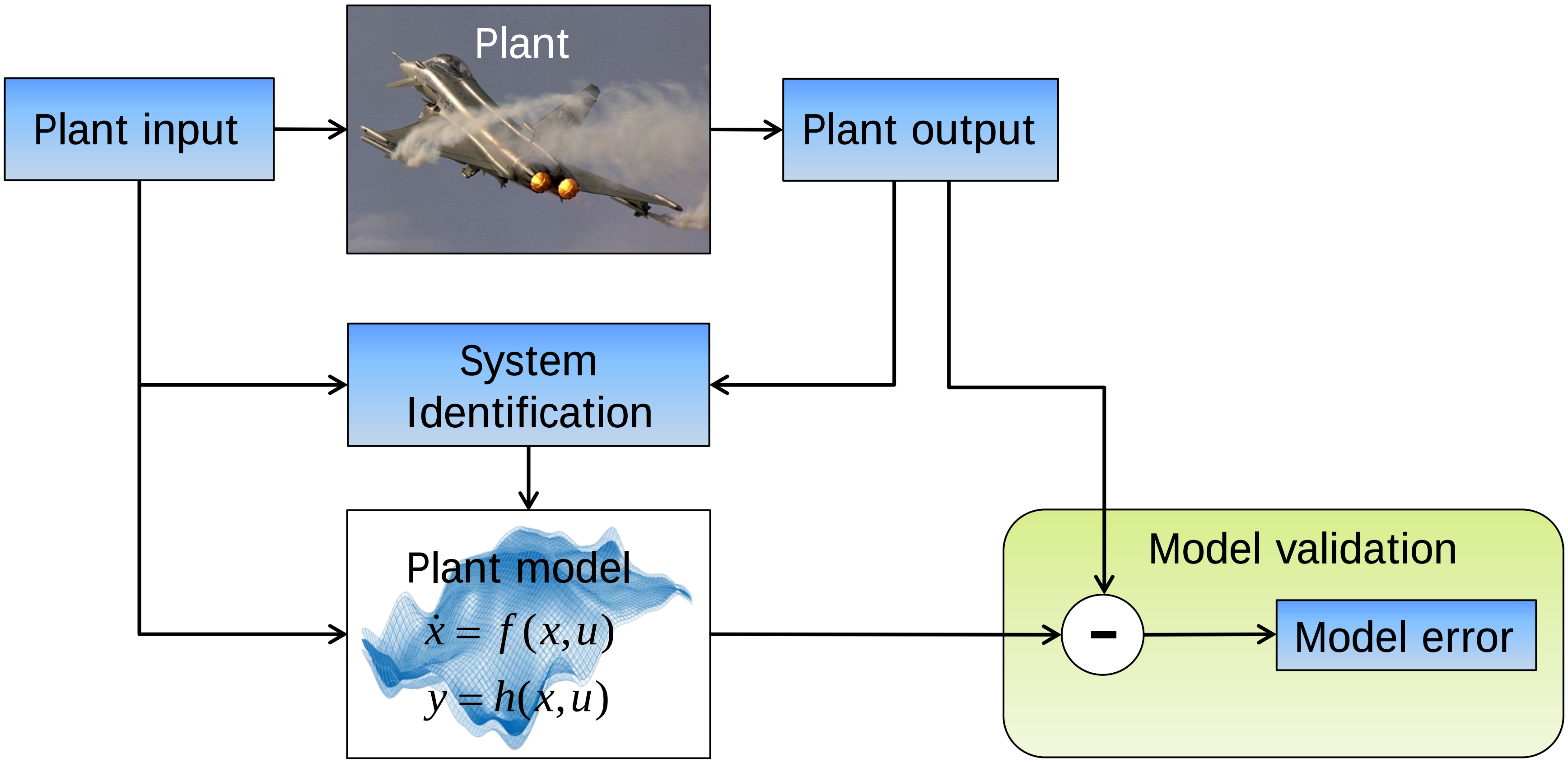
Introduction: How do we create models?

System Identification is the process of creating a model of a system based on its input/output behaviour.



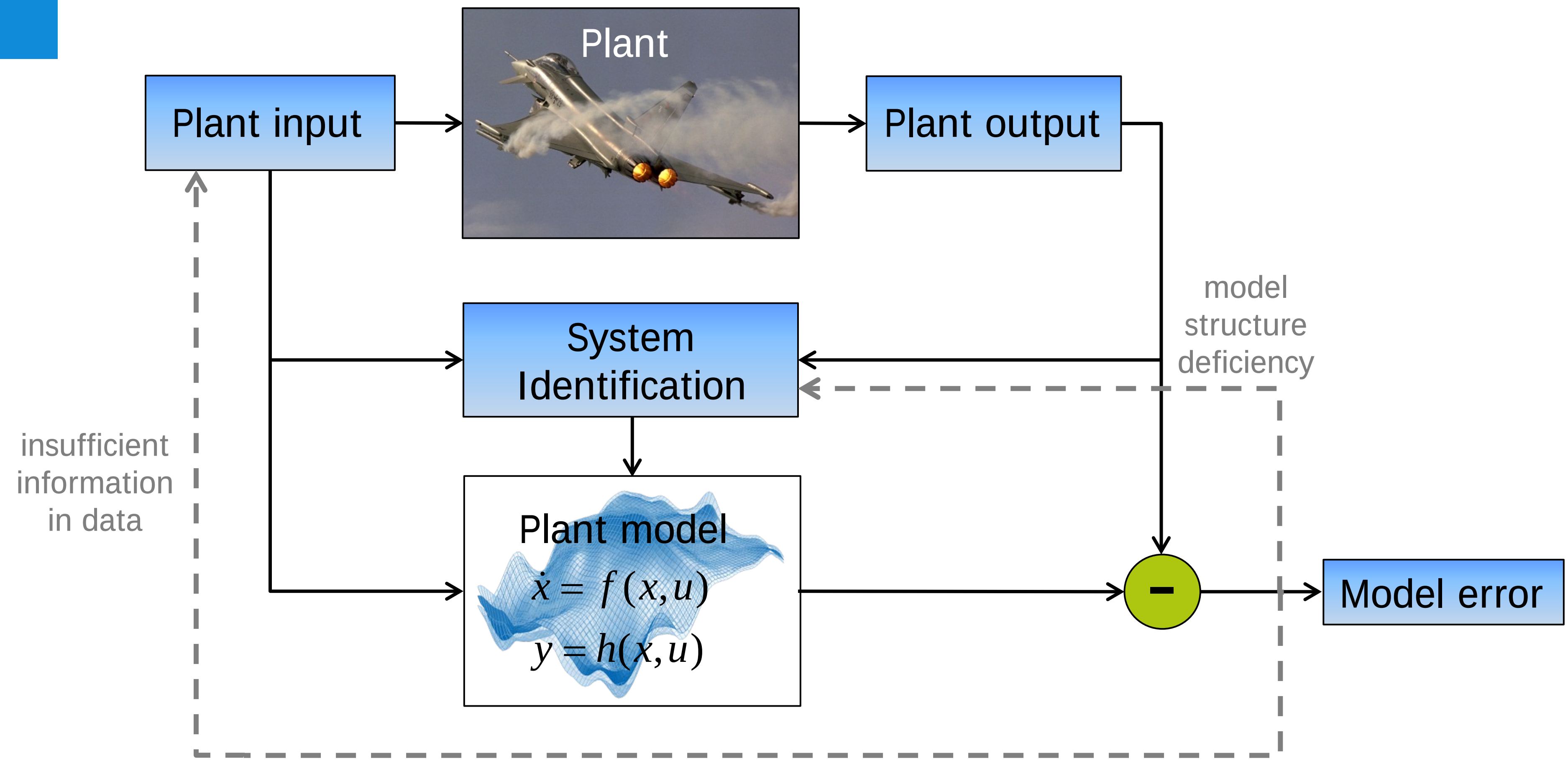
Introduction: How do we create models?

An essential element of the system identification process is *model validation*.

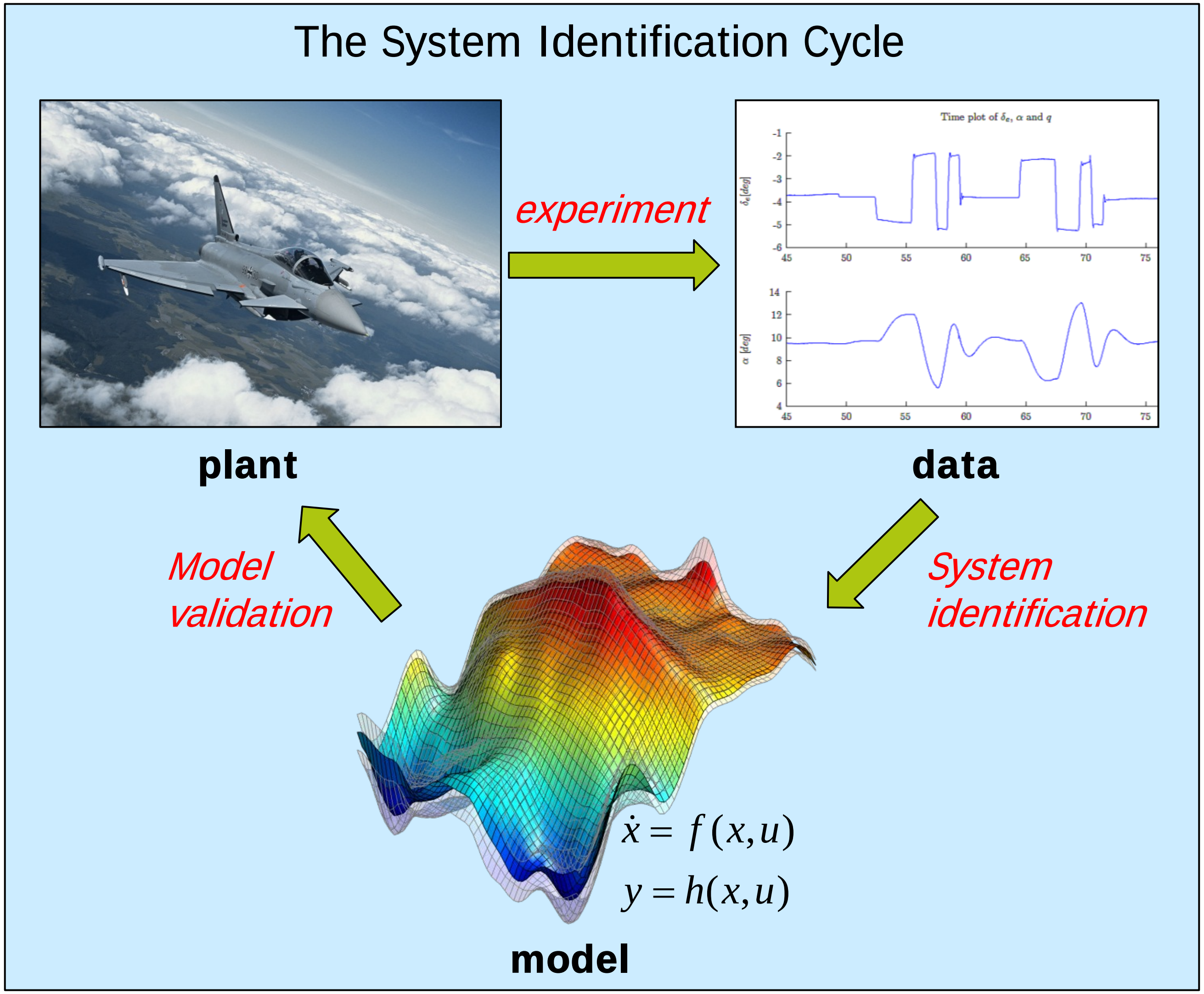


Introduction: How do we create models?

With model validation, System Identification becomes a cycle...



SysID High Level Overview



SysID High Level Overview

Phases of the System Identification Cycle:

Experiment phase

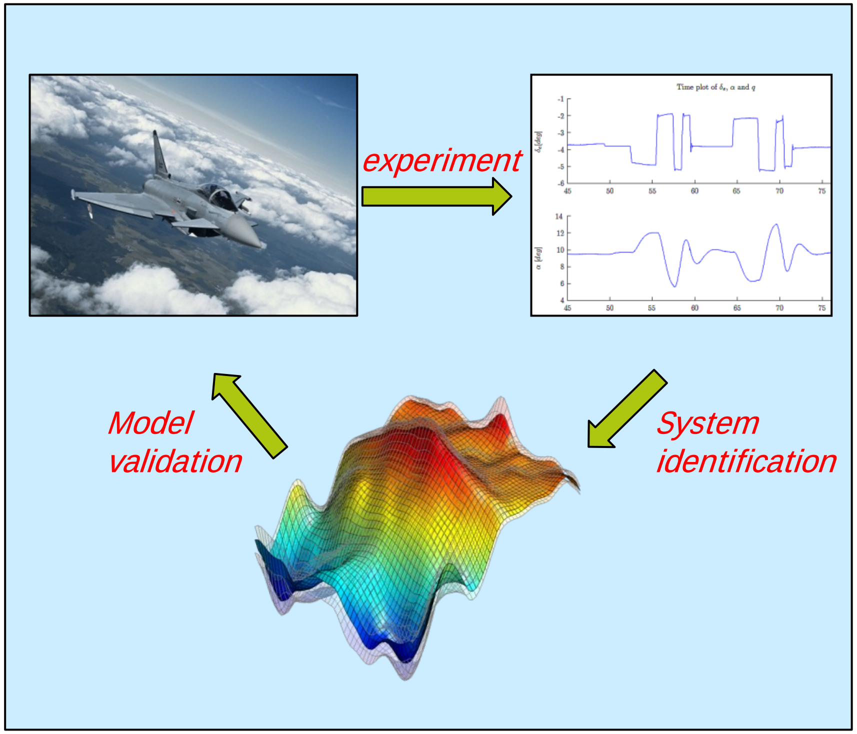
- Plant analysis
- Experiment design and execution
- Data logging and pre-processing

Model identification phase

- State estimation
- Model structure definition
- Parameter estimation

Model validation phase

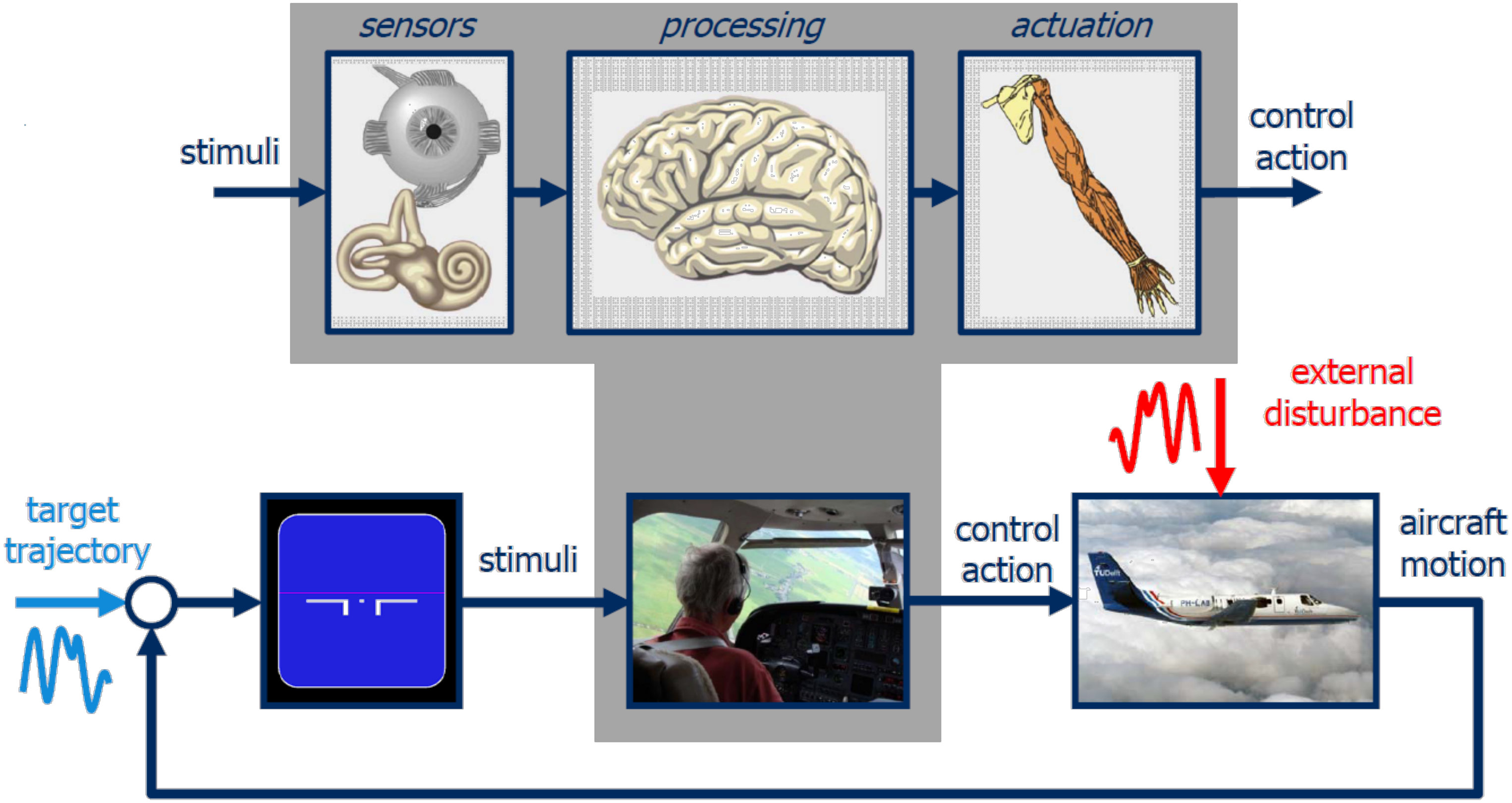
- Model validation



Next Lectures…

L2,3: System Identification Experiments

closed-loop pilot model identification



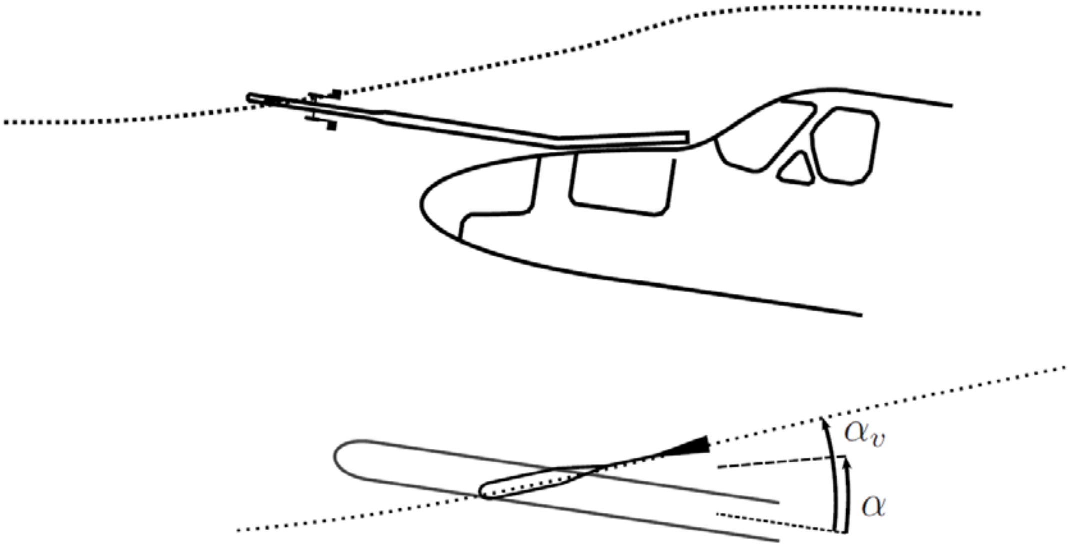
Next Lectures...

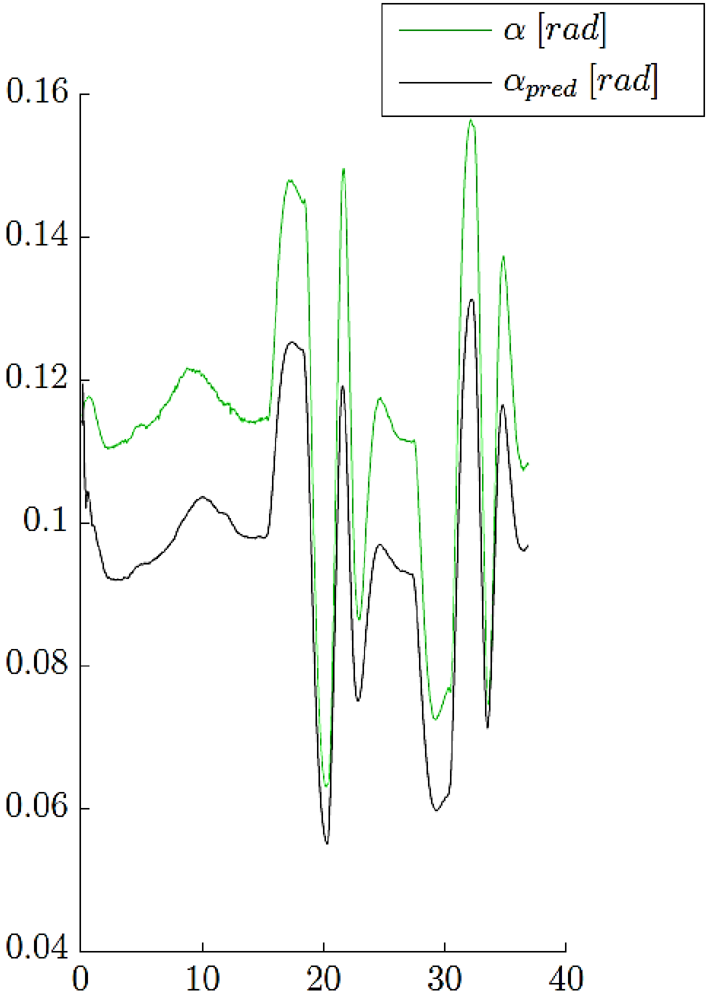
L2,3: System Identification Experiments

Aerodynamic model identification

Next Lectures...

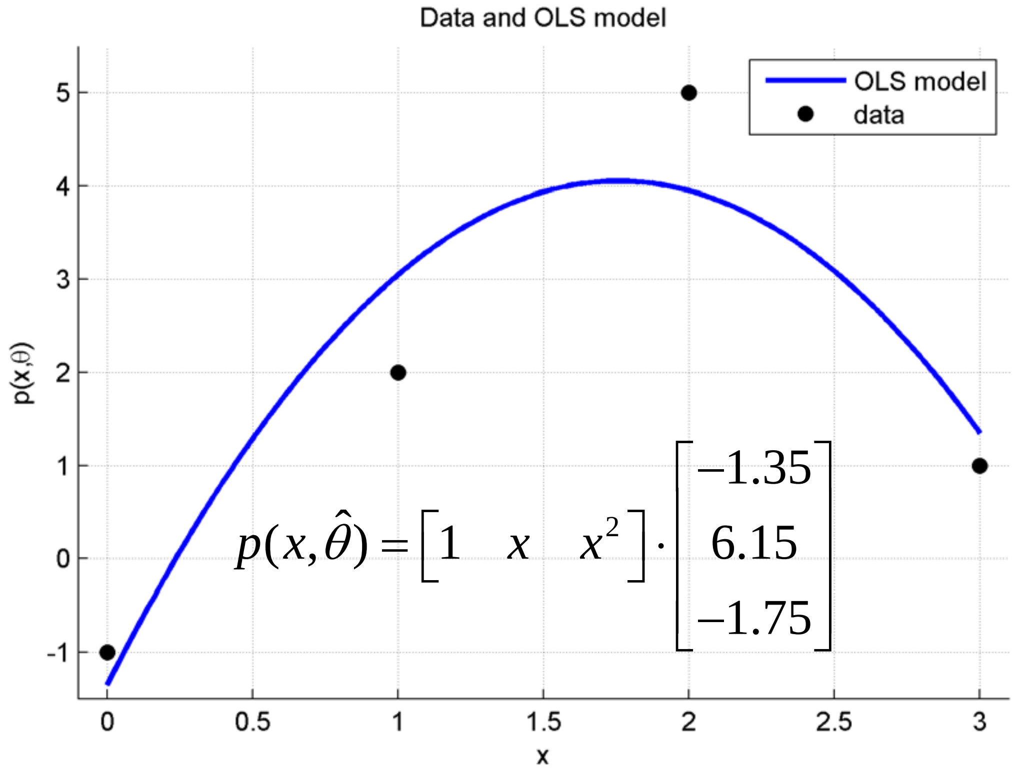
L4,5,6: State Estimation





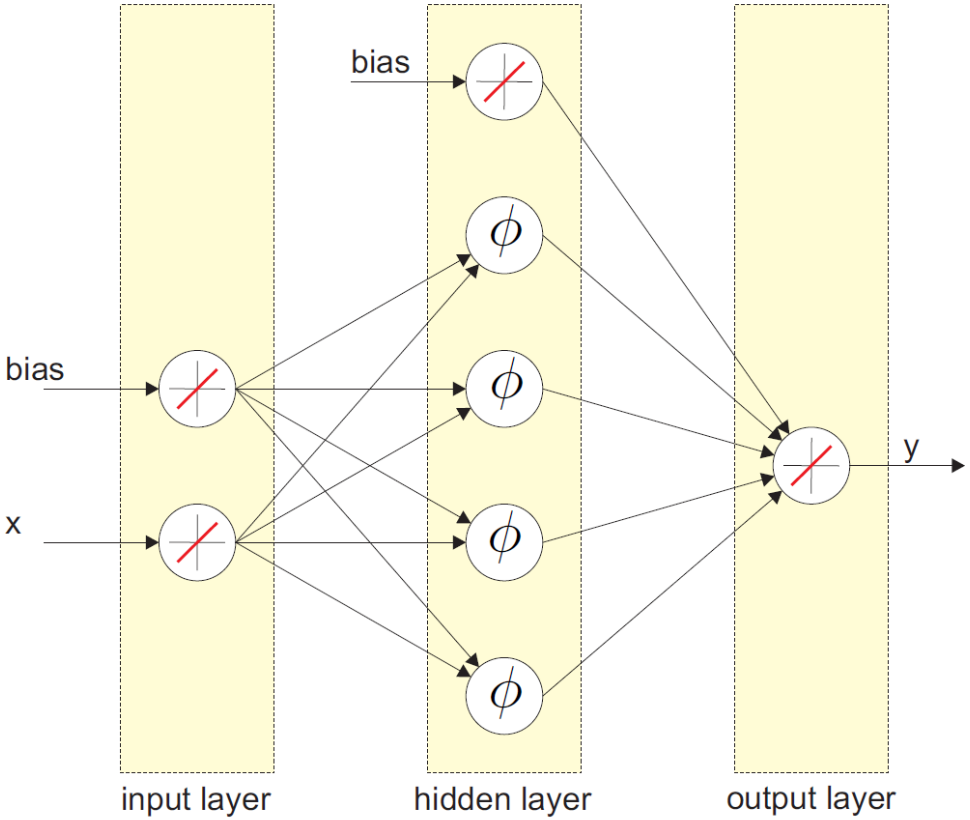
Next Lectures…

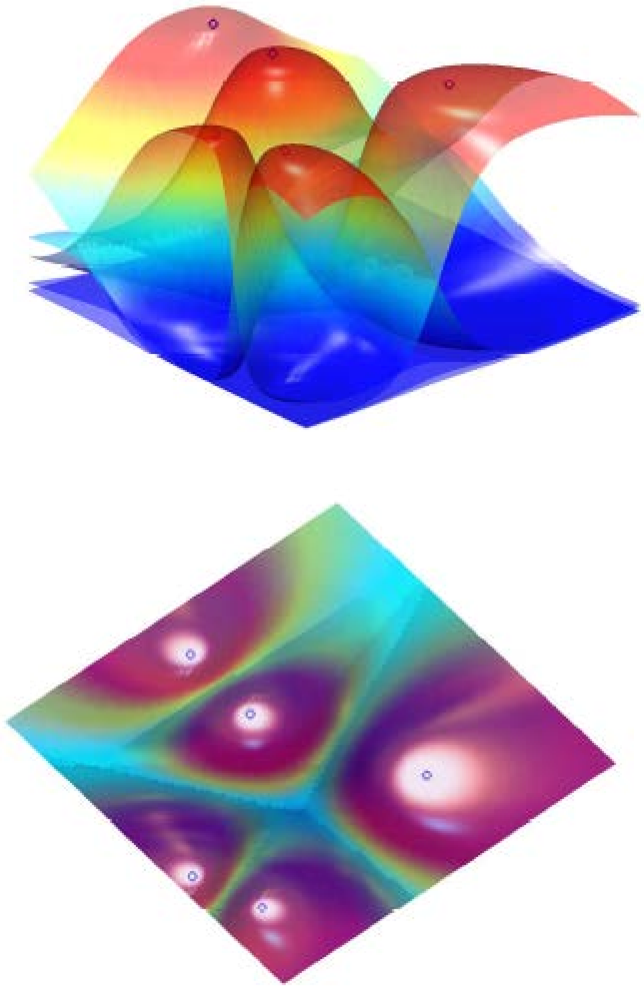
L7,8: Parameter Estimation



Next Lectures...

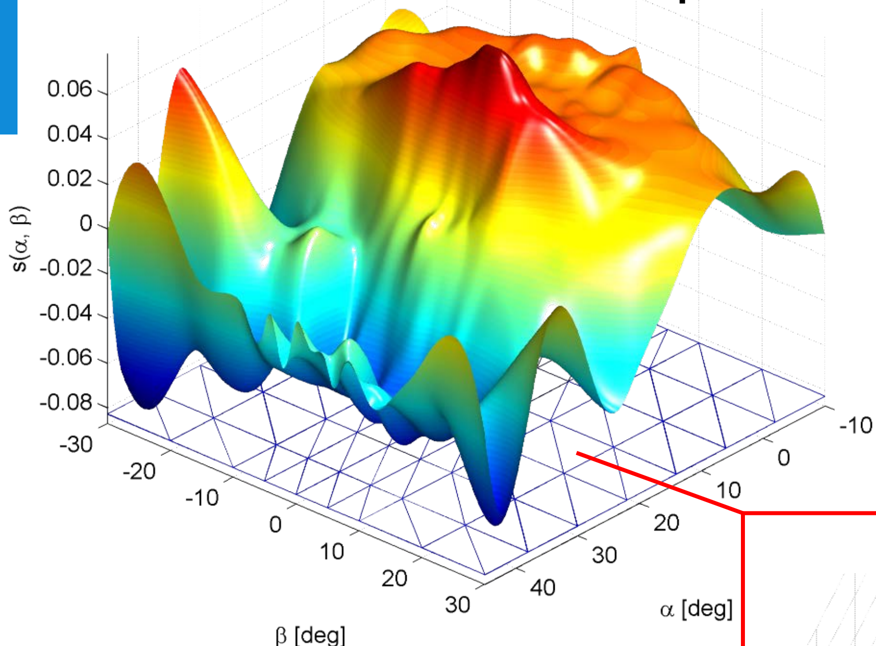
L9: Neural Networks



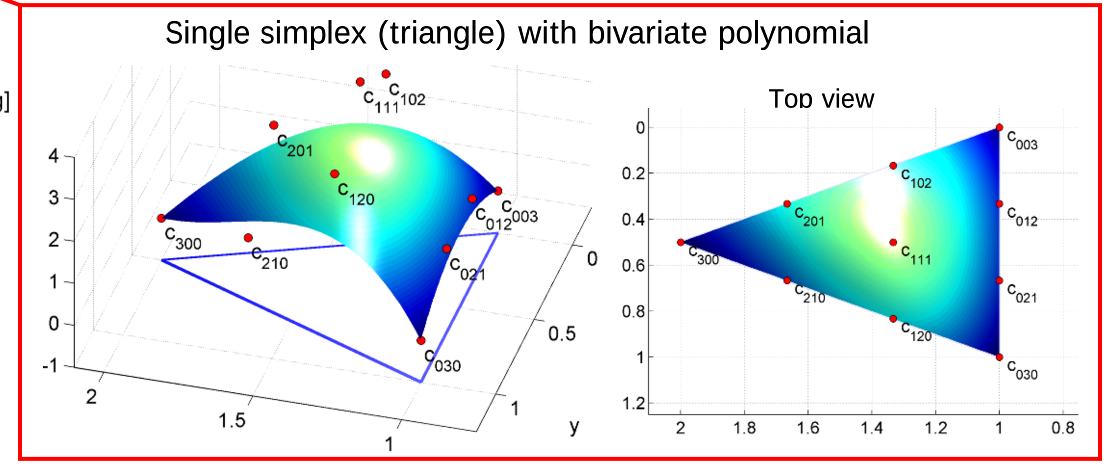


Next Lectures…

L10,11: Multivariate Splines

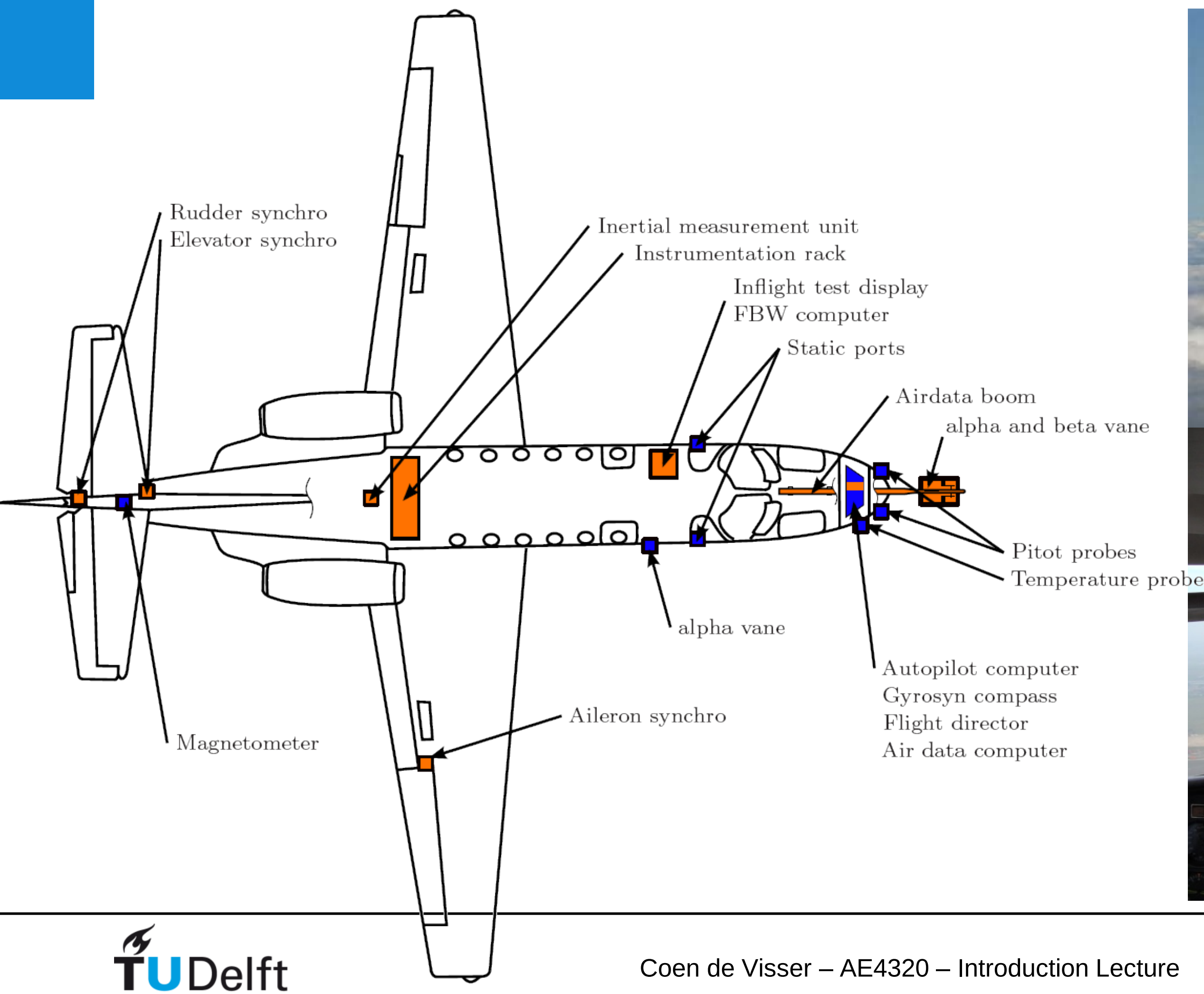


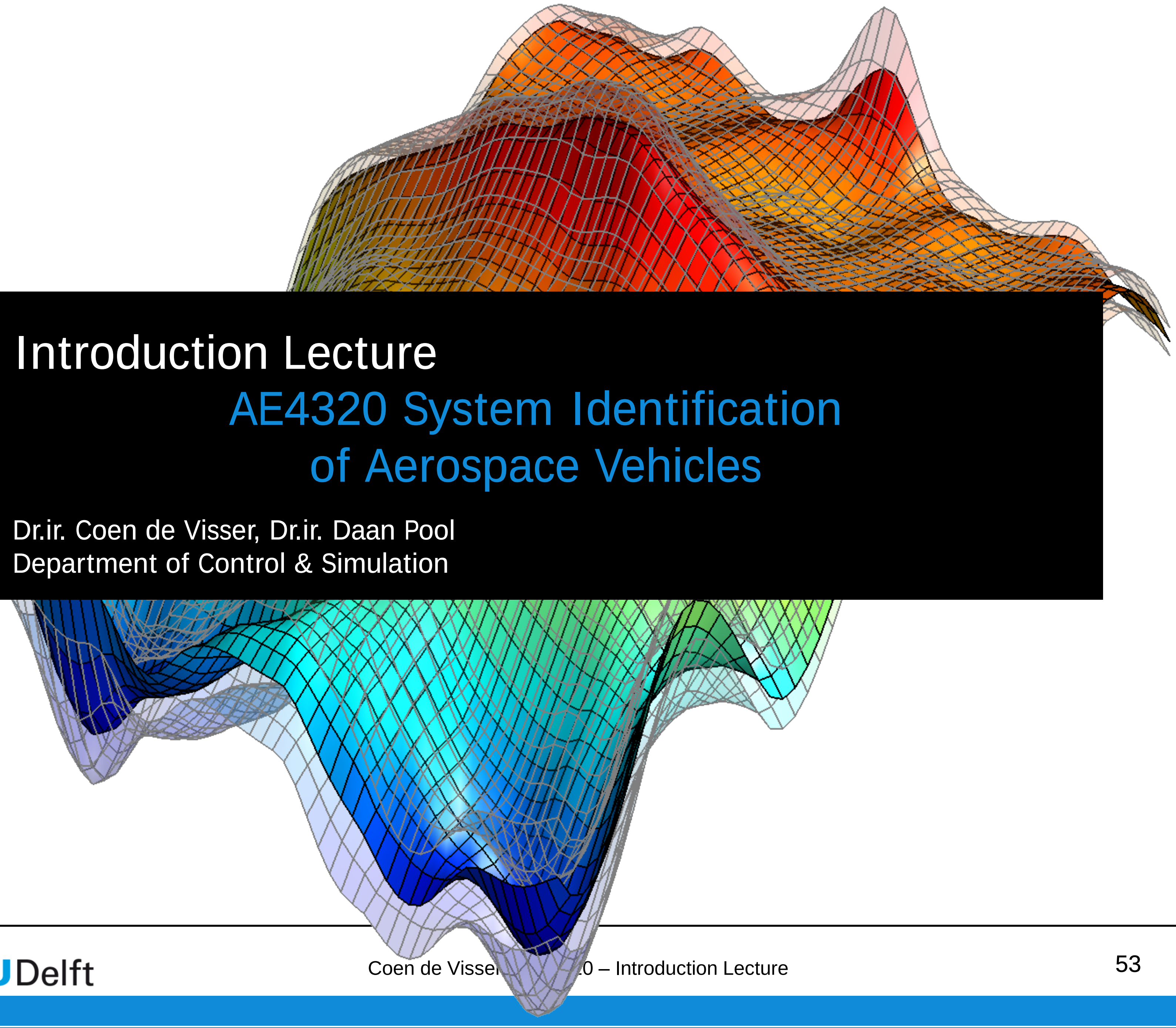
Spline model: F-16 leading edge flap deflection effect on pitching moment.



Next Lectures…

L12: Model validation & Course conclusion





Introduction Lecture

AE4320 System Identification of Aerospace Vehicles

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