



# How to Validate Stochastic Finite Element Models from Uncertain Experimental Modal Data

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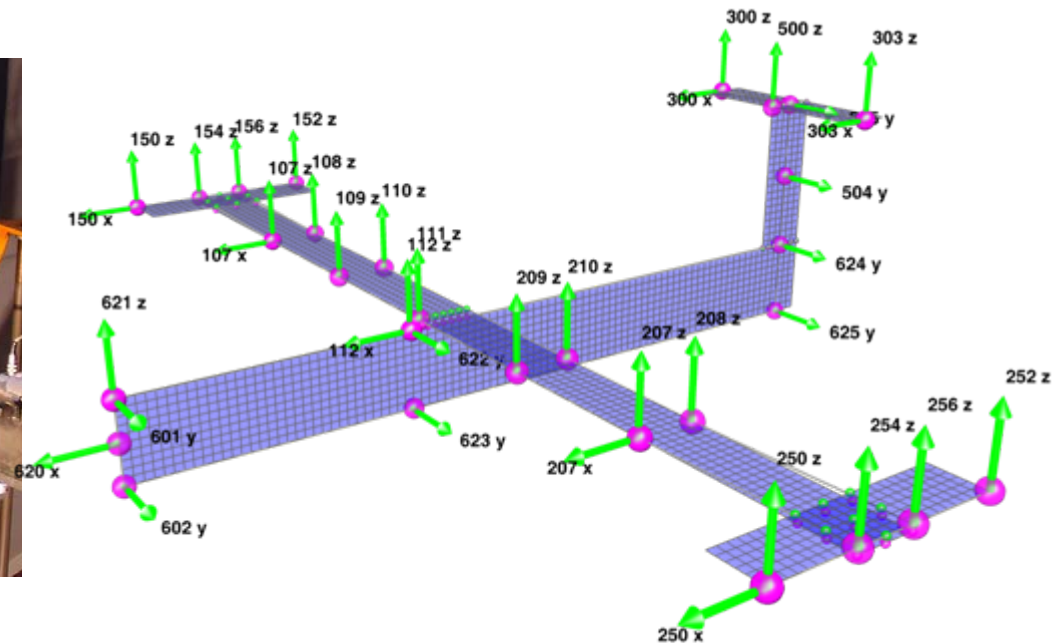
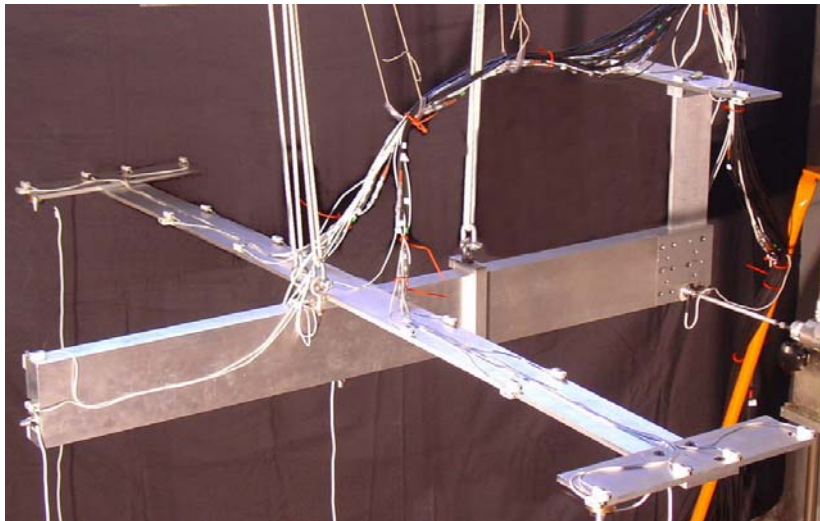
# Outline/ Motivation

- **Validation of Finite Element Models** on basis of modal data (eigenfrequencies and mode shapes) determined from Modal Survey Test or Ground Vibration Test (GVT)
- Use of gradient based **Computational Model Updating Procedures**
- State of the art: **deterministic approach** (a single experimentally determined set of modal data is used to identify a deterministic Finite Element Model)
- Goal: **probabilistic approach** (use multiple experimentally determined test data sets to identify a Finite Element Model with stochastic parameters)

# Motivation

## Modal Data Uncertainty

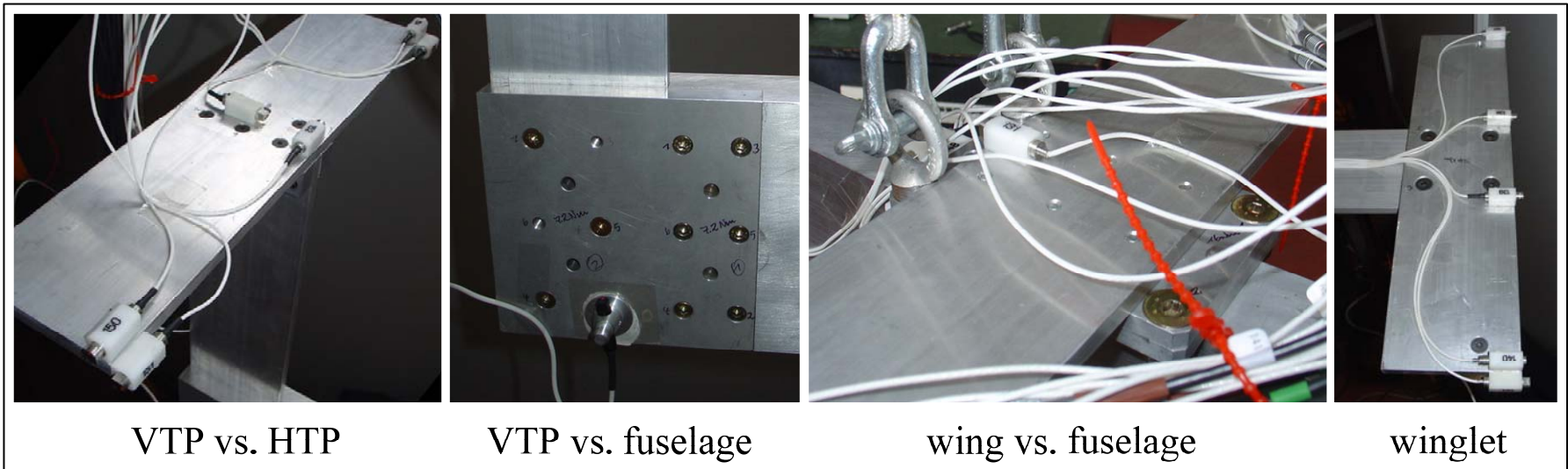
- DLR laboratory benchmark structure **AIR**craft **MODEL** (GARTEUR SM-AG19 replica)
- Made of aluminium with 6 beam like components connected by bolted joints



# Motivation

## A Source of Modal Data Uncertainty

➤ the uncertainty of **joint stiffness** parameters are generally **unknown**



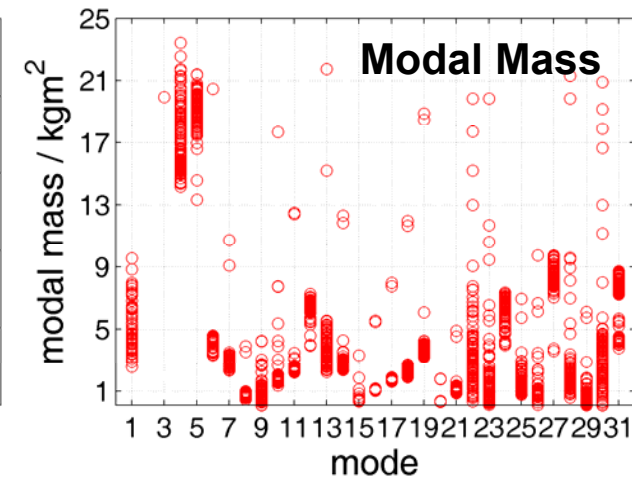
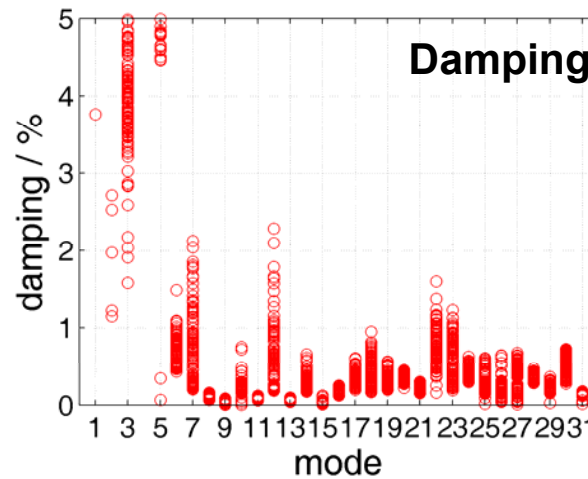
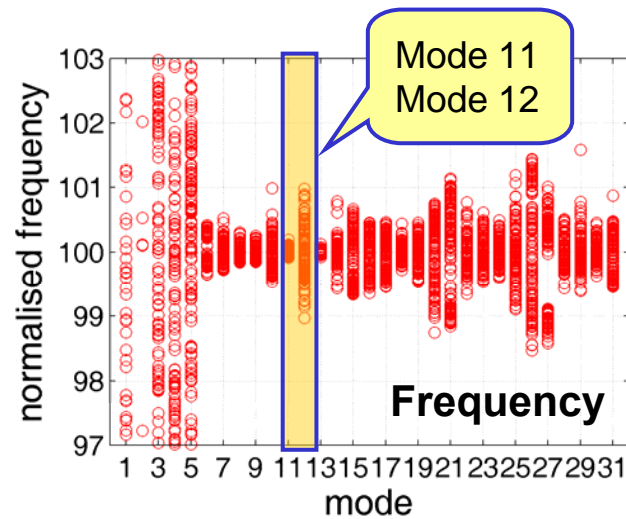
**Repeated Modal Survey Test on AIRMOD**



# Motivation

## Modal Data Uncertainty – Results of AIRMOD Test Campaign

- 130 times assembled, disassembled, reassembled and re-tested with random excitation and subsequent automated modal parameter estimation

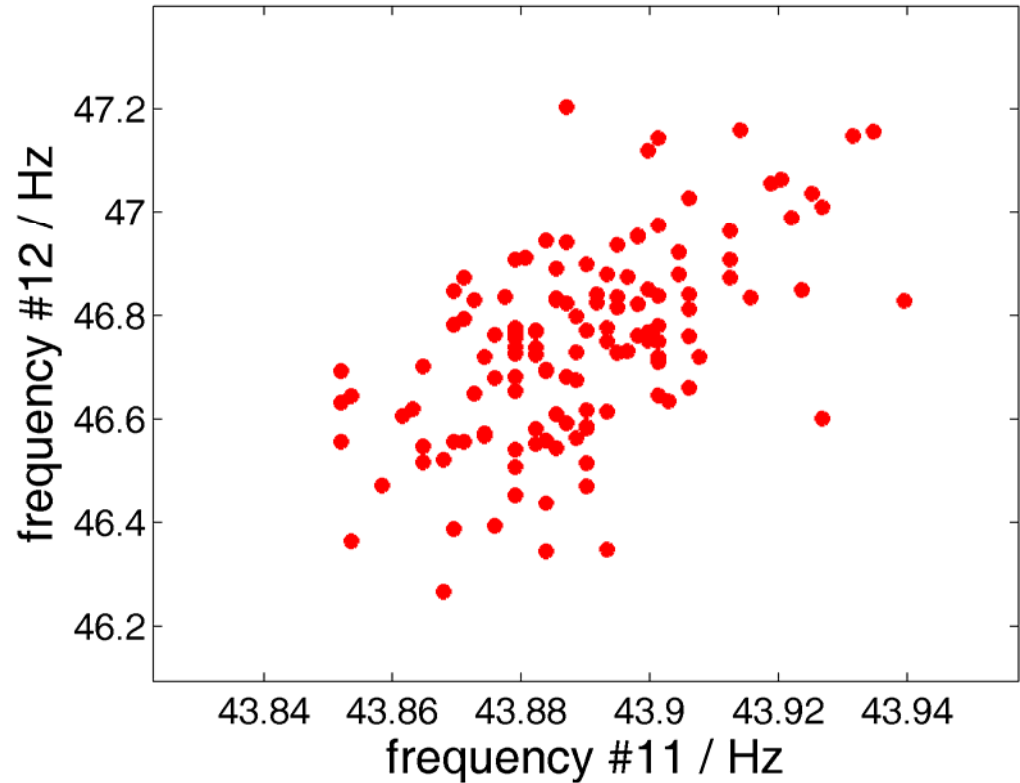


- Significant variation on modal parameters!

# Introduction

## Frequency Clouds

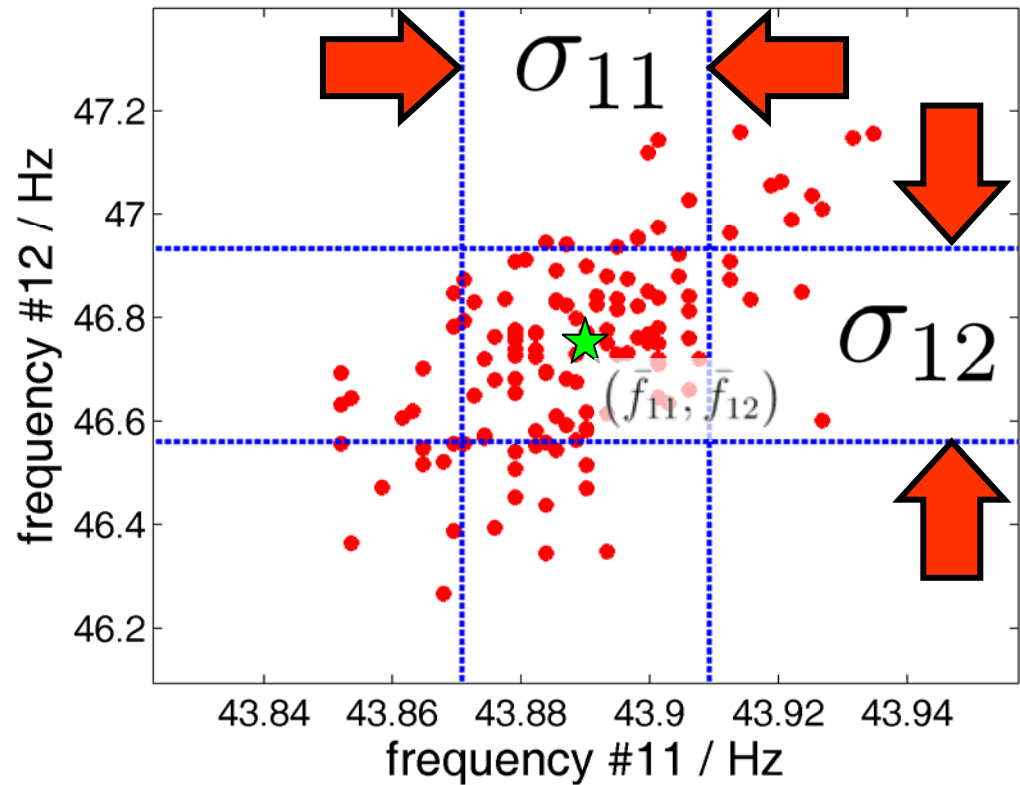
- a number of  $n$  tests has been performed
- →  $n$  **frequency pairs**  $(f_{11,1}, f_{12,1}), (f_{11,2}, f_{12,2}), \dots, (f_{11,n}, f_{12,n})$  can be plotted
- a scatter diagram makes the correlation between two frequencies visible



# Introduction

## Frequency Clouds

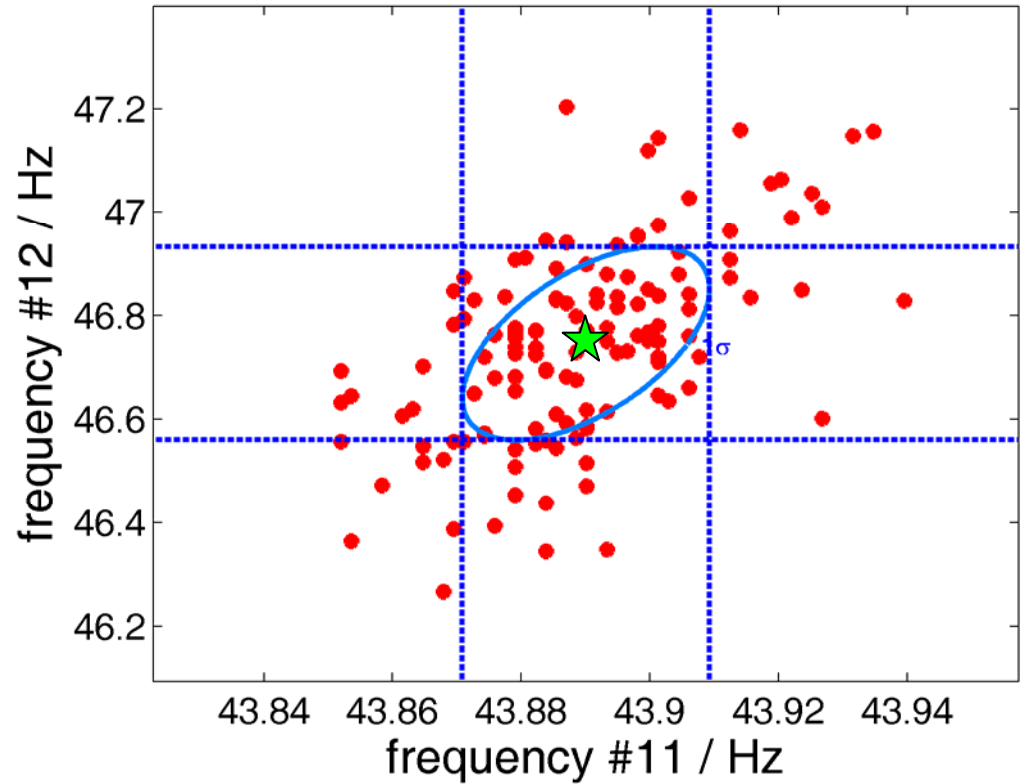
- The mean values  $(\bar{f}_{11}, \bar{f}_{12})$  and the standard deviation  $\sigma_{11}$  and  $\sigma_{12}$
- In case of correlated frequency pairs the direction of the frequency cloud is important



# Introduction

## Frequency Clouds

- The so called **covariance ellipse** is a contour line of equal probability
- Here:  $1 \times \sigma$

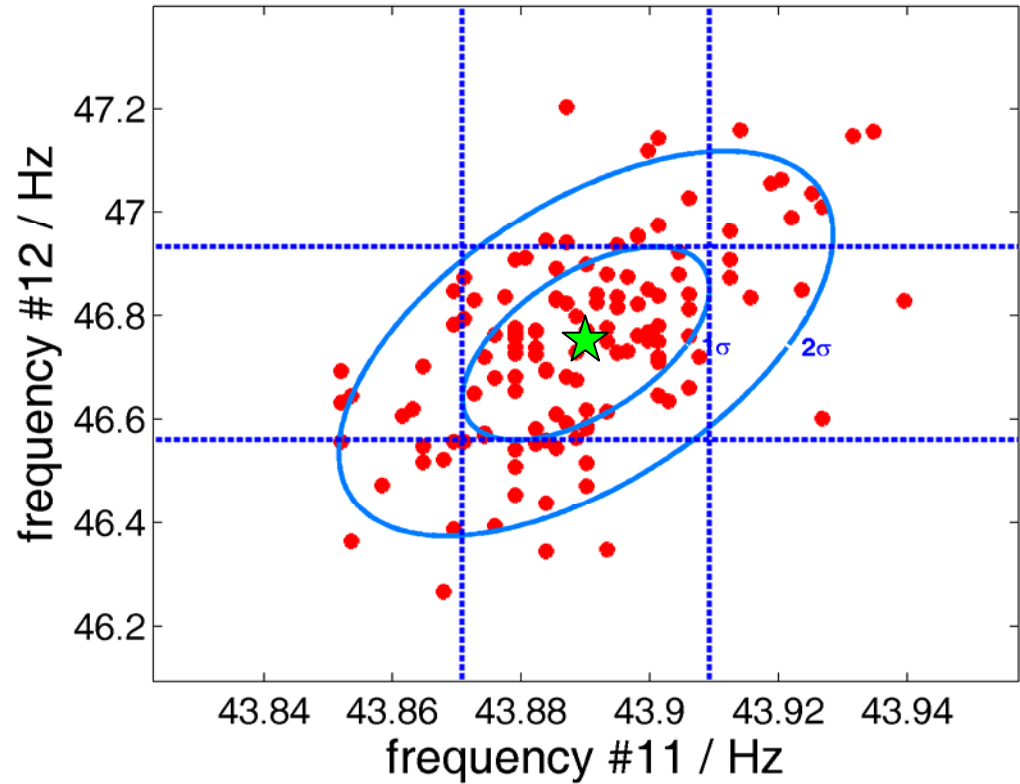




# Introduction

## Frequency Clouds

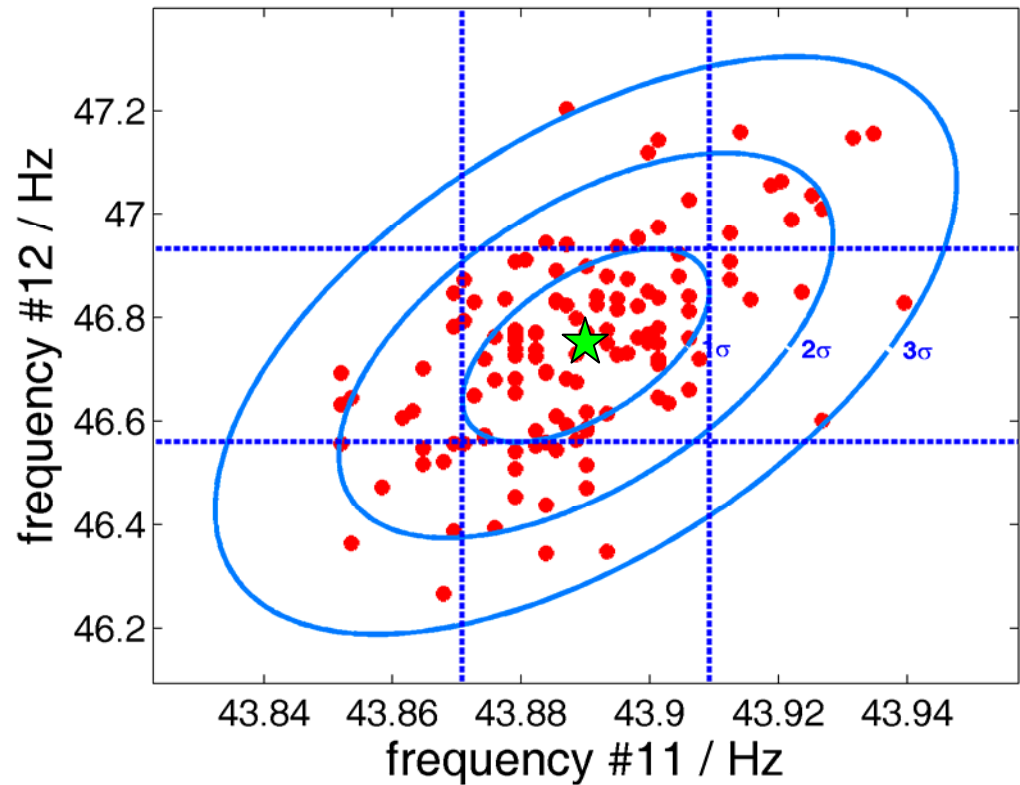
- The so called **covariance ellipse** is a contour line of equal probability
- Here:  $2 \times \sigma$



# Introduction

## Frequency Clouds

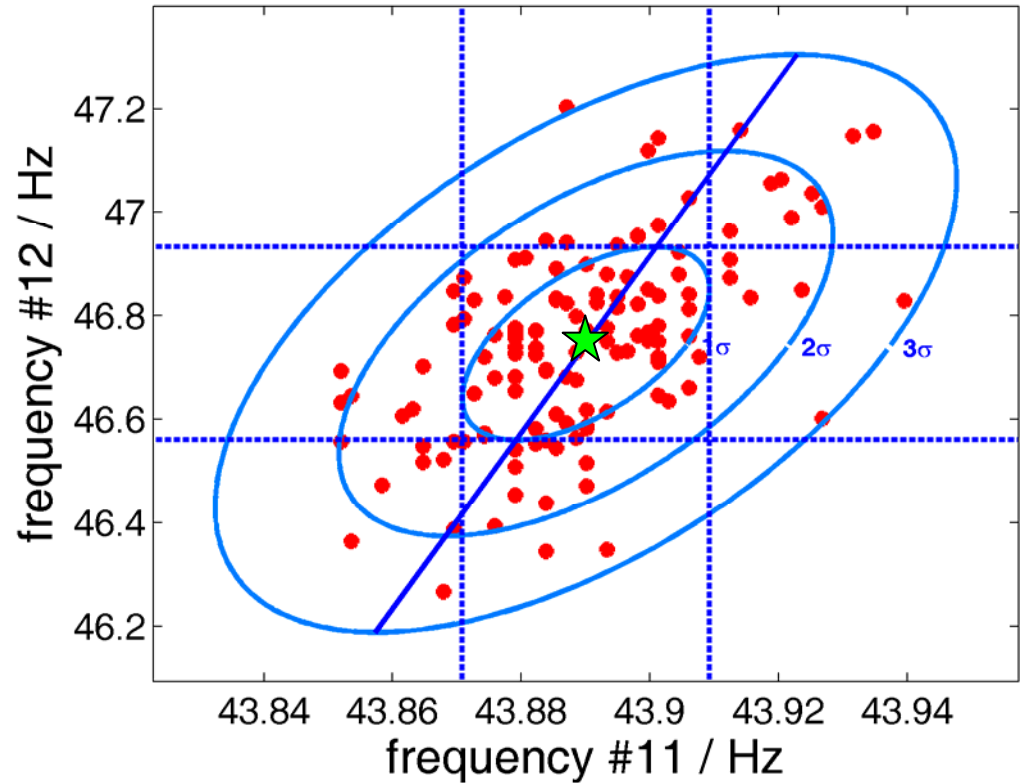
- The so called **covariance ellipse** is a contour line of equal probability
- Here:  $3 \times \sigma$



# Introduction

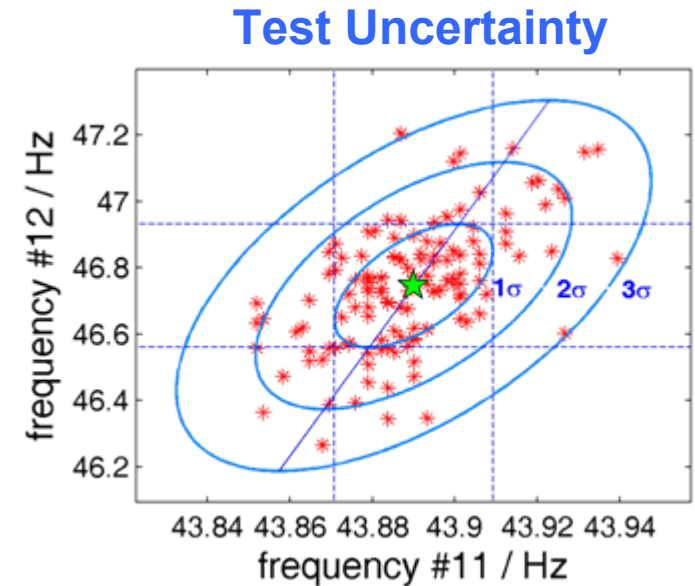
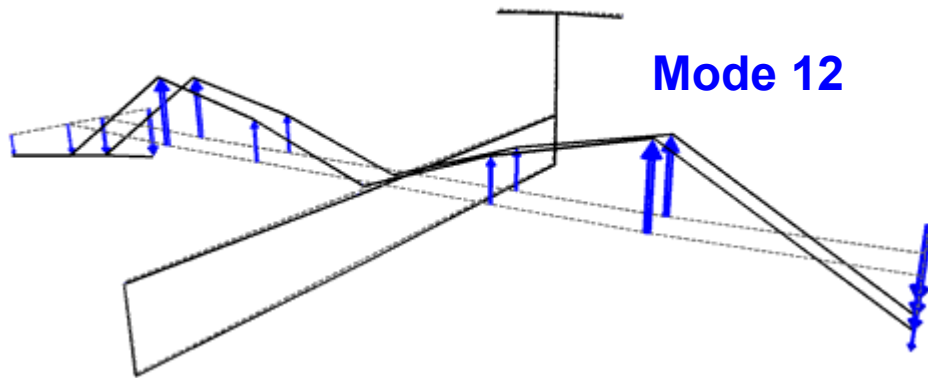
## Frequency Clouds

- the **orientation** of the ellipse can be visualised by the **principal axes**
- It shows if the two frequencies are **positively** or **negatively correlated**

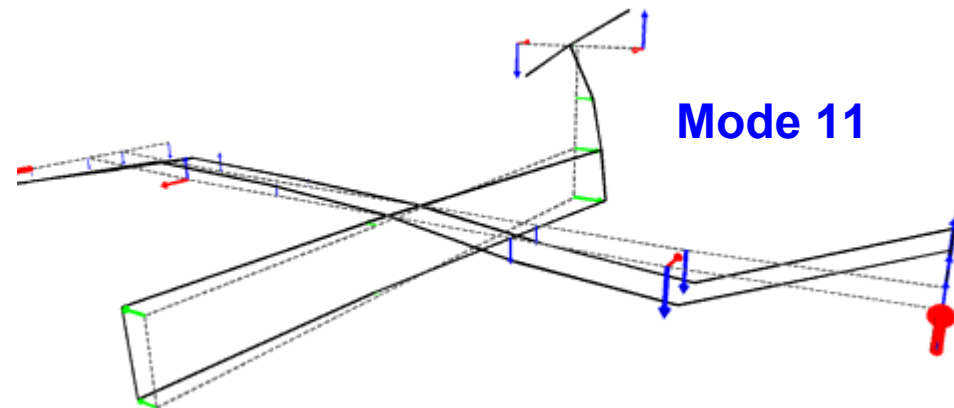


# Introduction

## Frequency Clouds - Test Data

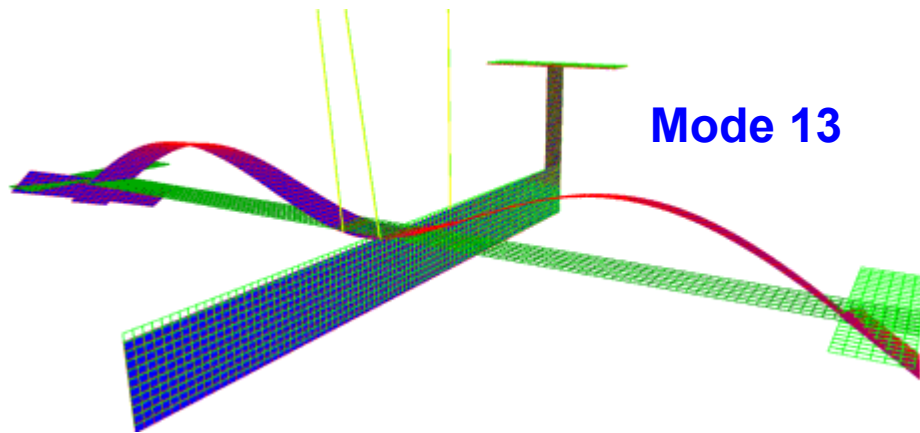


- Uncertain experimental modal data by **multiple** tests on nominal identical structures
- Uncertainty and correlation of modal data becomes visible if two frequencies are plotted against each other

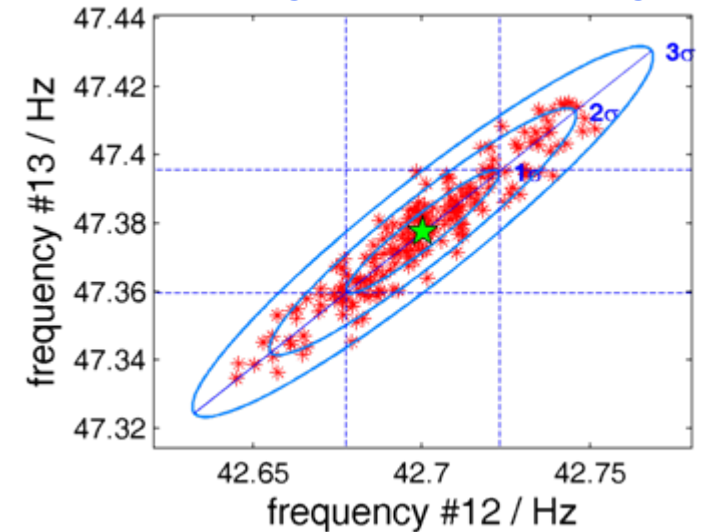


# Introduction

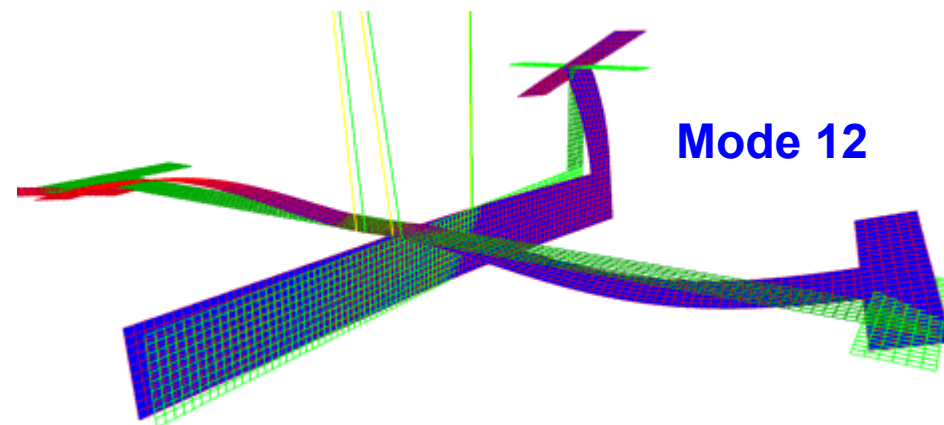
## Frequency Clouds - Analysis Data



## Analysis Uncertainty



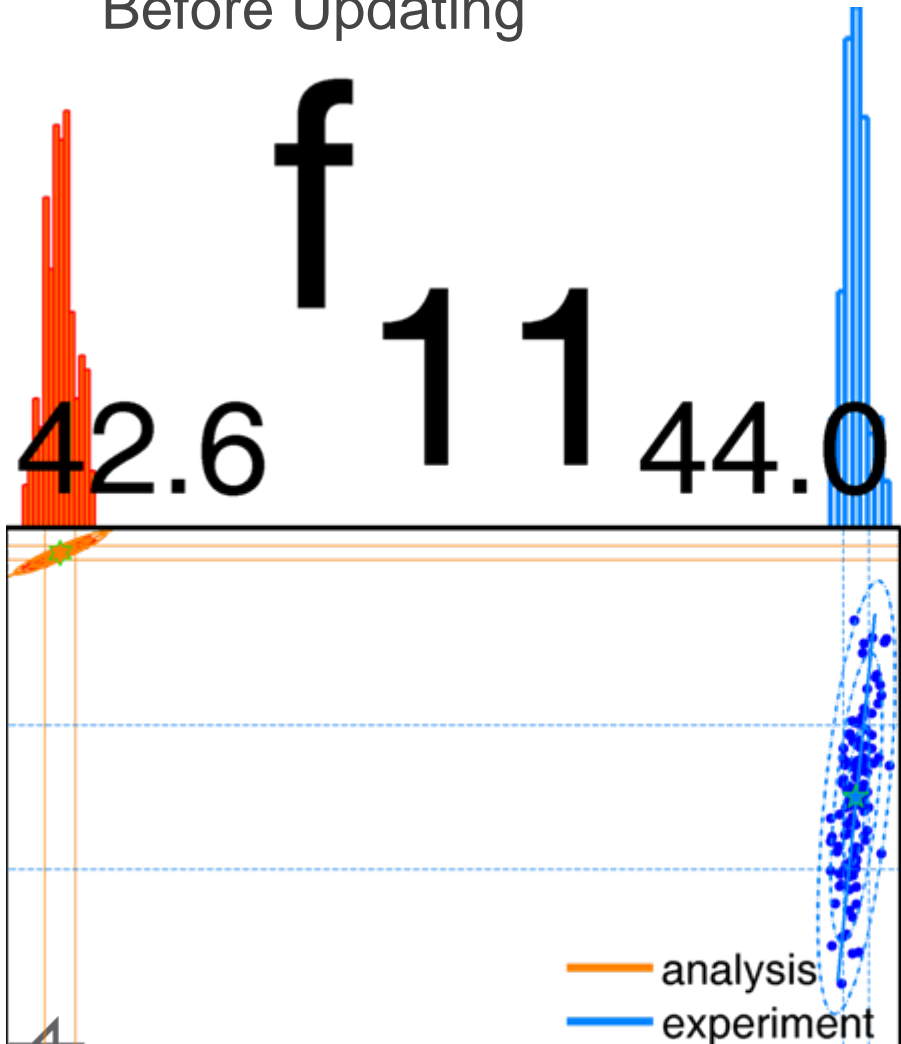
- Uncertain analysis modal data by **randomising** a number of **design parameters**
- here: **Monte Carlo Simulation** is utilised in combination with **Latin Hypercube Sampling**





# Introduction

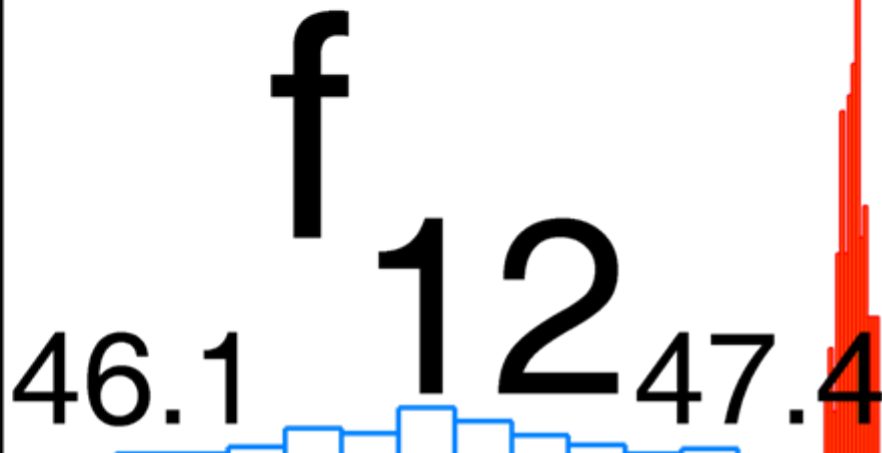
Before Updating



## Goal:

- match frequency clouds
- identify parameter uncertainty

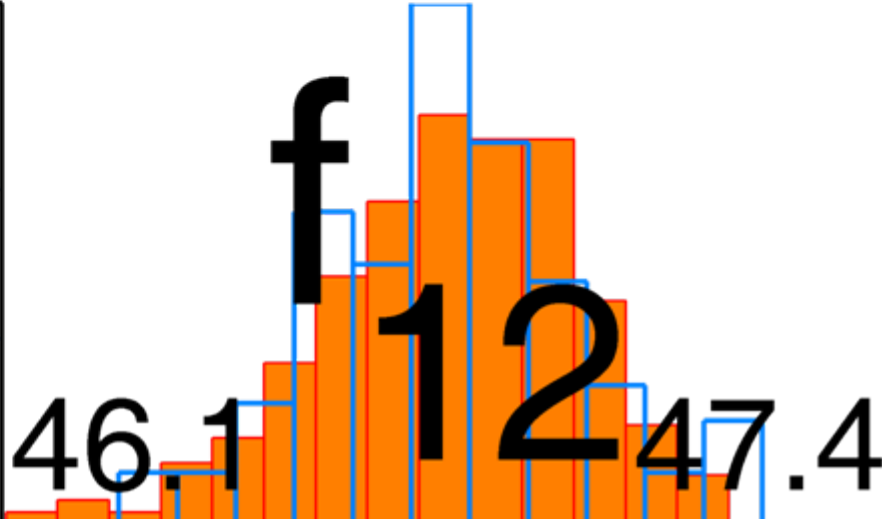
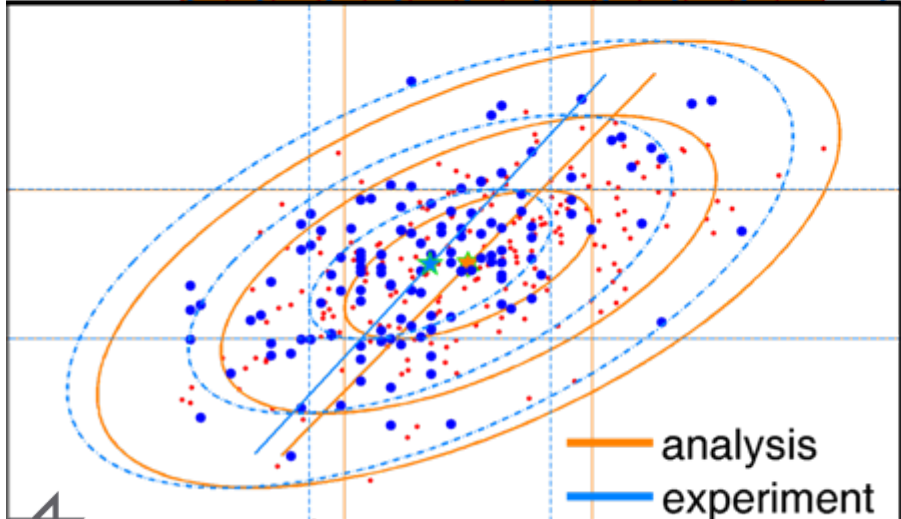
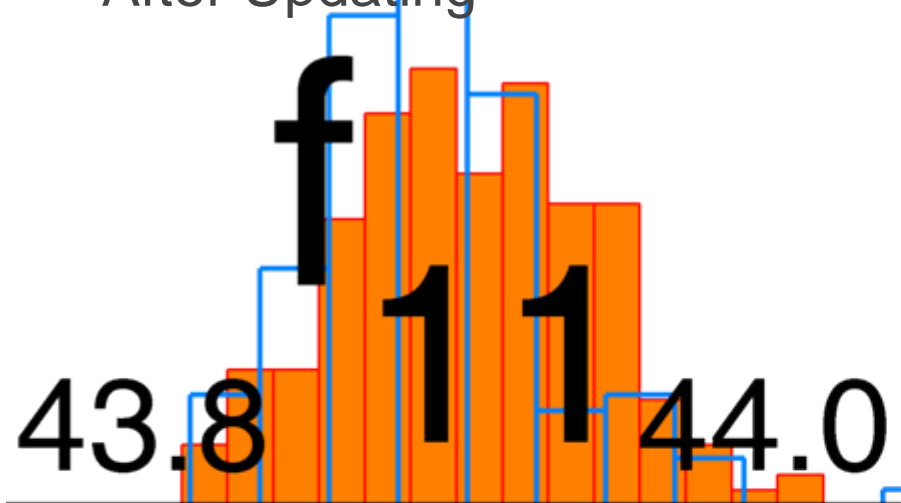
→ an inverse approach is needed to identify/quantify the **uncertain** FE model parameters, **S**tochastic **M**odel **U**dating (SMU)



# Introduction

## After Updating

If clouds are adjusted the correct **model parameter covariance** has been identified!



# Stochastic Model Updating

## Mean Parameter Adjustment

- the **difference** between mean **analytical** and **measured** values can be assembled in a **weighted residual vector**

$$\{\bar{\varepsilon}_w\} = [W_v](\{\bar{v}_m\} - \{\bar{v}_a(p)\})$$

- the vector of analytical values  $\{v_a\}$  can be described by a **linearized Taylor series** where  $[G]_i$  represents the **sensitivity matrix**

$$\{\bar{v}_a(p)\}_{i+1} = \{\bar{v}_a\}_i + [G]_i\{\Delta\bar{p}\}_i$$

- by minimizing following **objective function**

$$J = \{\bar{\varepsilon}\}^T [W_\varepsilon] \{\bar{\varepsilon}\} + \{\Delta\bar{p}\}^T [W_{p,\varepsilon}] \{\Delta\bar{p}\} \rightarrow \min$$

a regularization term  $[W_{p,\varepsilon}]_i$  is used in case of ill-conditioning to improve convergence

# Stochastic Model Updating

## Mean Parameter Adjustment

- the **parameter changes** are derived using the pseudoinverse of  $[G]_i$

$$\{\Delta\bar{p}\}_i = [T_\varepsilon]_i \{\bar{r}\}_i \quad \text{with} \quad \{\bar{r}\}_i = \{\bar{v}_m\} - \{\bar{v}_a\}_i$$

- where  $[T]$  is the transformation matrix

$$[T_\varepsilon]_i = ([G]_i^T [W_\varepsilon] [G]_i + [W_{p,\varepsilon}]_i)^{-1} [G]_i^T [W_\varepsilon]$$

# Stochastic Model Updating

## Covariance Matrix Adjustment

- the **difference** of the **covariance matrix** of the **measured samples** and the corresponding **analytical covariance matrix** can be summarized in a **residual matrix**

$$[S_{\Delta}]_i = [S_{v_m}] - [S_{v_a(p)}]_i$$

- the analytical covariance matrix can be derived from the Taylor series expansion of the analytical vector under the **assumption** of  $\{v_a\}$  and  $\{\Delta p\}$  to be **uncorrelated** at iteration step  $i$

$$\begin{aligned} [S_{v_a(p)}]_{i+1} &= \left[ \text{Cov} \left( \{v_a\}_i + [G]_i \{\Delta p\}_i, \{v_a\}_i + [G]_i \{\Delta p\}_i \right) \right] \\ &= [S_{v_a}]_i + [G]_i [S_{\Delta p}]_i [G]_i^T \end{aligned}$$



# Stochastic Model Updating

## Covariance Matrix Adjustment

- by minimizing following **objective function** with the **Frobenius Norm** of the **residual matrix**  $[S_\Delta]$

$$J_S = \frac{1}{2} \left\| [W_S][S_\Delta][W_S]^T \right\|_F^2 \rightarrow \min$$

- the parameter **covariance matrix changes** (increments) are derived from

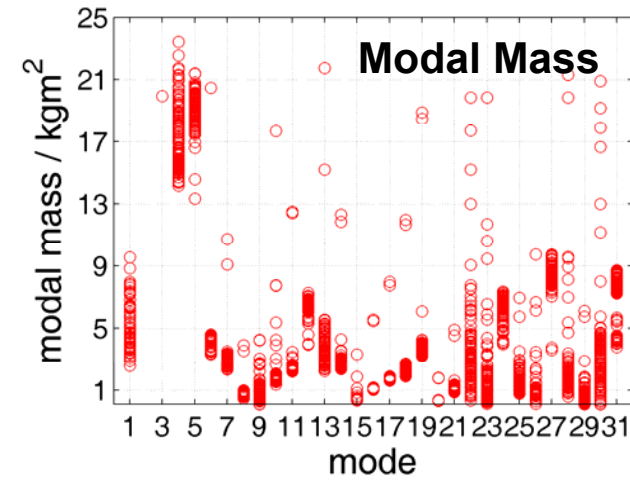
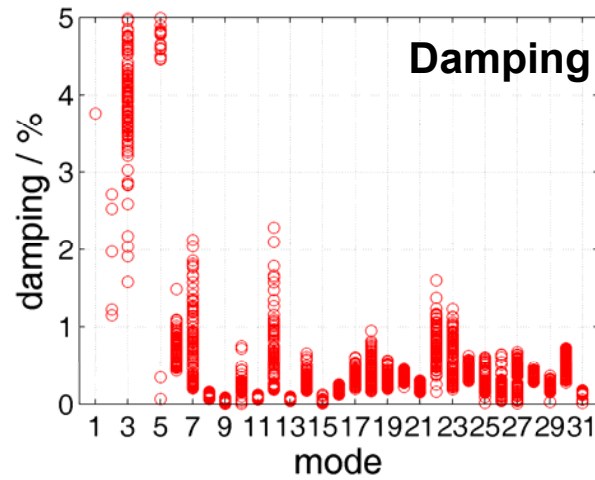
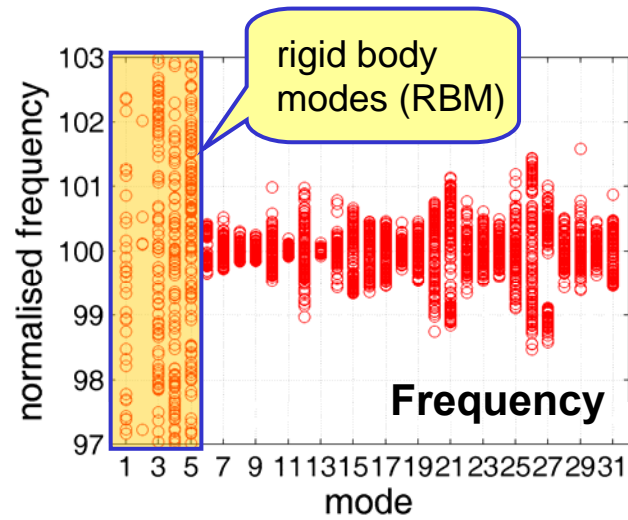
$$[S_{\Delta p}]_i = [T_\Sigma]_i [R]_i [T_\Sigma]_i^T \quad \text{with } [R]_i = [S_{v_m}] - [S_{v_a}]_i$$

- and the **transformation matrix**  $[T_\Sigma]$

$$[T_\Sigma]_i = \left( [G]_i^T [W_\Sigma][G]_i + [W_{p,\Sigma}]_i \right)^{-1} [G]_i^T [W_\Sigma]$$

# Test Case – AIRMOD

## Rigid Body Modes



# Test Case – AIRMOD

## Rigid Body Modes

A/C Yaw 56 samples

	mean	std
f:	0.23	0.02 Hz
d:	17.36	4.78 %

A/C Roll 122 samples

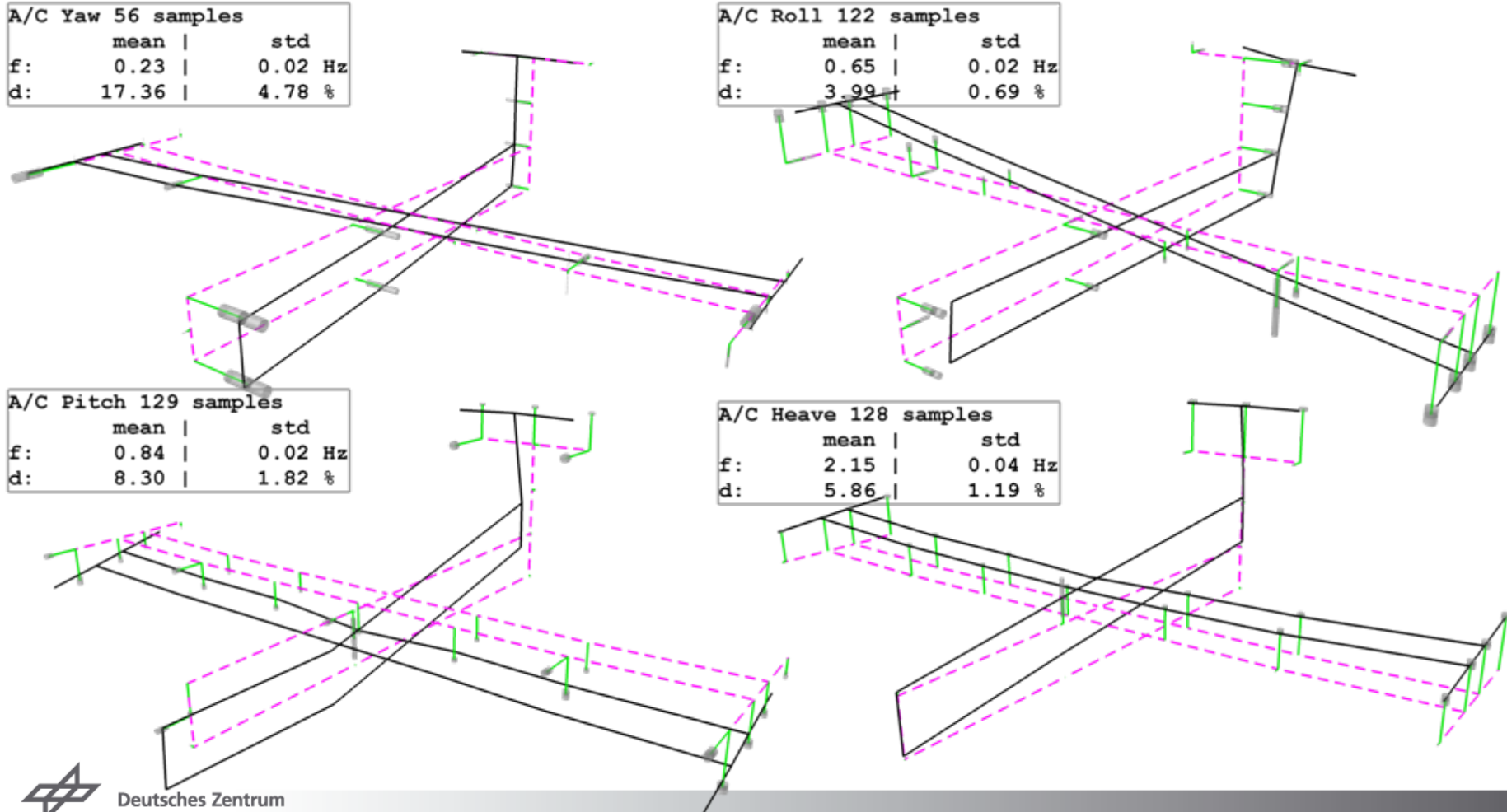
	mean	std
f:	0.65	0.02 Hz
d:	3.99	0.69 %

A/C Pitch 129 samples

	mean	std
f:	0.84	0.02 Hz
d:	8.30	1.82 %

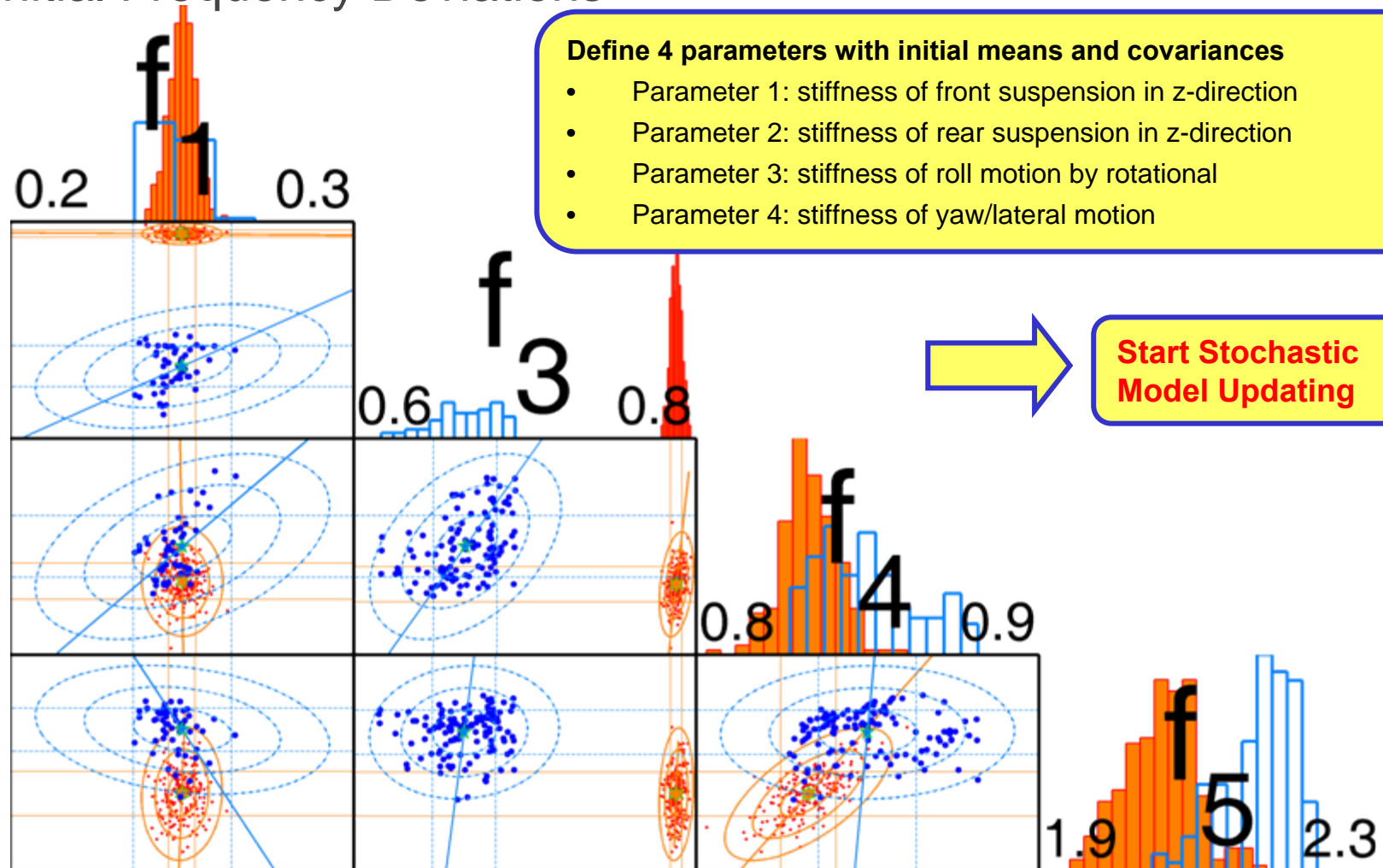
A/C Heave 128 samples

	mean	std
f:	2.15	0.04 Hz
d:	5.86	1.19 %



# Test Case – AIRMOD rigid body modes

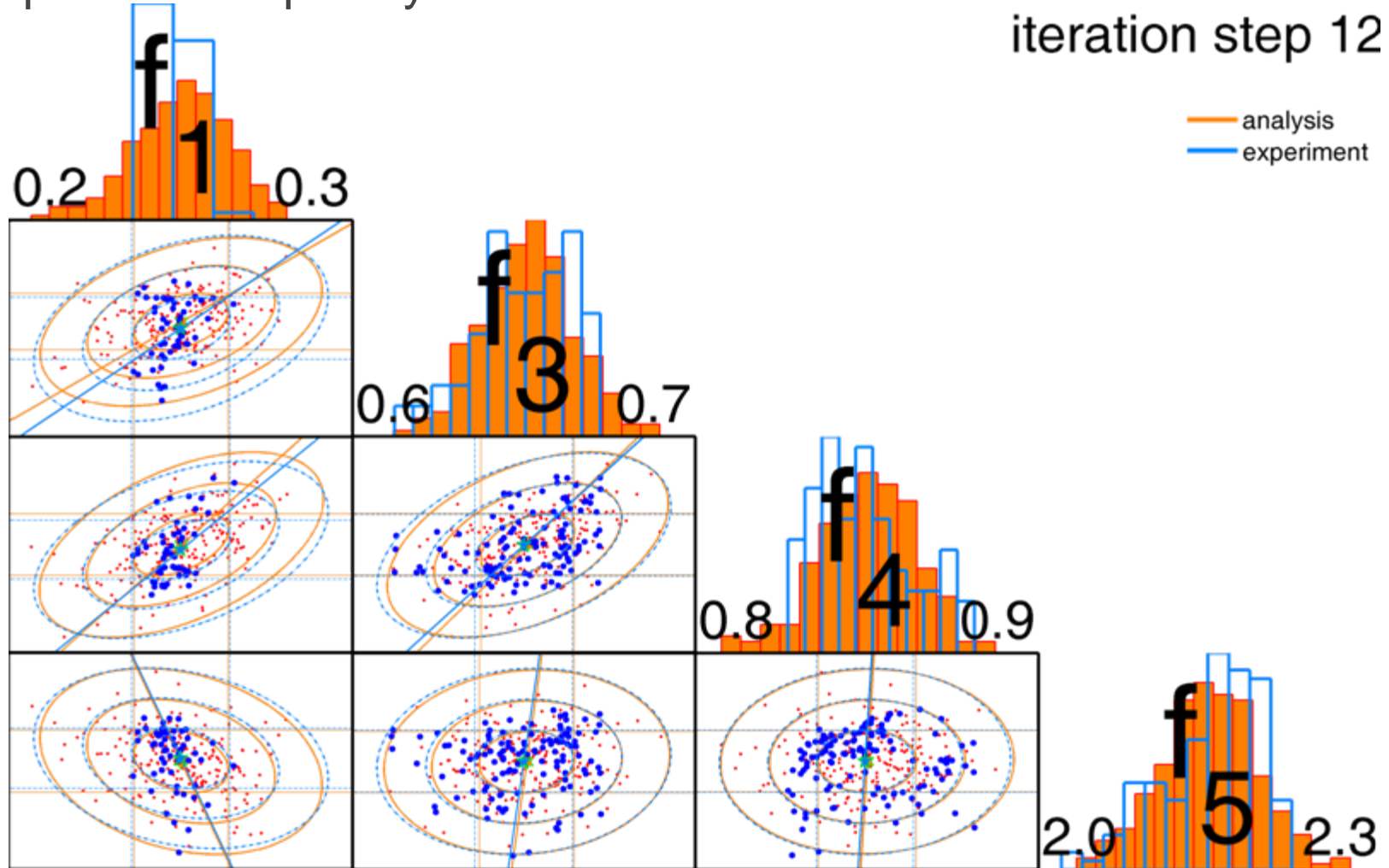
## Initial Frequency Deviations



# Test Case – AIRMOD rigid body modes

## Updated Frequency Deviations

iteration step 12

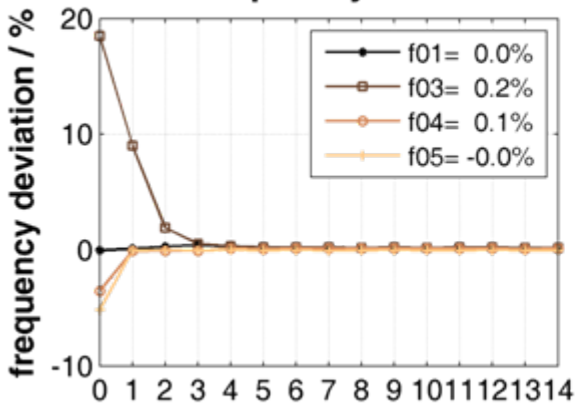




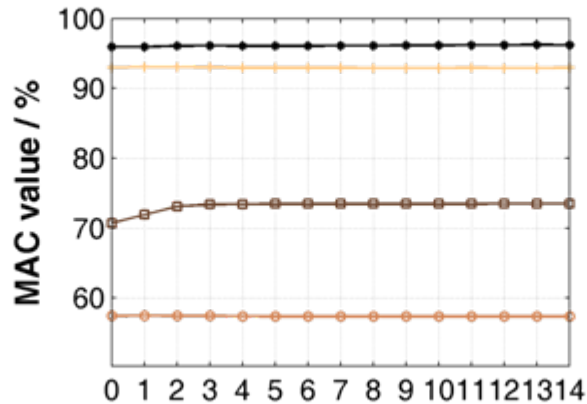
# Test Case – AIRMOD rigid body modes

## Convergence

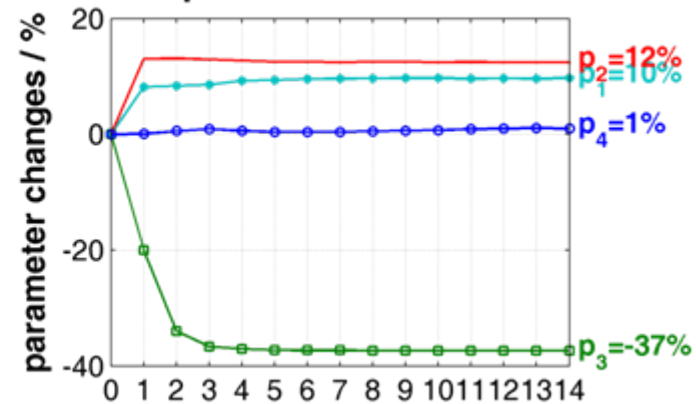
frequency error



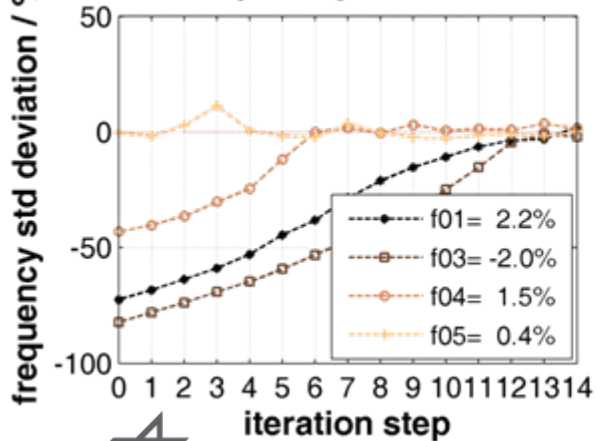
MAC



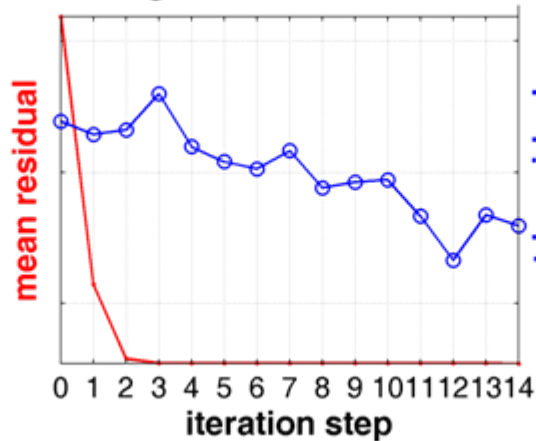
parameter means



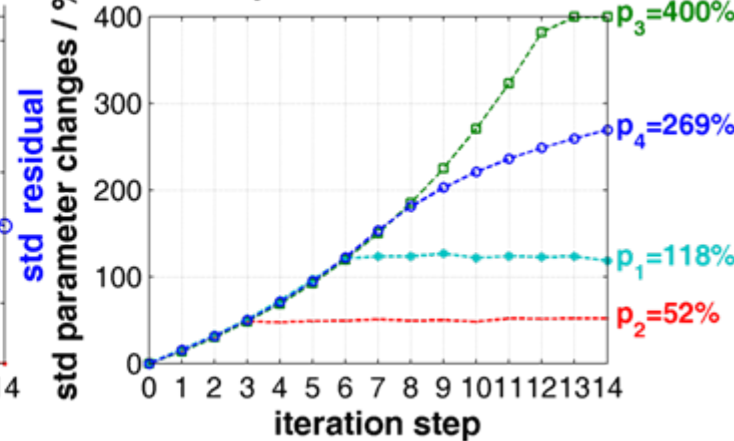
frequency std error



weighted cost function



parameter std



# Conclusions and Outlook

- Conventional model updating procedure has been extended by an equation adjusting the model parameter covariances
- Developed algorithm was applied to the rigid body modes of an aircraft like laboratory structure AIRMOD
- Test case shows a good convergence
- Frequency clouds match well: adjusted parameters represent the uncertainty of the measurement data
- In a second step the elastic modes will be updated



**Thank you for your attention!**

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