

# Robust Analysis using RoMuIOC for the Longitudinal Control of a Civil Aircraft

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# Introduction

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- Test robust analysis tools on aerospace industrial application
- LMIs for parameter-dependent Lyapunov functions results
- Two type of results based on two different uncertain models
- Stability and performances (pole location,  $H_\infty$ ,  $H_2$ , impulse-to-peak)
  
- RoMuIOC
- Tests performed using the RoMuIOC toolbox
- LMIs in YALMIP format, solved using SeDuMi and SDPT3
- Indications on the numerical performances of the toolbox
  
- Aircraft motion in the vertical plane (longitudinal)
- LTI uncertain modeling of the non-linear aircraft and the control
- Models that cover the flight envelope

- ① Uncertain modeling
- ② LMIs for parameter-dependent Lyapunov functions results
- ③ RoMulOC toolbox
- ④ Numerical results
- ⑤ Conclusions

# 1 Uncertain modeling

## ■ Aircraft motion in the vertical plane (longitudinal)

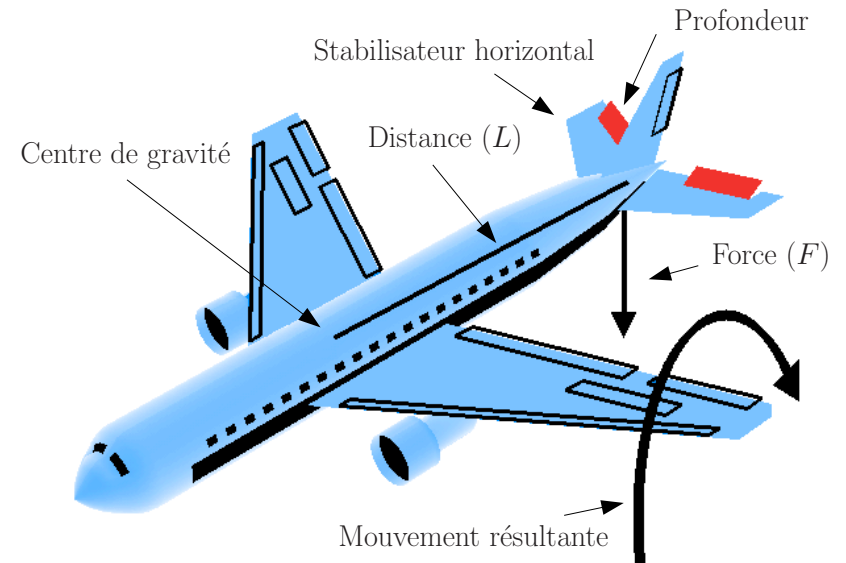
Actuators: elevators

Dynamics: angle of attack + pitch rate

Sensors: modeled as first order

Control: gain scheduled dynamic

Closed-loop system of order 9

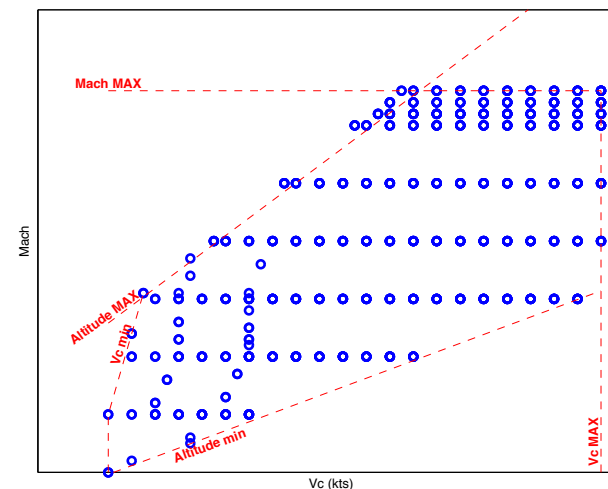


## ■ Non-linear model + controller are linearized at 633 flight configurations

6 parameters:

weight, balance, speed,

Mach nb, altitude, motor thrust.



# 1 Uncertain modeling

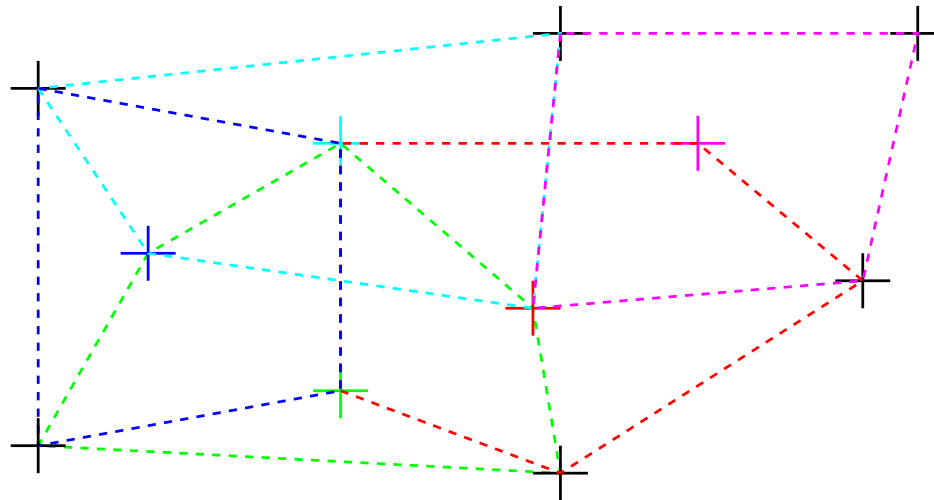
▲ Analysis of each 633 LTI models

gives small information on robustness for the total flight envelope

▲ LFT model can be build to have a parameter-dependent LTI representation of the whole flight envelope: uncertainty blocs of size 150!

■ Adopted strategy: build uncertain models valid around each flight configuration

● Union of local uncertain models covers the flight envelope



● Robust analysis gives upper bounds on performances achievable locally

# 1 Uncertain modeling

- Adopted strategy: build uncertain models valid around each flight configuration
- For a given flight configuration  $\theta_i$ 
  - algorithm gives its neighbors in parametric space  $\theta_{j \in N(i)}$ .
- Heuristic algorithm combines
  - Euclidian distance in the 6D space  $\theta$  + search along parametric directions.
- Tuned to provide 8 to 12 neighbors with a mean value of 11.19.
- Uncertain model around  $\theta_i$  is defined as the convex hull of models at  $\theta_{j \in N(i)}$

$$\begin{pmatrix} \dot{x} \\ z \end{pmatrix} = \begin{bmatrix} A_i(\zeta) & B_i(\zeta) \\ C_i(\zeta) & D_i(\zeta) \end{bmatrix} \begin{pmatrix} x \\ w \end{pmatrix} = \sum_{j \in N(i)} \zeta_j \begin{bmatrix} A_j & B_j \\ C_j & D_j \end{bmatrix} \begin{pmatrix} x \\ w \end{pmatrix}$$
$$: \sum \zeta_j = 1, \zeta_j \geq 0$$

# 1 Uncertain modeling

- Uncertain model around  $\theta_i$  is defined as the convex hull of models at  $\theta_{j \in N(i)}$

$$\begin{pmatrix} \dot{x} \\ z \end{pmatrix} = \begin{bmatrix} A_i(\zeta) & B_i(\zeta) \\ C_i(\zeta) & A_i(\zeta) \end{bmatrix} \begin{pmatrix} x \\ w \end{pmatrix} = \sum_{j \in N(i)} \zeta_j \begin{bmatrix} A^{[j]} & B^{[j]} \\ C^{[j]} & D^{[j]} \end{bmatrix} \begin{pmatrix} x \\ w \end{pmatrix}$$

$$: \sum \zeta_j = 1, \zeta_j \geq 0$$

- Each uncertain model is also converted in LFT form

$$\begin{pmatrix} \dot{x} \\ z_\Delta \\ z \end{pmatrix} = \begin{bmatrix} A_i & B_{\Delta i} & B_i \\ C_{\Delta i} & \mathbf{0} & D_{\Delta w i} \\ C_i & D_{z \Delta i} & D_{\Delta i} \end{bmatrix} \begin{pmatrix} x \\ w_\Delta \\ w \end{pmatrix}, \quad w_\Delta = \sum_{j \in N(i)} \zeta_j \Delta^{[j]} z_\Delta$$

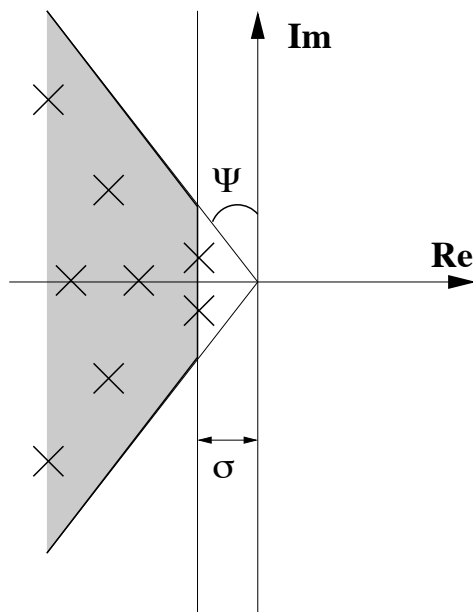
$$: \sum \zeta_j = 1, \zeta_j \geq 0$$

# 1 Uncertain modeling

## ■ Performances to be tested

- Stability

- Pole location



- $H_2$  norm - measure of control effort due to noise

( $w$  additive noise on measurements,  $z = u$  control signal)

- $H_\infty$  norm - stability margin w.r.t. dynamic uncertainty

( $w$  additive signal on control  $u$ ,  $z = y$  measurements)

- Impulse-to-peak - control peak to initial conditions

( $w$  impulse on state vector,  $z = u$  control signal)



- ① Uncertain modeling
- ② LMI for parameter-dependent Lyapunov functions results
- ③ RoMulOC toolbox
- ④ Numerical results
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## 2 LMIs for parameter-dependent Lyapunov functions results

■ 2 results for polytopic models

● ‘Quadratic stability’ -  $V(x) = x^T P x$  independent of uncertain parameters

$$A^{[j]T} P + P A^{[j]} < \mathbf{0} , \quad P > \mathbf{0}$$

● Polytopic PDLF -  $V(x) = x^T \left( \sum \zeta_j P^{[j]} \right) x$

‘Slack variable’ approach [SCL 00]

$$\begin{bmatrix} \mathbf{0} & P^{[j]} \\ P^{[j]} & \mathbf{0} \end{bmatrix} < F \begin{bmatrix} A^{[j]} & -\mathbf{1} \end{bmatrix} + \begin{bmatrix} A^{[j]T} \\ -\mathbf{1} \end{bmatrix} F^T , \quad P^{[j]} > \mathbf{0}$$

■ 1 result for LFT models

● Quadratic PDLF -  $V(x) = x^T \begin{bmatrix} \mathbf{1} & \Delta^T \end{bmatrix} \hat{P} \begin{bmatrix} \mathbf{1} \\ \Delta \end{bmatrix} x$ ,  $\Delta = \sum \zeta_j \Delta^{[j]}$

‘Quadratic separation’ approach [Iwasaki 01]

$$\mathcal{L}(\hat{P}, \Theta) < \mathbf{0} \quad , \quad \begin{bmatrix} \mathbf{1} & \Delta^{[j]T} \end{bmatrix} \Theta \begin{bmatrix} \mathbf{1} \\ \Delta^{[j]} \end{bmatrix} \leq \mathbf{0} \quad , \quad \hat{P} > \mathbf{0}$$

■ Results of all three methods are extended to deal with the performance criteria (pole location,  $H_2$ ,  $H_\infty$  and impulse-to-peak)

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### ■ Robust Multi-Objective Control toolbox

- Freely distributed at `www.laas.fr/OLOCEP/romuloc`
- Includes uncertain modeling features

```
>> usys_h2
```

```
Uncertain model : polytope 11 vertices
```

```
          n=9      mw=2      mu=1
```

```
  n=9      dx  =  A*x +  Bw*w +  Bu*u
```

```
  pz=1      z  =  Cz*x + Dzw*w
```

```
  py=2      y  =  Cy*x           + Dy*u
```

```
continuous time ( dx: derivative )
```

### 3 RoMulOC toolbox

#### ■ Robust Multi-Objective Control toolbox

- Freely distributed at [www.laas.fr/OLOCEP/romuloc](http://www.laas.fr/OLOCEP/romuloc)
- Includes uncertain modeling features

```
>> usys_hinf
```

```
Uncertain model : LFT
```

```
----- WITH -----
```

```
          n=9      md=6      mw=1      mu=1
```

```
  n=9      dx  =  A*x +  Bd*wd +  Bw*w +  Bu*u
```

```
pd=7      zd  =  Cd*x              + Ddw*w + Ddu*u
```

```
pz=3      z   =  Cz*x + Dzd*wd + Dzw*w
```

```
py=2      y   =  Cy*x
```

```
continuous time ( dx : derivative operator )
```

```
----- AND -----
```

```
wd = #1 * zd
```

```
index      size      constraint                                name
```

```
#1          6x7      polytope 11 vertices      real
```

### ■ Robust Multi-Objective Control toolbox

- Freely distributed at `www.laas.fr/OLOCEP/romuloc`
- LMI formulas pre-coded - easy to generate

```
quiz = ctrpb('a', LyapType) + h2(usys_h2)
```

LyapType defines the method to be applied

h2 or stability, dstability, hinfty, i2p: performance to test

quiz contains the LMI constraints and variables in YALMIP format

- Solve the LMI problem with any solver

```
result = solvesdp(quiz, sdpsettings(...))
```

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## 4 Numerical results

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Table 1: LMI sizes and times for stability tests

	No. of vars	No. of rows	Mean time
quad-poly	45	110	0.25s
PDLF-poly	676	215	0.93s
PDLF-LFT	456	221	1.08s

## 4 Numerical results

Table 2: Results for settling time criterion

	$\sigma\%$	Mean time per LMIs	Mean nb iter
quad-poly	15.27%	0.35s	7.29
PDLF-poly	2.38%	1.35s	1.95
PDLF-LFT	2.38%	1.45s	1.96

- Robust upper bound on  $\sigma$  optimized by bisection (iterative LMI algorithm)
- $\sigma\%$ : Gap between robust upper bound and worst case on vertices

## 4 Numerical results

Table 3: Results for damping criterion

	$\psi\%$	Mean time per LMIs	Mean nb iter
quad-poly	11.40%	0.46s	6.45
PDLF-poly	1.44%	1.76s	1.25
PDLF-LFT	1.62%	1.52s	1.75

Table 4: Damping criterion for two particular flight points

$i$	$\psi_m(i)$	$\psi^*(i)$		
		quad-poly	PDLF-poly	PDLF-LFT
15	0.7286	0.5408	0.7213	0.6650
517	0.4978	0.4200	0.4735	0.4766

## 4 Numerical results

Table 5: Results for robust  $\mathcal{H}_\infty$  cost

	$\gamma_\infty\%$	Mean time	Less conservative
quad-poly	39.64%	0.55s	
PDLF-poly	0.19%	2.38s	52
PDLF-LFT	0.26%	9.04s	2

Table 6: Results for robust impulse-to-peak criterion

	$\gamma_{i2p}\%$	Mean time	Less conservative
quad-poly	43.59%	0.81s	
PDLF-poly	27.98%	2.66s	500
PDLF-LFT	30.16%	6.39s	0

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## 5 Conclusions

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- Parameter-dependent Lyapunov type results tested on an industrial application
- Overall test over 633 points takes 3 hours on a PC
  - (negligible compared to Monte Carlo tests on high order non-linear model)
- May be used at the control design phase to pre-validate (or not) a control law
- Gives information on robust stability and performances
  - Can be used to retune LPV controllers in regions of the flight domain.
- PDLF results show very low conservatism
- PDLF-Poly always better than PDLF-LFT (can it be proved?)
- No severe numerical problem - Validates the coding of LMIs in RoMuLOC
- `www.laas.fr/OLOCEP/romuloc`