

EXPLORATION DE DONNÉES POUR L'OPTIMISATION DE TRAJECTOIRES AÉRIENNES

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Encadrant Safety Line: Baptiste Gregorutti

Soutenance de thèse, 26 octobre 2018



CONTEXT

MOTIVATION

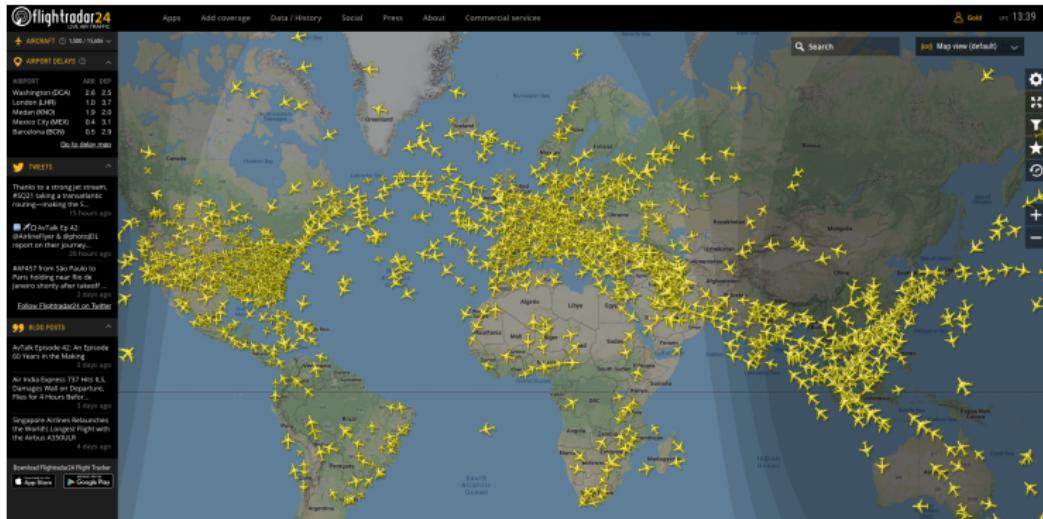


FIGURE: World air traffic - source: www.flightradar24.com

MOTIVATION

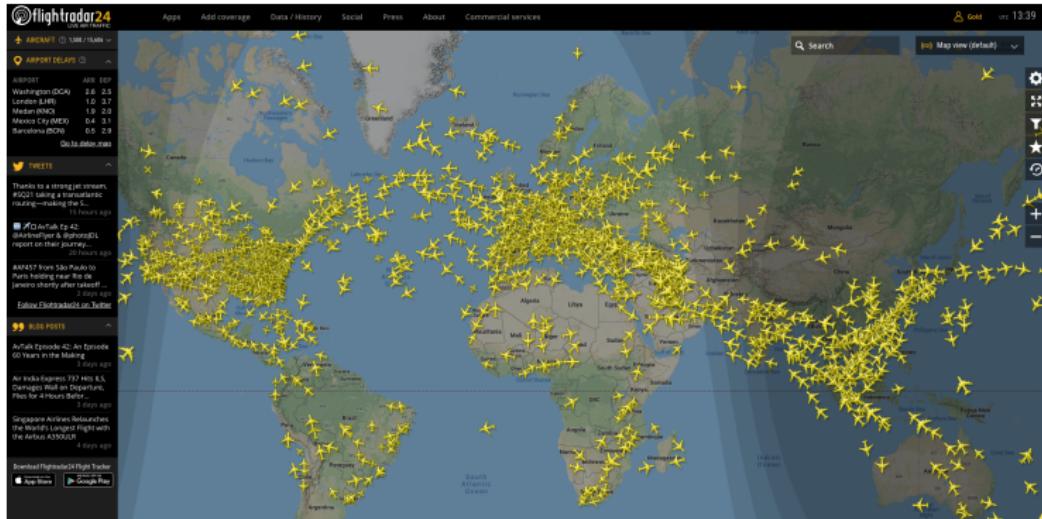


FIGURE: World air traffic - source: www.flightradar24.com

- 20 000 airplanes — 80 000 flights per day,

MOTIVATION

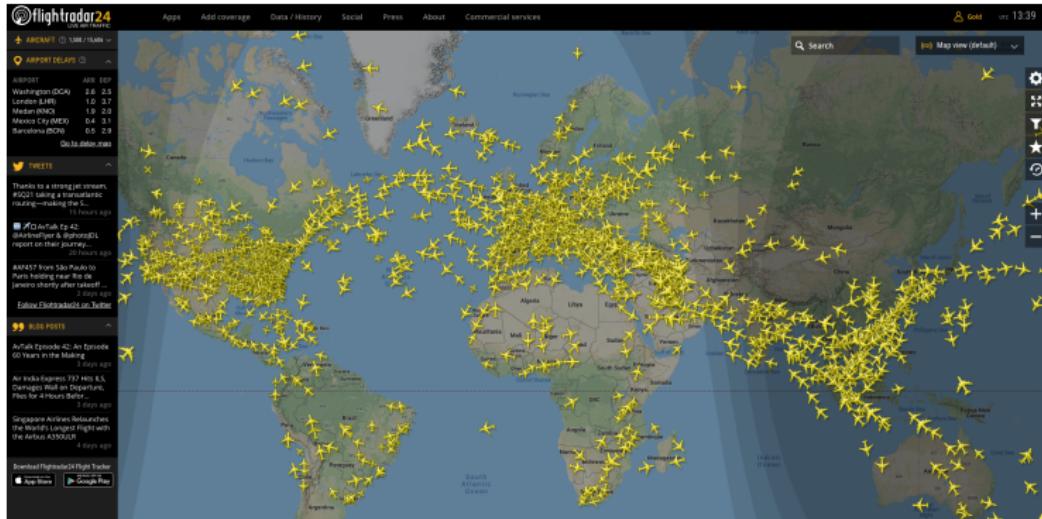
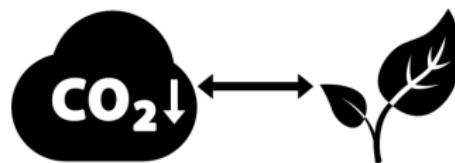


FIGURE: World air traffic - source: www.flightradar24.com

- 20 000 airplanes — 80 000 flights per day,
- Should double until 2033,

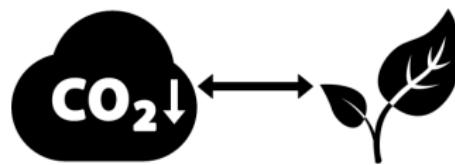
MOTIVATION

- Most polluting means of transportation,



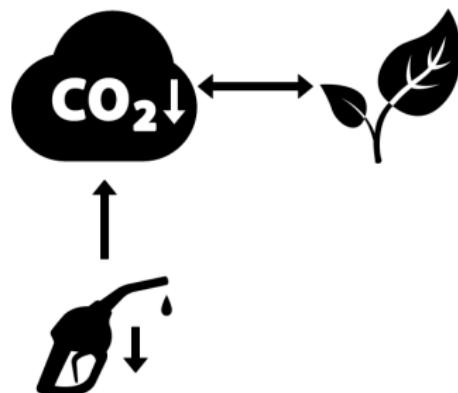
MOTIVATION

- Most polluting means of transportation,
- Responsible for 3% of CO_2 emissions,



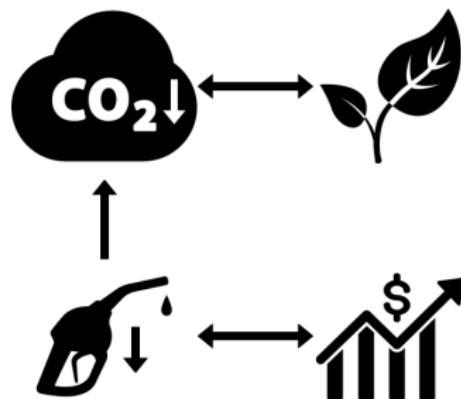
MOTIVATION

- Most polluting means of transportation,
- Responsible for 3% of CO_2 emissions,



MOTIVATION

- Most polluting means of transportation,
- Responsible for 3% of CO_2 emissions,
- Fuel \simeq 30% of an airline operational cost,



MOTIVATION

How to tackle this problem ?

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- 1 New hardware ?

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- 1 New hardware ?
- 2 **Better use of existing fleet,**

MOTIVATION

How to tackle this problem ?

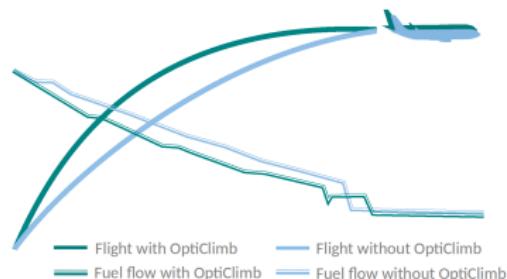
- 1 New hardware ?
- 2 **Better use of existing fleet,**
 - Climb is the most consuming flight phase...

MOTIVATION

How to tackle this problem ?

- 1 New hardware ?
- 2 Better use of existing fleet,

- Climb is the most consuming flight phase...
- Mostly rectilinear trajectories at full thrust,

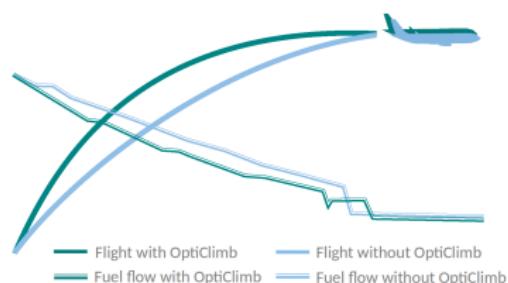


MOTIVATION

How to tackle this problem ?

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- 2 Better use of existing fleet,

- Climb is the most consuming flight phase...
- Mostly rectilinear trajectories at full thrust,
- Thousands of variables recorded every second,

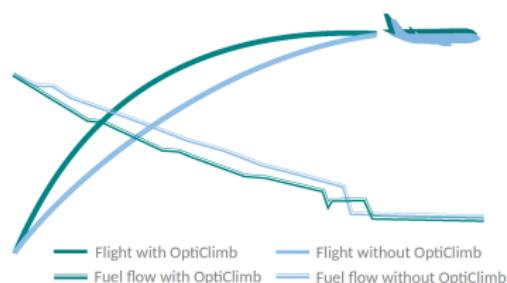


MOTIVATION

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OPTICLIMB



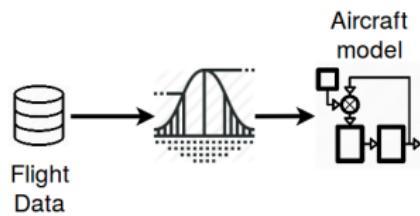
Flight
Data

Time



Many days before flight...

OPTICLIMB

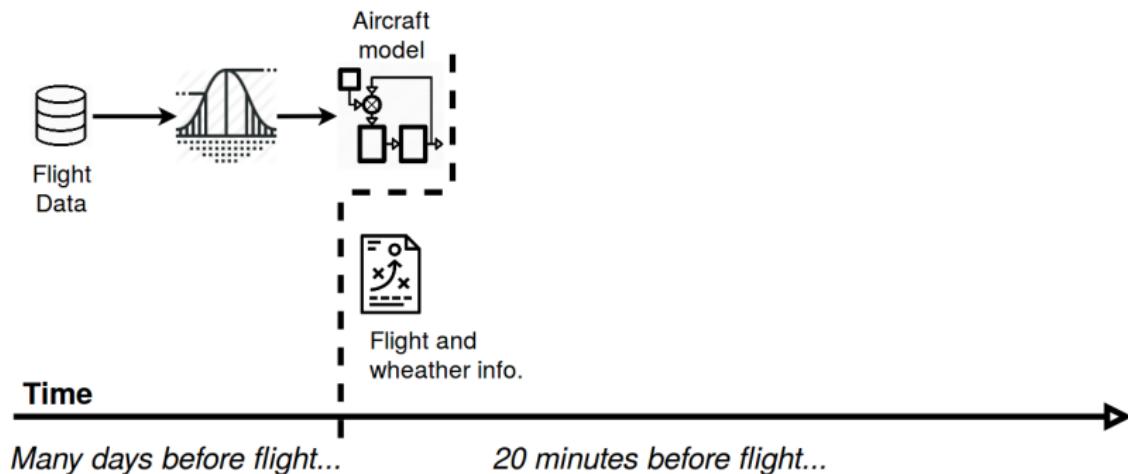


Time

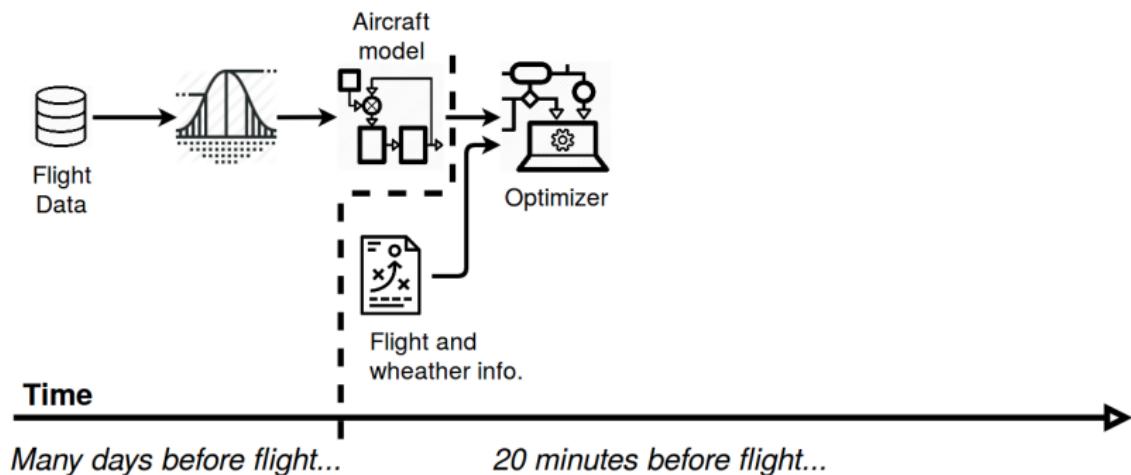


Many days before flight...

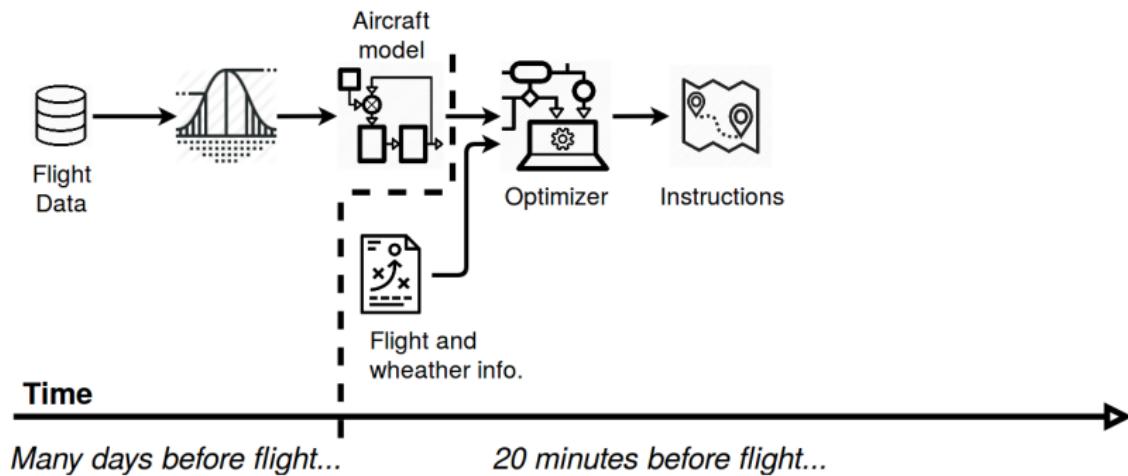
OPTICLIMB



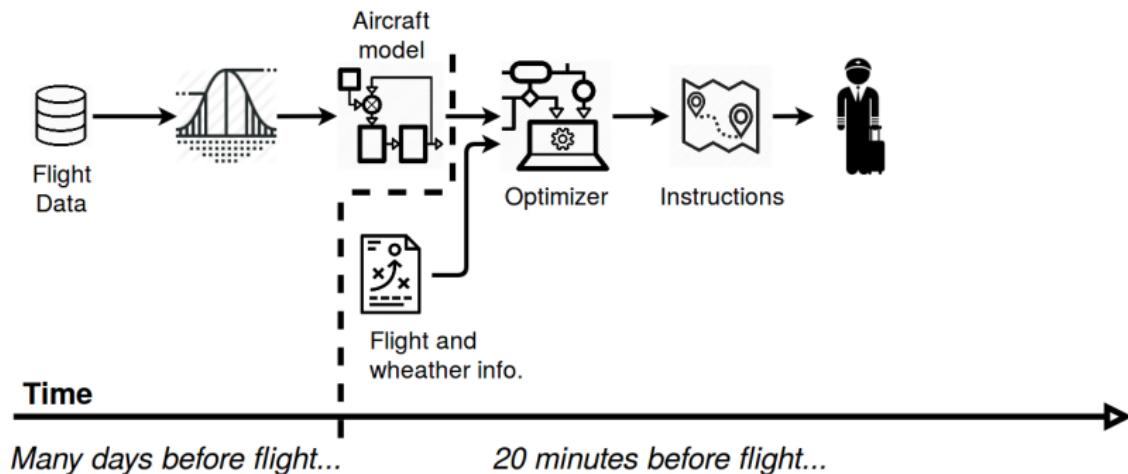
OPTICLIMB



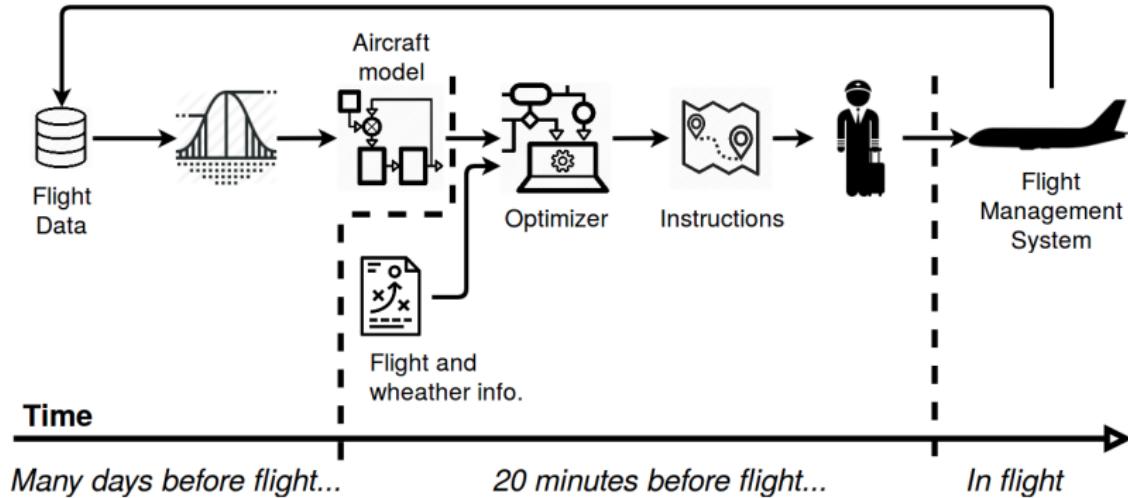
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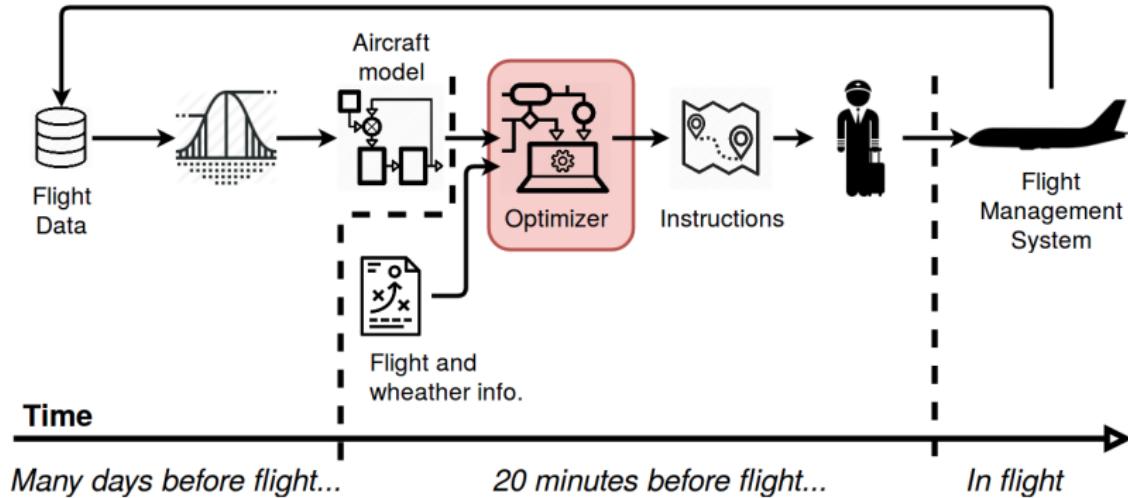
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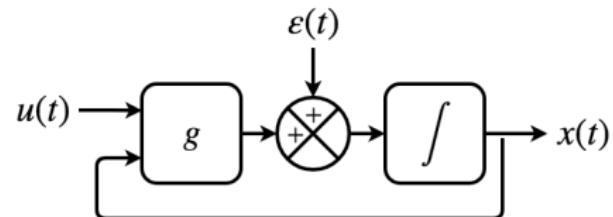
OPTICLIMB



TRAJECTORY OPTIMIZATION

Dynamics:

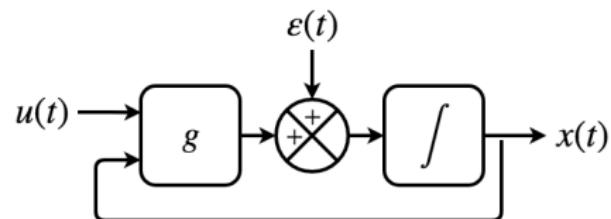
$$\dot{x}(t) = g(\mathbf{u}(t), \mathbf{x}(t)) + \varepsilon(t)$$



TRAJECTORY OPTIMIZATION

Dynamics:

$$\dot{x}(t) = g(\mathbf{u}(t), \mathbf{x}(t)) + \varepsilon(t)$$

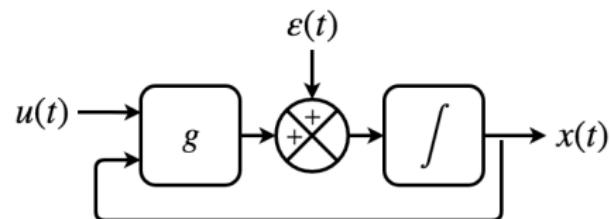


Optimization objective: $\int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt$

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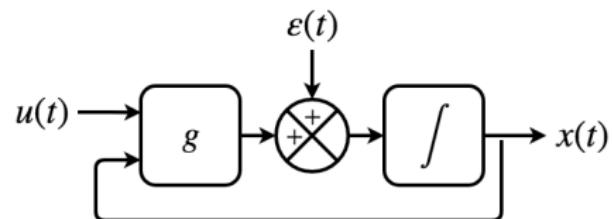


Optimization objective: $\int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt \Leftarrow \text{min}$,

TRAJECTORY OPTIMIZATION

Dynamics:

$$\dot{x}(t) = g(\mathbf{u}(t), \mathbf{x}(t)) + \varepsilon(t)$$

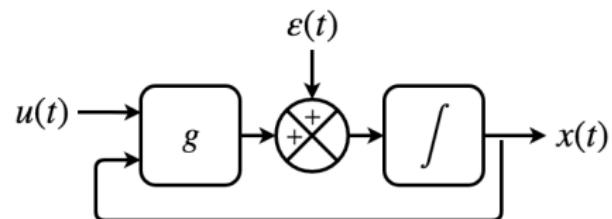


Optimization objective: $\int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt \Leftarrow \text{↗, } \text{📍, } \text{⌚️}$

TRAJECTORY OPTIMIZATION

Dynamics:

$$\dot{x}(t) = g(\mathbf{u}(t), \mathbf{x}(t)) + \varepsilon(t)$$



Optimization objective: $\int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt \Leftarrow \text{fuel}, \text{path}, \text{time}$

Flight constraints:

$$\begin{cases} \Phi(\mathbf{x}(0), \mathbf{x}(t_f)) \in K_\Phi \\ \mathbf{u}(t) \in U_{ad}, \quad \mathbf{x}(t) \in X_{ad}, \\ c(\mathbf{u}(t), \mathbf{x}(t)) \leq 0, \end{cases}$$

Initial and final conditions
Flight domain
Operational path constraints

TRAJECTORY OPTIMIZATION

OPTIMAL CONTROL PROBLEM

$$\begin{aligned} & \min_{(\mathbf{x}, \mathbf{u}) \in \mathbb{X} \times \mathbb{U}} \int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt, \\ \text{s.t. } & \left\{ \begin{array}{ll} \dot{\mathbf{x}}(t) = g(\mathbf{u}(t), \mathbf{x}(t)) + \varepsilon(t), & \text{a.e. } t \in [0, t_f], \\ \Phi(\mathbf{x}(0), \mathbf{x}(t_f)) \in K_\Phi, & \\ \mathbf{u}(t) \in U_{ad}, \quad \mathbf{x}(t) \in X_{ad}, & \text{a.e. } t \in [0, t_f], \\ c(\mathbf{u}(t), \mathbf{x}(t)) \leq 0, & \text{a.e. } t \in [0, t_f]. \end{array} \right. \end{aligned} \quad (\text{OCP})$$

TRAJECTORY OPTIMIZATION

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TRAJECTORY OPTIMIZATION

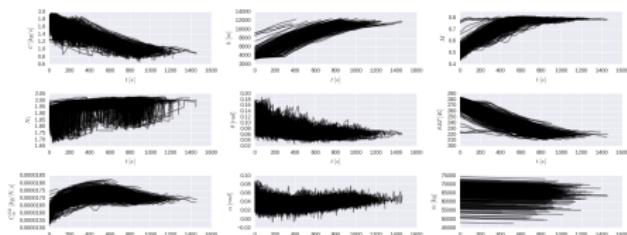
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SYSTEM IDENTIFICATION



Black box



QAR data

TRAJECTORY OPTIMIZATION

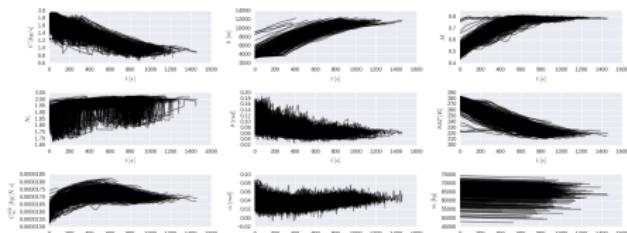
APPROXIMATE OPTIMAL CONTROL PROBLEM

$$\begin{aligned} & \min_{(\mathbf{x}, \mathbf{u}) \in \mathbb{X} \times \mathbb{U}} \int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt, \\ \text{s.t. } & \left\{ \begin{array}{ll} \dot{\mathbf{x}}(t) = \hat{\mathbf{g}}(\mathbf{u}(t), \mathbf{x}(t)), & \text{a.e. } t \in [0, t_f], \\ \Phi(\mathbf{x}(0), \mathbf{x}(t_f)) \in K_\Phi, & \\ \mathbf{u}(t) \in U_{ad}, \quad \mathbf{x}(t) \in X_{ad}, & \text{a.e. } t \in [0, t_f], \\ c(\mathbf{u}(t), \mathbf{x}(t)) \leq 0, & \text{a.e. } t \in [0, t_f]. \end{array} \right. \end{aligned} \quad (\text{A OCP})$$

SYSTEM IDENTIFICATION

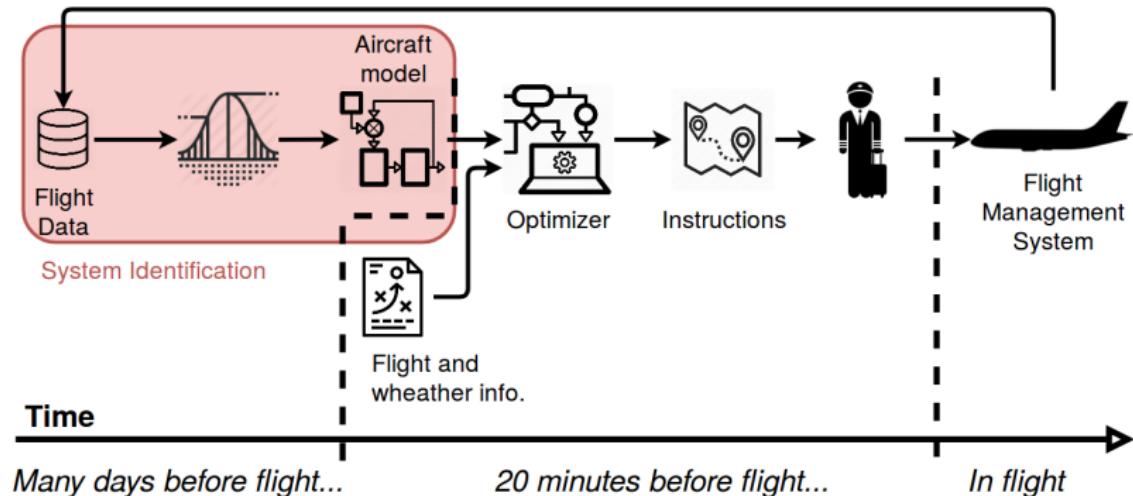


Black box



QAR data

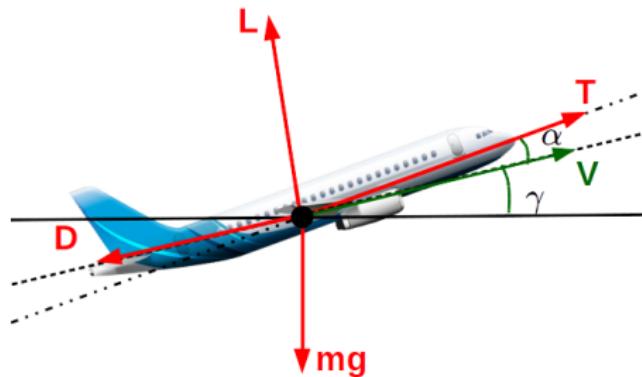
SYSTEM IDENTIFICATION



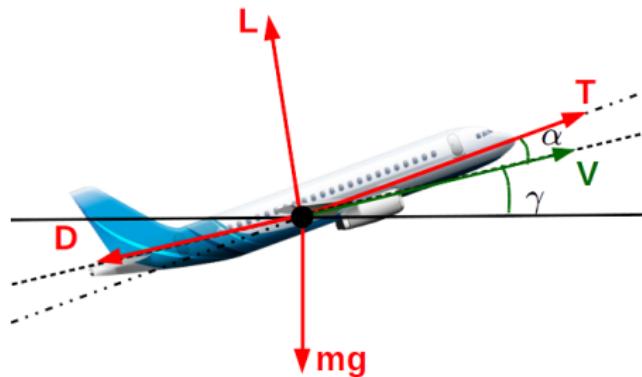
- 1** Context - *Chapter 1*
- 2** System Identification - *Chapter 4*
- 3** Trajectory Acceptability - *Chapters 5 and 6*

SYSTEM IDENTIFICATION

FLIGHT DYNAMICS

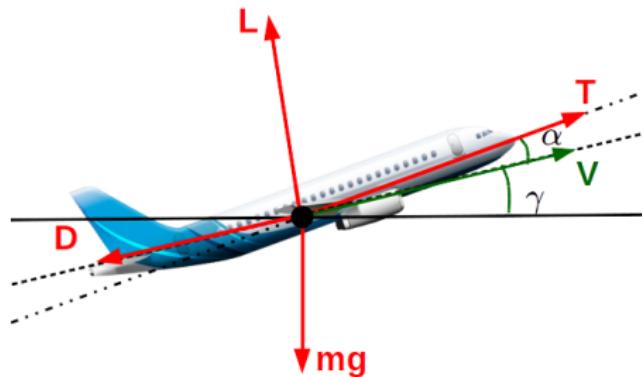


FLIGHT DYNAMICS



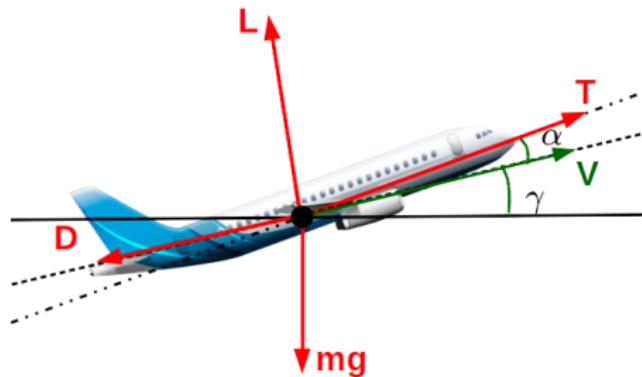
$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T \cos \alpha - D - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T \sin \alpha + L - mg \cos \gamma}{mV} \\ \dot{m} = -\frac{T}{I_{sp}} \end{array} \right.$$

FLIGHT DYNAMICS



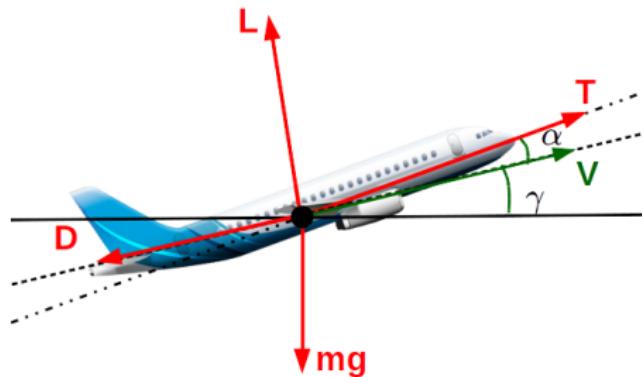
$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma + \dot{W}_z \\ \dot{V} = \frac{T \cos \alpha - D - mg \sin \gamma - m \dot{W}_{xv}}{m} \\ \dot{\gamma} = \frac{(T \sin \alpha + L) \cos \mu - mg \cos \gamma - m \dot{W}_{zv}}{mV} \\ \dot{m} = -\frac{T}{I_{sp}} \end{array} \right.$$

FLIGHT DYNAMICS



$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T \cos \alpha - D - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T \sin \alpha + L - mg \cos \gamma}{mV} \\ \dot{m} = -\frac{T}{I_{sp}} \end{array} \right.$$

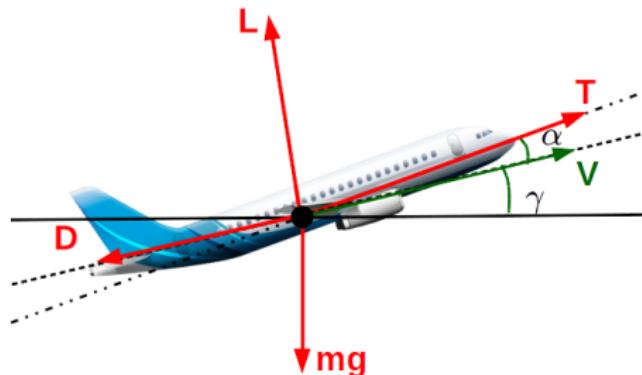
FLIGHT DYNAMICS



States: $x = (h, V, \gamma, m)$

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T \cos \alpha - D - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T \sin \alpha + L - mg \cos \gamma}{mV} \\ \dot{m} = -\frac{T}{I_{sp}} \end{array} \right.$$

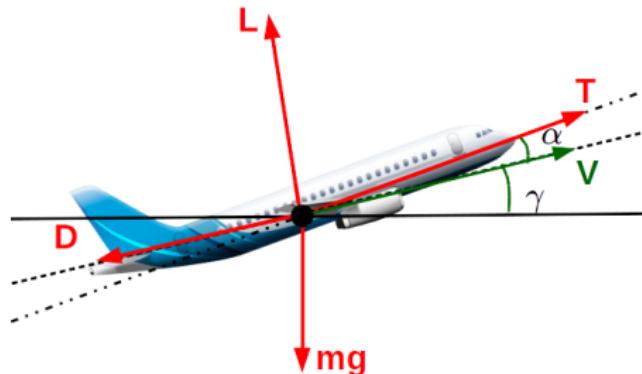
FLIGHT DYNAMICS



States: $x = (h, V, \gamma, m)$
Controls: $u = (\alpha, N_1)$

$$\begin{cases} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T \cos \alpha - D - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T \sin \alpha + L - mg \cos \gamma}{mV} \\ \dot{m} = -\frac{T}{I_{sp}} \end{cases}$$

FLIGHT DYNAMICS



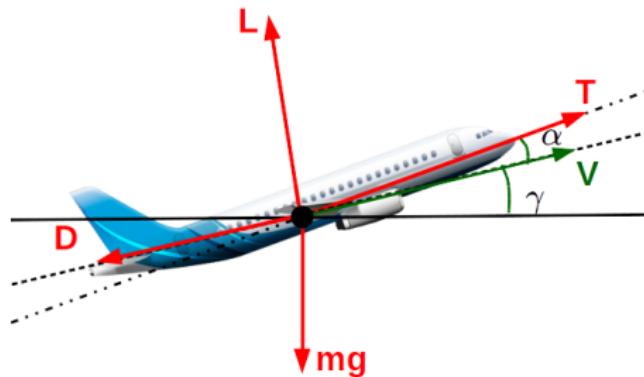
States: $x = (h, V, \gamma, m)$

Controls: $u = (\alpha, N_1)$

Unknown functions of x, u

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FLIGHT DYNAMICS



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$$\begin{cases} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T(u, x) \cos \alpha - D(u, x) - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T(u, x) \sin \alpha + L(u, x)}{mV} - mg \cos \gamma \\ \dot{m} = -\frac{T(u, x)}{I_{sp}(u, x)} \end{cases}$$

PHYSICAL MODELS OF NESTED FUNCTIONS

$$\begin{cases} T \text{ function of } (N_1, M, \rho) \\ D \text{ function of } (q, M, \alpha) \\ L \text{ function of } (q, M, \alpha) \\ I_{sp} \text{ function of } (SAT, M, h) \end{cases}$$

PHYSICAL MODELS OF NESTED FUNCTIONS

$$\left\{ \begin{array}{l} T \text{ function of } (N_1, M, \rho) = \varphi_T(\mathbf{x}, \mathbf{u}) \\ D \text{ function of } (q, M, \alpha) = \varphi_D(\mathbf{x}, \mathbf{u}) \\ L \text{ function of } (q, M, \alpha) = \varphi_L(\mathbf{x}, \mathbf{u}) \\ I_{sp} \text{ function of } (SAT, M, h) = \varphi_{I_{sp}}(\mathbf{x}, \mathbf{u}) \end{array} \right.$$

PHYSICAL MODELS OF NESTED FUNCTIONS

$$\begin{cases} T(\mathbf{x}, \mathbf{u}, \quad) = N_1 \times P_T(\rho, M) \\ D(\mathbf{x}, \mathbf{u}, \quad) = q \times P_D(\alpha, M) \\ L(\mathbf{x}, \mathbf{u}, \quad) = q \times P_L(\alpha, M) \\ I_{sp}(\mathbf{x}, \mathbf{u}, \quad) = SAT \times P_{Isp}(h, M) \end{cases}$$

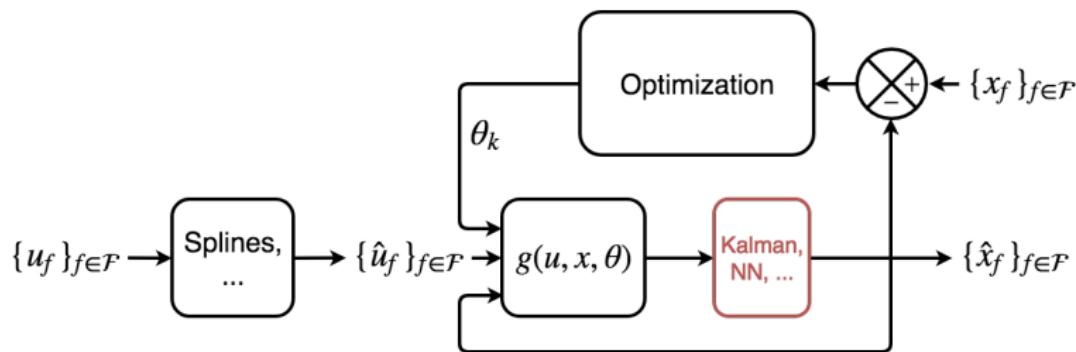
PHYSICAL MODELS OF NESTED FUNCTIONS

$$\left\{ \begin{array}{l} T(\mathbf{x}, \mathbf{u}, \boldsymbol{\theta}_T) = N_1 \times P_T(\rho, M) = X_T \cdot \boldsymbol{\theta}_T \\ D(\mathbf{x}, \mathbf{u}, \boldsymbol{\theta}_D) = q \times P_D(\alpha, M) = X_D \cdot \boldsymbol{\theta}_D \\ L(\mathbf{x}, \mathbf{u}, \boldsymbol{\theta}_L) = q \times P_L(\alpha, M) = X_L \cdot \boldsymbol{\theta}_L \\ I_{sp}(\mathbf{x}, \mathbf{u}, \boldsymbol{\theta}_{Isp}) = SAT \times P_{Isp}(h, M) = X_{Isp} \cdot \boldsymbol{\theta}_{Isp} \end{array} \right.$$

$$X_T = N_1 \begin{pmatrix} 1 \\ \rho \\ M \\ \rho^2 \\ \rho M \\ M^2 \\ \vdots \end{pmatrix}, X_D = X_L = q \begin{pmatrix} 1 \\ \alpha \\ M \\ \alpha^2 \\ \alpha M \\ M^2 \\ \vdots \end{pmatrix}, X_{Isp} = SAT \begin{pmatrix} 1 \\ h \\ M \\ h^2 \\ hM \\ M^2 \\ \vdots \end{pmatrix}.$$

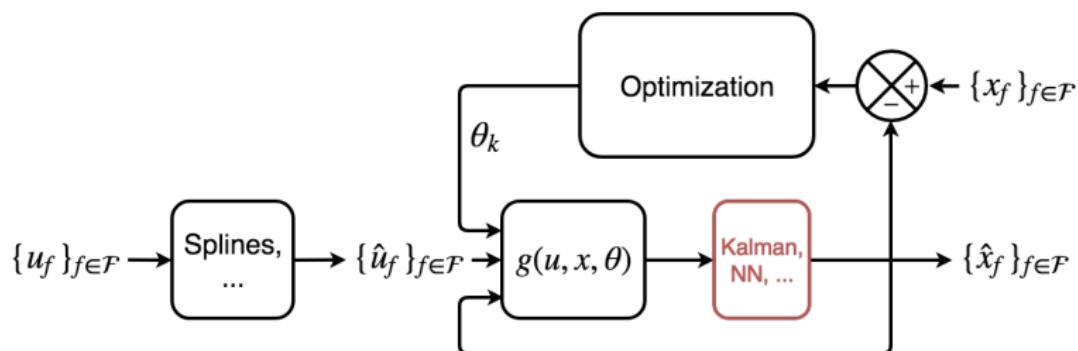
STATE-OF-THE-ART - [JATEGAONKAR, 2006]

- Output-Error Method
- Filter-Error Method



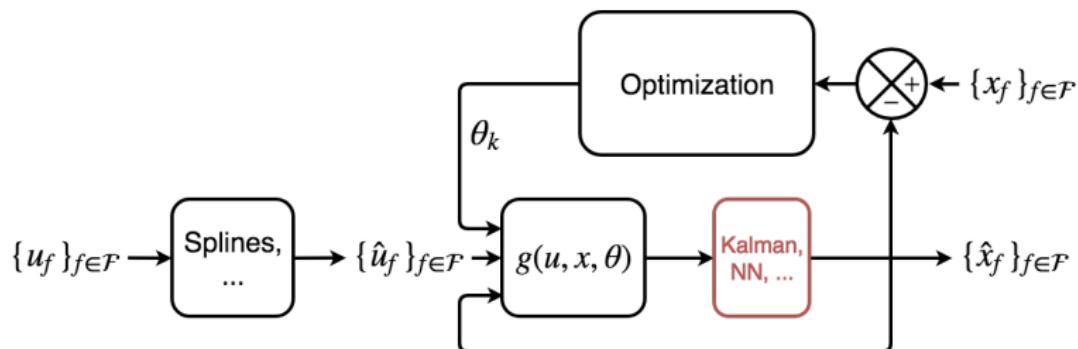
STATE-OF-THE-ART - [JATEGAONKAR, 2006]

- Output-Error Method
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- } Less scalable to many trajectories



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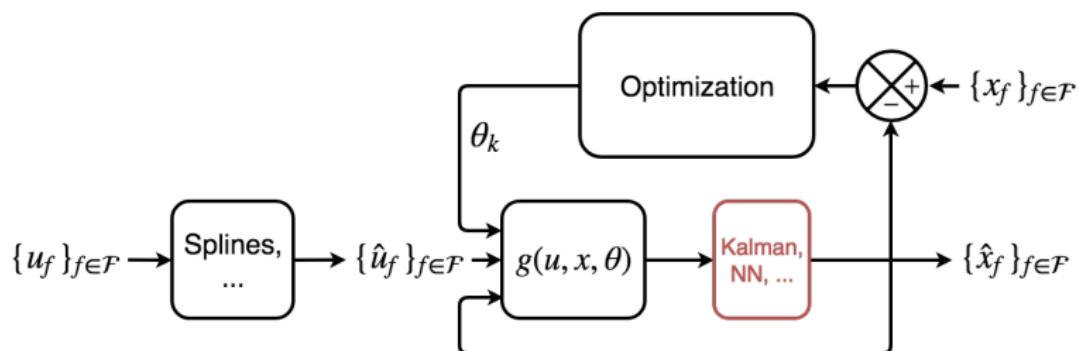


■ Equation-Error Method

$$\dot{\mathbf{x}}(t) = g(\mathbf{u}(t), \mathbf{x}(t), \boldsymbol{\theta}) + \varepsilon(t), \quad t \in [0, t_f]$$

STATE-OF-THE-ART - [JATEGAONKAR, 2006]

- Output-Error Method
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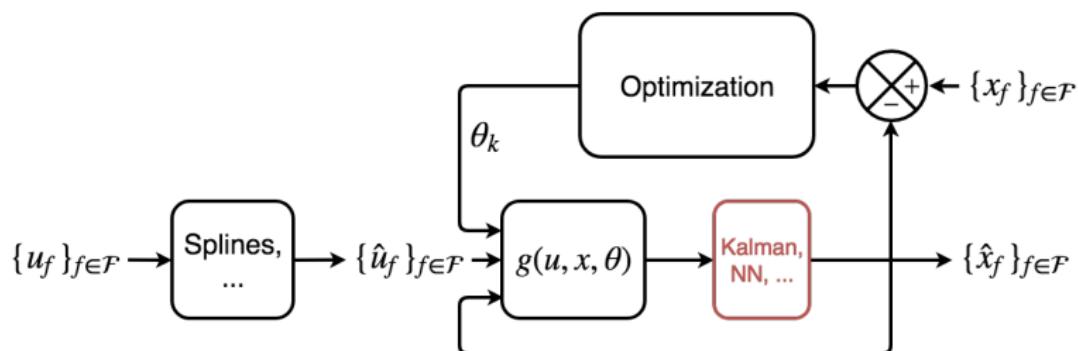


■ Equation-Error Method

$$\dot{x}_i = g(\mathbf{u}_i, \mathbf{x}_i, \boldsymbol{\theta}) + \varepsilon_i, \quad i = 1, \dots, N$$

STATE-OF-THE-ART - [JATEGAONKAR, 2006]

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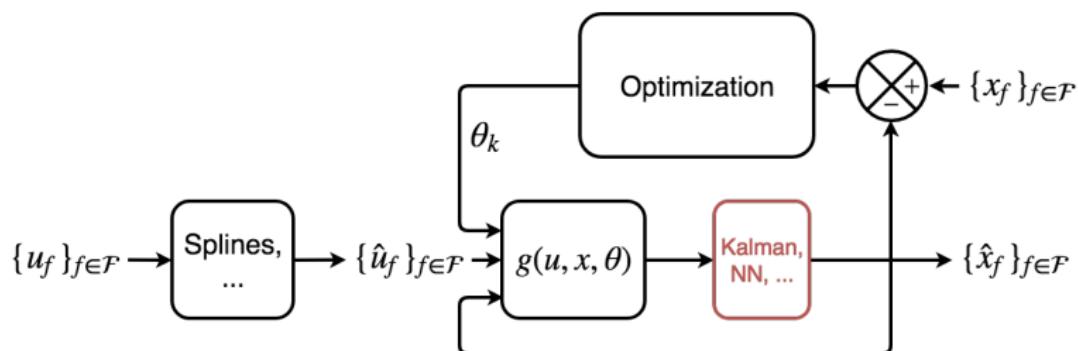


- **Equation-Error Method**

$$\min_{\theta} \sum_{i=1}^N \ell(\dot{x}_i, g(\mathbf{u}_i, \mathbf{x}_i, \theta))$$

STATE-OF-THE-ART - [JATEGAONKAR, 2006]

- Output-Error Method
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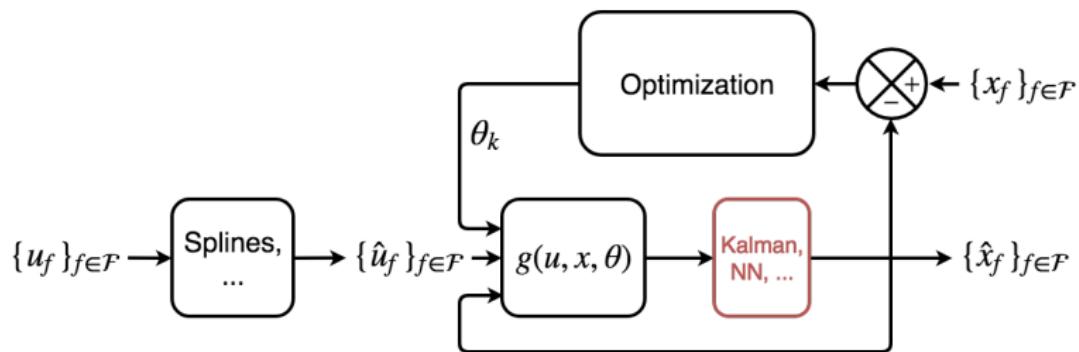


- **Equation-Error Method** Ex: *(Nonlinear) Least-Squares*

$$\min_{\theta} \sum_{i=1}^N \left\| \dot{x}_i - g(\mathbf{u}_i, \mathbf{x}_i, \theta) \right\|_2^2$$

STATE-OF-THE-ART - [JATEGAONKAR, 2006]

- Output-Error Method
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- **Equation-Error Method** Ex: *(Nonlinear) Least-Squares*

$$\min_{\theta} \sum_{i=1}^N \left\| Y(\mathbf{u}_i, \mathbf{x}_i, \dot{\mathbf{x}}_i) - G(\mathbf{u}_i, \mathbf{x}_i, \dot{\mathbf{x}}_i, \theta) \right\|_2^2$$

LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ \dot{V} = \frac{T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T) \cos \alpha - D(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_D) - mg \sin \gamma}{m} \\ \dot{\gamma} = \frac{T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T) \sin \alpha + L(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_L) - mg \cos \gamma}{mV} \\ \dot{m} = -\frac{T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T)}{I_{sp}(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_{Isp})} \end{array} \right.$$

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- Nonlinear in states and controls

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- Nonlinear in states and controls
- Nonlinear in parameters

LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ m\dot{V} + mg \sin \gamma = T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T) \cos \alpha - D(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_D) \\ mV\dot{\gamma} + mg \cos \gamma = T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T) \sin \alpha + L(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_L) \\ 0 = T(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_T) + \dot{m}l_{sp}(\mathbf{u}, \mathbf{x}, \boldsymbol{\theta}_{lsp}) \end{array} \right.$$

- Nonlinear in states and controls
- Nonlinear in parameters

LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ m\dot{V} + mg \sin \gamma = (X_T \cdot \theta_T) \cos \alpha - X_D \cdot \theta_D + \varepsilon_1 \\ mV\dot{\gamma} + mg \cos \gamma = (X_T \cdot \theta_T) \sin \alpha + X_L \cdot \theta_L + \varepsilon_2 \\ 0 = X_T \cdot \theta_T + \dot{m}(X_{Isp} \cdot \theta_{Isp}) + \varepsilon_3 \end{array} \right.$$

$$\overbrace{Y(\mathbf{u}, \mathbf{x}, \dot{\mathbf{x}})} \quad \overbrace{G(\mathbf{u}, \mathbf{x}, \dot{\mathbf{x}}, \boldsymbol{\theta})}$$

- Nonlinear in states and controls
- ~~Nonlinear in parameters~~ → Linear in parameters

LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ m\dot{V} + mg \sin \gamma = (\mathbf{X}_T \cdot \boldsymbol{\theta}_T) \cos \alpha - X_D \cdot \boldsymbol{\theta}_D + \varepsilon_1 \\ mV\dot{\gamma} + mg \cos \gamma = (\mathbf{X}_T \cdot \boldsymbol{\theta}_T) \sin \alpha + X_L \cdot \boldsymbol{\theta}_L + \varepsilon_2 \\ 0 = X_T \cdot \boldsymbol{\theta}_T + \dot{m}(\mathbf{X}_{Isp} \cdot \boldsymbol{\theta}_{Isp}) + \varepsilon_3 \end{array} \right.$$

$$\overbrace{Y(\mathbf{u}, \mathbf{x}, \dot{\mathbf{x}})} \quad \overbrace{G(\mathbf{u}, \mathbf{x}, \dot{\mathbf{x}}, \boldsymbol{\theta})}$$

- Nonlinear in states and controls
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LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{Ispm} \cdot \theta_{Isp} + \varepsilon_3 \end{array} \right.$$

- Nonlinear in states and controls
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- Nonlinear in states and controls
- ~~Nonlinear in parameters~~ → Linear in parameters
- Structured
- Coupling

LEVERAGING THE DYNAMICS STRUCTURE

$$\left\{ \begin{array}{l} \dot{h} = V \sin \gamma \\ Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{Ispm} \cdot \theta_{Isp} + \varepsilon_3 \end{array} \right.$$

- Nonlinear in states and controls
- ~~Nonlinear in parameters~~ → Linear in parameters
- Structured
- Coupling ↪ **Multi-task Learning**

MULTI-TASK REGRESSION

Aircraft:

$$\begin{cases} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{lspm} \cdot \theta_{lsp} + \varepsilon_3 \end{cases}$$

General:

$$\begin{cases} Y_1 = X_{c,1} \cdot \theta_c + X_1 \cdot \theta_1 + \varepsilon_1 \\ Y_2 = X_{c,2} \cdot \theta_c + X_2 \cdot \theta_2 + \varepsilon_2 \\ \vdots \\ Y_K = X_{c,K} \cdot \theta_c + X_K \cdot \theta_K + \varepsilon_K \end{cases}$$

Coupling parameters, **Task specific parameters**

Many other examples:

- *Giant squid neurons* [FitzHugh, 1961, Nagumo et al., 1962],
- *Susceptible-infectious-recovered models* [Anderson and May, 1992],
- *Mechanical systems*,...

MULTI-TASK REGRESSION

Aircraft:

$$\begin{cases} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{lspm} \cdot \theta_{lsp} + \varepsilon_3 \end{cases}$$

General:

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Coupling parameters , Task specific parameters

Multi-task Linear Least-Squares:

$$\min_{\theta} \sum_{k=1}^K \sum_{i=1}^N (Y_{k,i} - X_{c,k,i} \cdot \theta_c - X_{k,i} \cdot \theta_k)^2$$

MULTI-TASK REGRESSION

Aircraft:

$$\begin{cases} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{lspm} \cdot \theta_{lsp} + \varepsilon_3 \end{cases}$$

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Coupling parameters , Task specific parameters

Multi-task Linear Least-Squares:

$$\min_{\theta} \sum_{i=1}^N \|Y_i - X_i \theta\|_2^2$$

with $\theta = (\theta_c, \theta_1, \dots, \theta_K) \in \mathbb{R}^p$, $p = d_c + \sum_{k=1}^K d_k$,
 $Y_i \in \mathbb{R}^K$ and $X_i \in \mathbb{R}^{K \times p}$.

MULTI-TASK REGRESSION

Aircraft:

$$\begin{cases} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ Y_3 = X_T \cdot \theta_T + X_{lspm} \cdot \theta_{lsp} + \varepsilon_3 \end{cases}$$

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$$\begin{cases} Y_1 = X_{c,1} \cdot \theta_c + X_1 \cdot \theta_1 + \varepsilon_1 \\ Y_2 = X_{c,2} \cdot \theta_c + X_2 \cdot \theta_2 + \varepsilon_2 \\ \vdots \quad \vdots \\ Y_K = X_{c,K} \cdot \theta_c + X_K \cdot \theta_K + \varepsilon_K \end{cases}$$

Coupling parameters, **Task specific parameters**

Multi-task Linear Least-Squares:

Block-sparse Coupling Structure

$$\min_{\theta} \sum_{i=1}^N \left\| \begin{pmatrix} Y_{1,i} \\ \vdots \\ Y_{K,i} \end{pmatrix} - \begin{pmatrix} X_{c,1,i}^\top & X_{1,i}^\top & 0 & 0 & \dots & 0 \\ X_{c,2,i}^\top & 0 & X_{2,i}^\top & 0 & \dots & 0 \\ \vdots & 0 & 0 & \ddots & 0 & 0 \\ X_{c,K,i}^\top & 0 & 0 & \dots & 0 & X_{K,i}^\top \end{pmatrix} \begin{pmatrix} \theta_c \\ \theta_1 \\ \vdots \\ \theta_K \end{pmatrix} \right\|_2^2$$

FEATURE SELECTION

Our model:

$$T = N_1(\theta_{T,1} + \theta_{T,2}\rho + \theta_{T,3}M + \theta_{T,4}\rho^2 + \theta_{T,5}\rho M + \theta_{T,6}M^2 + \theta_{T,7}\rho^3 + \theta_{T,8}\rho^2M + \theta_{T,9}\rho M^2 + \theta_{T,10}M^3 + \theta_{T,11}\rho^4 + \theta_{T,12}\rho^3M + \theta_{T,13}\rho^2M^2 + \theta_{T,14}\rho M^3 + \theta_{T,15}M^4).$$

Mattingly's model [Mattingly et al., 1992]:

$$T = N_1(\theta_{T,1}\rho + \theta_{T,2}\rho M^3).$$

FEATURE SELECTION

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⇒ High risk of overfitting

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Our (sparse) model:

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Mattingly's model [Mattingly et al., 1992]:

$$T = N_1(\theta_{T,1}\rho + \theta_{T,2}\rho M^3).$$

Sparse models are:

- Less susceptible to overfitting,
- More compliant with physical models,
- More interpretable,
- Lighter/Faster.

BLOCK-SPARSE LASSO

Lasso [Tibshirani, 1994]: $\{(X_i, Y_i)\}_{i=1}^N \subset \mathbb{R}^{d+1}$ i.i.d sample,

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^N (Y_i - X_i \cdot \boldsymbol{\theta})^2 + \lambda \|\boldsymbol{\theta}\|_1.$$

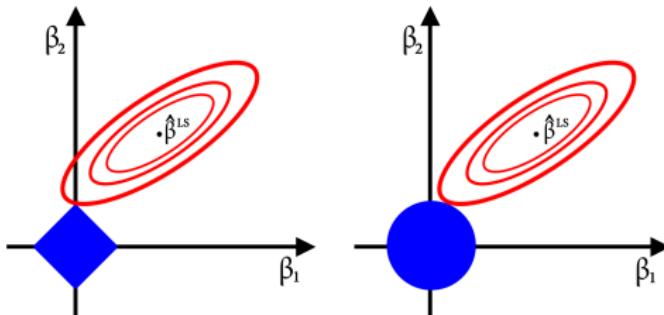


FIGURE: 1 Sparsity induced by L^1 norm in Lasso.

BLOCK-SPARSE LASSO

$$\min_{\boldsymbol{\theta}} \sum_{k=1}^K \sum_{i=1}^N (Y_{k,i} - X_{c,k,i} \cdot \boldsymbol{\theta}_c - X_{k,i} \cdot \boldsymbol{\theta}_k)^2 + \lambda_c \|\boldsymbol{\theta}_c\|_1 + \sum_{k=1}^K \lambda_k \|\boldsymbol{\theta}_k\|_1$$

BLOCK-SPARSE LASSO

Block-sparse structure preserved \rightsquigarrow **Equivalent to Lasso problem**

$$\min_{\boldsymbol{\theta}} \sum_{k=1}^K \sum_{i=1}^N (Y_{k,i} - X_{c,k,i} \cdot \boldsymbol{\theta}_c - X_{k,i} \cdot \boldsymbol{\theta}_k)^2 + \lambda_c \|\boldsymbol{\theta}_c\|_1 + \sum_{k=1}^K \lambda_k \|\boldsymbol{\theta}_k\|_1$$

BLOCK-SPARSE LASSO

Block-sparse structure preserved \rightsquigarrow **Equivalent to Lasso problem**

$$\min_{\beta} \sum_{i=1}^N \|Y_i - B_i\beta\|_2^2 + \lambda_c \|\beta\|_1$$

with $\beta = (\boldsymbol{\theta}_c, \frac{\lambda_1}{\lambda_c} \boldsymbol{\theta}_1, \dots, \frac{\lambda_K}{\lambda_c} \boldsymbol{\theta}_K) \in \mathbb{R}^p$, $p = d_c + \sum_{k=1}^K d_k$,
 $Y_i \in \mathbb{R}^K$ and $B_i \in \mathbb{R}^{K \times p}$.

BLOCK-SPARSE LASSO

Block-sparse structure preserved \rightsquigarrow **Equivalent to Lasso problem**

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^N \|Y_i - X_i \boldsymbol{\theta}\|_2^2 + \lambda_c \|\boldsymbol{\theta}\|_1$$

with $\boldsymbol{\theta} = (\boldsymbol{\theta}_c, \boldsymbol{\theta}_1, \dots, \boldsymbol{\theta}_K) \in \mathbb{R}^p$, $p = d_c + \sum_{k=1}^K d_k$,
 $Y_i \in \mathbb{R}^K$ and $X_i \in \mathbb{R}^{K \times p}$,

In practice, we choose $\lambda_k = \lambda_c$, for all $k = 1, \dots, 3$ and

$$X_i = \begin{pmatrix} X_{T1,i}^\top & -X_{D,i}^\top & 0 & 0 \\ X_{T2,i}^\top & 0 & X_{L,i}^\top & 0 \\ X_{T,i}^\top & 0 & 0 & X_{Ispm,i}^\top \end{pmatrix}, \quad Y_i = \begin{pmatrix} Y_{1,i} \\ Y_{2,i} \\ Y_{3,i} \end{pmatrix}$$

BOOTSTRAP IMPLEMENTATION

High correlations between features...

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⇒ **Inconsistent selections via the lasso !**

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Bolasso - Bach [2008]

training data $\mathcal{T} = \{(X_i, Y_i)\}_{i=1}^N \subset \mathbb{R}^{K \times (K+1)} \times \mathbb{R}^K$,

Require: number of bootstrap replicates b ,

L^1 penalty parameter λ_c ,

- 1: **for** $k = 1$ **to** b **do**
 - 2: Generate bootstrap sample \mathcal{T}_k ,
 - 3: Compute Block sparse Lasso estimate $\hat{\theta}^k$ from \mathcal{T}_k ,
 - 4: Compute support $J_k = \{j, \hat{\theta}_j^k \neq 0\}$,
 - 5: **end for**
 - 6: Compute intersection $J = \bigcap_{k=1}^b J_k$,
 - 7: Compute $\hat{\theta}_J$ from selected features using Least-Squares.
-

BOOTSTRAP IMPLEMENTATION

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- Consistency even under high correlations proved in Bach [2008],

BOOTSTRAP IMPLEMENTATION

High correlations between features...
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Bolasso - Bach [2008]

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-

- Consistency even under high correlations proved in Bach [2008],
- Efficient implementations exist: LARS [Efron et al., 2004].

PROBLEM WITH INTRA-GROUP CORRELATIONS

$$\min_{\theta} \sum_{i=1}^N \|Y_i - X_i \theta\|_2^2 + \lambda_c \|\theta\|_1 \Rightarrow \hat{\theta}_T = \hat{\theta}_{Ispl} = 0!$$

PROBLEM WITH INTRA-GROUP CORRELATIONS

$$\min_{\theta} \sum_{i=1}^N \|Y_i - X_i \theta\|_2^2 + \lambda_c \|\theta\|_1 \Rightarrow \hat{\theta}_T = \hat{\theta}_{Ispl} = 0!$$

$$\begin{cases} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ 0 = X_T \cdot \theta_T + X_{Ispl} \cdot \theta_{Ispl} + \varepsilon_3 \end{cases}$$

PROBLEM WITH INTRA-GROUP CORRELATIONS

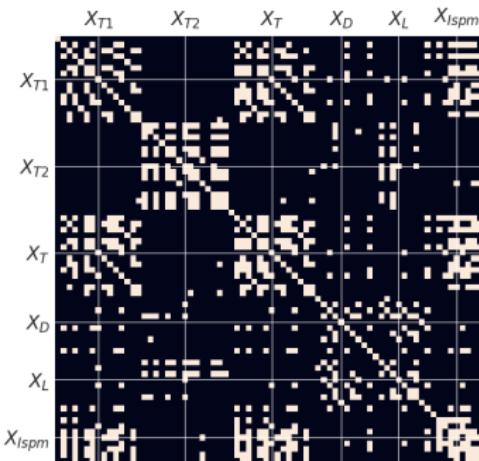
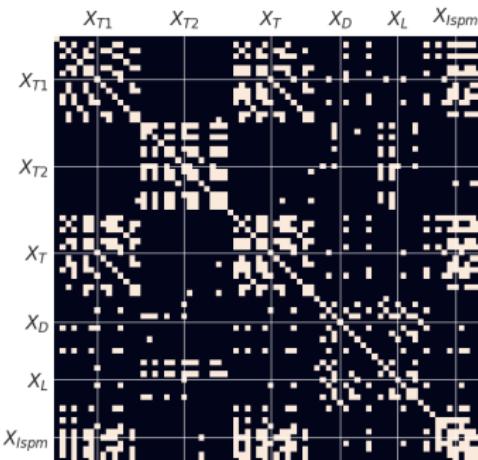


FIGURE: Features correlations
higher than 0.9 in absolute
value in white.

PROBLEM WITH INTRA-GROUP CORRELATIONS



$\Rightarrow \theta \mapsto \sum_{i=1}^N \|Y_i - X_i\theta\|_2^2$ not injective...

III-posed problem !

FIGURE: Features correlations higher than 0.9 in absolute value in white.

PROBLEM WITH INTRA-GROUP CORRELATIONS

$$\left\{ \begin{array}{l} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ 0 = X_T \cdot \theta_T + X_{Ispm} \cdot \theta_{Isp} + \varepsilon_3 \end{array} \right.$$

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^N \|Y_i - X_i \boldsymbol{\theta}\|_2^2 + \lambda_c \|\boldsymbol{\theta}\|_1$$

Prior model \tilde{l}_{sp} from Roux [2005] $\rightsquigarrow \tilde{l}_{sp,i} = \tilde{l}_{sp}(\mathbf{u}_i, \mathbf{x}_i)$, $i = 1, \dots, N$.

PROBLEM WITH INTRA-GROUP CORRELATIONS

$$\left\{ \begin{array}{l} Y_1 = X_{T1} \cdot \theta_T - X_D \cdot \theta_D + \varepsilon_1 \\ Y_2 = X_{T2} \cdot \theta_T + X_L \cdot \theta_L + \varepsilon_2 \\ 0 = X_T \cdot \theta_T + X_{Ispm} \cdot \theta_{Isp} + \varepsilon_3 \end{array} \right.$$

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^N \left(\|Y_i - X_i \boldsymbol{\theta}\|_2^2 + \lambda_t \|\tilde{I}_{sp,i} - X_{Isp,i} \cdot \boldsymbol{\theta}_{Isp}\|_2^2 \right) + \lambda_c \|\boldsymbol{\theta}\|_1$$

Prior model \tilde{I}_{sp} from Roux [2005] $\rightsquigarrow \tilde{I}_{sp,i} = \tilde{I}_{sp}(\mathbf{u}_i, \mathbf{x}_i)$, $i = 1, \dots, N$.

PROBLEM WITH INTRA-GROUP CORRELATIONS

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$$\min_{\theta} \sum_{i=1}^N \left(\|Y_i - X_i \theta\|_2^2 + \lambda_t \|\tilde{I}_{sp,i} - X_{Isp,i} \cdot \theta_{Isp}\|_2^2 \right) + \lambda_c \|\theta\|_1$$

Prior model \tilde{I}_{sp} from Roux [2005] $\rightsquigarrow \tilde{I}_{sp,i} = \tilde{I}_{sp}(\mathbf{u}_i, \mathbf{x}_i)$, $i = 1, \dots, N$.

PROBLEM WITH INTRA-GROUP CORRELATIONS

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$$\min_{\theta} \sum_{i=1}^N \| \tilde{Y}_i - \tilde{X}_i \theta \|_2^2 + \lambda_c \|\theta\|_1$$

$$\tilde{Y}_i = \begin{pmatrix} Y_{1,i} \\ Y_{2,i} \\ 0 \\ \sqrt{\lambda_t} \tilde{I}_{sp,i} \end{pmatrix}, \quad \tilde{X}_i = \begin{pmatrix} X_{T1,i}^\top & -X_{D,i}^\top & 0 & 0 \\ X_{T2,i}^\top & 0 & X_{L,i}^\top & 0 \\ X_{T,i}^\top & 0 & 0 & X_{Ispm,i}^\top \\ 0 & 0 & 0 & \sqrt{\lambda_t} X_{Isp,i}^\top \end{pmatrix},$$

Prior model \tilde{I}_{sp} from Roux [2005] $\rightsquigarrow \tilde{I}_{sp,i} = \tilde{I}_{sp}(\mathbf{u}_i, \mathbf{x}_i)$, $i = 1, \dots, N$.

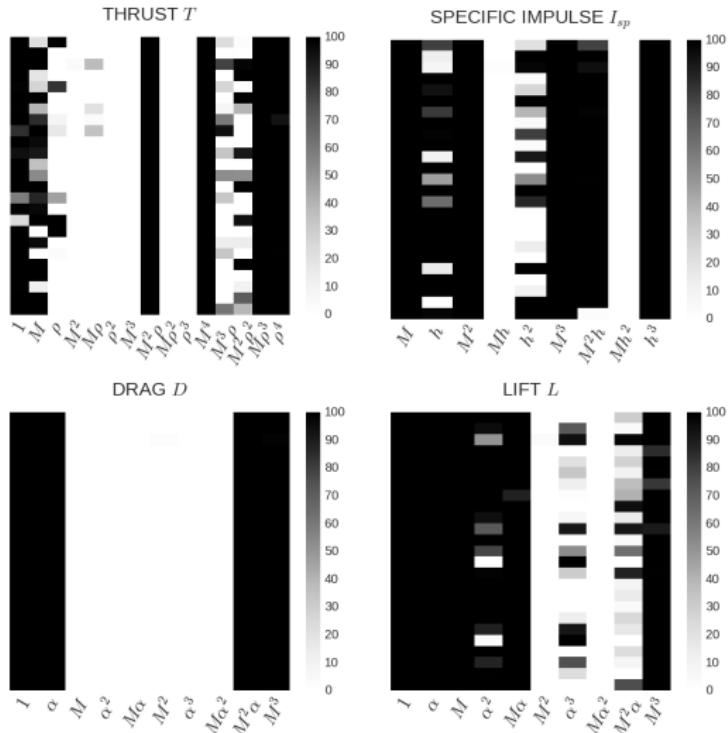
FEATURE SELECTION RESULTS

- 25 different B737-800,
- 10 471 flights = 8 261 619 observations,

FEATURE SELECTION RESULTS

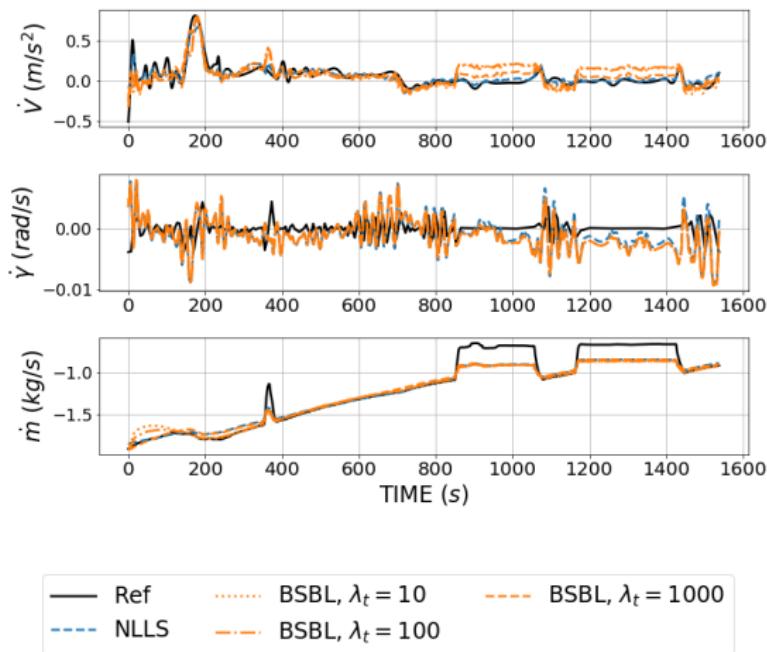
- 25 different B737-800,
- 10 471 flights = 8 261 619 observations,
- Block sparse Bolasso used for T , D , L and I_{sp} ,
- We expect similar model structures,

FEATURE SELECTION RESULTS

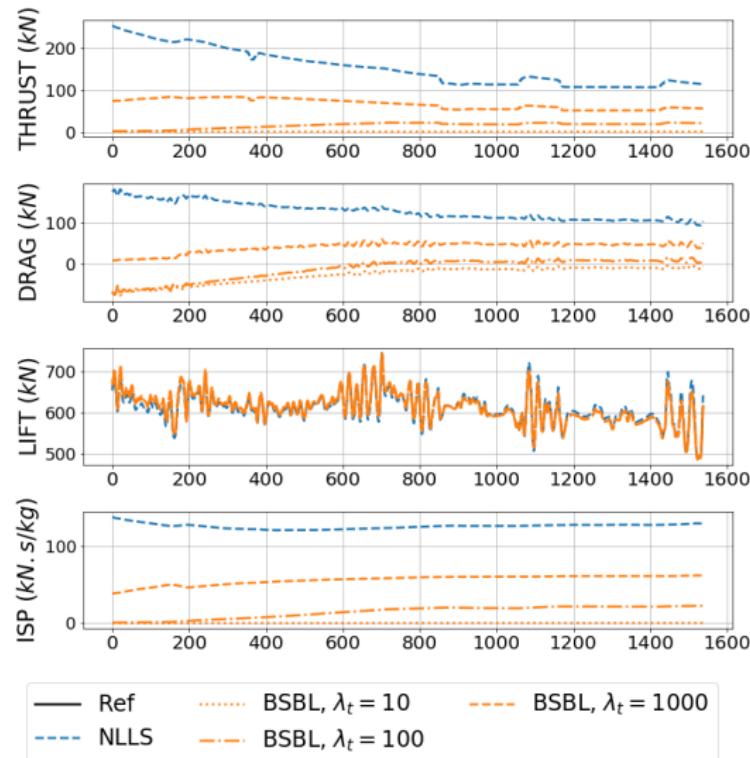


Feature selection results for the thrust, drag, lift and specific impulse models.

ACCURACY OF DYNAMICS PREDICTIONS



REALISM OF HIDDEN ELEMENTS



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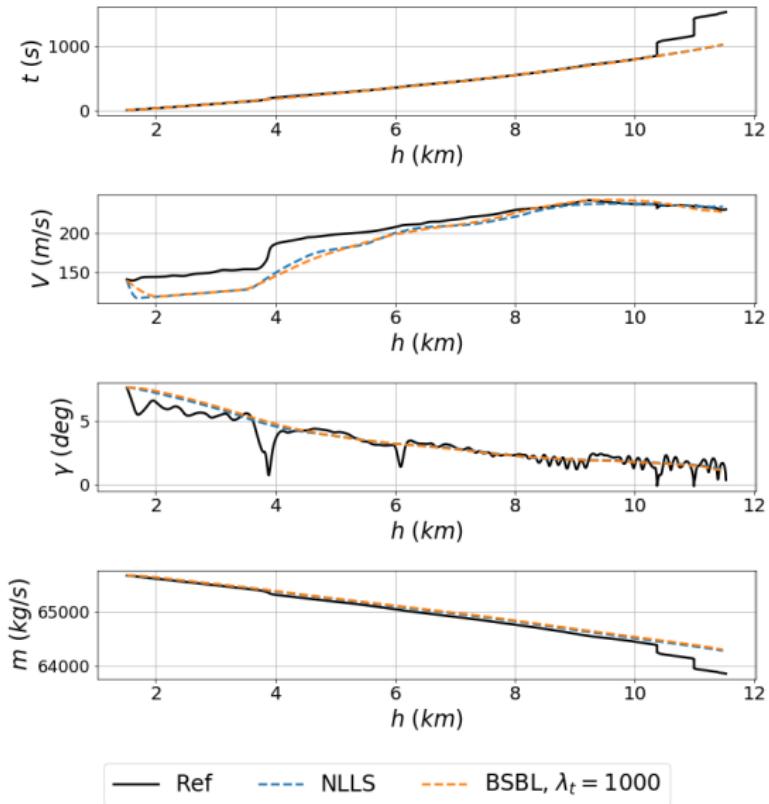
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For practical applications: $t \leftrightarrow h$

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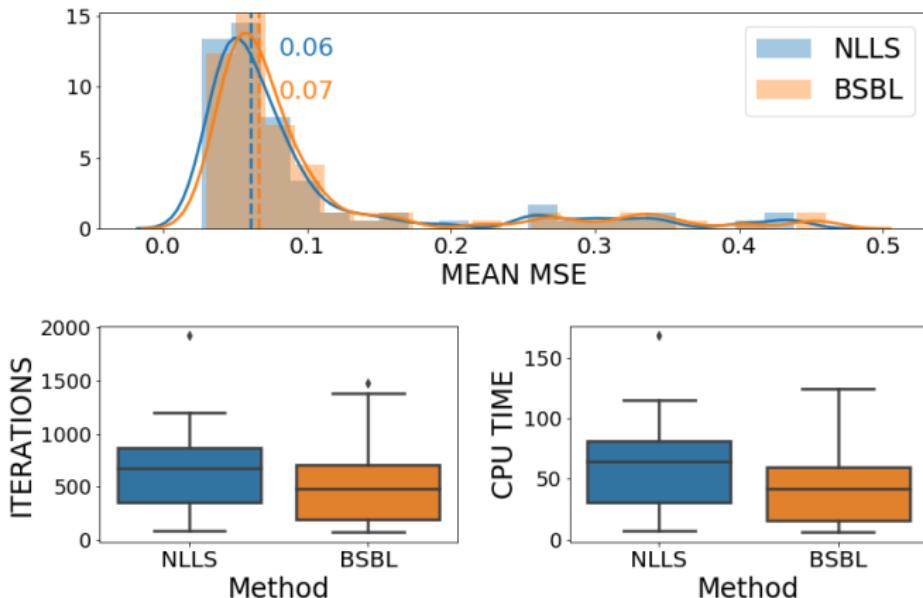


FIGURE: Distribution of the off-sample simulation error and boxplot of the optimization number of iterations and CPU time.

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TRAJECTORY ACCEPTABILITY

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Air Traffic Control²

How can we quantify the closeness from the optimized trajectory to the set of real flights?

OPTIMIZED TRAJECTORY LIKELIHOOD

Assumption: We suppose that the real flights are observations of the same functional random variable $Z = (Z_t)$ valued in $\mathcal{C}(\mathbb{T}, E)$, with E compact subset of \mathbb{R}^d and $\mathbb{T} = [0, t_f]$.

How likely is it to draw the optimized trajectory from the law of Z ?

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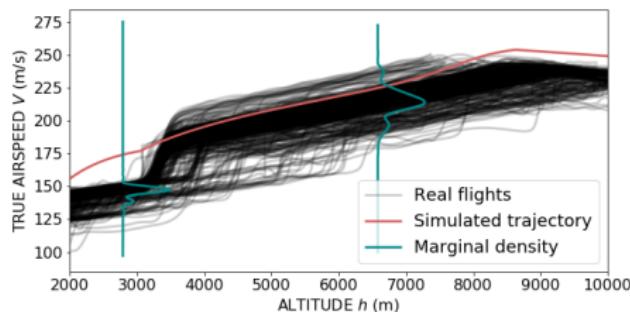
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- Standard approach in Functional Data Analysis: use Functional Principal Component Analysis to decompose the data in a small number of coefficients
- Or: we can use the marginal densities



HOW DO WE AGGREGATE THE MARGINAL LIKELIHOODS?

- f_t marginal density of Z , i.e. probability density function of Z_t ,
- \mathbf{y} new trajectory,
- $f_t(\mathbf{y}(t))$ marginal likelihood of \mathbf{y} at t , i.e. likelihood of observing $Z_t = \mathbf{y}(t)$.

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$$\text{MML}(Z, \mathbf{y}) = \frac{1}{t_f} \int_0^{t_f} \psi[f_t, \mathbf{y}(t)] dt,$$

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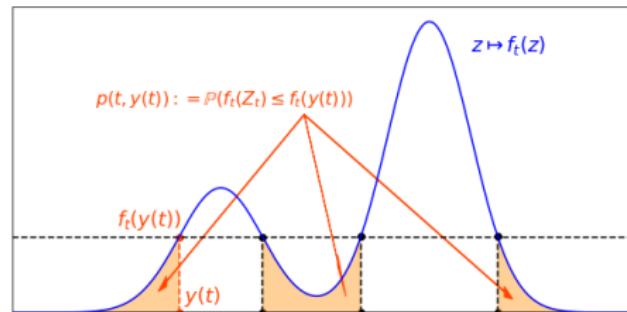
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HOW DO WE DEAL WITH SAMPLED CURVES?

In practice, the m trajectories are sampled at variable discrete times:

$$\mathcal{T}^D := \{(t_j^r, z_j^r)\}_{\substack{1 \leq j \leq n \\ 1 \leq r \leq m}} \subset \mathbb{T} \times E, \quad z_j^r := \mathbf{z}^r(t_j^r),$$

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Hence, we approximate the MML using a Riemann sum which aggregates consistent estimators $\hat{f}_{\tilde{t}_j}^m$ of the marginal densities $f_{\tilde{t}_j}$:

$$\text{EMML}_m(\mathcal{T}^D, \mathcal{Y}) := \frac{1}{t_f} \sum_{j=1}^{\tilde{n}} \psi[\hat{f}_{\tilde{t}_j}^m, y_j] \Delta \tilde{t}_j.$$

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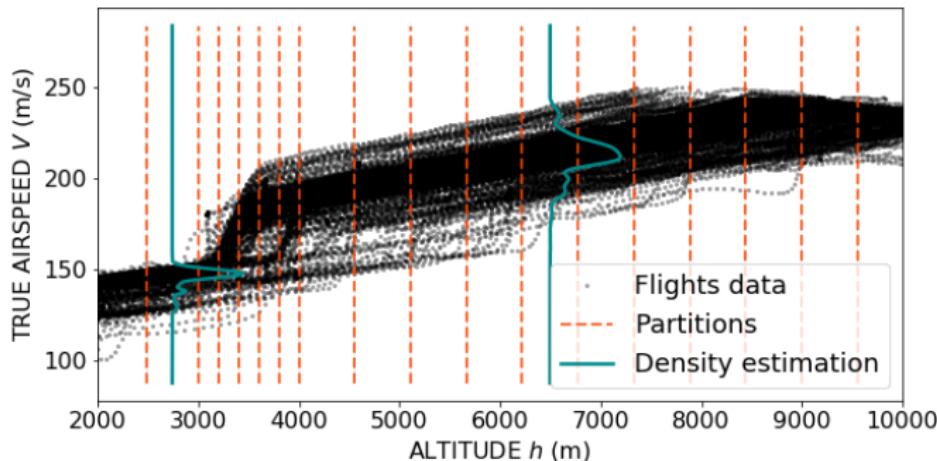
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 - 2 **We can use a fine partitioning of the time domain.**

PARTITION BASED MARGINAL DENSITY ESTIMATION



Idea: to average in time the marginal densities over small bins by applying classical multivariate density estimation techniques to each subset.

CONSISTENCY

We denote by:

- $\Theta : \mathcal{S} \rightarrow L^1(E, \mathbb{R}_+)$ multivariate density estimation statistic,
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$\nu \in L^\infty(E, \mathbb{R}_+)$ density function of T , s.t.

$$\nu_+ := \text{ess} \sup_{t \in \mathbb{T}} \nu(t) < \infty, \quad \nu_- := \text{ess} \inf_{t \in \mathbb{T}} \nu(t) > 0.$$

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ASSUMPTION 3 - SHRINKING BINS

The homogeneous partition $\{B_\ell^m\}_{\ell=1}^{q_m}$ of $[0; t_f]$, with binsize b_m , is s.t.

$$\lim_{m \rightarrow \infty} b_m = 0, \quad \lim_{m \rightarrow \infty} mb_m = \infty.$$

CONSISTENCY

ASSUMPTION 4 - I.I.D. CONSISTENCY

- \mathcal{G} arbitrary family of probability density functions on E , $\rho \in \mathcal{G}$,
- S_ρ^N i.i.d sample of size N drawn from ρ valued in \mathcal{S} .

The estimator obtained by applying Θ to S_ρ^N , denoted by

$$\hat{\rho}^N := \Theta[S_\rho^N] \in L^1(E, \mathbb{R}_+),$$

is a (pointwise) consistent density estimator, uniformly in ρ :

For all $z \in E, \varepsilon > 0, \alpha_1 > 0$, there is $N_{\varepsilon, \alpha_1} > 0$ such that, for any $\rho \in \mathcal{G}$,

$$N \geq N_{\varepsilon, \alpha_1} \Rightarrow \mathbb{P} \left(\left| \hat{\rho}^N(z) - \rho(z) \right| < \varepsilon \right) > 1 - \alpha_1.$$

CONSISTENCY

THEOREM 1

Under assumptions 1 to 4, for any $z \in E$ and $t \in \mathbb{T}$, $\hat{f}_{\ell^m(t)}^m(z)$ consistently approximates the marginal density $f_t(z)$ as the number of curves m grows:

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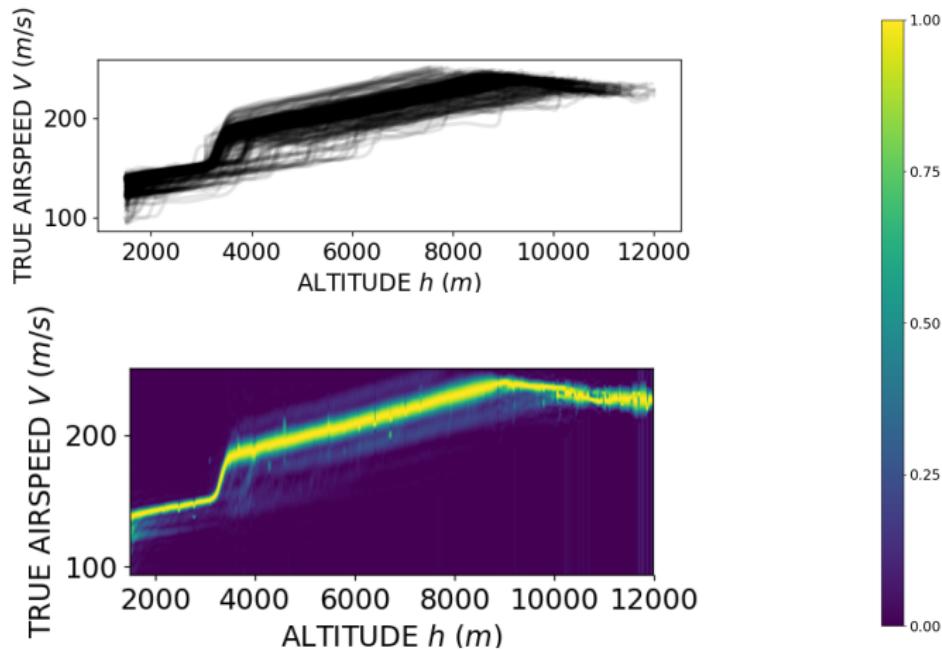
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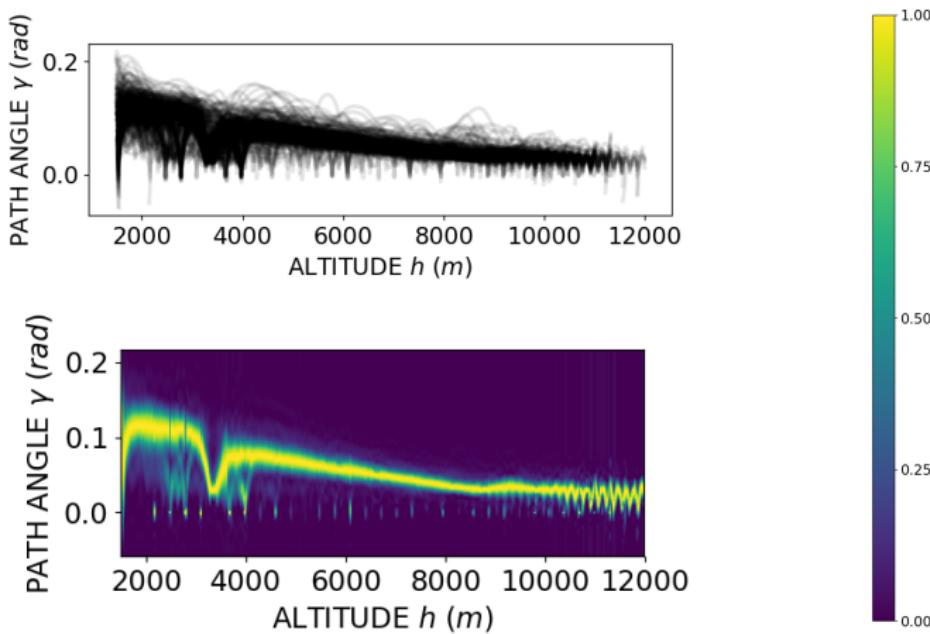
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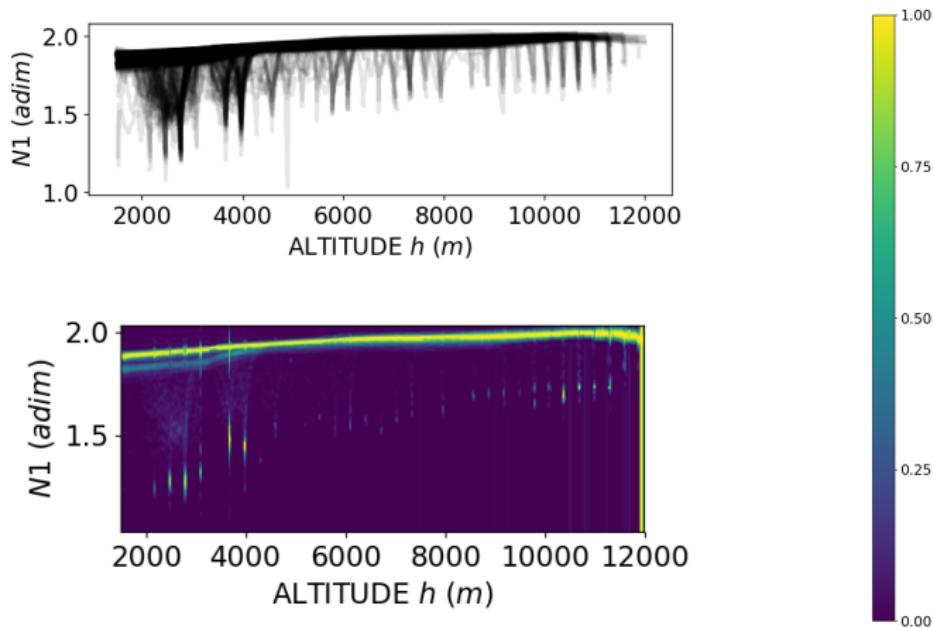
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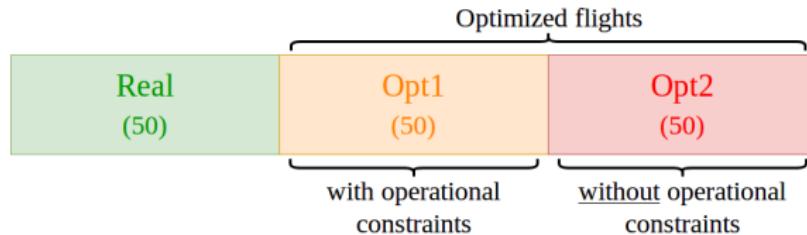
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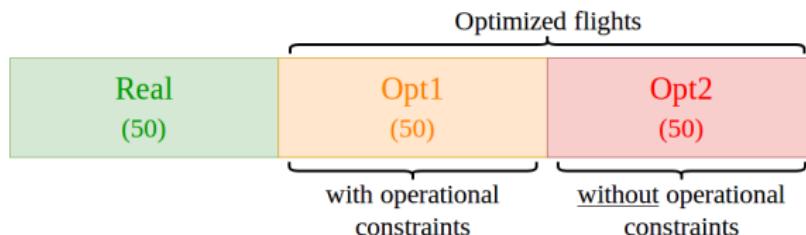
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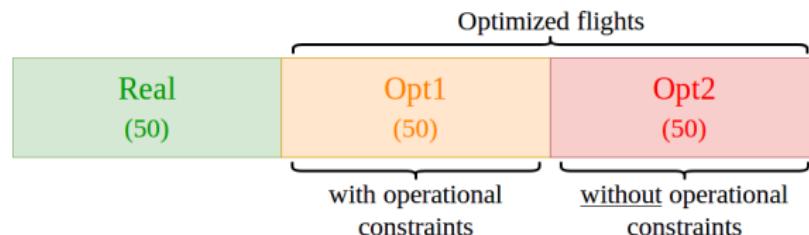


- Discrimination power comparison with (gmm-)FPCA and (integrated) LS-CDE:

VAR.	ESTIMATED LIKELIHOODS		
	REAL	OPT1	OPT2
MML	0.63 ± 0.07	0.43 ± 0.08	0.13 ± 0.02
FPCA	0.16 ± 0.12	$6.4\text{E-}03 \pm 3.8\text{E-}03$	$3.6\text{E-}03 \pm 5.4\text{E-}03$
LS-CDE	0.77 ± 0.05	0.68 ± 0.04	0.49 ± 0.06

HOW GOOD IS IT COMPARED TO OTHER METHODS?

- Training set of $m = 424$ flights $\simeq 334\,531$ point observations,
- Test set of 150 flights



- Discrimination power comparison with (gmm-)FPCA and (integrated) LS-CDE:

VAR.	ESTIMATED LIKELIHOODS			TR. TIME
	REAL	OPT1	OPT2	
MML	0.63 ± 0.07	0.43 ± 0.08	0.13 ± 0.02	5s
FPCA	0.16 ± 0.12	$6.4\text{E-}03 \pm 3.8\text{E-}03$	$3.6\text{E-}03 \pm 5.4\text{E-}03$	20s
LS-CDE	0.77 ± 0.05	0.68 ± 0.04	0.49 ± 0.06	14H

MML PENALTY

The MML can be used not only to assess the optimization solutions, but also to penalize the optimization itself:

$$\begin{aligned} & \min_{(\mathbf{x}, \mathbf{u}) \in \mathbb{X} \times \mathbb{U}} \int_0^{t_f} C(\mathbf{u}(t), \mathbf{x}(t)) dt \\ \text{s.t. } & \left\{ \begin{array}{l} \dot{\mathbf{x}}(t) = \hat{g}(\mathbf{u}(t), \mathbf{x}(t)), \quad \text{a.e. } t \in [0, t_f], \\ \text{Other constraints...} \end{array} \right. \end{aligned} \quad (\text{AOCP})$$

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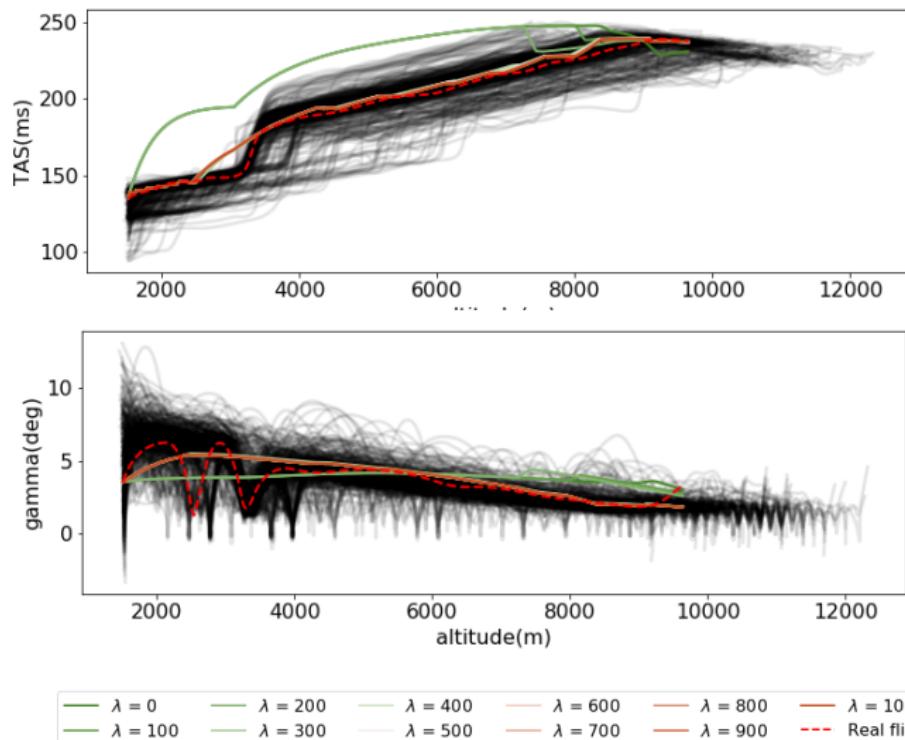
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- λ sets trade-off between a fuel minimization and a likelihood maximization,

PENALTY EFFECT



CONSUMPTION X ACCEPTABILITY TRADE-OFF

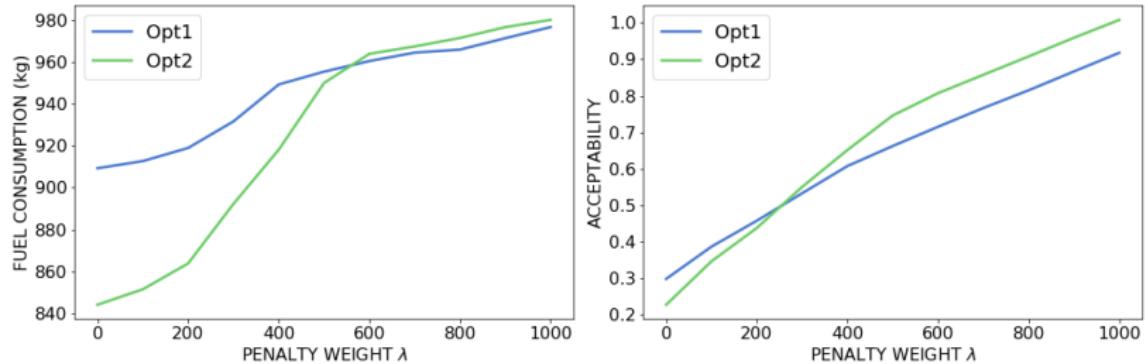


FIGURE: Average over 20 flights of the fuel consumption and MML score (called acceptability here) of optimized trajectories with varying MML-penalty weight λ .

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 - Showed that it can be used in optimal control problems to obtain solutions close to optimal, and still realistic.

THANK YOU FOR YOUR ATTENTION

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