HOW CAN WE INCORPORATE

THE BEATLES

IN LOCAL RATIONAL MODELLING?

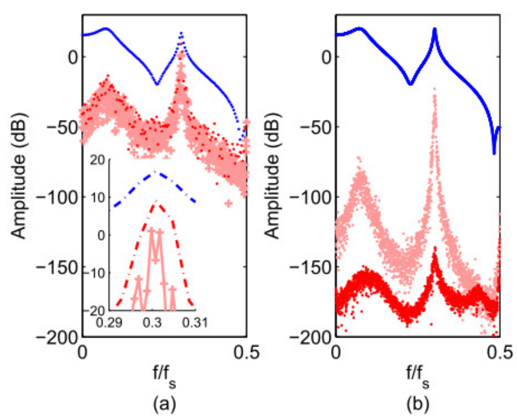
Photo taken by Bruce McBroom

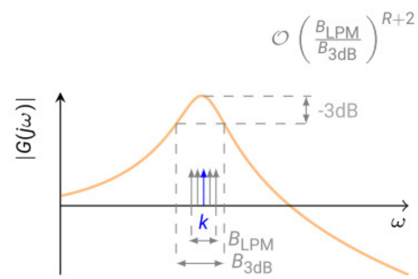
FRF Measurements with local parametric modelling

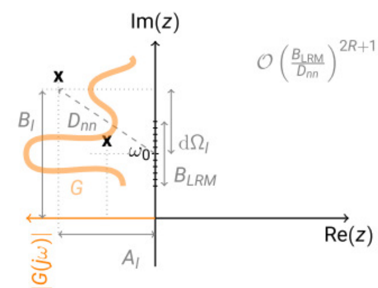
Dieter Verbeke & Johan Schoukens

Polynomial vs. rational:

- Approximation error
- Pole-zero cancellation







VRIJE UNIVERSITEIT BRUSSEL

Finite sample input design for data perturbation methods in linear regression problems

Sándor Kolumbán – Eindhoven University of Technology
Balázs Csanád Csáji – Institute for Computer Science and Control, Hungarian Academy of Sciences

$$Y = X\theta_0 + E$$
$$E \sim f_E(\cdot)$$
$$X = QR$$
$$\theta_0 \in \mathbb{R}^{n_\theta}$$
$$Y, E \in \mathbb{R}^n$$
$$X \in \mathbb{R}^{n \times n_\theta}$$
$$(\mathcal{G}, \cdot) : f_E(x) = f_E(Gx)$$

D-optimal design

$$\mathcal{C}_\alpha \sim \max_X \det(X^T X) = \max_R \det(R^T R)$$

Data perturbation

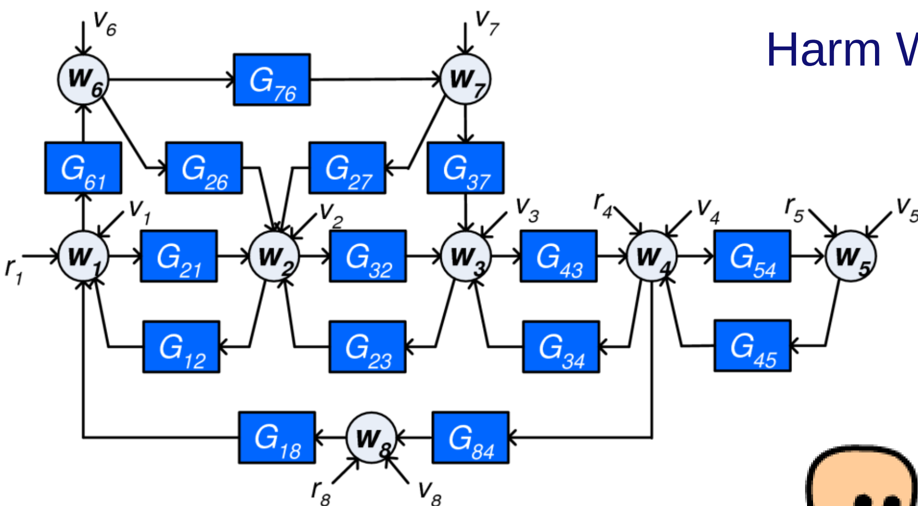
$$\mathcal{C}_\alpha \sim \max_R \det(R^T R) \max_Q \mathbb{E}[\det(I_{n_\theta} - Q^T G^T Q Q^T G Q)]$$

- Input remains optimal in the asymptotic sense
- Improvement in statistical power
- Significant reduction in expected volume (25% on example)

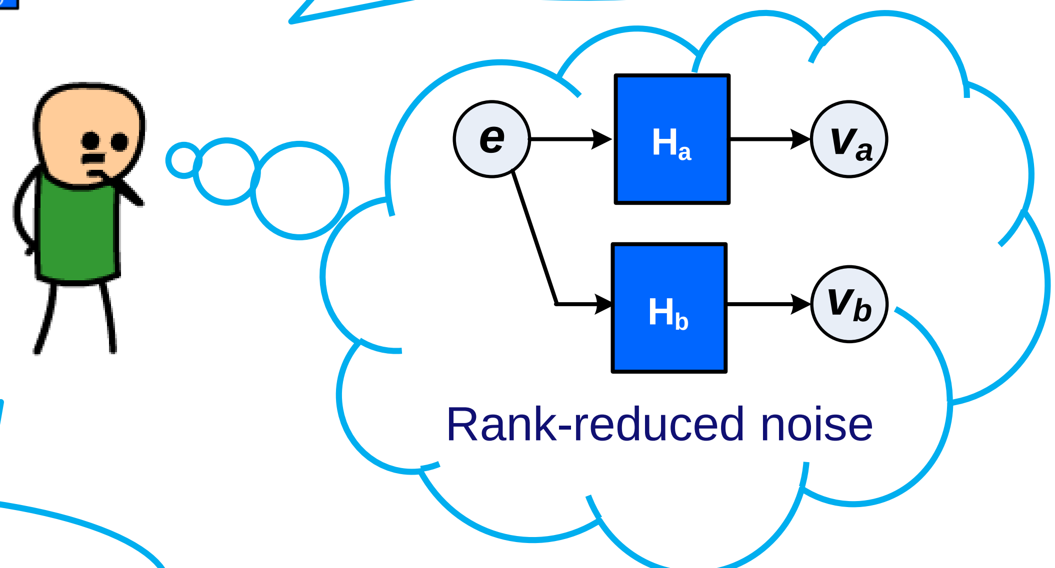
NETWORKS THENETWORKCENTER.NL EURANDOM MTA SZTAKI TU/e Technische Universiteit Eindhoven University of Technology

Maximum likelihood estimation in dynamic networks with rank-reduced noise

Harm Weerts, Paul Van den Hof, Arne Dankers



Why assume noise is full rank?



Generalize maximum likelihood?

Lower bound at 0 variance?

Optimal mass transport priors for large inverse problems

Johan Karlsson
Axel Ringh

KTH Royal Institute of Technology

Use optimal mass transport prior (μ_0) for image reconstruction:

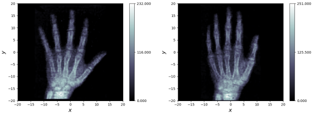
$$\min_{\mu_1} \quad \gamma T_\epsilon(\mu_0, \mu_1) + \|\nabla \mu_1\|_1$$

$$\text{s. t. } \|A\mu_1 - w\|_2 \leq \kappa.$$

- Computationally demanding for large problems (images).

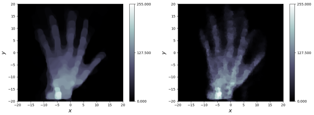
Contribution:

- Methodology for efficient computation of proximal operator of the transport cost.
- Solve optimization problem using first order method.
- Apply to medical imaging (CT).



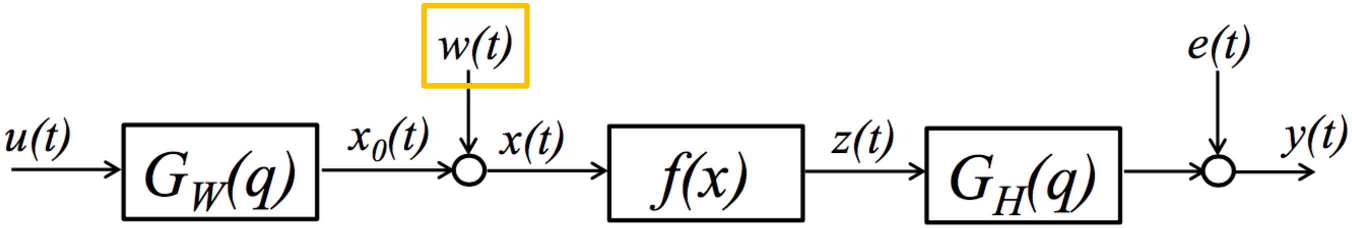
(a) Phantom (b) Prior

Reconstructions:



(c) TV-only (d) Optimal transport + TV

Maximum Likelihood identification of Wiener-Hammerstein systems in presence of process noise



BLA

consistent

Poles/zeros are known

PEM

To find the split

inconsistent

Splitting and parameter estimation via **Maximum Likelihood**

$$p_y(\theta; Z) = \left(\frac{1}{2\pi\sqrt{\sigma_e^2\sigma_w^2}}\right)^N \prod_{t=1}^{N} \int_{-\infty}^{\infty} \mathrm{e}^{-\frac{1}{2}E(x(t),\theta)}\mathrm{d}x(t)$$

Consistent estimate retrieved

Using Linear Predictors and PEMs for Nonlinear Identification

M. Abdalmoaty and H. Hjalmarsson

General nonlinear model: $Y = \mathcal{M}(U, W; \theta^\circ)$

$Y := \begin{bmatrix} y_1 & y_2 \ldots y_N \end{bmatrix}$ a vector of outputs, $U := \begin{bmatrix} u_1 & u_2 \ldots u_N \end{bmatrix}$ a vector of inputs

$W \sim p(W; \theta)$ (unknown) vector of disturbances.

Goal: find an estimator $(Y, U) \mapsto \hat{\theta}(Y, U)$

Likelihood: $p(Y|U;\theta) = \int_W p(Y, W|U;\theta) dW,$

Optimal prediction: $\hat{y}_{t|t-1}(\theta) = \int_{y_t} y_t p(y_t|Y_{t-1};\theta) dy_t$

State-of-the-art solutions:
use partilce smoother or MCMC to get
Monte Carlo approximations.

A simple consistent solution

optimally weighted PEM based on a linear predictor

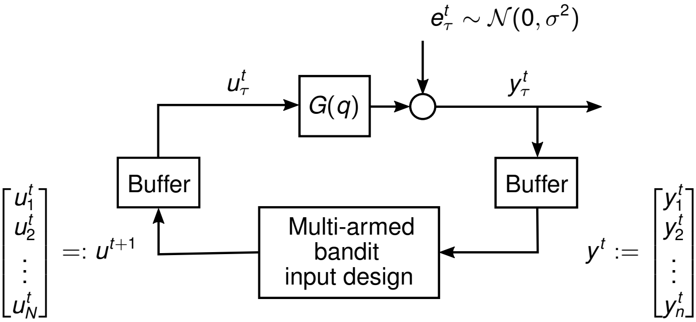
$$\hat{Y}(\theta) := (I - L^{-1}(U,\theta))Y + L^{-1}(U,\theta)\mu(U,\theta),$$

$$\mathcal{E}(\theta) := Y - \hat{Y}(\theta)$$

$$\hat{\theta} := \arg\min_{\theta \in \Theta} \ell(\mathcal{E}(\theta), \theta)$$

A stochastic multi-armed bandit approach to nonparametric $\mathcal{H}_\infty$-norm estimation

Matias Müller, Patricio E. Valenzuela, Alexandre Proutiere, Cristian R. Rojas



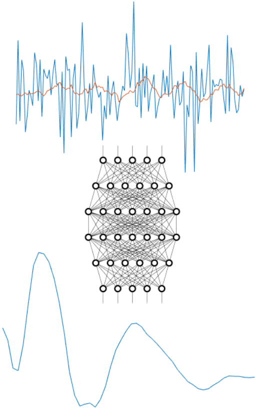
UPPSALA UNIVERSITET

Data-driven impulse response estimation using deep learning

Carl Andersson Department of Information Technology

Uppsala University

- **Problem:** Estimate the impulse response from input/output pair using regularized least square
- **Previous work - Gaussian process:** Create a regularization matrix using a Gaussian Process prior
- **Our work - Deep learning:** Create a regularization matrix using Deep learning



UPPSALA
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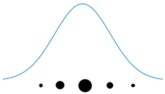
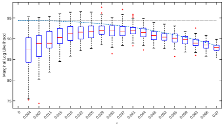
Bias-variance trade-off for high-dimensional particle filters using artificial process noise

Anna Wigren, Fredrik Lindsten and Lawrence Murray

Department of Information Technology, Uppsala University

- Particle filter = sequential inference method where probability densities are represented using weighted particles
- Problem: Degenerates for high-dimensional systems, such as spatio-temporal models
- Idea: Modify the model by adding artificial process noise to make use of the optimal proposal
- Improves the performance by introducing a higher bias but lowers the variance





Identification of stable positive systems*

Jack Umenberger
Department of IT, Uppsala University

Ian R. Manchester
ACFR, University of Sydney

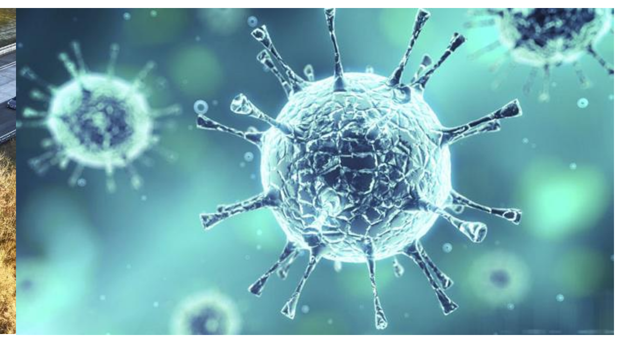
Generic LTI systems: stability theory from **energy** dissipation

- Leads to **quadratic Lyapunov** functions, $V(x) = x'Px$

Positive LTI systems: stability theory from **mass** dissipation

Number (of cars)

Distance (between cars)



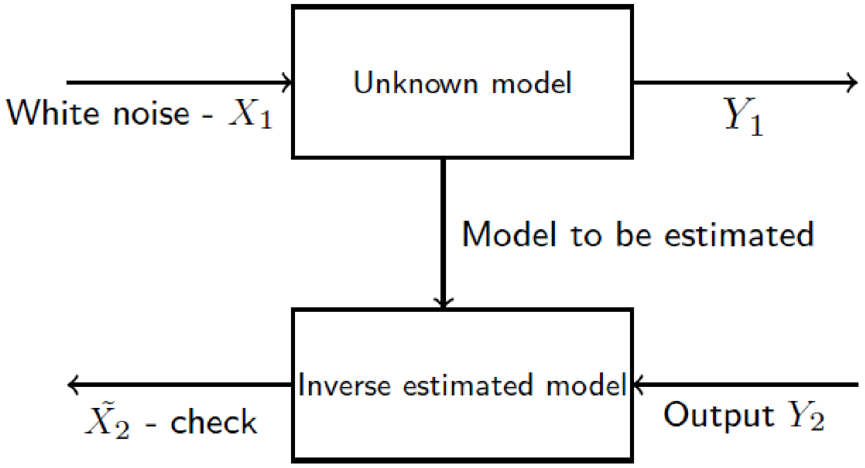
Concentration (of pathogens)

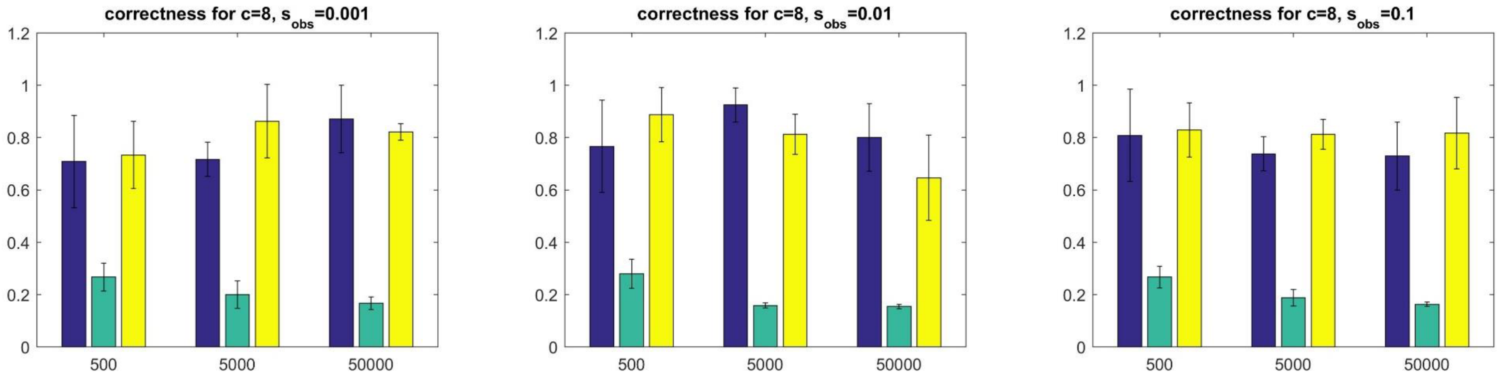
- Leads to (simpler) **linear Lyapunov** functions, $V(x) = p'x$
- Improved scalability during identification, e.g., QPs instead of SDPs.
- Amenable to distributed optimization, e.g., ADMM.

* **New results since CDC'16. Work done in Sydney.**

A Time Series Clustering Algorithm Based on Inverse Modelling

Oliver Lauwers, Thomas Devenyns, Bart De Moor

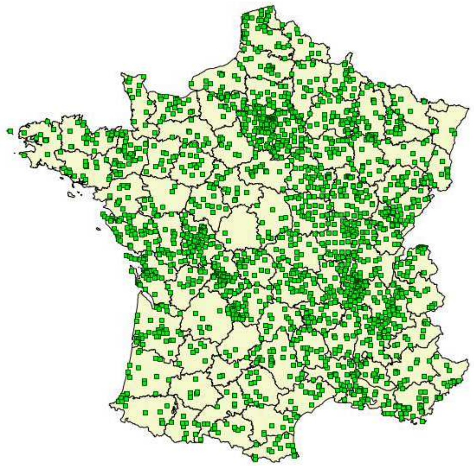




Dynamic models for bird population - Partial differential equation identification

Régis OUVRARD, Lauriane MOUYSSET and Frédéric JIGUET

Bird data for 2002-2014



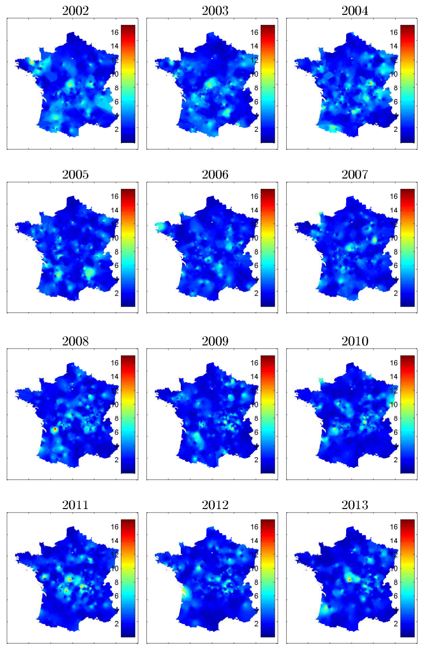
A French national monitoring:

- Skilled ornithologists
- Standardized protocol to count birds

Motivation

- The improvement of the **population dynamic models** of birds
- To understand past dynamics of birds to **agricultural changes**
- An help to take **biodiversity goals into public policies** into account

European Stonechat *Saxicola torquatus*

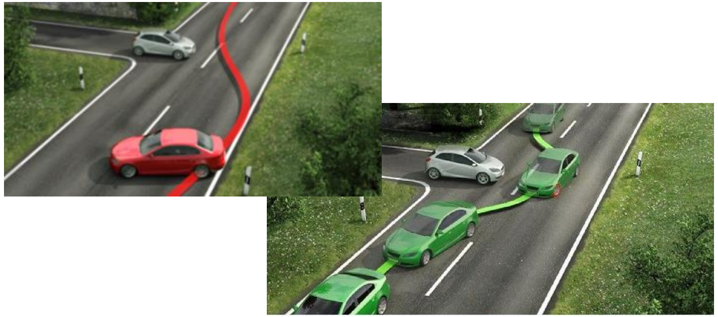


Keywords

- PDE models
- Levenberg-Marquardt algorithm
- Galerkin method
- Proper Orthogonal Decomposition

How can we use the knowledge about tires to improve safety and handling performances of autonomous cars?

- For motorsport & passenger cars purpose



LUXEMBOURG CENTRE
SYSTEMS BIOMEDICINE

Genome-Wide Dynamical Data Analysis and Network Inference of the Gene Regulatory Network of Human T Cells

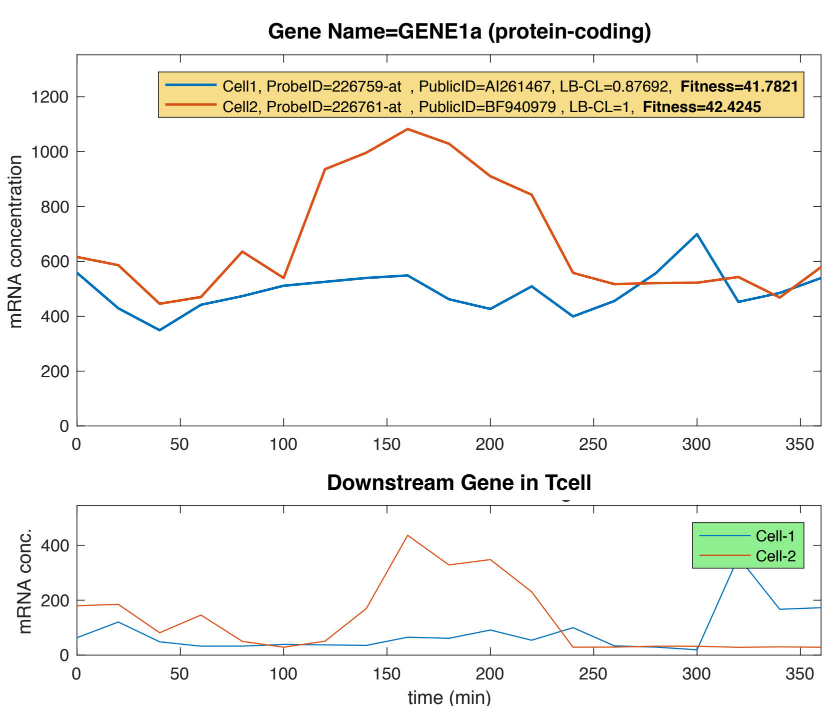
UNIVERSITÉ DU
LUXEMBOURG

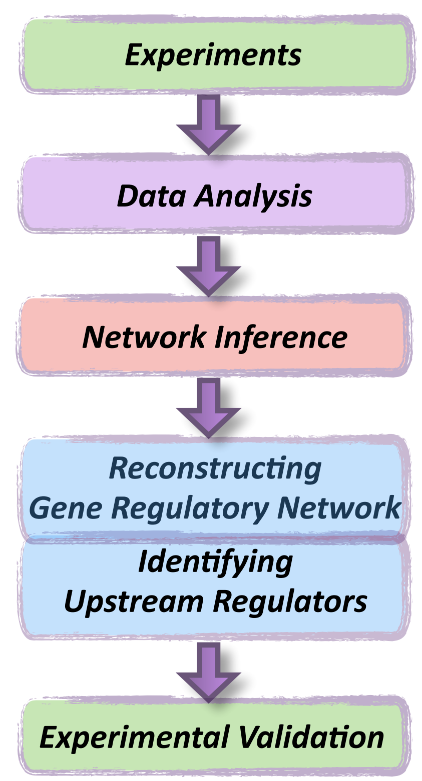
Stefano Magni, Rucha Sawlekar, Jorge Gonçalves
- Systems Control Group -

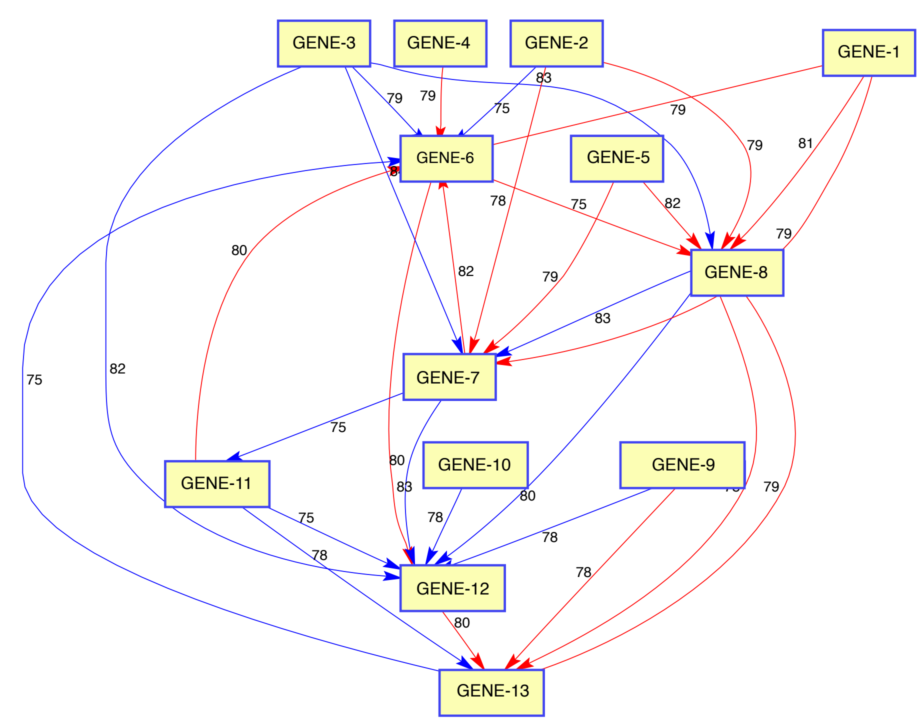
Poster 16 - Session A

We apply **network inference** to **time-series data** of **gene expression** with the goals of:

- Reconstructing the **gene regulatory networks** of Treg and Teff cells, and
- Identifying potential **upstream regulators** for genes of interest.

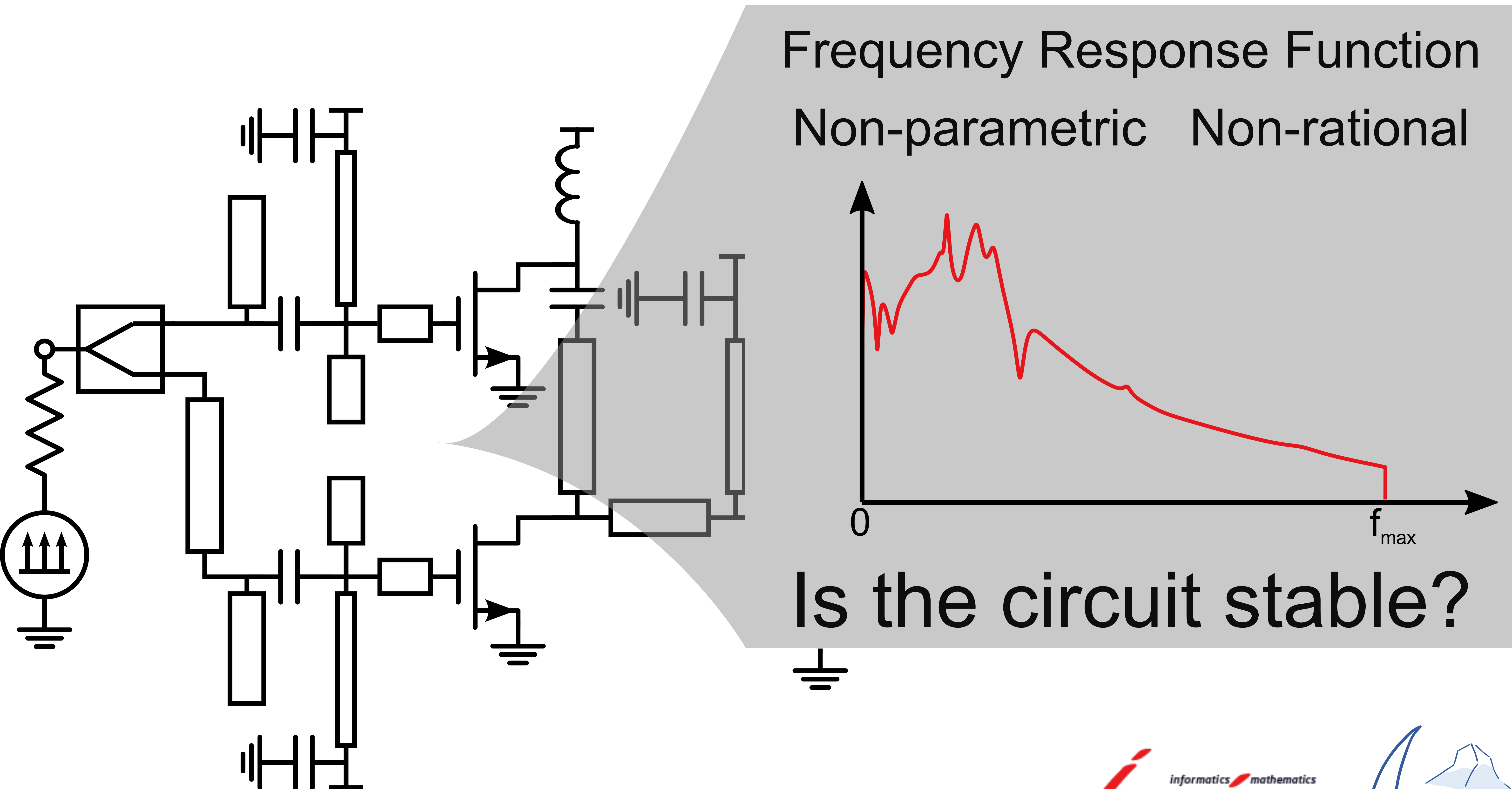






A Functional approach to stability analysis of linear systems

A. Cooman, F. Seyfert, M. Olivi, S. Chevillard and L. Baratchart



Circadian Gene Regulatory Network (GRN) Inference and Characterisation by Linear Time Invariant (LTI) Systems Identification

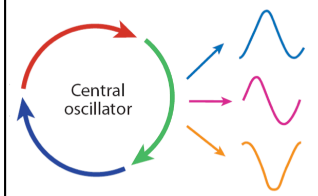
Laurent Mombaerts, Jorge Goncalves

Luxembourg Centre for Systems Biomedecine

Background

Input

- Light
- Temperature
- Water status
- Stress feedback

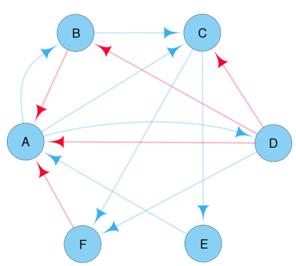


Output

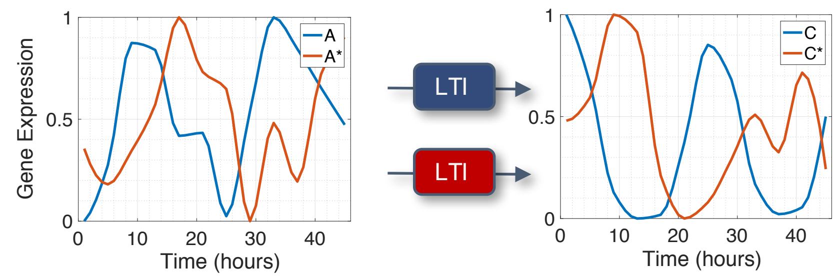
- Photosynthesis
- Growth
- Flowering
- Stress signaling

Network Inference

$$\frac{dx}{dt}(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t)$$



Characterisation of Local Changes



How different are dynamics?

δ_v = || LTI − LTI ||

In Combination with Centrality Measures

$$x_v = \frac{\frac{1}{\lambda_C}\sum_{t\in C} a_{v,t,C}\, x_{t,C}}{\frac{1}{\lambda_D}\sum_{t\in D} a_{v,t,D}\, x_{t,D}} \qquad x_v = \frac{x_{v,C}}{x_{v,L}}$$

LCSB

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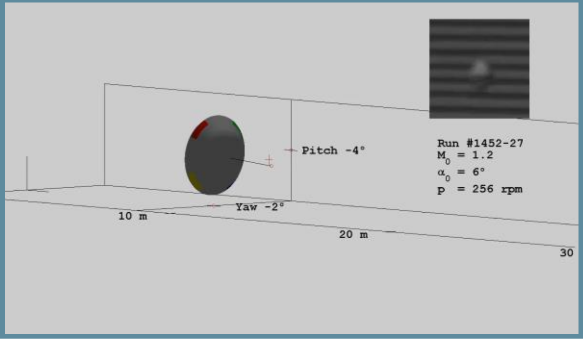
LPV model identification of aerodynamic coefficients based on free-flight data

D. Machala, M. Albisser, S. Dobre, M. Gilson, F. Collin



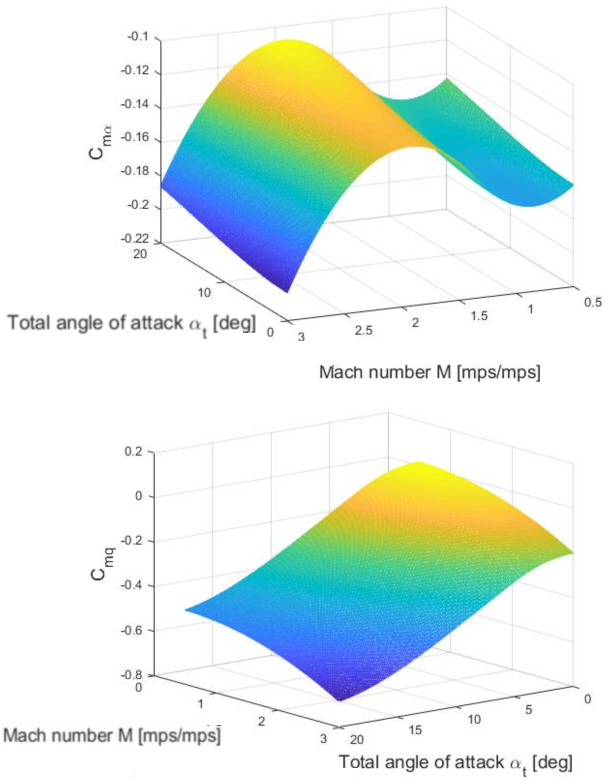
Goal: Identification of the aerodynamic coefficients of flying vehicles

Context:

- In-flight behavior is described by a nonlinear state-space model
- Data is available from free-flight measurements
- LPV modelling can be used both for identification and GNC research activities

Preliminary analysis:

- Development of a grey-box LPV model of a vehicle in flight
- Model validation using measurements



Nonlinear coefficient functions: $C_{m\alpha}$ *and* C_{mq}

Nonlinear grey-box model → LPV modelling → LPV system identification → Model validation

French German Research Institute of Saint-Louis

DERIVATIVE-FREE ONLINE LEARNING OF INVERSE DYNAMICS MODELS

Diego Romeres, Mattia Zorzi, Alessandro Chiuso
DEPARTMENT OF INFORMATION ENGINEERING
UNIVERSITY OF PADOVA

- Derivative Free Inverse Dynamics

$$\begin{bmatrix} \text{pos} \\ \text{vel} \\ \text{acc} \end{bmatrix} \to \text{Torque} \quad \Longrightarrow \quad f_\theta(\text{pos}) \to \text{Torque}$$

- Semiparametric Modelling

Physics + Data-driven methods

- Robotic Experiments