Bounding the uncertainty in identification for control

Paul Van den Hof

Delft Center for Systems and Control
Delft University of Technology

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Contents

- Identification for control
- An engineer's perspective to iteration
- The central issue: uncertainty bounding
- Achievements and challenges

"Here is a dynamical process with which you are allowed to experiment (preferably cheap).

Design and implement a high-performance control system".

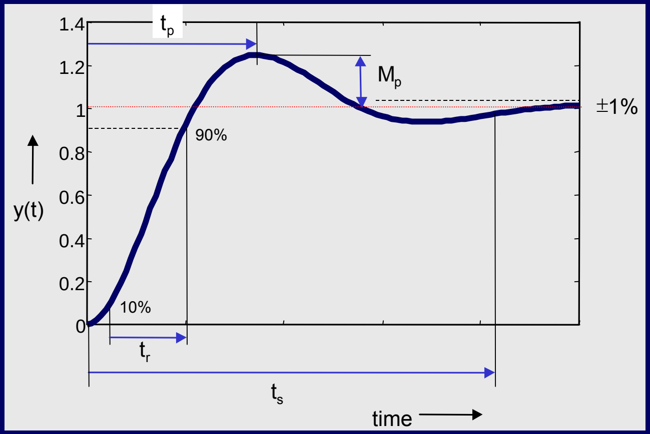
Issues involved:

- Experiment design
- Modelling / identification
- Characterization of disturbances and uncertainties
- Choice of performance measure
- Control design and implementation

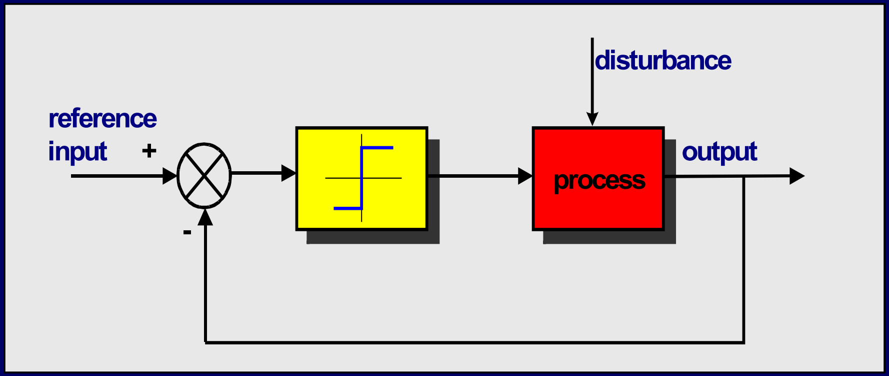
experimental issues dependent on application area

Classical experiments for finding control-relevant dynamics

- Ziegler/Nichols tuning rules for PID-controllers



- Relay feedback: amplitude and frequency at -180° phase



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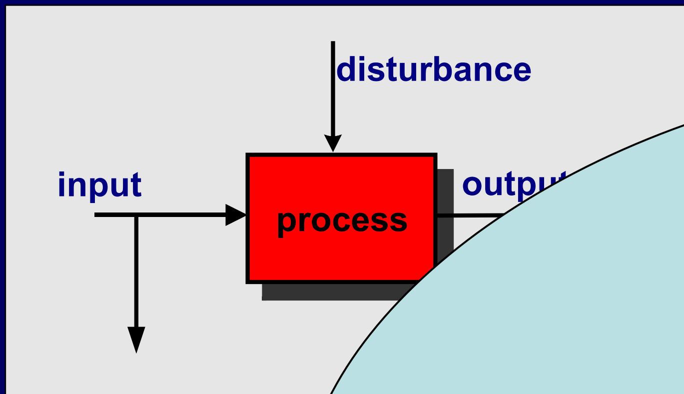
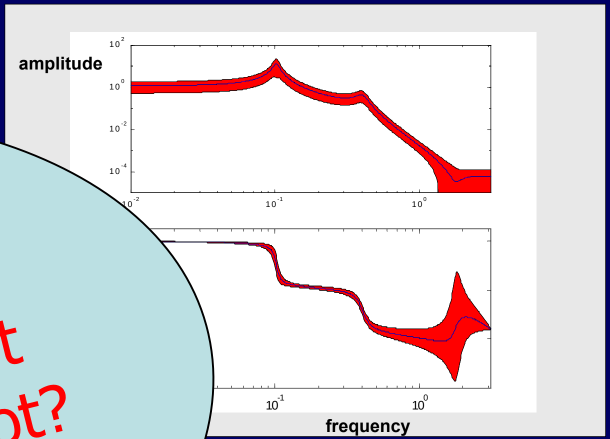
- Ad-hoc simple cases to be extended to general methodology for model-based control, including issues of robustness induced by model uncertainties

- Adaptive control so far only solves particular parts of the problem

Experiments:

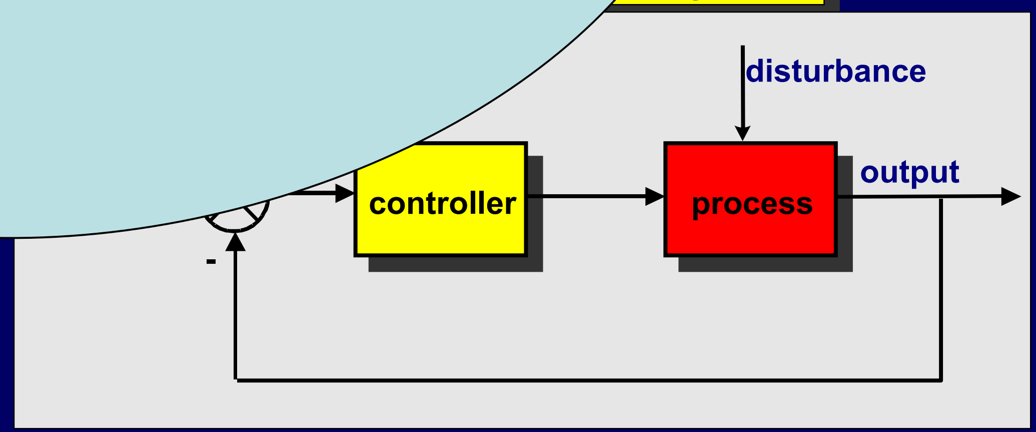




Iden

Is it realistic to assume that this can be done in one shot?

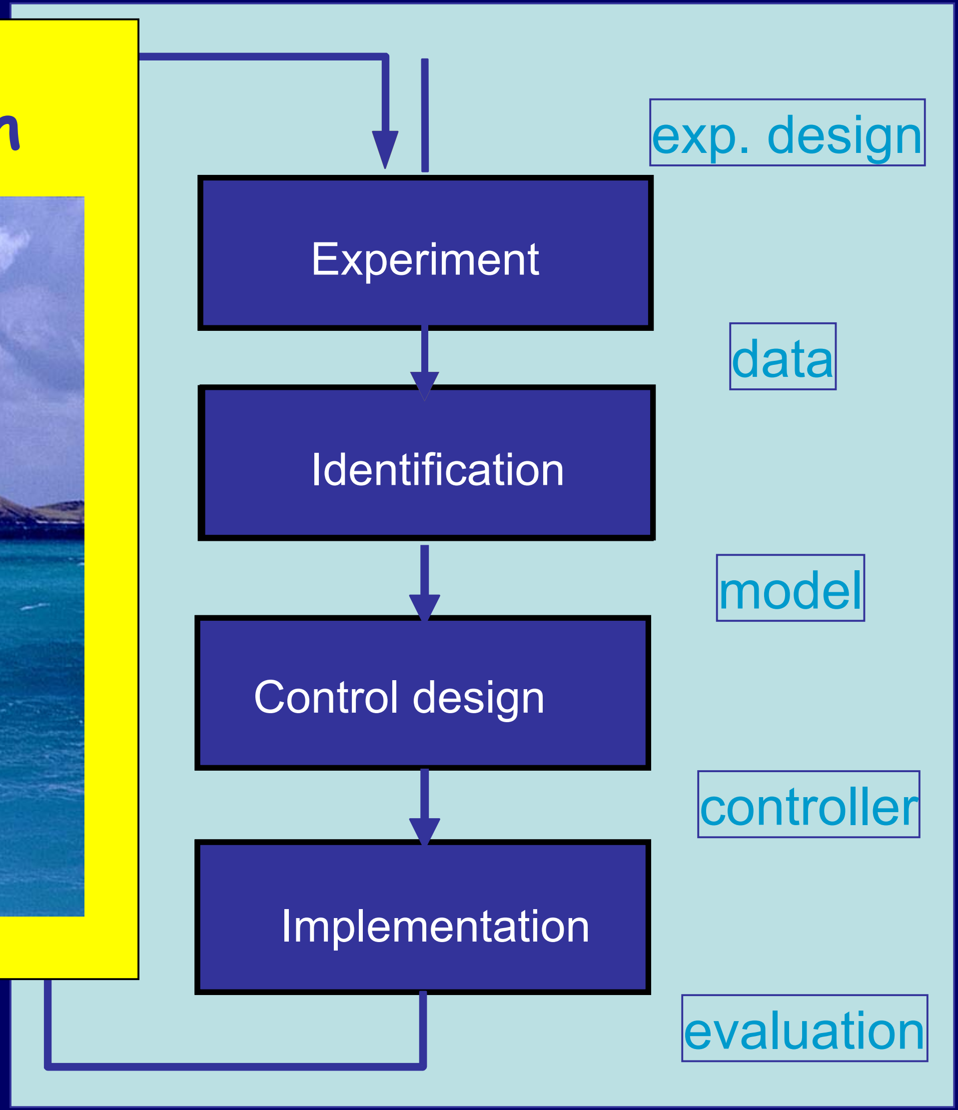
l system



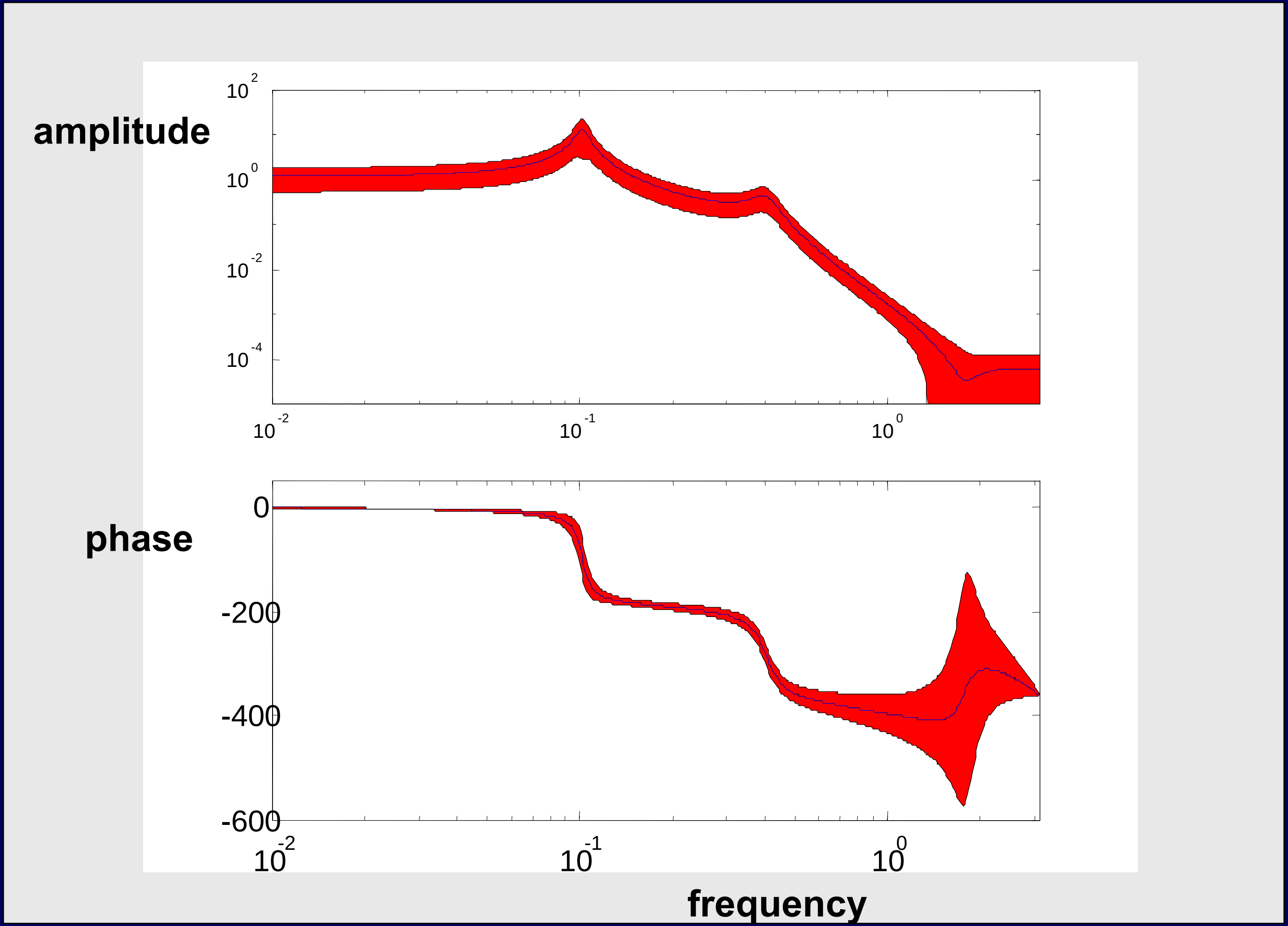
Model → Contr

Windsurfer approach

is learning
(Schrama, 1992; Gevers, 1993)



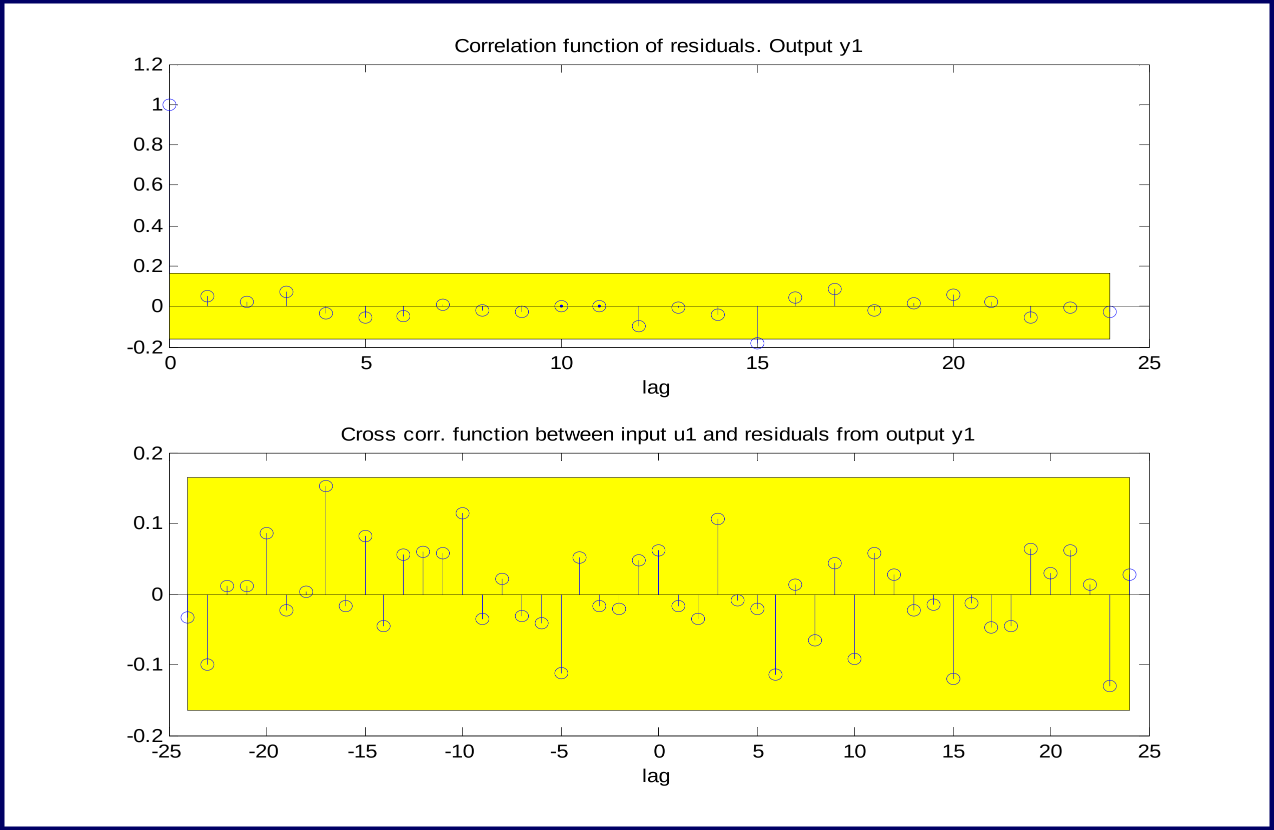
Uncertainty regions with probability α



Classical reasoning for quantifying uncertainty

- Let identified models pass a validation test
- Assume that the real system belongs to the model set ($S \in M$)
- Use analytical (variance) expressions for quantifying parameter variance and resulting model variance

Residual tests



$\hat{R}_{\varepsilon}(\tau)$

$\hat{R}_{\varepsilon u}(\tau)$

When model passes test, there is no evidence in the data that the model is wrong

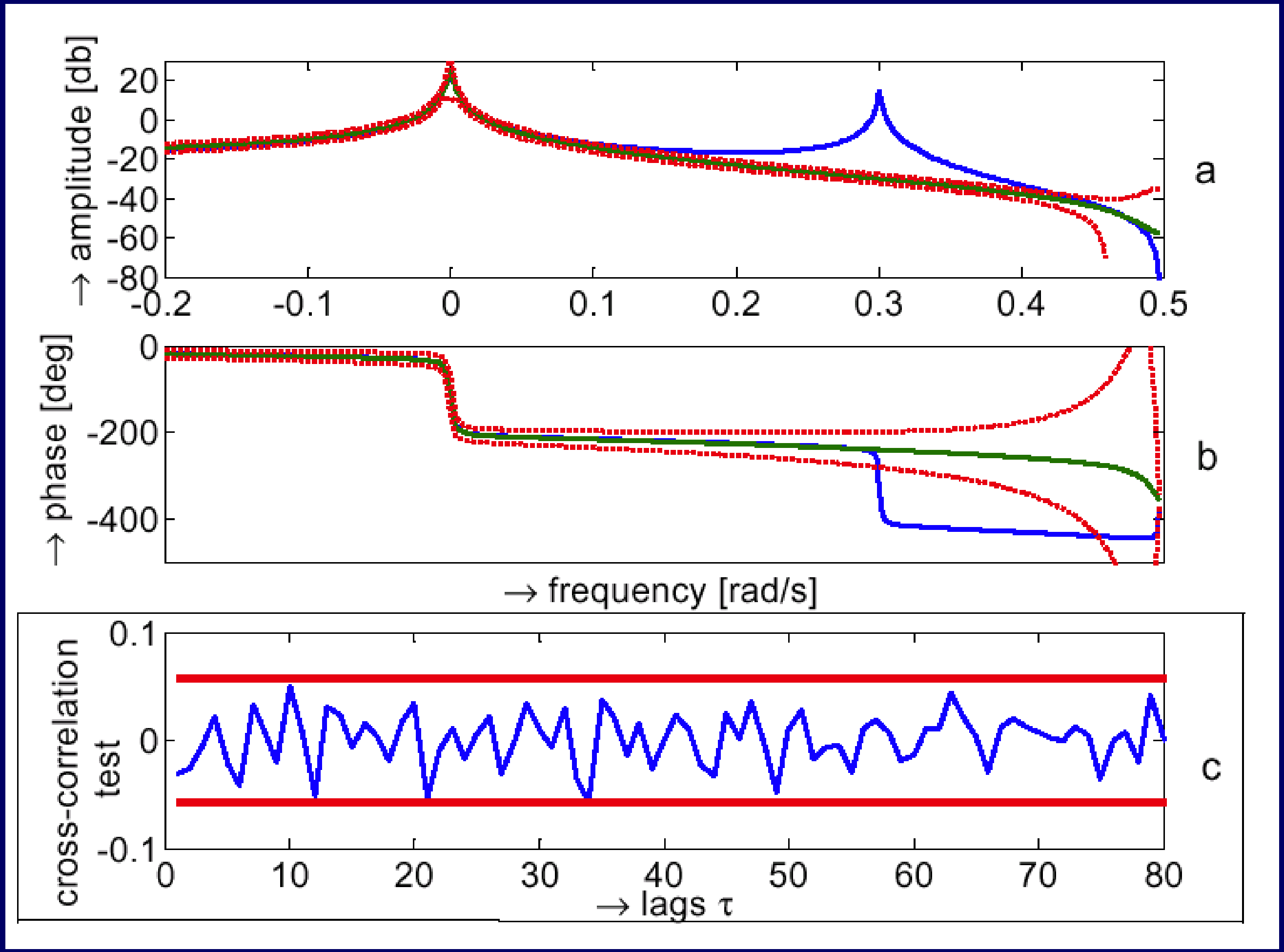
Classical reasoning for quantifying uncertainty

- Let identified models pass a validation test
- Assume that the real system belongs to the model set
  (S ϵ M)
- Use analytical (variance) expressions for quantifying parameter variance and resulting model variance

However

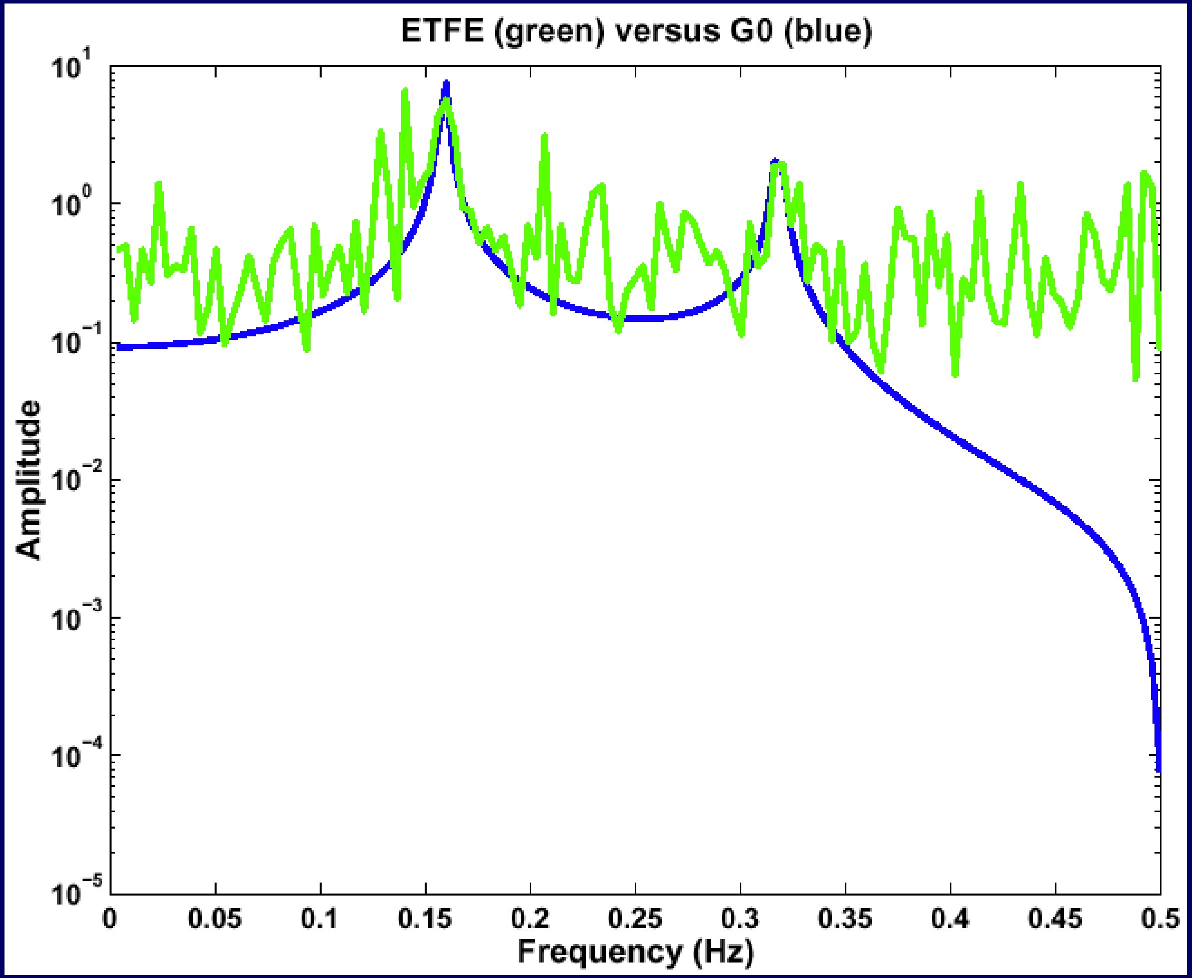
- Validation does not guarantee S ϵ M
  validation is input-dependent
- Assumption preferably replaced by quantified condition
- Bias has to be taken into account when bounding uncertainty

Intriguing example – 4th order process; 2nd order model; white input



$\hat{R}_{\varepsilon u}(\tau)$

Intriguing example – 4th order process; 2nd order model



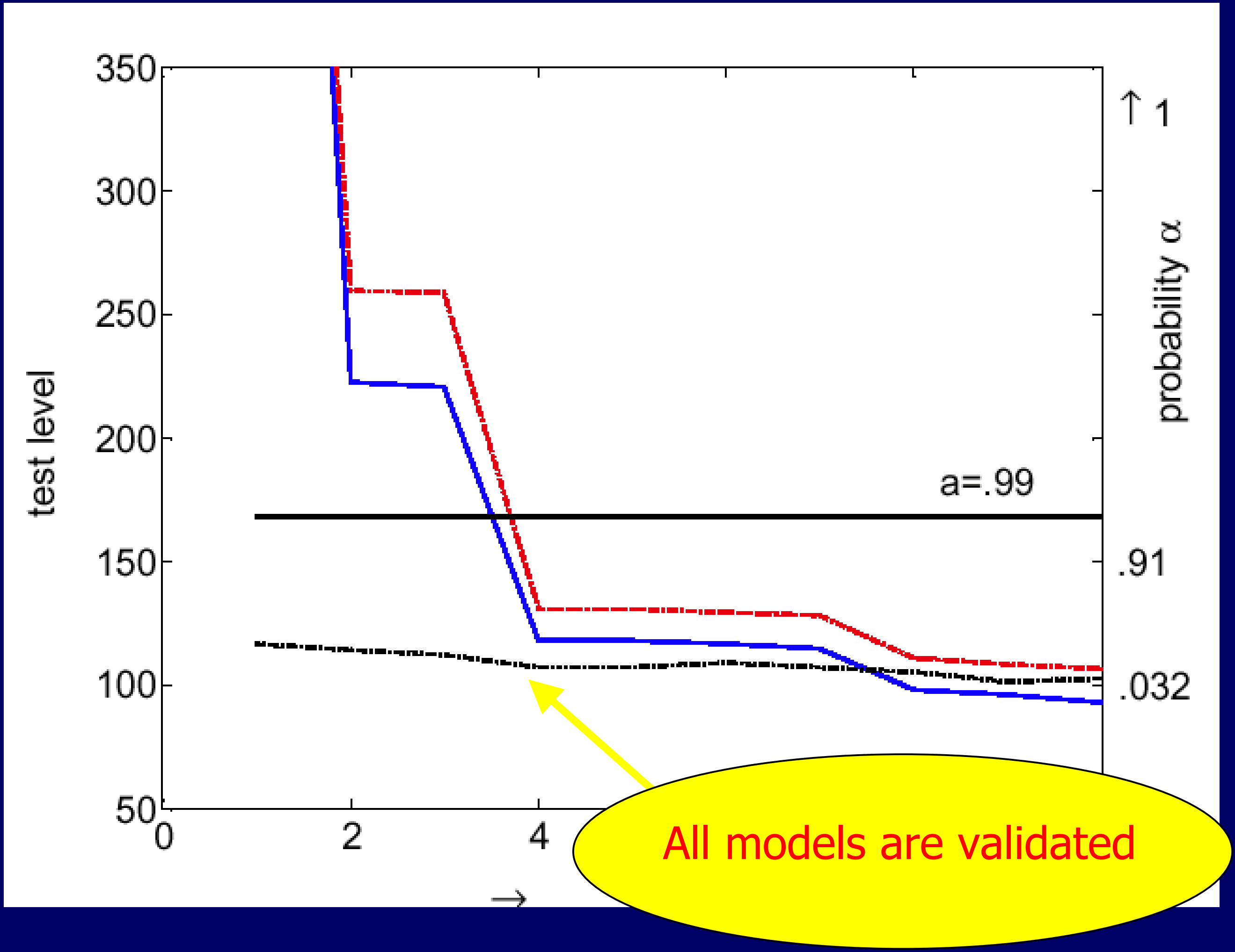
Problems:

- Due to undermodelling, the noise is overestimated, leading to conservative 99% confidence bounds;

- Structure within $\hat{R}_{\varepsilon u}(\tau)$ is not recognized

- "Solution": improve noise modelling and apply vector valued test

Intriguing example – Vector-valued test over 128 lags



Exact noise model
Improved estimate
From residual

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However

Even if we can improve validation test, it remains dependent on input-data
(no expressions possible about frequency areas that are not excited)

→ Best case scenario (validation implies no-bias) is questionable

Argument for incorporating bias-term in quantifying model ucertainty

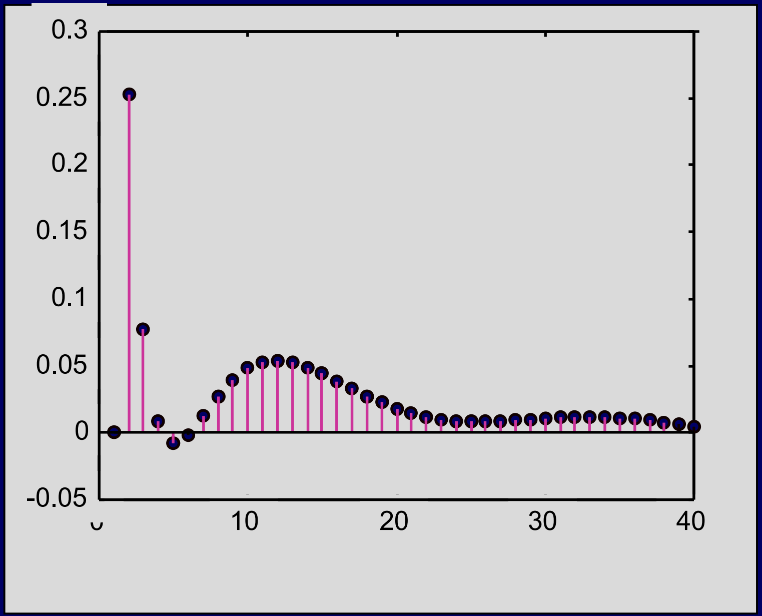
Dedicated procedures for uncertainty bounding

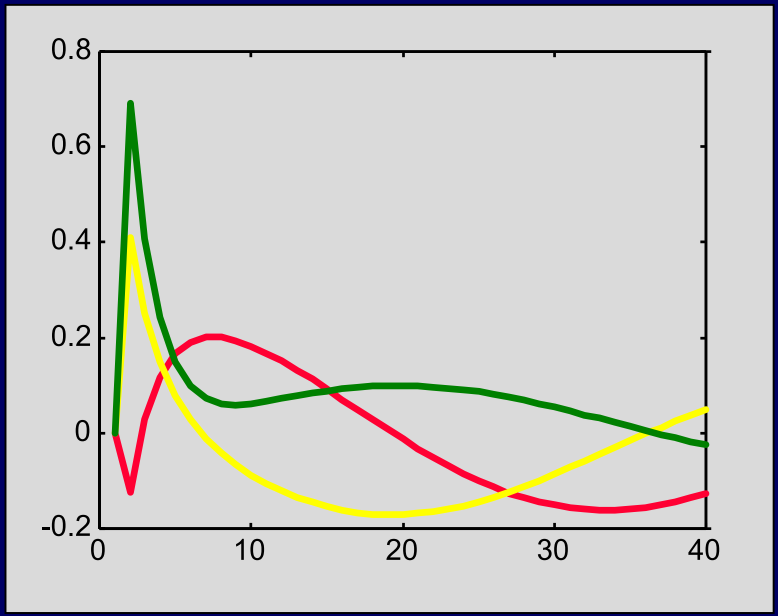
- Estimating carrier models with linearly parametrized models (linear regression)
- Taking account of bias by either bounding this term deterministic (Hakvoort, De Vries, Van den Hof, 1994, 1997), e.g.

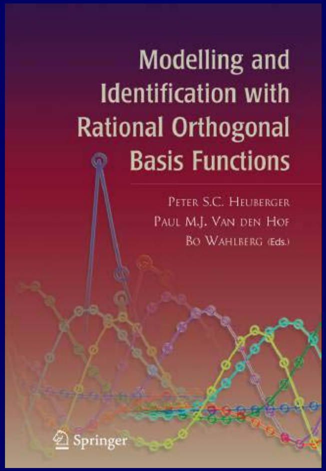
$$G_0(z) = \sum_{k=0}^{\infty} g_0(k) F_k(z) \qquad |g_0(k)| \leq M\rho^k$$ a priori

  or
  probabilistic (stochastic embedding; Goodwin et al. 1992), or
  high-order modelling (model error modelling, Ljung, 1999)
- Leading to ellipsoidal uncertainty areas in parameter and f-domain, valid with a prechosen level of probability

Linear parametrizations with flexible structures



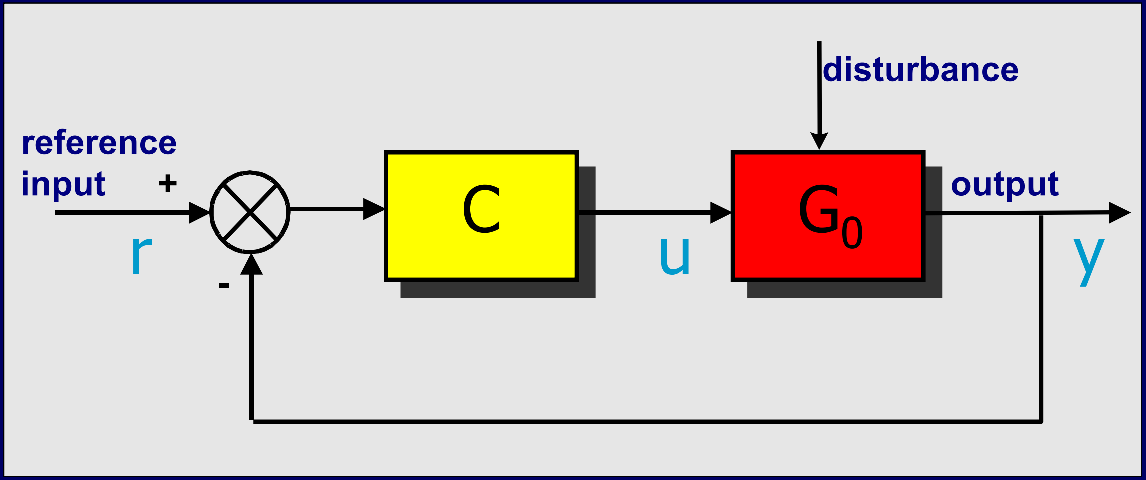




Modelling and Identification with
Rational orthogonal basis functions
(Heuberger, Van den Hof, Wahlberg, Eds., 2005)

With several chapters of our Hungarian partners,
József Bokor and Zóltan Szabó

Closed-loop identification



Advantage: loop signals u and y are shaped with sensitivity function $S = 1/(1+CG_0)$:

Identification of models, such that $\frac{CG_0}{1+CG_0} - \frac{C\widehat{G}}{1+C\widehat{G}}$ is small: models relevant for C.

Controlled experiments excite u and y in the right f-region, while keeping signal amplitudes bounded

Achievements

- Insight into the structural relation between model construction and control
- Tools for closed-loop identification and uncertainty bound quantification
- Robustness analysis/synthesis tools for identified uncertainty models
- Iterative schemes for modelling and control tuning, renewing “classical” adaptive control

Challenges ahead

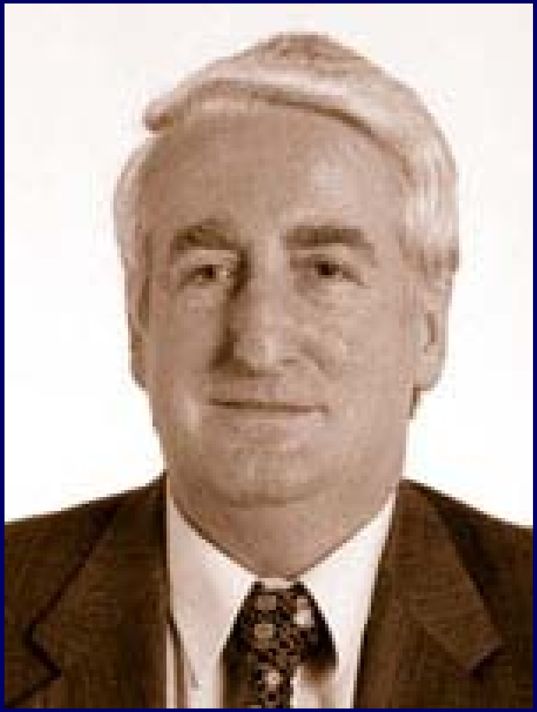
- Design of cheap experiments:
  - least disturbing,
  - satisfying process constraints
  - minimum length,

  providing sufficient information for performance improvement

  Problem: "all" theory is asymptotic in N

  Most important for process control applications

- Performance monitoring: when is re-identification economically viable?



Congratulations László !!