

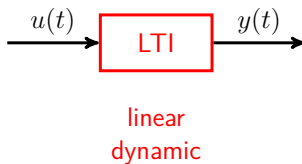


Vrije Universiteit Brussel

## Block-oriented modeling

Maarten Schoukens    Koen Tiels

# Introduction



Block-oriented models consist of  
linear dynamics and static nonlinearities

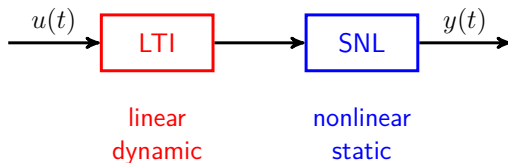
LTI

linear  
dynamic

SNL

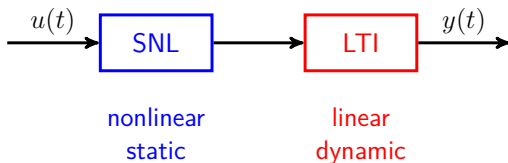
nonlinear  
static

Block-oriented models consist of  
linear dynamics and static nonlinearities



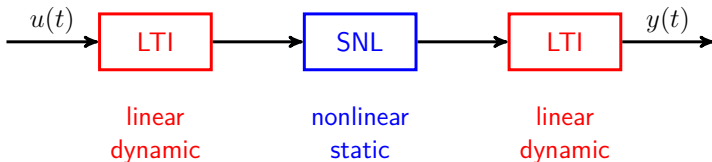
► Wiener

Block-oriented models consist of  
linear dynamics and static nonlinearities



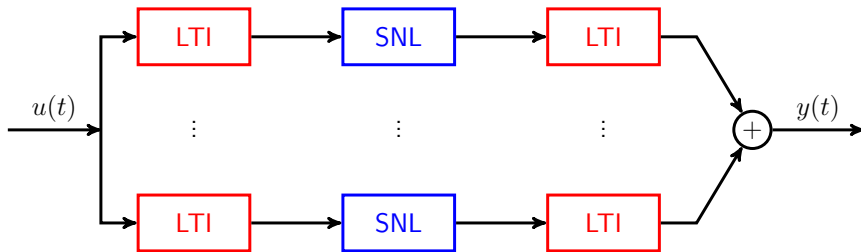
- ▶ Wiener
- ▶ Hammerstein

Block-oriented models consist of  
linear dynamics and static nonlinearities



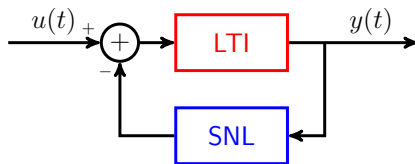
- ▶ Wiener
- ▶ Hammerstein
- ▶ Wiener-Hammerstein

## Block-oriented models consist of linear dynamics and static nonlinearities



- ▶ Wiener
- ▶ Hammerstein
- ▶ Wiener-Hammerstein
- ▶ parallel Wiener-Hammerstein

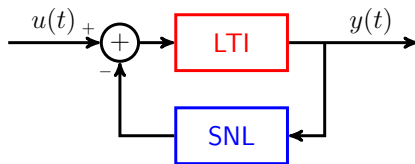
# Block-oriented models consist of linear dynamics and static nonlinearities



- ▶ Wiener
- ▶ Hammerstein
- ▶ Wiener-Hammerstein
- ▶ parallel Wiener-Hammerstein
- ▶ nonlinear feedback



# Block-oriented models consist of linear dynamics and static nonlinearities

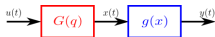


- ▶ Wiener
- ▶ Hammerstein
- ▶ Wiener-Hammerstein
- ▶ parallel Wiener-Hammerstein
- ▶ nonlinear feedback
- ▶ ...

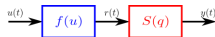
*Which model to choose?*

# Outline

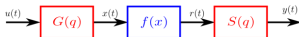
- ▶ Which block structure to choose?
- ▶ How to identify the chosen block structure?



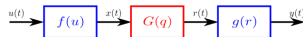
Wiener



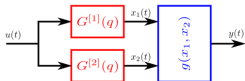
Hammerstein



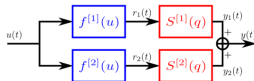
Wiener-Hammerstein



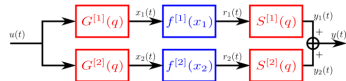
Hammerstein-Wiener



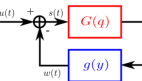
Parallel Wiener



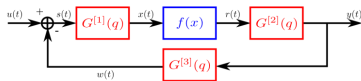
Parallel Hammerstein



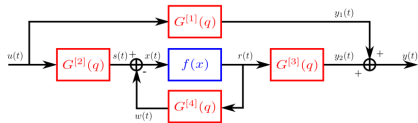
Parallel Wiener-Hammerstein



Simple Feedback



Wiener-Hammerstein Feedback



Linear Fractional Representation (LFR)

# Structure detection

- Bussgang's theorem
- $\epsilon$  – approximation
- Structure detection

# Bussgang's Theorem

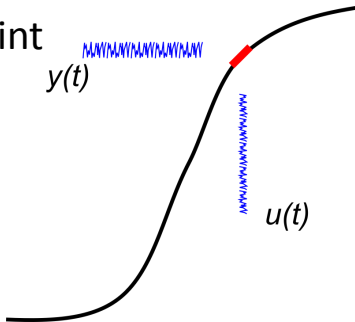
Stationary Gaussian input

→ Static nonlinearity  $\approx$  static gain

$$f(u) = \gamma u$$

# $\varepsilon$ - Approximation

Small signal around a setpoint



Taylor approximation

→ Static nonlinearity  $\approx$  static gain

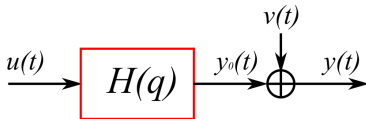
$$f(u) = \gamma u$$

# Structure detection

- BLA,  $\varepsilon$  - Approximation @ different setpoints
  - Change offset
  - Change power spectrum

# Structure detection

- Linear-Time-Invariant (LTI)



$$G_{bla}(q) = H(q)$$

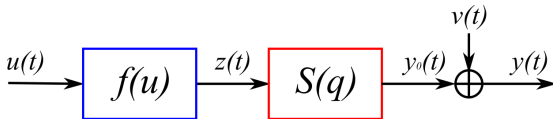
➔ No changes



	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein			
Wiener			
Wiener-Hammerstein			
Parallel WH			
Feedback			
LFR			

# Structure detection

- Hammerstein



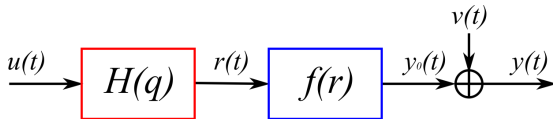
$$G_{bla}(q) = \gamma S(q)$$

➔ Only gain factor

	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener			
Wiener-Hammerstein			
Parallel WH			
Feedback			
LFR			

# Structure detection

- Wiener



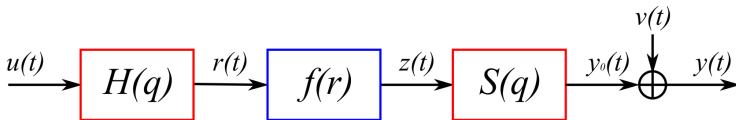
$$G_{bla}(q) = \gamma H(q)$$

➔ Only gain factor

	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener	Variable	Fixed	Fixed
Wiener-Hammerstein			
Parallel WH			
Feedback			
LFR			

# Structure detection

- Wiener-Hammerstein



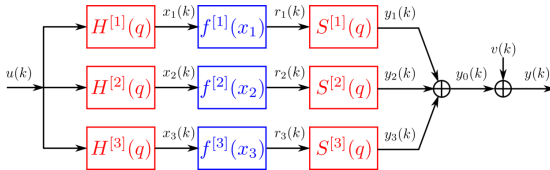
$$G_{bla}(q) = \gamma H(q)S(q)$$

➔ Only gain factor

	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener	Variable	Fixed	Fixed
Wiener-Hammerstein	Variable	Fixed	Fixed
Parallel WH			
Feedback			
LFR			

# Structure detection

- Parallel Wiener-Hammerstein



$$G_{bla}(q) = \sum_i \gamma_i H^{[i]}(q) S^{[i]}(q)$$

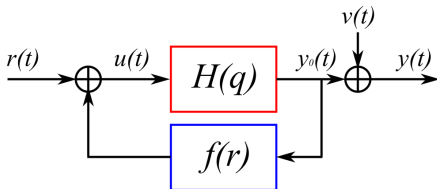
➔ Moving zeros, fixed poles



	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener	Variable	Fixed	Fixed
Wiener-Hammerstein	Variable	Fixed	Fixed
Parallel WH	Variable	Fixed	Variable
Feedback			
LFR			

# Structure detection

- Feedback system



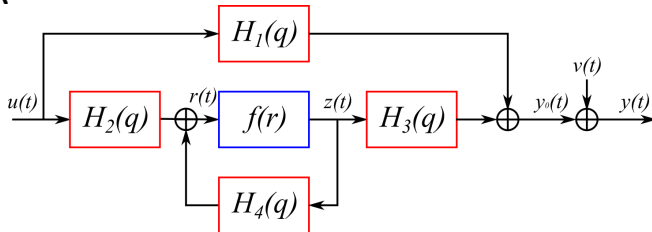
$$G_{\varepsilon}(q) = \frac{H(q)}{1 + \gamma H(q)}$$

➔ Fixed zeros, moving poles

	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener	Variable	Fixed	Fixed
Wiener-Hammerstein	Variable	Fixed	Fixed
Parallel WH	Variable	Fixed	Variable
Feedback	Variable	Variable	Fixed
LFR			

# Structure detection

- LFR



$$G_{\varepsilon}(q) = H_1(q) + \frac{\gamma H_2(q) H_3(q)}{1 + \gamma H_4(q)}$$

➔ Moving zeros, moving poles

	Gain	Poles	Zeros
Linear Time Invariant	Fixed	Fixed	Fixed
Hammerstein	Variable	Fixed	Fixed
Wiener	Variable	Fixed	Fixed
Wiener-Hammerstein	Variable	Fixed	Fixed
Parallel WH	Variable	Fixed	Variable
Feedback	Variable	Variable	Fixed
LFR	Variable	Variable	Variable

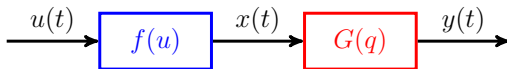
# Structure detection

- BLA,  $\varepsilon$  – approximation @  $\neq$  setpoints
- Only gain change
  - Hammerstein, Wiener, Wiener-Hammerstein, ...
- Zeros shift
  - Parallel feed-forward structure
- Poles shift
  - Feedback present

# Outline

- ▶ Which block structure to choose?
- ▶ How to identify the chosen block structure?
  - ▶ Hammerstein model
  - ▶ Wiener model
  - ▶ Orthonormal basis functions

## Identification of a Hammerstein model

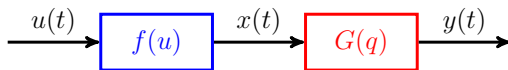


$$f(u) = \sum_{d=0}^D \beta_d u^d$$

$$G(q) = \frac{B(q, \theta)}{A(q, \theta)}$$



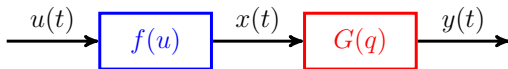
## Step 1: Estimate a nonparametric BLA



Random-phase multisine excitation:

$$u^{[m]}(t) = \sum_{k=1}^{N_F} A_k \sin(2\pi k f_0 t + \phi_k^{[m]})$$

## Step 1: Estimate a nonparametric BLA



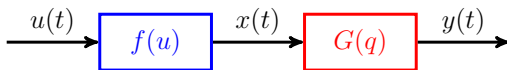
Random-phase multisine excitation:

$$u^{[m]}(t) = \sum_{k=1}^{N_F} A_k \sin(2\pi k f_0 t + \phi_k^{[m]})$$

FRF:

$$G_{BLA}(k) = \frac{1}{M} \sum_{m=1}^M \frac{Y^{[m]}(k)}{U^{[m]}(k)}$$

## Step 1: Estimate a nonparametric BLA



Random-phase multisine excitation:

$$u^{[m]}(t) = \sum_{k=1}^{N_F} A_k \sin(2\pi k f_0 t + \phi_k^{[m]})$$

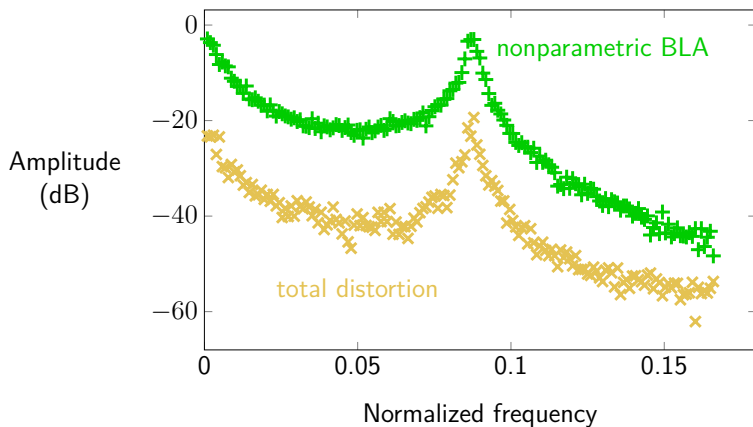
FRF:

$$G_{BLA}(k) = \frac{1}{M} \sum_{m=1}^M \frac{Y^{[m]}(k)}{U^{[m]}(k)}$$

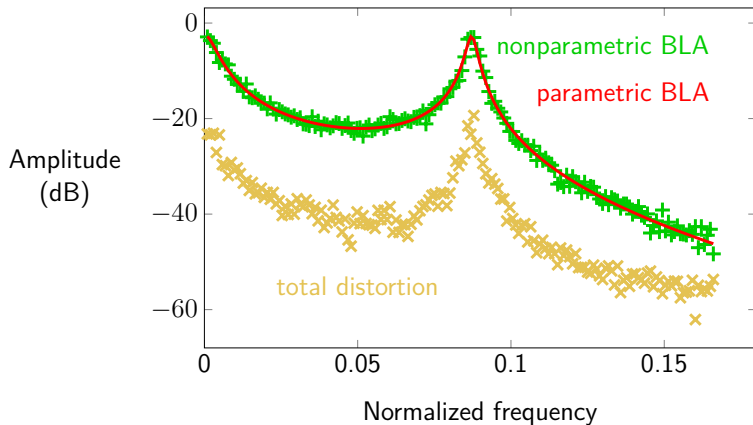
Nonparametric noise model:

$$\sigma_{G_{BLA}}^2(k) = \sigma_{NL}^2(k) + \sigma_{noise}^2(k)$$

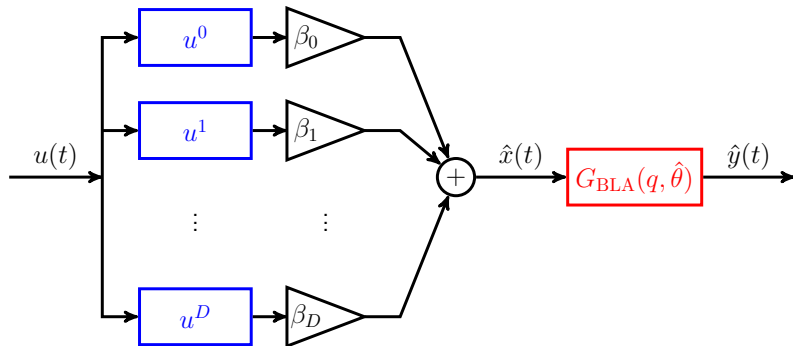
## Step 2: Estimate a parametric BLA



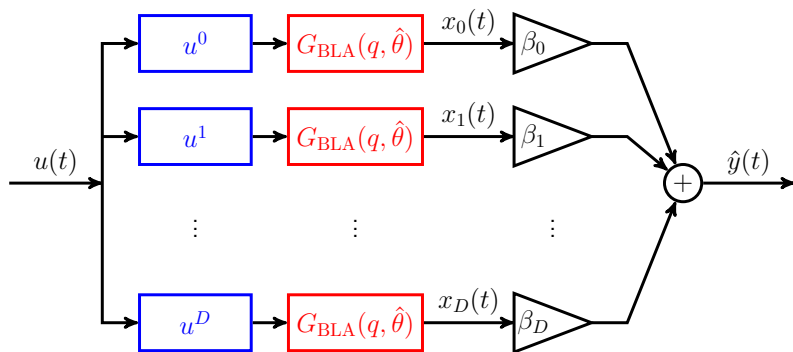
## Step 2: Estimate a parametric BLA



### Step 3: Estimate the polynomial coefficients

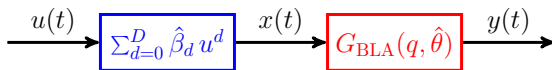


### Step 3: Estimate the polynomial coefficients



$$\hat{\beta} = \arg \min_{\beta} \left\| y(t) - \sum_{d=0}^D \beta_d x_d(t) \right\|_2^2$$

## Step 4: Do a nonlinear optimization of all parameters



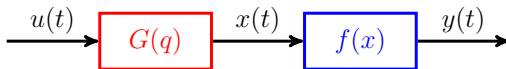
Nonlinear optimization of  $\beta$  and  $\theta$  simultaneously.



# Outline

- ▶ Which block structure to choose?
- ▶ How to identify the chosen block structure?
  - ▶ Hammerstein model
  - ▶ Wiener model
  - ▶ Orthonormal basis functions

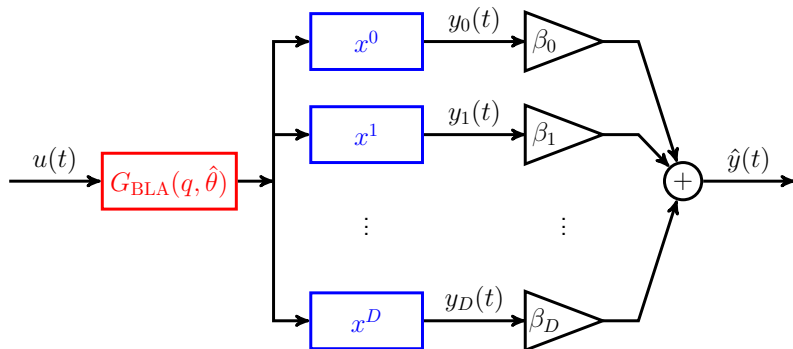
## Identification of a Wiener model



$$G(q) = \frac{B(q, \theta)}{A(q, \theta)}$$

$$f(u) = \sum_{d=0}^D \beta_d x^d$$

### Step 3: Estimate the polynomial coefficients

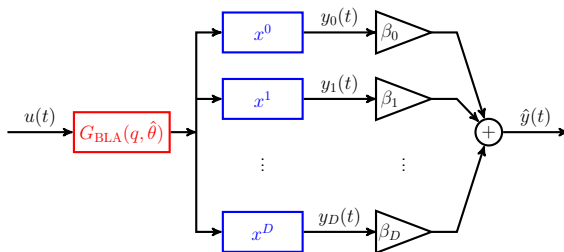


$$\hat{\beta} = \arg \min_{\beta} \left\| y(t) - \sum_{d=0}^D \beta_d y_d(t) \right\|_2^2$$

# Outline

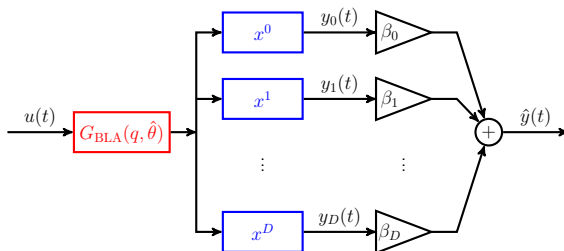
- ▶ Which block structure to choose?
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## Motivation for orthonormal basis functions



$$\hat{\beta} = \arg \min_{\beta} \left\| y(t) - \sum_{d=0}^D \beta_d y_d(t) \right\|_2^2 \quad \text{possibly ill-conditioned}$$

# Motivation for orthonormal basis functions



$$\hat{\beta} = \arg \min_{\beta} \left\| y(t) - \sum_{d=0}^D \beta_d y_d(t) \right\|_2^2 \quad \text{possibly ill-conditioned}$$

Linear dynamics	→	Rational orthonormal basis functions
Static nonlinearities	→	Hermite polynomials

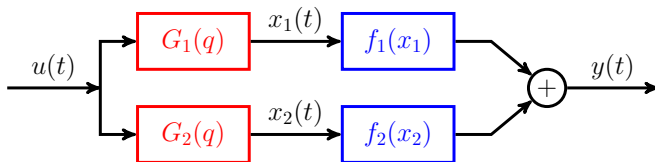
## Rational OBFs are determined by their pole locations

$$F_k(q) = \frac{\sqrt{1 - |\xi_k|^2}}{q - \xi_k} \prod_{i=1}^{k-1} \frac{1 - \xi_i^* q}{q - \xi_i}$$

all-pass filter

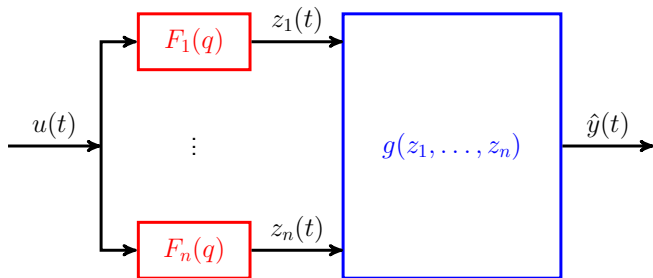
Pole locations $\xi_k$	OBFs
origin	FIR
real pole	Laguerre
complex conjugate pair	Kautz
repeated poles	Generalized OBFs
arbitrary	Takenaka-Malmquist

## Example: Approximation of a parallel Wiener system





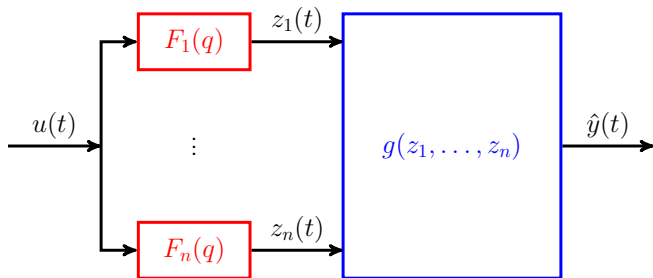
## Step 1: Estimate the linear dynamics



$F_k$ : rational orthonormal basis functions

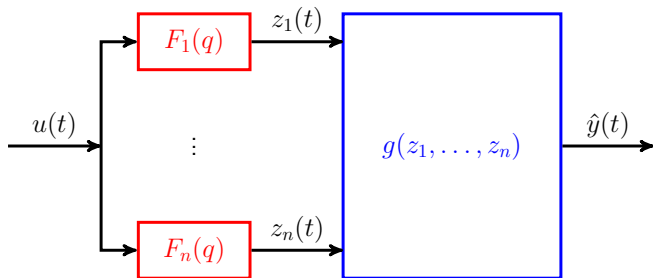
$g$ : multivariate Hermite polynomials

## Step 1: Estimate the linear dynamics



pole locations  $\rightarrow$  orthonormal basis functions

## Step 1: Estimate the linear dynamics

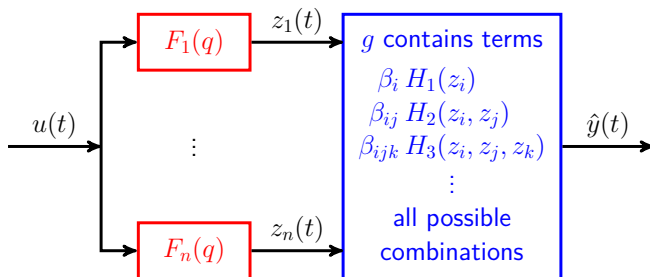


pole locations  $\rightarrow$  orthonormal basis functions

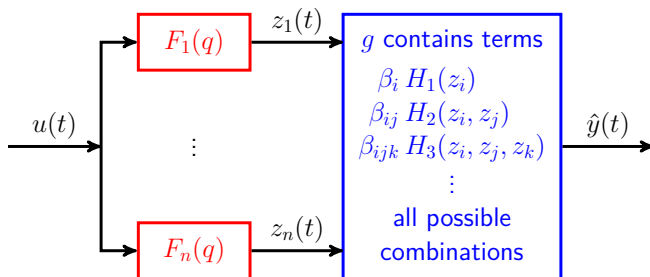


best linear approximation

## Step 2: Estimate the polynomial coefficients

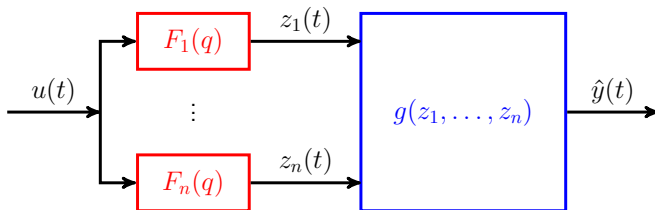


The model is linear-in-the-parameters



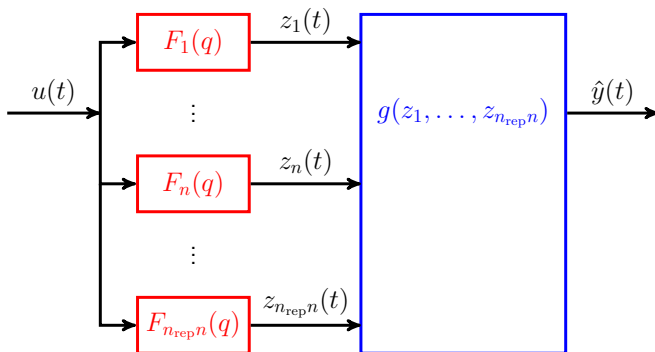
Prior knowledge can be incorporated  
via user-specified pole locations

$$\{\hat{p}_1, \dots, \hat{p}_n\} \Rightarrow \{F_1, \dots, F_n\}$$

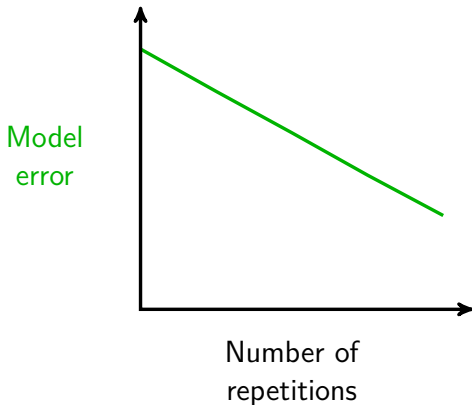


Prior knowledge can be incorporated  
via user-specified pole locations

$$\begin{aligned}\{\hat{p}_1, \dots, \hat{p}_n\} &\Rightarrow \{F_1, \dots, F_n\} \\ \{\hat{p}_1, \dots, \hat{p}_n\} &\Rightarrow \{F_{n+1}, \dots, F_{2n}\} \\ &\vdots \qquad \qquad \qquad \vdots\end{aligned}$$

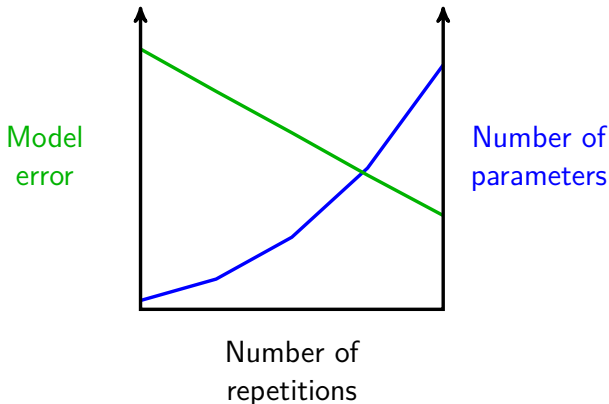


The extra basis functions compensate for a pole mismatch

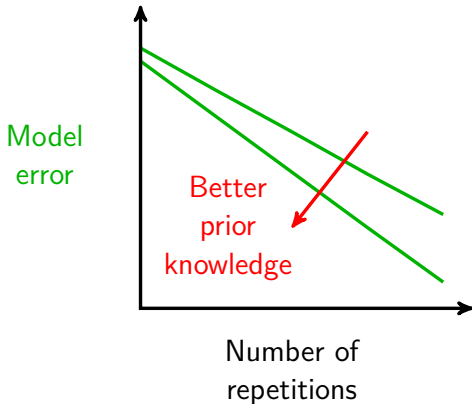




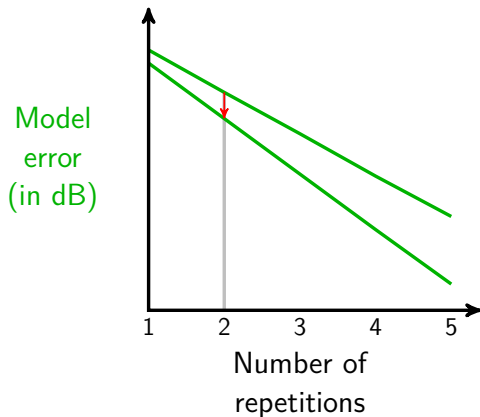
The number of parameters increases rapidly with the number of orthonormal basis functions



## Better prior knowledge allows for better models



## Iteratively update the pole locations



- 1) Estimate a high-order nonlinear model
- 2) Extract a low-order linear model

# Overview

- ▶ Structure detection via BLA
- ▶ Identification of some block structures
  - ▶ Hammerstein
  - ▶ Wiener
  - ▶ Parallel Wiener