

# ESS101- Modeling and Simulation

## Lecture 13

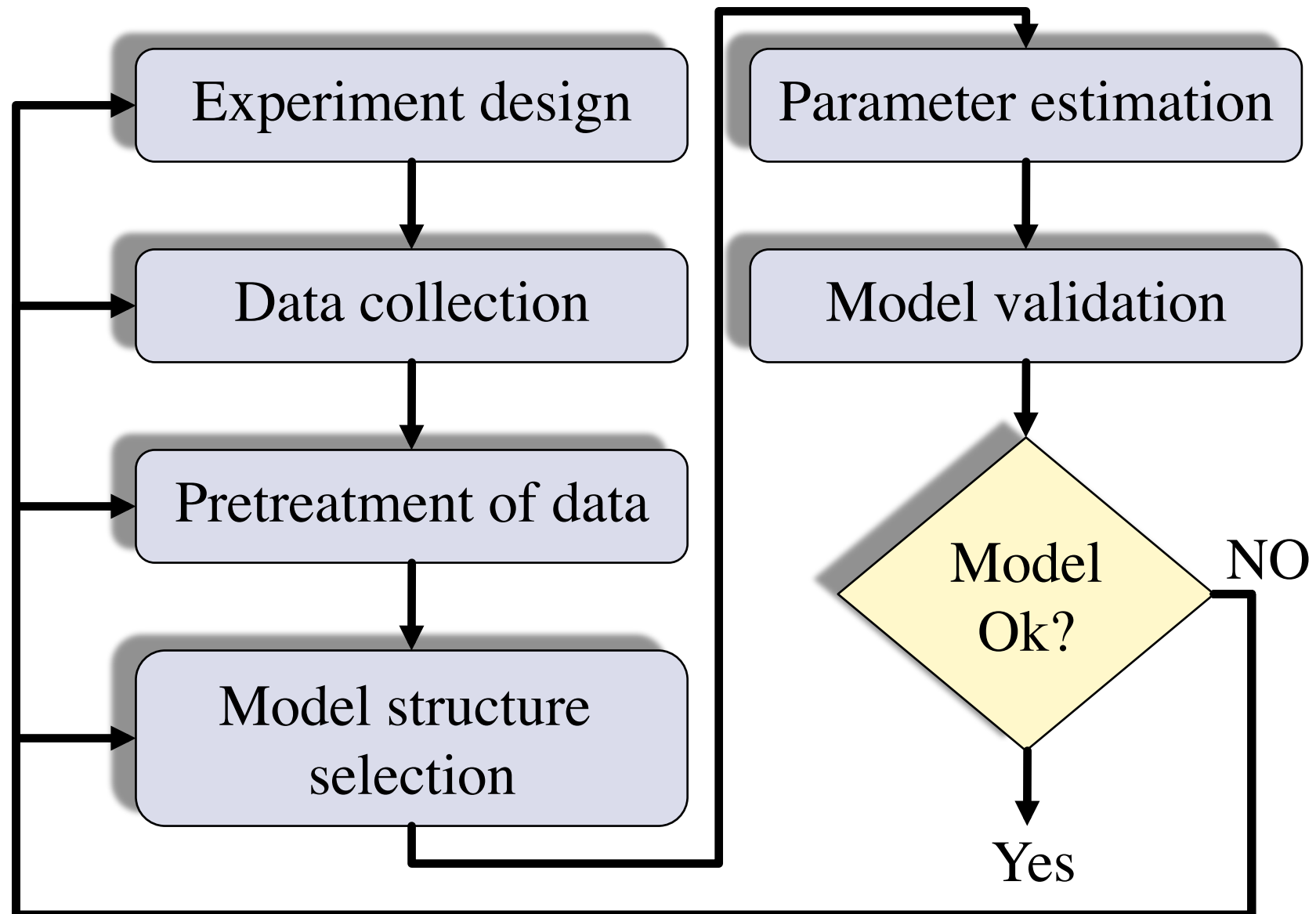
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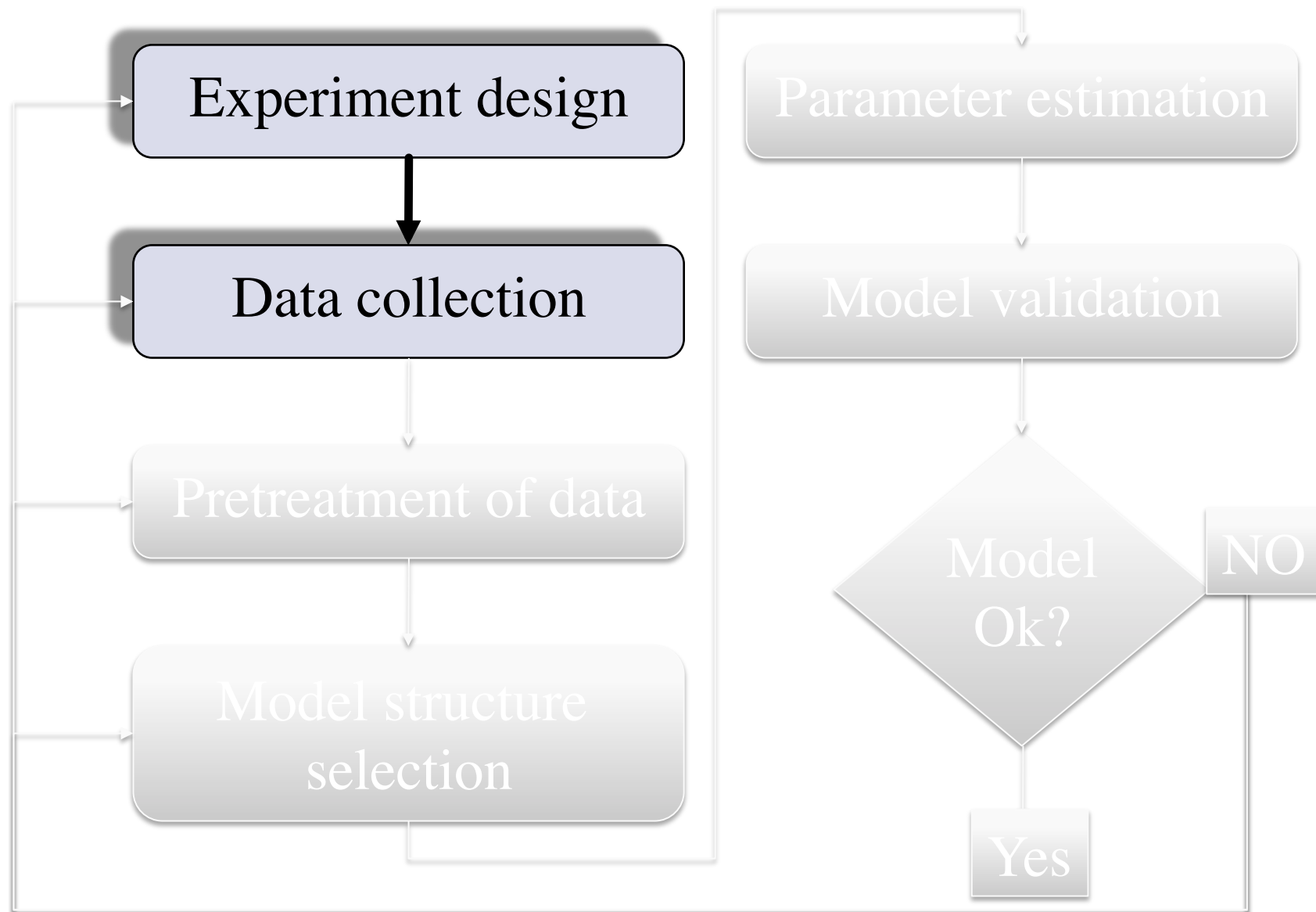
# Today (Chapter 10)

- ➡ Working principle in parametric identification
  - ➡ Experiment design
  - ➡ Pretreatment of data
  - ➡ Model structure selection
  - ➡ Model validation

# Working principle



# Working principle



# Experiment design

- ☞ Choice of the input signal (if possible)\*
- ☞ Detection of feedback\*
- ☞ Sampling time

\* Data can be collected only under normal operation of the plant

# Experiment design

 Choice of the input signal (if possible)\*

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# Experiment design. The input signal

***Criterion:*** excite all the features of the system (see Excitation on Lecture 9). E.g.,

- steady state behavior
- transient response
- response to different frequencies

***Telegraph signal.*** A signal randomly switching between *two levels*.

***Q1:*** how to select the two levels?

***Q2:*** how to select the switching frequency?

# Experiment design. The input signal

**Q1:** how to select the two levels?

- Usual input levels
- Maximum allowed signals levels
- Nonlinearities
  - Input signals levels within a range

**Q2:** how to select the switching frequency?

- Frequency within the system bandwidth
- Let the system get to steady state



# Experiment design. The input signal.

## Procedure

1. (If possible) Get a step response
2. Calculate the system bandwidth through, e.g., the settling time

$$T_a^1 \cong \frac{3}{\omega_B} \quad T_a^2 \cong \frac{3}{\xi \omega_B}$$

3. Set the maximum switching frequency within the system bandwidth
4. Hold the input constant for at least the settling time

# Experiment design

✓ Choice of the input signal (if possible)\*

 **Detection of feedback\***

 Sampling time

\* Data can be collected only under normal operation of the plant

# Experiment design. Feedback

Consider the system

$$y(t) + ay(t - 1) = bu(t - 1) + e(t)$$

under the feedback control law

$$u(t) = -fy(t)$$

The corresponding predictor is:

$$\hat{y}(t, \vartheta) = \underbrace{(-bf - a)}_{\vartheta} y(t - 1)$$

$$\exists \infty \hat{a}, \hat{b} : -\hat{b}f - \hat{a} = \hat{\vartheta} \quad \textit{identifiability issues}$$

# Experiment design. Feedback

Define the input as

$$u(t) = f(r(t) - y(t))$$

The corresponding predictor is:

$$\hat{y}(t | \vartheta) = (-bf - a)y(t - 1) + br(t - 1)$$

***Observe that*** spectral analysis does not work with feedback

# Experiment design

- ✓ Choice of the input signal (if possible)\*
- ✓ Detection of feedback\*

 **Sampling time**

\* Data can be collected only under normal operation of the plant

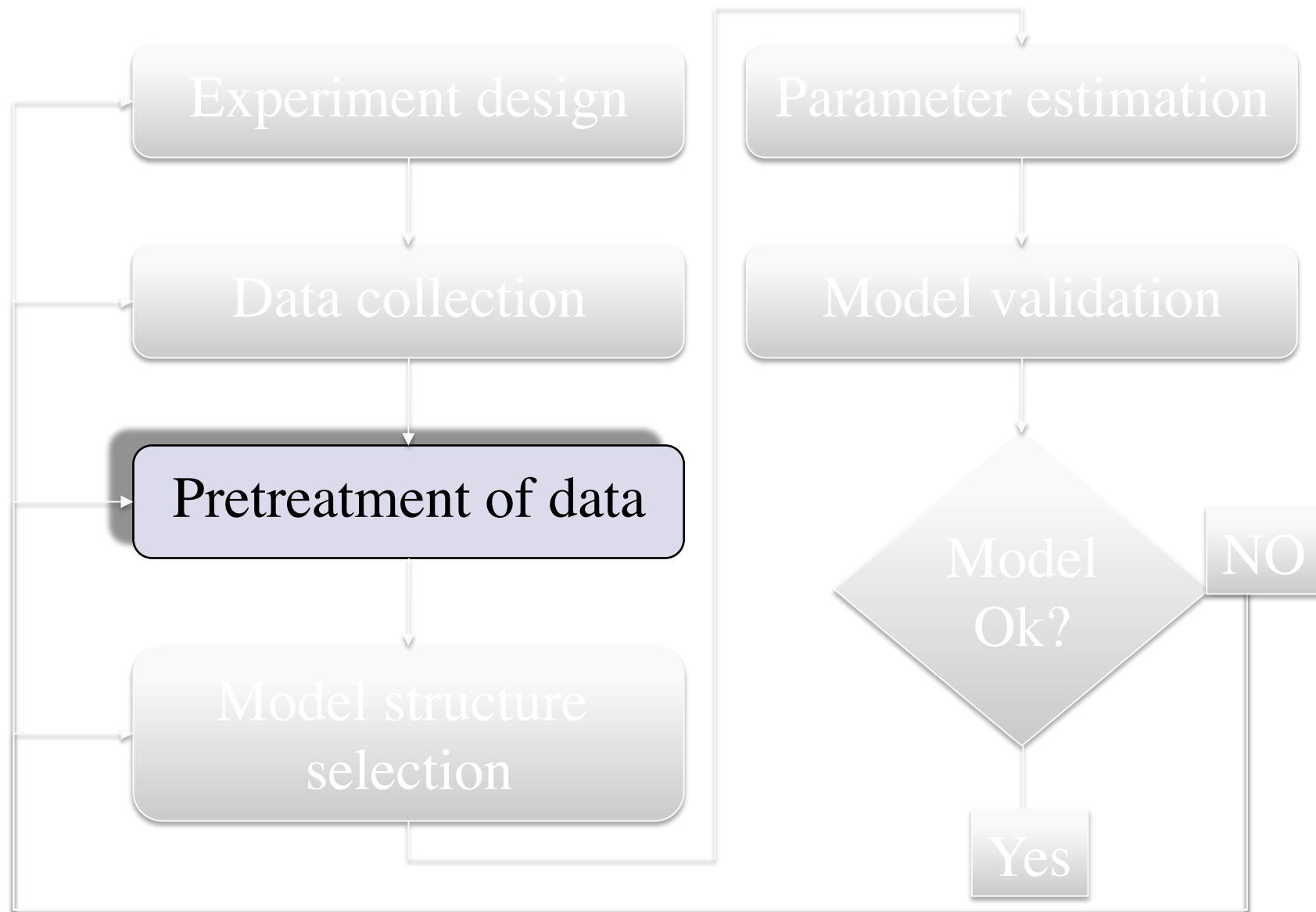
# Experiment design. The sampling time

- **Evaluate the step response.** Chose the sampling time as 1/10 of the rise time.
- **Sampling frequency greater than the Nyquist frequency:**

$$\omega_s > 2\omega_c$$

- **Aliasing.** Before sampling, low pass filter the signal with cut-off frequency at the Nyquist frequency.

# Working principle



# Pretreatment of data

- Subtract the mean values and drift
  - If data is collected at steady state
- Outliers
  - Wrong data due to, e.g., spikes
- Low pass filter (anti-aliasing filter)
  - High frequency components due to not well designed anti-aliasing filters

Matlab command:  
**detrend**



# Model structure selection

## ☞ Tailor made models

### *Pro:*

- ✌ Minimal set of parameters
- ✌ High quality model

### *Cons:*

- ✗ Physical modeling efforts required
- ✗ Computationally expensive numerical optimization

## ☞ Ready made models

### *Pro:*

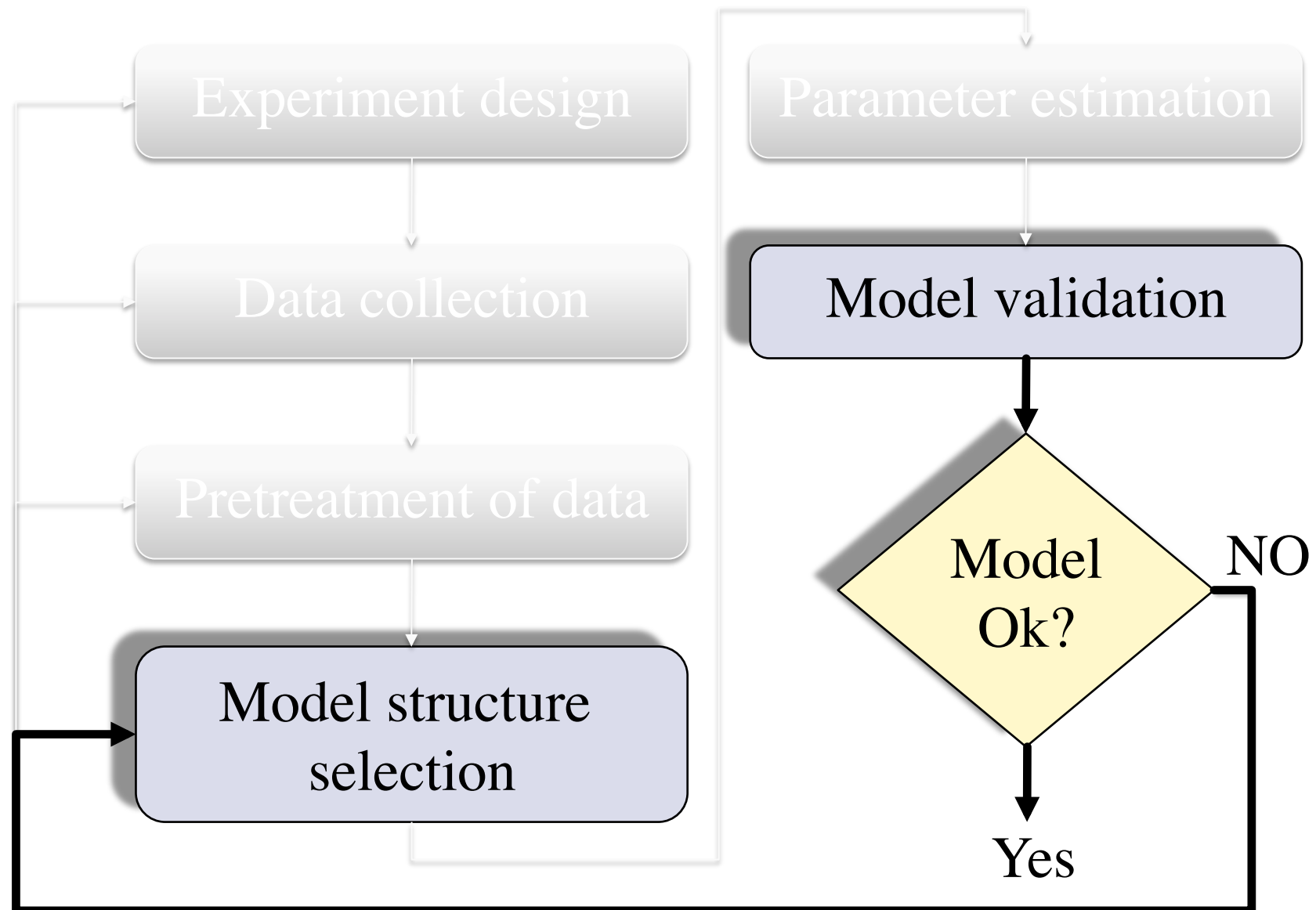
- ✌ No additional modeling effort
- ✌ Computationally efficient (ARX)

### *Cons:*

- ✗ Bias and variance

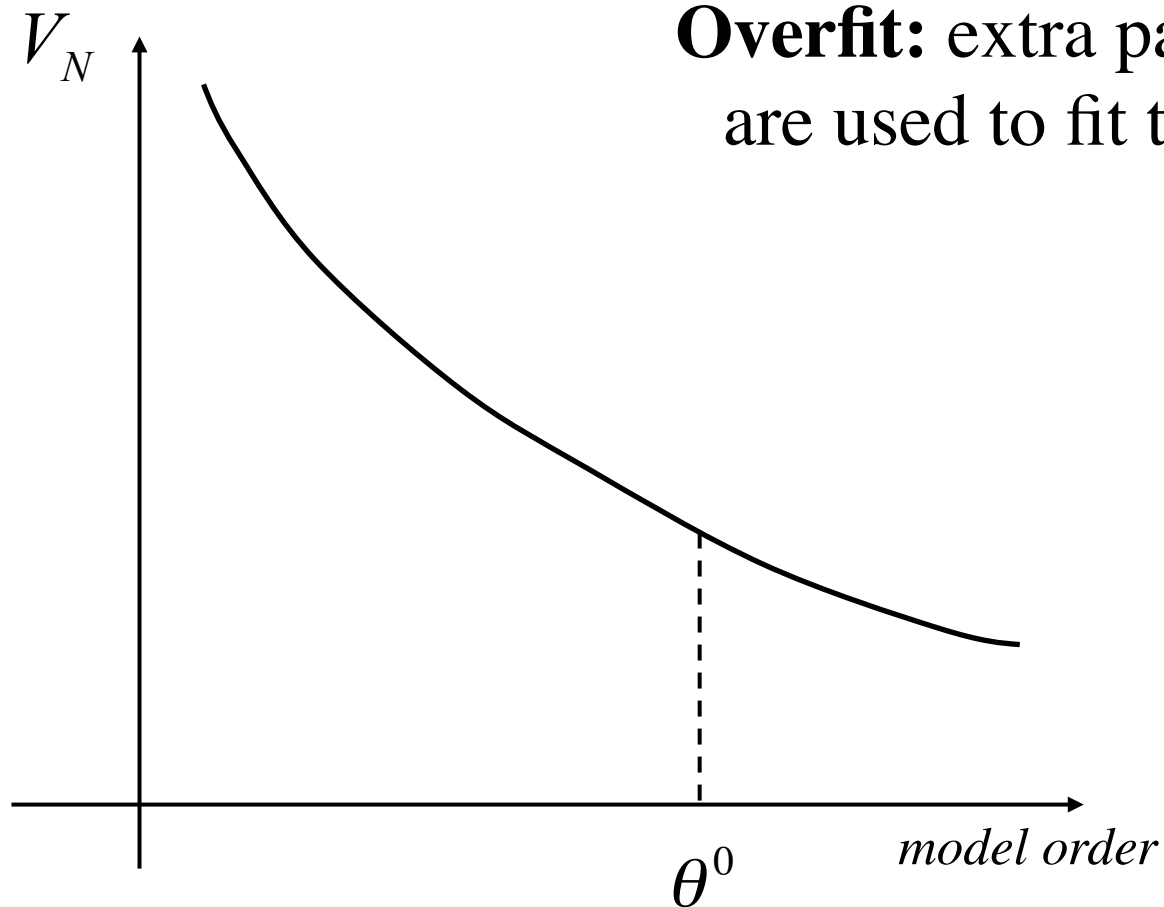
***Conclusion.*** Start with the simplest (ARX) and complicate if needed.

# Working principle



# Model structure selection

***Cross validation.*** Test the model by using fresh data



**Overfit:** extra parameters are used to fit the noise

# Model structure selection

Reformulate the identification problem as:

$$\min_{d, \theta} f(d, \theta) \sum_{t=1}^N \varepsilon^2(t, \theta) \quad \text{with} \quad d = \dim(\theta) \quad \text{and}$$

***Akaike's Information Criterion (AIC):***

$$f(d, \theta) = 1 + \frac{2d}{N}$$

***Final Prediction Error (FPE):***

$$f(d, \theta) = \frac{1 + d/N}{N(1 - d/N)}$$

***Moreover*** compare the frequency responses

# Model evaluation. Residual analysis

Evaluate the residuals:

$$\varepsilon(t) = y(t) - \hat{y}(t | \hat{\vartheta}_N)$$

$$\hat{R}_{\varepsilon u}(\tau) = \frac{1}{N} \sum_{t=1}^N \varepsilon(t + \tau) u(t)$$

- Feedback.

$$\hat{R}_{\varepsilon u}(\tau) \neq 0, \tau < 0$$

- Delay and estimate of  $n_b$   $\hat{R}_{\varepsilon u}(\tau_0) \neq 0$