

# Computer Science

## Jerzy Świątek

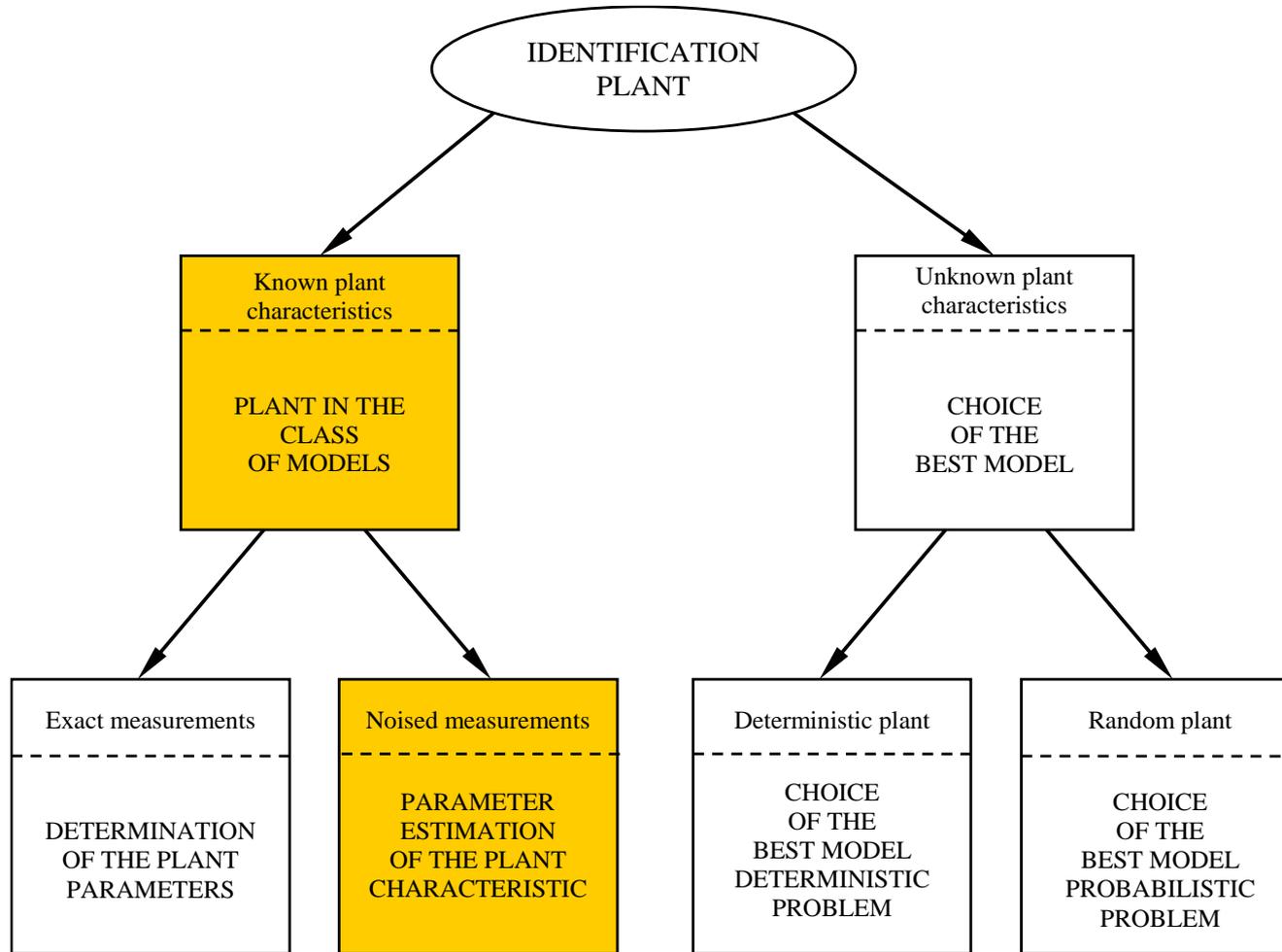
### Systems Modelling and Analysis

*Choose yourself and new technologies*

#### L.3c. Estimation of the plant parameter with random value



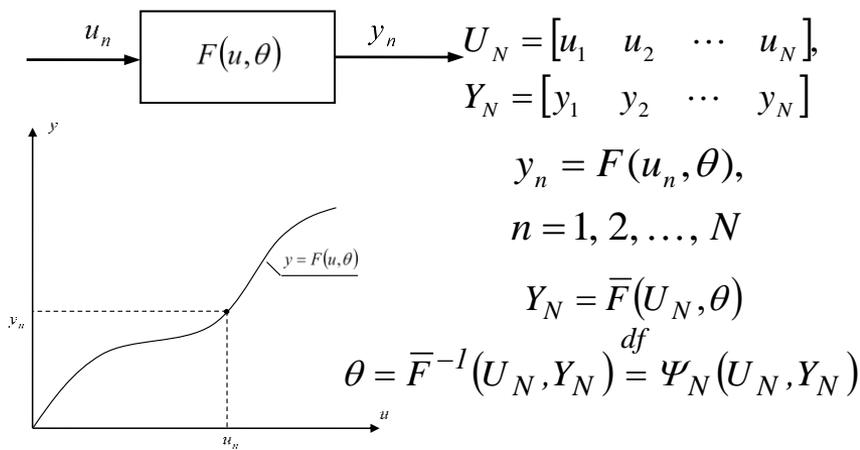
Project co-financed from the EU European Social Fund



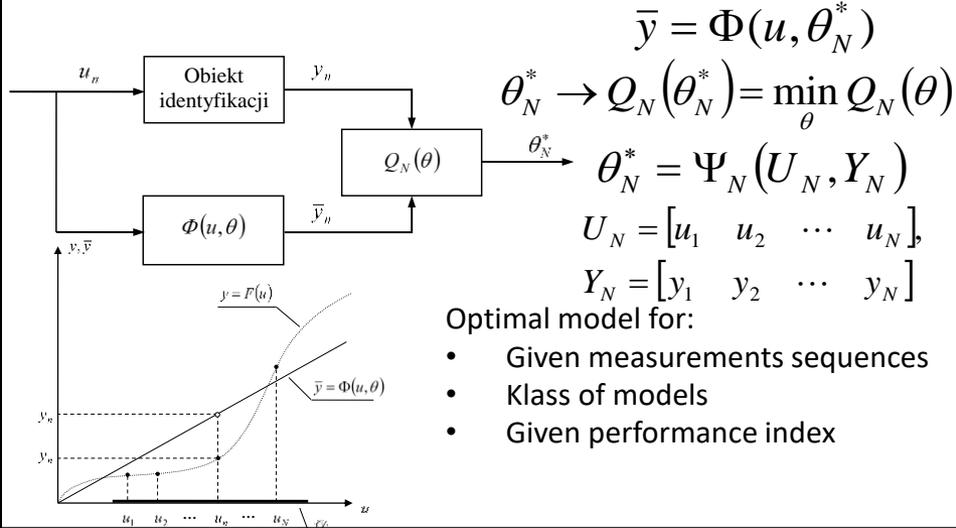


### Plant in the class of model

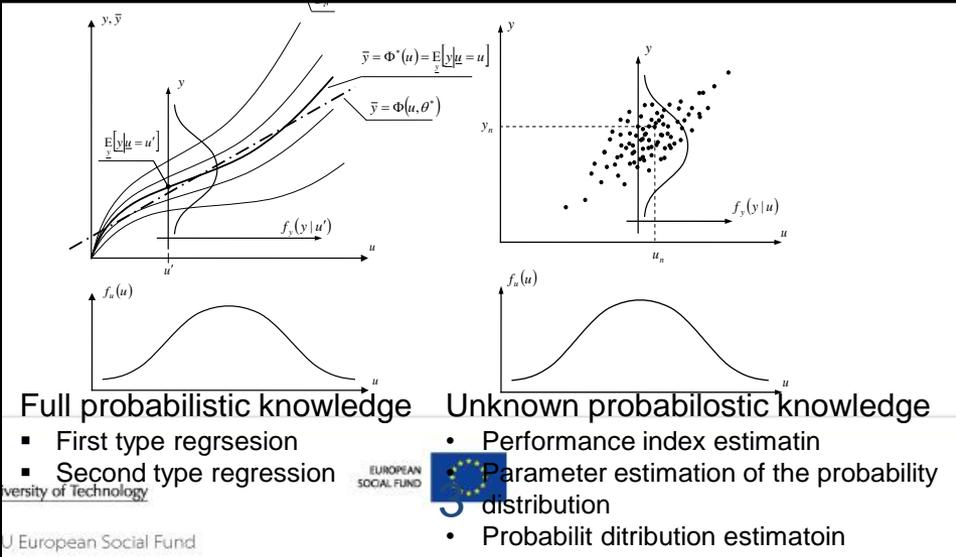
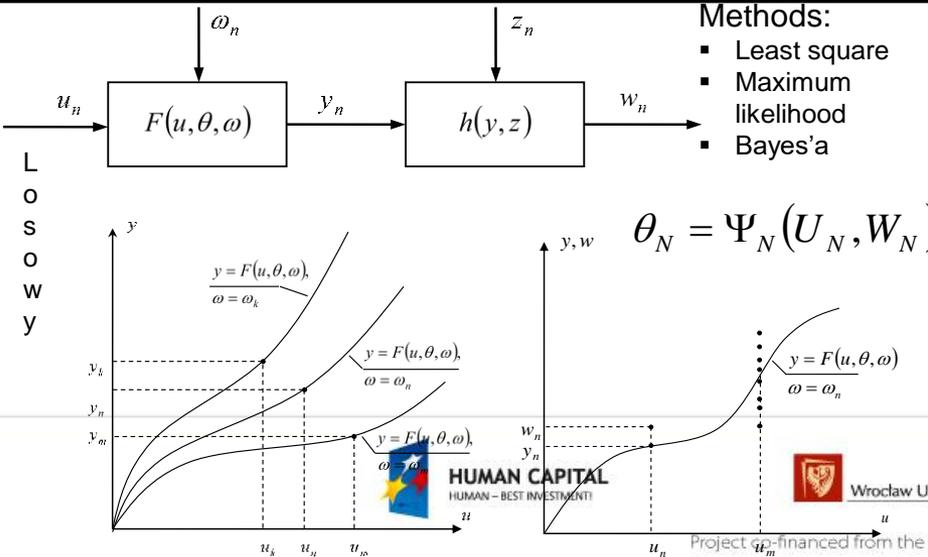
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### Choice of the best model

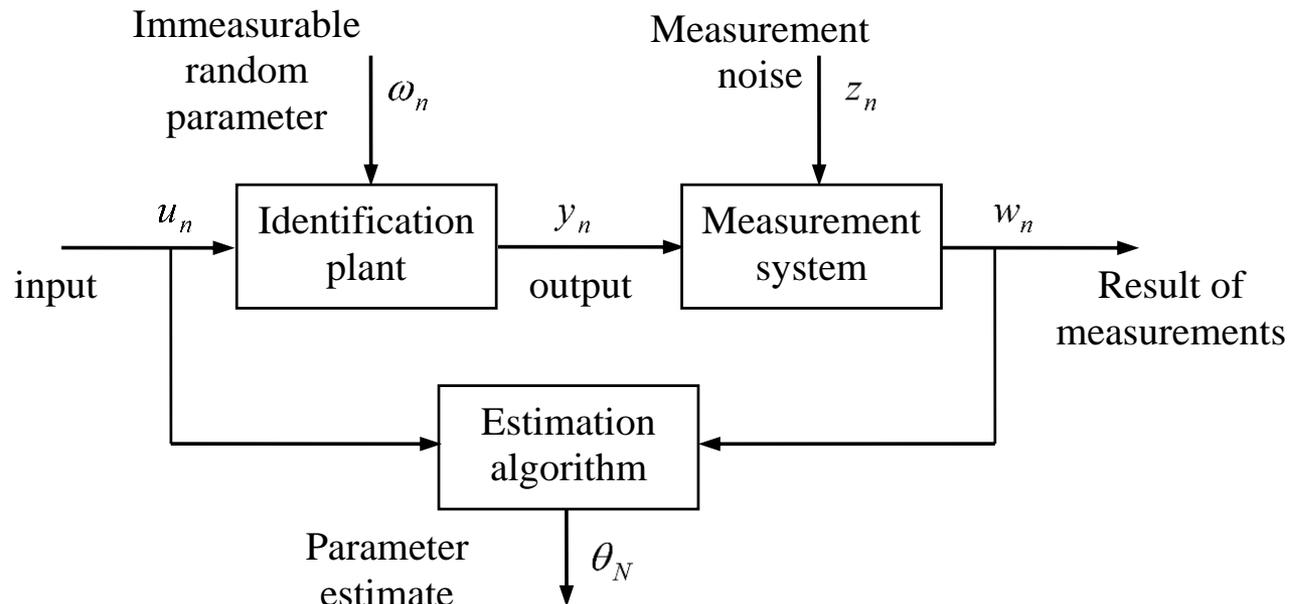


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# Plant parameter estimation problem

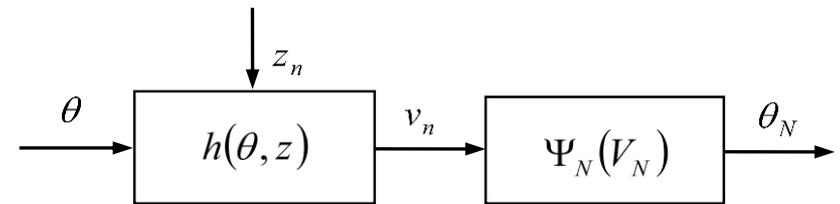




# Noised measurements of the physical values

- Problem formulation

Measurement system description:  $v = h(\theta, z)$



where:  $v \in \mathcal{V}$ ,  $h$  – known one-to-one function

$$h: \Theta \times \mathcal{Z} \rightarrow \mathcal{V}, \quad z = h_z^{-1}(\theta, v)$$

examples of  $h$ :  $v = h(\theta, z) = \theta + z$

$$v = h(\theta, z) = \theta \cdot z$$

$\mathcal{W}$  – measurements domain ( $\dim \theta = \dim z = L$ )

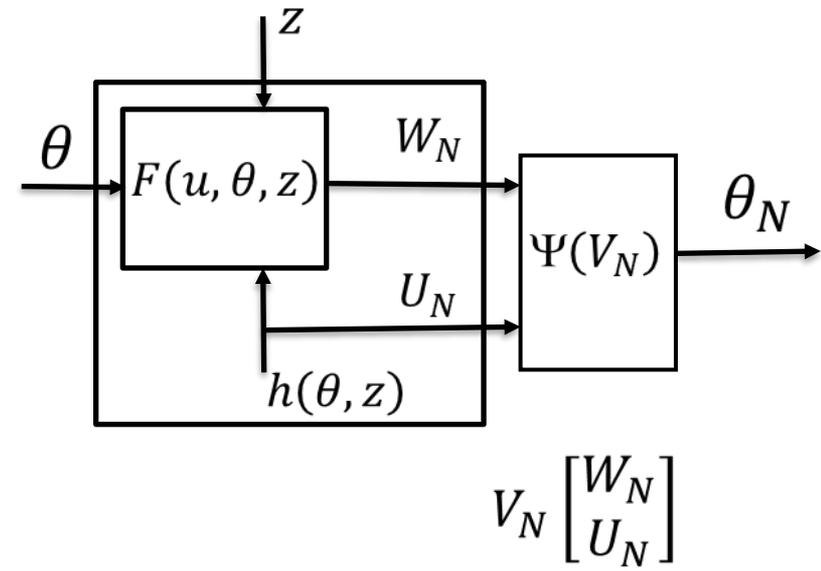
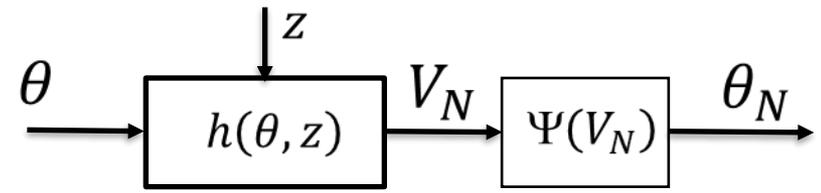


# Noised measurements of the physical values

General form of estimation algorithm:

$$\theta_N = \Psi_N(V_N)$$

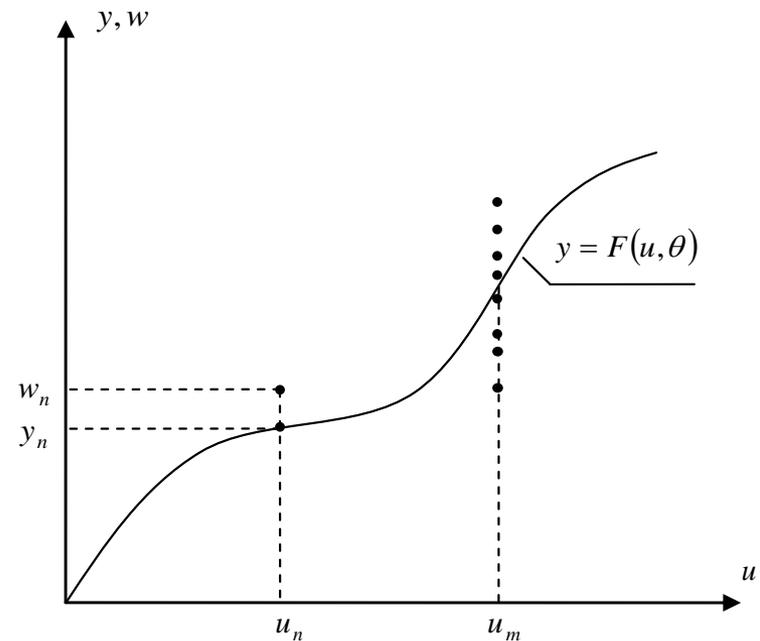
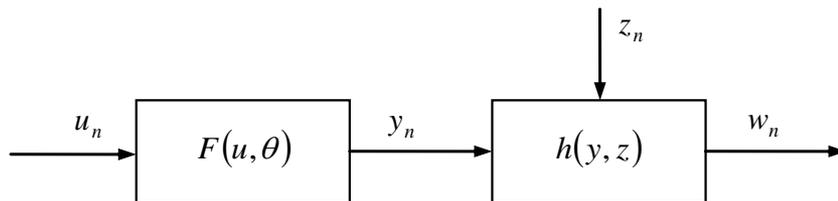
- Solution:
  - Least square method
  - Maximum likelihood method
  - Bayesian method





# Deterministic plant, noised measurements of the plant output

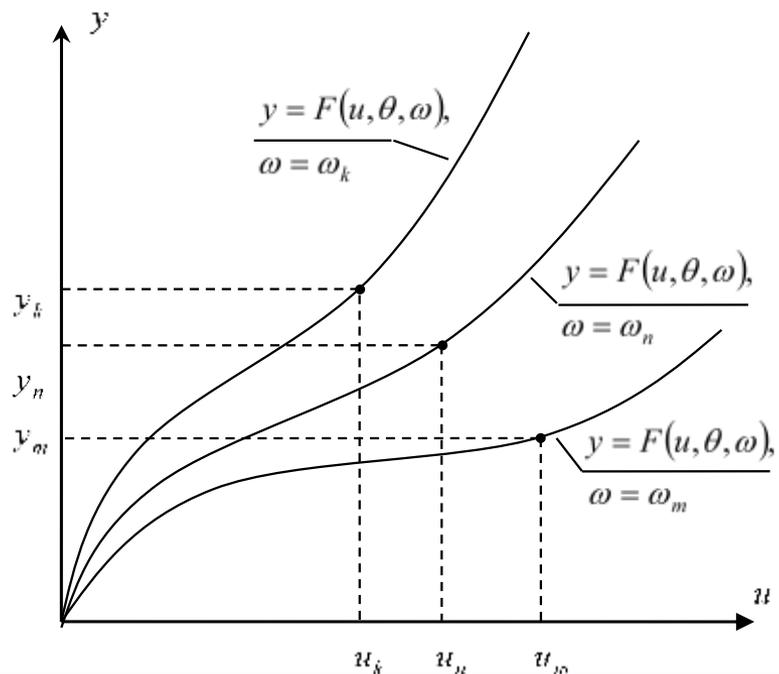
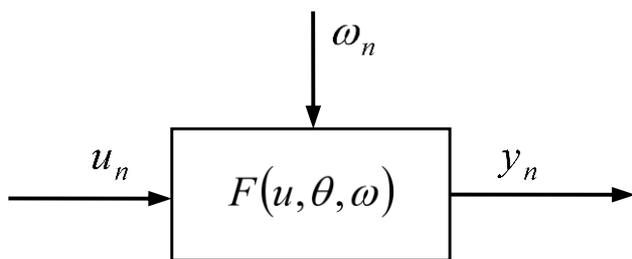
- Noised measurements of the identification plant known static characteristics





# Immeasurable random plant parameter

- Measurements of plant characteristic with random parameter





# Immeasurable random plant parameter

- Problem formulation

Plant characteristic:  $y = F(u, \theta, \omega)$

Random plant parameter:  $\omega \in \Omega \subseteq \mathcal{R}^L$ , ( $\dim y = \dim \omega = L$ )

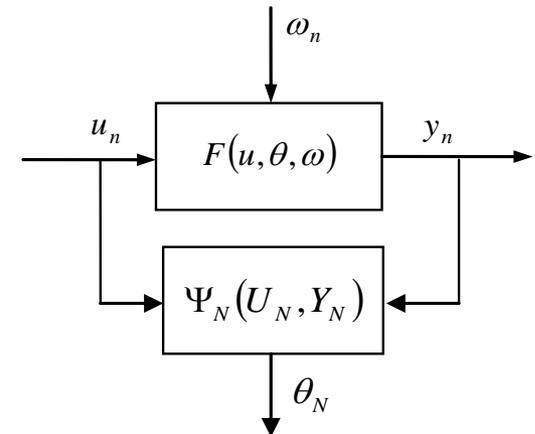
$F$  – one-to-one mapping  $\omega = F_{\omega}^{-1}(u, \theta, y)$

$\omega_n$  – value of random variable  $\omega$  from  $\Omega \subseteq \mathcal{R}^L$

Probability density function  $f_{\omega}(\omega)$  is given

Measurements:  $U_N = [u_1 \quad u_2 \quad \cdots \quad u_N]$ ,  $Y_N = [y_1 \quad y_2 \quad \cdots \quad y_N]$

Estimation algorithm:  $\theta_N = \Psi_N(U_N, Y_N)$





# Noised measurements of the physical values

- Solution:
  - Least square method
  - Maximum likelihood method
  - Bayesian method

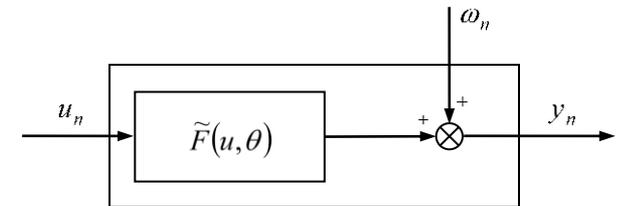


# Least square method

## Assumptions:

$$y = F(u, \theta, \omega) = \tilde{F}(u, \theta) + \omega \quad \text{– plant characteristic}$$

$$E[\underline{\omega}] = 0 \quad \text{Var}[\underline{\omega}] < \infty$$



## Calculations:

Least square method minimizes empirical variance:

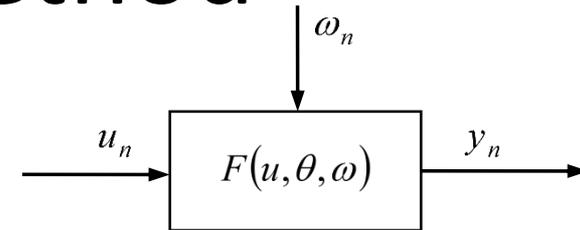
$$\text{Var}_{\omega N}(U_N, Y_N, \theta) = \frac{1}{N} \sum_{n=1}^N (y_n - \tilde{F}(u_n, \theta))^2$$

Estimation algorithm has the form:

$$\theta_N = \Psi_N(U_N, Y_N) \rightarrow \text{Var}_{\omega N}(U_N, Y_N, \theta_N) = \min_{\theta \in \Theta} \text{Var}_{\omega N}(U_N, Y_N, \theta)$$



# Maximum likelihood method



## Assumptions:

$\omega_n$  is value of random variable  $\underline{\omega}$ , with probability density function  $f_{\omega}(\omega)$

For a given input  $u_n$ , output  $y_n, n = 1, 2, \dots, N$  is measured

Sequence  $y_n, n = 1, 2, \dots, N$  contains values of random variable  $\underline{y}$ :  $\underline{y} = F(u, \theta, \underline{\omega})$

## Calculations:

Probability density function  $f_y(y, \theta; u) = f_{\omega}(F_{\omega}^{-1}(u, \theta, y)) \cdot |J_F|$

where  $J_F$  is Jacobi matrix:  $J_F = \frac{\partial F_{\omega}^{-1}(u, \theta, y)}{\partial y}$

Likelihood function:  $L_N(Y_N, \theta; U_N) = \prod_{n=1}^N f_y(y_n, \theta; u_n) = \prod_{n=1}^N f_{\omega}(F_{\omega}^{-1}(u_n, \theta, y_n)) |J_F|$

Estimation algorithm:  $\theta_N = \Psi_N(U_N, Y_N) \rightarrow L_N(Y_N, \theta_N; U_N) = \max_{\theta \in \Theta} L_N(Y_N, \theta; U_N)$



# Bayesian method's

## Assumptions:

Additionally  $\theta$  is value of random variable  $\underline{\theta}$ , with probability density function  $f_{\theta}(\theta)$

## Calculations:

$$r(\bar{\theta}, Y_N; U_N) \stackrel{df}{=} E_{\underline{\theta}}[L(\underline{\theta}, \bar{\theta}) | Y_N; U_N] = \int_{\Theta} L(\theta, \bar{\theta} = \bar{\Psi}(U_N, Y_N)) f'(\theta | Y_N; U_N) d\theta$$

$$f_y(y | \theta; u) = f_{\omega}(F_{\omega}^{-1}(u, \theta, y)) |J_F|$$

A'posteriori probability density function:

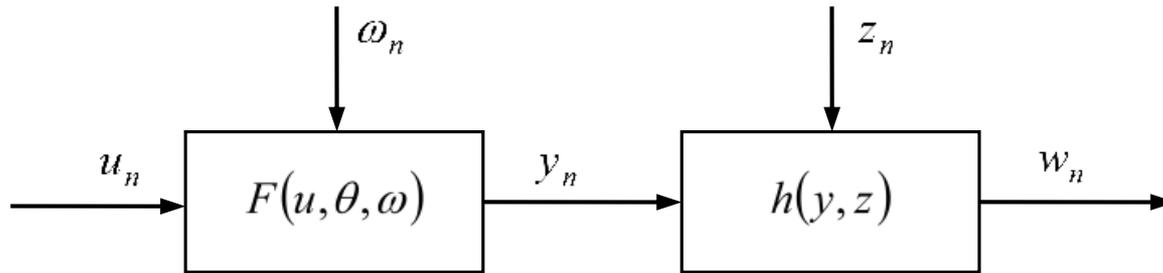
$$f'(\theta | Y_N; U_N) = \frac{f_{\theta}(\theta) \cdot \prod_{n=1}^N f_{\omega}(F_{\omega}^{-1}(u_n, \theta, y_n)) |J_F|}{\int_{\Theta} f_{\theta}(\theta) \cdot \prod_{n=1}^N f_{\omega}(F_{\omega}^{-1}(u_n, \theta, y_n)) |J_F| d\theta}$$

Estimation algorithm:  $\theta_N = \Psi_N(U_N, Y_N) \rightarrow r(\theta_N, Y_N; U_N) = \min_{\bar{\theta} \in \Theta} r(\bar{\theta}, Y_N; U_N)$



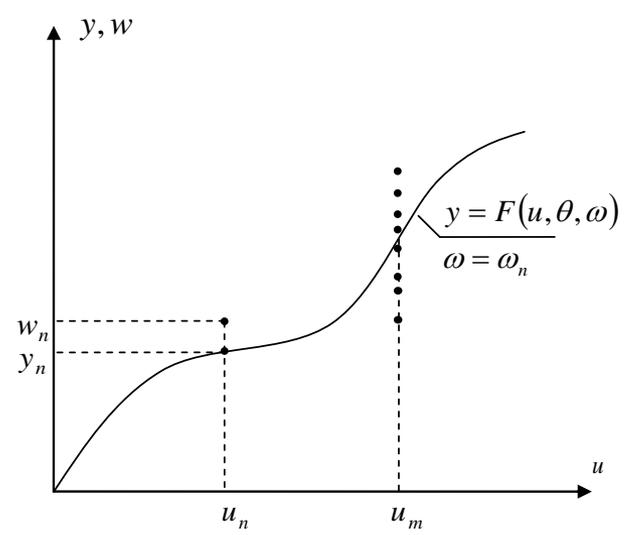
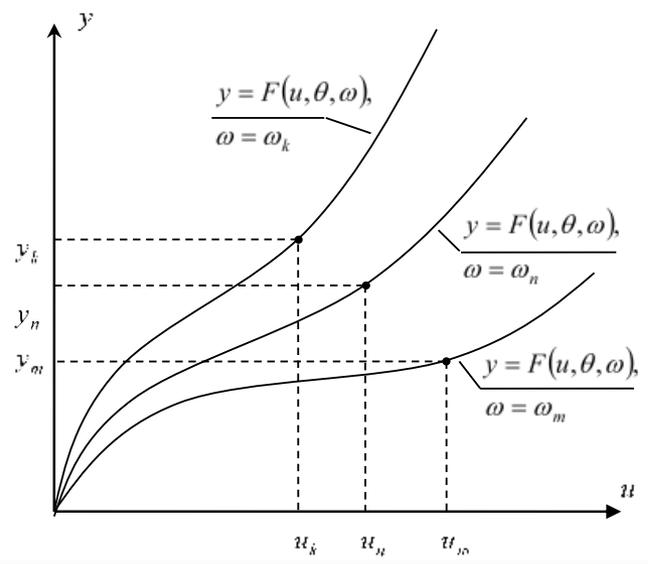
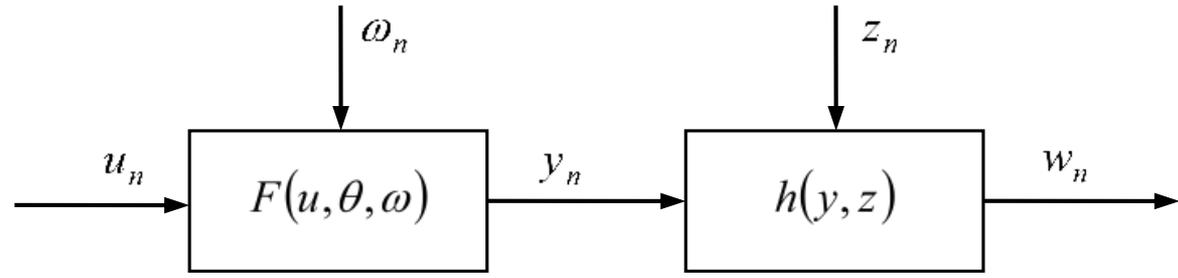
# Random plant parameter and measurement noise

- Noised measurement plant output with randomly changed parameters



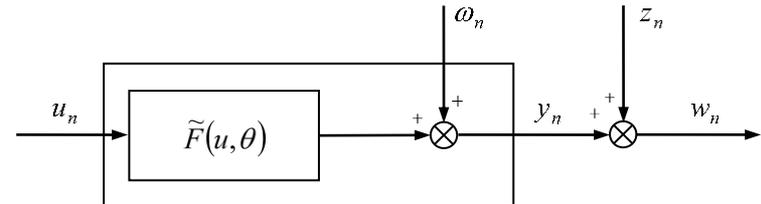


- Noised measurement plant output with randomly changed parameters





# Least square method



## Assumptions:

$\underline{z}$ ,  $\underline{\omega}$  – random variables such that  $E[\underline{\omega}] = 0$ ,  $Var[\underline{\omega}] < \infty$ ,  $E[\underline{z}] = 0$ ,  $Var[\underline{z}] < \infty$

Measurements are values of random variable:  $\underline{w} = \tilde{F}(u, \theta) + \underline{\omega} + \underline{z}$

## Calculations:

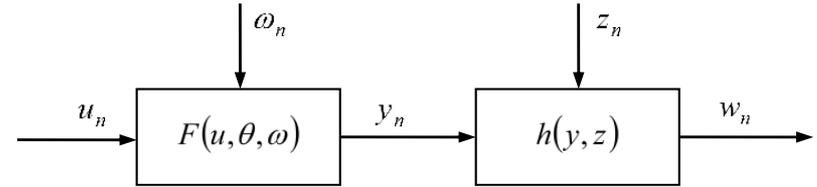
$$E[\underline{\omega} + \underline{z}] = 0, \quad Var[\underline{\omega} + \underline{z}] < \infty$$

Empirical variance:  $Var_{(\omega+z)N}(U_N, W_N, \theta) = \frac{1}{N} \sum_{n=1}^N (w_n - \tilde{F}(u_n, \theta))^2$

Estimation algorithm:  $\theta_N = \Psi_N(U_N, Y_N) \rightarrow Var_{(\omega+z)N}(U_N, W_N, \theta_N) = \min_{\theta \in \Theta} Var_{(\omega+z)N}(U_N, W_N, \theta)$



# Maximum likelihood method



## Assumptions:

$\omega_n$  is value of random variable  $\underline{\omega}$ , with probability density function  $f_{\omega}(\omega)$

$z_n$  is value of random variable  $\underline{z}$ , with probability density function  $f_z(z)$

$w_n, n = 1, 2, \dots, N$  are values of random variable  $\underline{w} = h(\underline{y}, \underline{z})$

For a given  $u_n, y_n, n = 1, 2, \dots, N$  are values of random variable  $\underline{y} = F(u, \theta, \underline{\omega})$

## Calculations:

Function  $h$  is no one to one mapping with respect  $(\underline{y}, \underline{z})$ , so we add identity  $\underline{y} = \underline{y}$  and we have:

$$\underline{w} = h(\underline{y}, \underline{z})$$

$$\underline{y} = \underline{y}$$

The inverse transformation:  $\underline{z} = h_z^{-1}(\underline{y}, \underline{w})$

$$\underline{y} = \underline{y}$$



# Maximum likelihood method

Jacobi matrix: 
$$J = \begin{bmatrix} \frac{\partial h_z^{-1}(y, w)}{\partial w} & \frac{\partial h_z^{-1}(y, w)}{\partial y} \\ \frac{\partial y}{\partial w} & \frac{\partial y}{\partial y} \\ \frac{\partial w}{\partial w} & \frac{\partial w}{\partial y} \end{bmatrix} = \begin{bmatrix} \frac{\partial h_z^{-1}(y, w)}{\partial w} & \frac{\partial h_z^{-1}(y, w)}{\partial y} \\ O_{L \times L} & I_{L \times L} \end{bmatrix}$$

where:  $O_{L \times L}$  is  $L$  – dimensional zero matrix,  $I_{L \times L}$  is  $L$  – dimensional unit matrix

Determinant of Jacobi matrix:

$$|J| = \left| \begin{bmatrix} \frac{\partial h_z^{-1}(y, w)}{\partial w} & \frac{\partial h_z^{-1}(y, w)}{\partial y} \\ O_{L \times L} & I_{L \times L} \end{bmatrix} \right| = \left| \frac{\partial h_z^{-1}(y, w)}{\partial w} \right| = |J_h|$$



# Maximum likelihood method

Joint probability density function of random variables  $(w, y)$ :

$$f_w(w, y, \theta; u) = f_z(h_z^{-1}(y, w))f_y(y, \theta; u)|J| = f_z(h_z^{-1}(y, w))f_\omega(F_\omega^{-1}(u, \theta, y))|J_F||J_h|$$

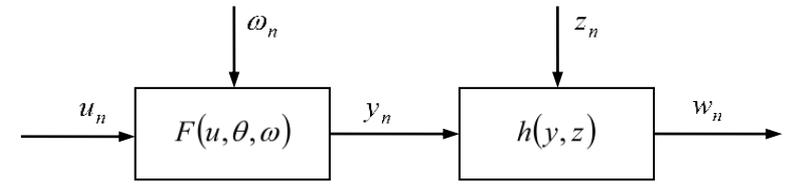
Marginal probability density function of random variable  $w$ :

$$f_w(w, \theta; u) = \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w))f_y(y, \theta; u)|J|dy = \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w))f_\omega(F_\omega^{-1}(u, \theta, y))|J_F||J_h|dy$$

Likelihood function:

$$L_N(W_N, \theta; U_N) = \prod_{n=1}^N f_w(w_n, \theta; u_n) =$$

$$= \prod_{n=1}^N \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w_n))f_\omega(F_\omega^{-1}(u_n, \theta, y))|J_F||J_h|dy$$



Estimation algorithm:  $\theta_N = \Psi_N(U_N, Y_N) \rightarrow L_N(W_N, \theta_N; U_N) = \max_{\theta \in \Theta} L_N(W_N, \theta; U_N)$



# Bayesian method's

## Assumptions:

Additionally  $\theta$  is value of random variable  $\underline{\theta}$ , with probability density function  $f_{\theta}(\theta)$

For a given parametr  $\theta$  and input  $u_n$  the sequence  $y_n, n = 1, 2, \dots, N$  are values of random variable  $\underline{y}$  under condition  $\underline{\theta} = \theta$  and input is equal  $u$ .

$w_n, n = 1, 2, \dots, N$  are values of random variable  $\underline{w}$  under condition  $\underline{\theta} = \theta$

$z_n$  is value of random variable  $\underline{z}$ , with probability density function  $f_z(z)$

## Calculations:

$$\underline{w} = h(\underline{y}, \underline{z})$$

$$f_w(w|\theta; u) = \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w)) f_y(y|\theta; u) |J| dy = \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w)) f_{\omega}(F_{\omega}^{-1}(u, \theta, y)) |J_F| |J_h| dy$$



# Bayesian method's

A'posteriori probability density function:

$$f'(\theta|W_N; U_N) = \frac{\int_{\mathcal{Y}} f_{\theta}(\theta) \prod_{n=1}^N \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w_n)) f_{\omega}(F_{\omega}^{-1}(u_n, \theta, y)) |J_F| |J_h| dy}{\int_{\Theta} \int_{\mathcal{Y}} f_{\theta}(\theta) \prod_{n=1}^N \int_{\mathcal{Y}} f_z(h_z^{-1}(y, w_n)) f_{\omega}(F_{\omega}^{-1}(u_n, \theta, y)) |J_F| |J_h| dy d\theta}$$

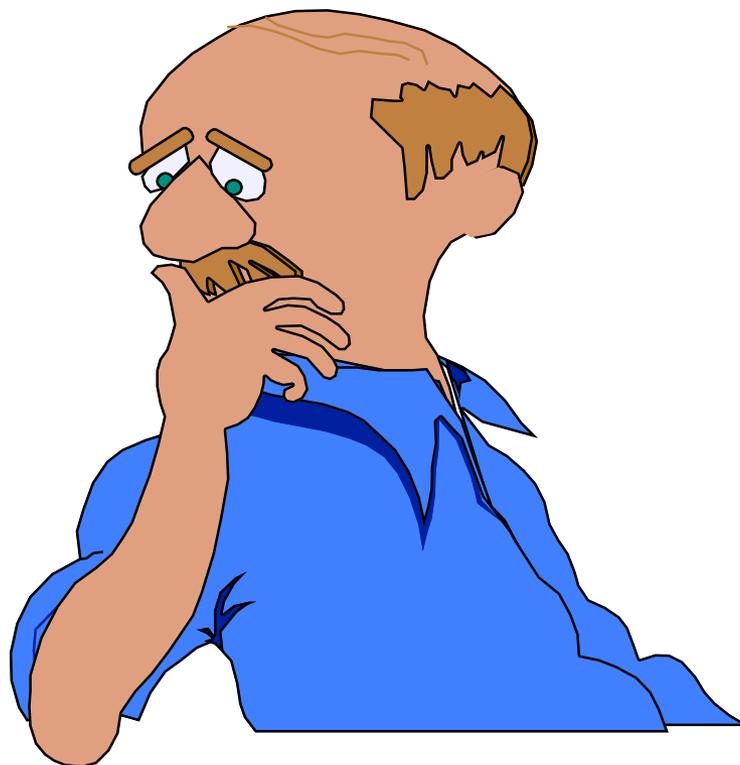
Conditional risk :

$$r(\bar{\theta}, Y_N; U_N) \stackrel{\text{df}}{=} E_{\underline{\theta}}[L(\underline{\theta}, \bar{\theta}) | W_N; U_N] = \int_{\Theta} L(\theta, \bar{\theta} = \bar{\Psi}(U_N, W_N)) f'(\theta | W_N; U_N) d\theta$$

Estimation algorithm:  $\theta_N = \Psi_N(U_N, W_N) \rightarrow r(\theta_N, W_N; U_N) = \min_{\bar{\theta} \in \Theta} r(\bar{\theta}, W_N; U_N)$



# Thank you for attention





# Least square method

$$w_n = u_n + z_n, \quad u_n = Ri_n, \quad n = 1, 2, \dots, N$$

$$\bar{z} \sim N(0, \sigma_z)$$

$$Var_N(R) = \sum_{n=1}^N (w_n - Ri_n)^2$$

$$R_N = \frac{\sum_{n=1}^N w_n i_n}{\sum_{n=1}^N (i_n)^2}$$



# Maximum likelihood method

$$w_n = u_n + z_n, \quad u_n = Ri_n \quad \bar{z} \sim N(m_z, \sigma_z)$$

$$f_z(z) = \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(z - m_z)^2}{2\sigma_z^2}\right) \quad f_R(R) = \frac{1}{\sqrt{2\pi\sigma_R}} \exp\left(-\frac{(R - m_R)^2}{2\sigma_R^2}\right)$$

$$z_n = w_n - Ri_n, \quad J = 1$$

$$f_w(w, R; i) = \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(w - Ri - m_z)^2}{2\sigma_z^2}\right)$$

$$\begin{aligned} L_N(W_N, R; I_N) &= \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(w_n - Ri_n - m_z)^2}{2\sigma_z^2}\right) = \\ &= \left(\frac{1}{\sqrt{2\pi\sigma_z}}\right)^N \exp\left(-\frac{\sum_{n=1}^N (w_n - Ri_n - m_z)^2}{2\sigma_z^2}\right) \end{aligned}$$

$$R_N = \frac{\sum_{n=1}^N (w_n - m_z) i_n}{\sum_{n=1}^N (i_n)^2}$$



$$R_N = \frac{\sum_{n=1}^N (w_n - m_z) i_n}{\sum_{n=1}^N (i_n)^2}$$





# Bayesian method's

$$w_n = u_n + z_n, \quad u_n = Ri_n \quad \bar{z} \sim N(m_z, \sigma_z) \quad \bar{R} \sim N(m_R, \sigma_R) \quad L(R, \bar{R}) = -\delta(R - \bar{R})$$

$$f_z(z) = \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(z - m_z)^2}{2\sigma_z^2}\right) \quad f_R(R) = \frac{1}{\sqrt{2\pi\sigma_R}} \exp\left(-\frac{(R - m_R)^2}{2\sigma_R^2}\right)$$

$$z_n = w_n - Ri_n, \quad J = 1$$

$$f_w(w; i) = \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(w - Ri - m_z)^2}{2\sigma_z^2}\right)$$

$$\begin{aligned} r(R, W_N; I_N) &= -\frac{1}{\sqrt{2\pi\sigma_R}} \exp\left(-\frac{(R - m_R)^2}{2\sigma_R^2}\right) \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_z}} \exp\left(-\frac{(w_n - Ri_n - m_z)^2}{2\sigma_z^2}\right) = \\ &= -\frac{1}{\sqrt{2\pi\sigma_R}} \left(\frac{1}{\sqrt{2\pi\sigma_z}}\right)^N \exp\left(-\frac{(R - m_R)^2}{2\sigma_R^2} - \frac{\sum_{n=1}^N (w_n - Ri_n - m_z)^2}{2\sigma_z^2}\right) \end{aligned}$$

$$R_N = \frac{m_R + \left(\frac{\sigma_R}{\sigma_z}\right)^2 \sum_{n=1}^N w_n i_n}{1 + \left(\frac{\sigma_R}{\sigma_z}\right)^2 \sum_{n=1}^N (i_n)^2}$$





# Immeasurable random plant parameter

$$u_n = Ri_n, \quad n = 1, 2, \dots, N$$

$$R = R_0 + \beta T = R_0 + \omega, \quad \omega = \beta T \quad \omega \sim N(m_\omega, \sigma_\omega)$$

$$f_\omega(\omega) = \frac{1}{\sqrt{2\pi\sigma_\omega}} \exp\left(-\frac{(\omega - m_\omega)^2}{2\sigma_\omega^2}\right)$$

$$u = Ri = (R_0 + \omega)i \rightarrow \omega = \frac{u}{i} - R_0, \quad J = \frac{1}{i}$$

$$R_{0N} = \frac{1}{N} \sum_{n=1}^N \frac{u_n}{i_n} - m_\omega$$

$$f_u(u; i, R_0) = \frac{1}{\sqrt{2\pi\sigma_\omega}} \exp\left(-\frac{\left(\frac{u}{i} - R_0 - m_\omega\right)^2}{2\sigma_\omega^2}\right) \frac{1}{i}$$

$$L_N(U_N, R_0; I_n) = \prod_{n=1}^N f_u(u_n; i_n, R) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_\omega}} \exp\left(-\frac{\left(\frac{u_n}{i_n} - R_0 - m_\omega\right)^2}{2\sigma_\omega^2}\right) \frac{1}{i_n} =$$

$$= \left(\frac{1}{\sqrt{2\pi\sigma_\omega}}\right)^N \exp\left(-\frac{\sum_{n=1}^N \left(\frac{u_n}{i_n} - R_0 - m_\omega\right)^2}{2\sigma_\omega^2}\right) \frac{1}{\prod_{n=1}^N i_n}$$





$$\begin{aligned} L_N(U_N, R_0; I_n) &= \prod_{n=1}^N f_u(u_n; i_n \cdot R) = \prod_{n=1}^N \frac{1}{\sqrt{2\pi\sigma_\omega}} \exp\left(-\frac{\left(\frac{u_n}{i_n} - R_0 - m_\omega\right)^2}{2\sigma_\omega^2}\right) \frac{1}{i_n} = \\ &= \left(\frac{1}{\sqrt{2\pi\sigma_\omega}}\right)^N \exp\left(-\frac{\sum_{n=1}^N \left(\frac{u_n}{i_n} - R_0 - m_\omega\right)^2}{2\sigma_\omega^2}\right) \frac{1}{\prod_{n=1}^N i_n} \end{aligned}$$

$$R_{0N} = \frac{\sum_{n=1}^N \left(\frac{u_n}{i_n} - m_\omega\right)}{N}$$



# Thank you for attention

