Wastewater Treatment Process Control

CONTENTS

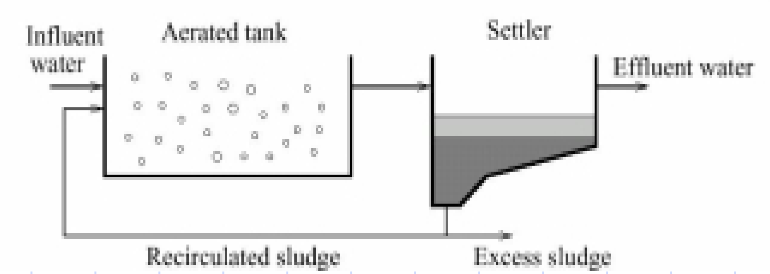
Oct. 2001

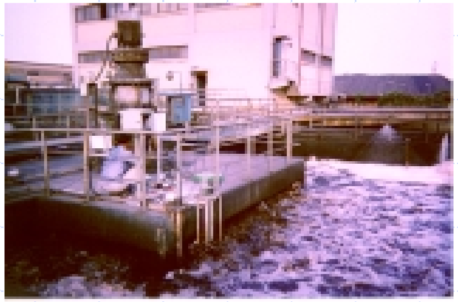
Introduction

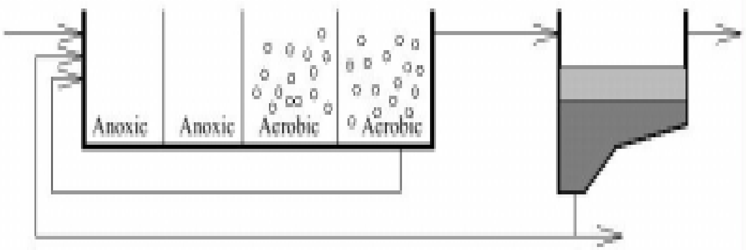
- Objective of WWTP management
  - Enhancing treated wastewater quality with min. cost
- Methodologies
  - Attaching additional equipments
  - Developing innovative processes
  - Elevating the process performance ➔ process control
- WWTP characteristics
  - Liberal incomings and rigorous outgoings
  - Too many unknowns and unreliable/unrealizable sensors
  - Bio-process
    - time-varying, nonlinear/stiff dynamics, multivariate,...

Typical WWTP: Activated sludge process (ASP):

ASP: colloidal organic matters are degraded in an aerobic bioreactor







Advanced ASP: nutrients are removed by altering oxic and anoxic bioreactor condition

Variables for ASP control

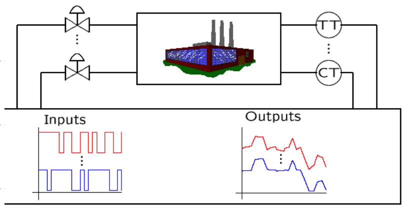
Measurement variables	Manipulated variables
flow rates in different plant units	air flow rate and its spatial distribution
BOD,COD,TOC	return sludge flow rate
Phosphorus fractions	waste sludge flow rate
Nitrogen in ammonia, nitrite and nitrate	additional carbon source for denitrification
pH	chemical dosage pumping rate
suspended solids in different units	feeding points for step feed control
alkalinity	
temperature	
dissolved oxygen in different locations	
air flow rates and air pressure	
sludge levels	
sludge flow rates	
gas flow rates and temperatures	

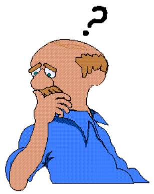
Conventional controllable variables
DO, MLSS, SBH, pH, HRT, SRT

WWTP control

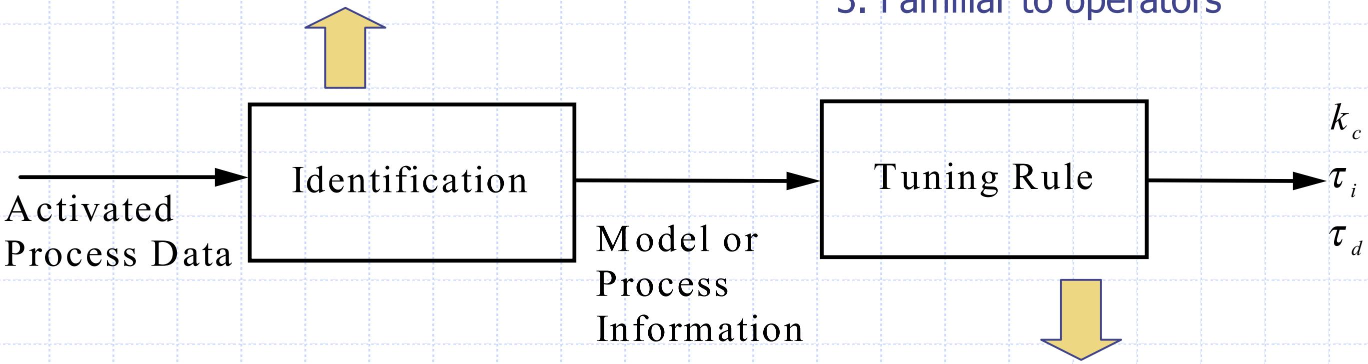
- ➔ Continuous process ID
- ➔ PID auto-tuning
- ➔ FB-FF control example
- ➔ Set point controller

Continuous process ID and PID auto-tuning





Why PID controller?
1. Simple
2. Robust
3. Familiar to operators



$$u(t) = k_c(y_s(t) - y(t)) + \frac{k_c}{\tau_i}\int_0^t (y_s(t) - y(t))dt + k_c\tau_d \frac{d(y_s(t) - y(t))}{dt}$$

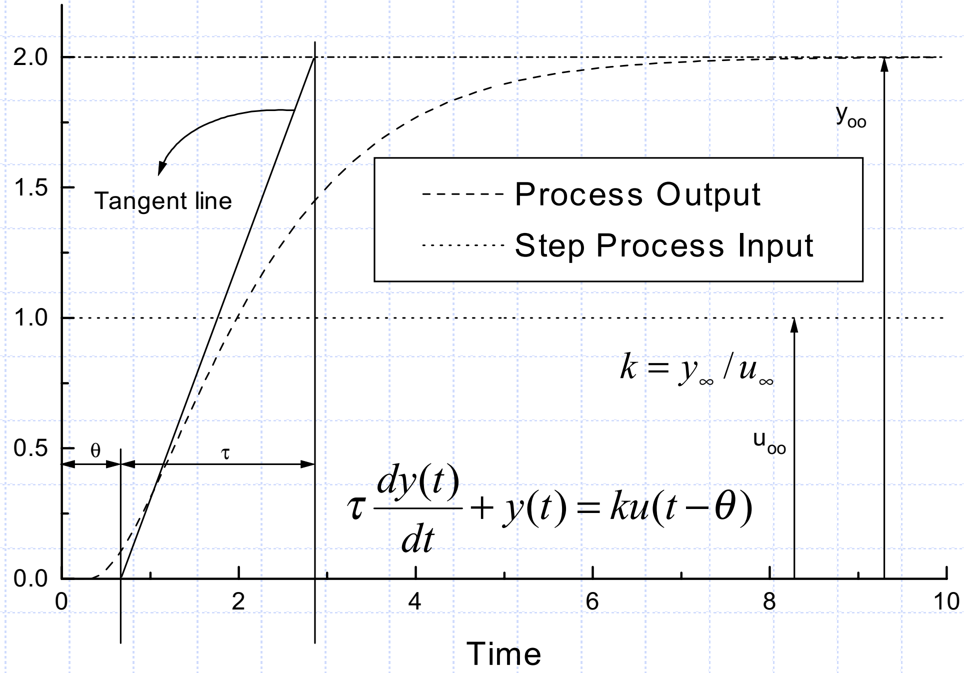
Why process ID prior PID setting?
PID tuning parameters are depend on process dynamics

PID controlling procedure

- PID tuning steps
  - step1. Process activation
  - step2. Process model generation (process dynamics)
  - step3. PID parameters calculation using tuning rules
- What is the auto-tuning?
  - automatic determination of step1-step3
- Examples
  - Step input → PRC → FOPTD → PID tuning rules
  - Relay Feedback or P-controller input→ G(jw) → PID tuning rules
  - Any Activation Signal → high order model → model reduction → FOPTD or SOPTD → PID tuning rules

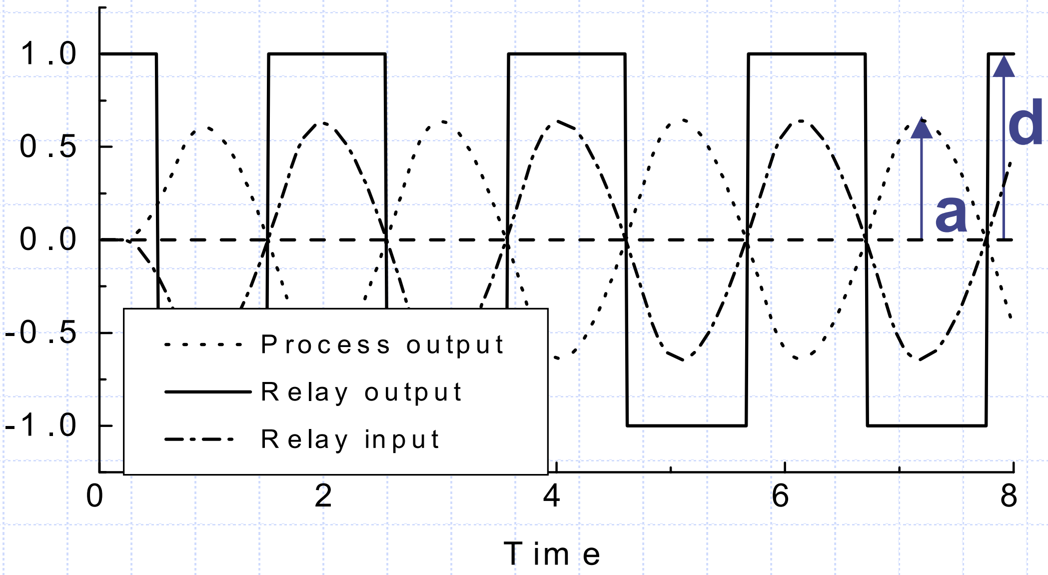
Conventional nonparametric ID: PRC

Good ID?
1. Accuracy
2. Simplicity
3. Amount of Information
4. Availability
5. Robustness



Auto-tuning method #1: Relay

1. **Astrom and Hagglund (1984)**
2. **Ultimate frequency data**
3. **Simple**
4. **No prior information on the process**



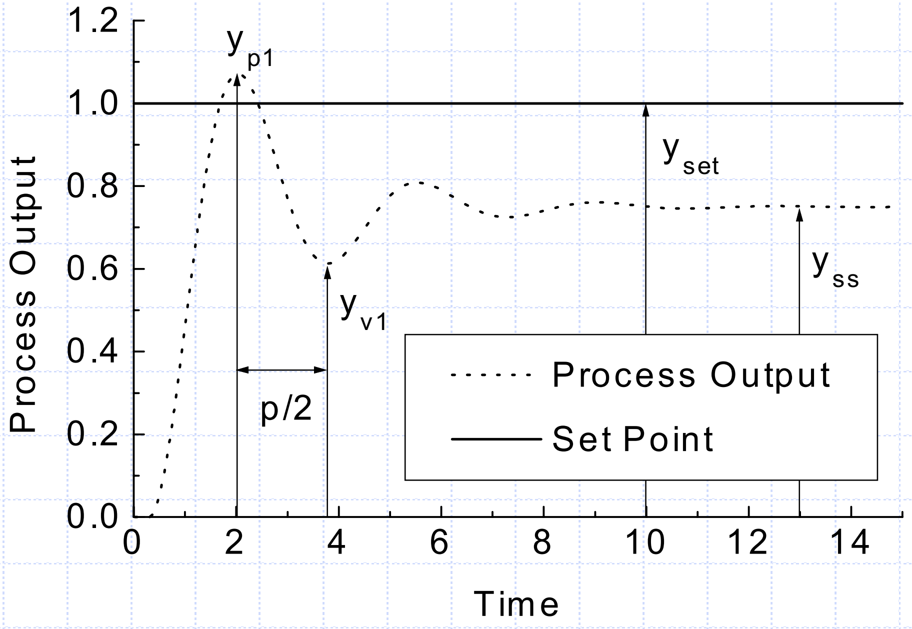
$$I(t) = a\sin(\omega t)$$

$$O(t) \approx \frac{4d}{\pi}\sin(\omega t)$$

$\Rightarrow$ $N(a) = \frac{4d}{\pi a}\exp(-0j) = \frac{4d}{\pi a}$ $\Rightarrow$ $1 + G(j\omega)N(a) = 0$ $\Rightarrow$ $G(j\omega) = -1/N(a)$

Auto-tuning method #2: P-controller

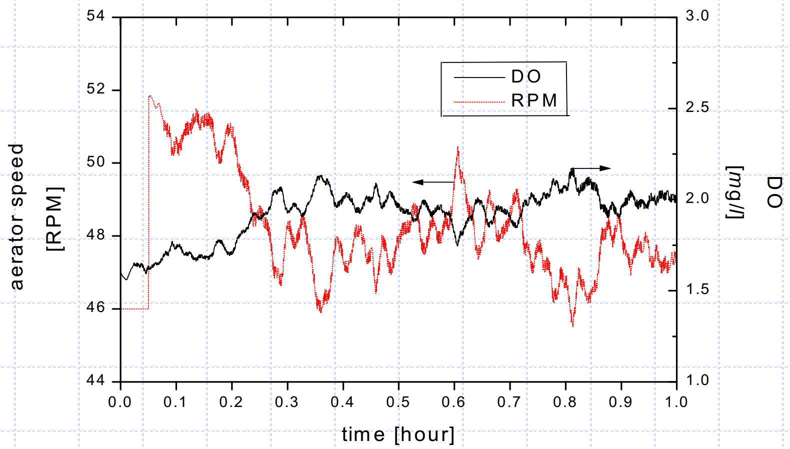
1. Yuwana and Seborg (1982)
2. FOPTD model
3. Prior determine the P gain

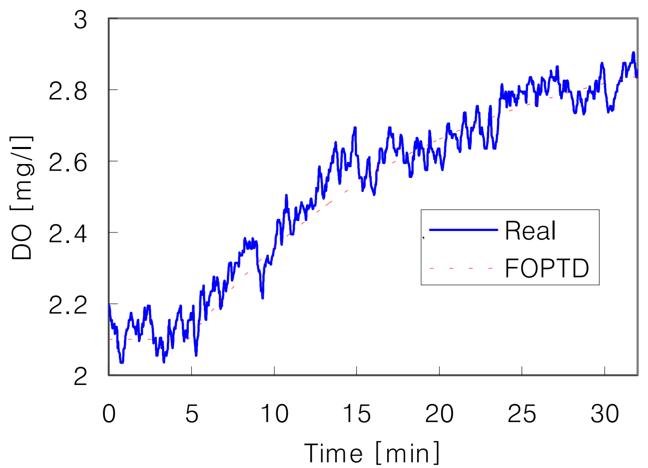


$$Y(s) = G_{cl}(s)\frac{y_{set}}{s} \approx \left\{ \frac{K_{cl}\exp(-\theta_{cl}s)}{\tau_{cl}s^2 + 2\tau_{cl}\zeta_{cl}s + 1} \right\} \frac{y_{set}}{s} \Rightarrow G_{cl}(s) \approx \frac{k_c G(s)}{1 + k_c G(s)} \Rightarrow G(s) \approx \frac{G_{cl}(s)}{k_c(1 - G_{cl}(s))}$$

Experimental result of DO process ID

Identification using integral transformation (Sung & Lee, 1998).



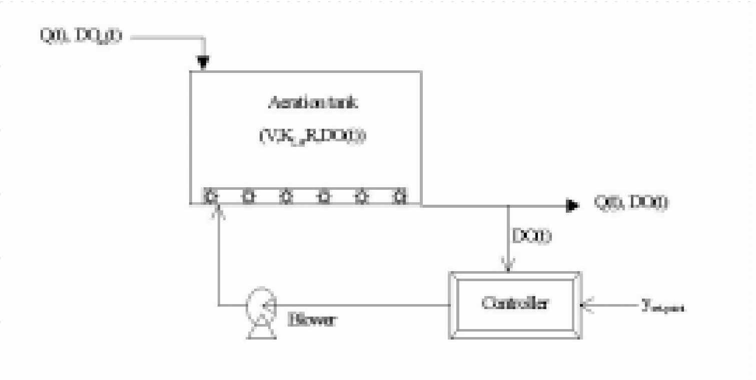


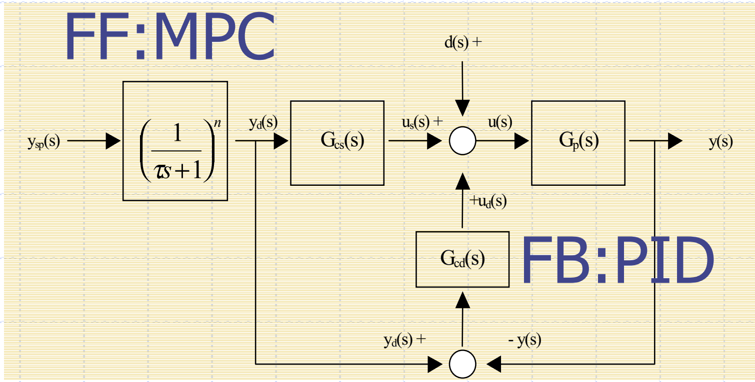
$$G_p(s) = \frac{-0.000012s^3 + 0.00098s^2 - 0.001s + 0.196}{-0.000003s^4 + 0.001s^3 - 0.0016s^2 + 0.325s + 1} \Rightarrow G_{FOPTD}(s) \cong \frac{0.2e^{-0.19s}}{0.35s+1} \Rightarrow$$

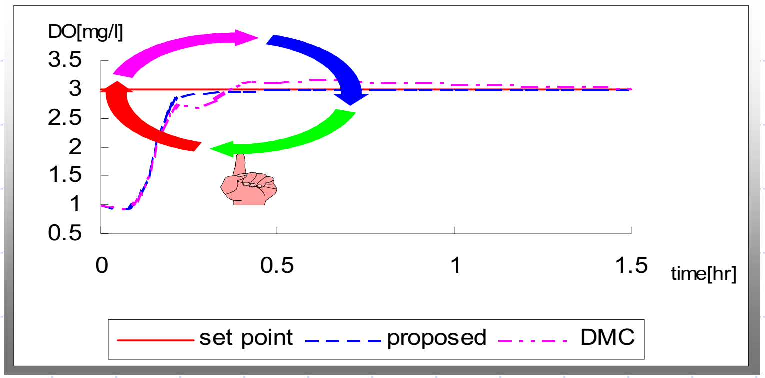
PID tuning

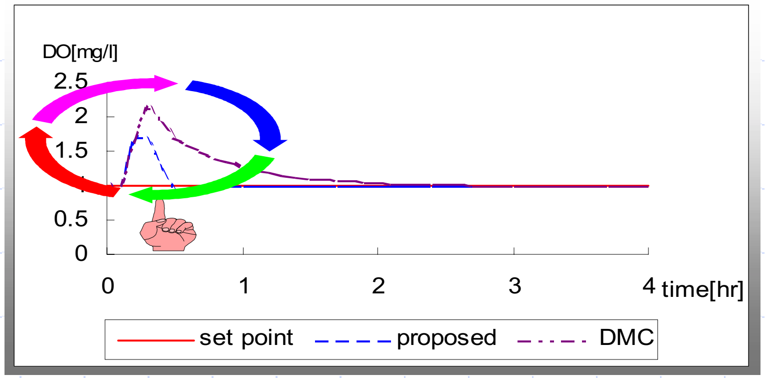
Advanced control example #1: FB & FF

DO control by continuous time model predictive control and PID controller



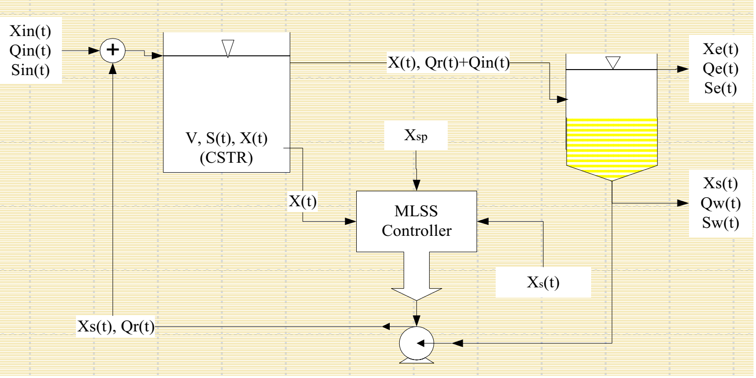


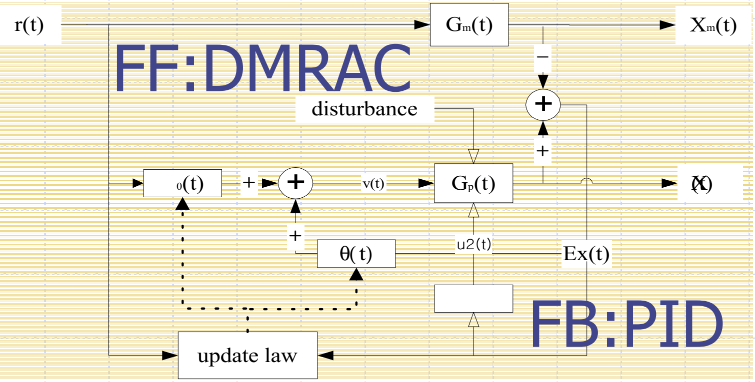


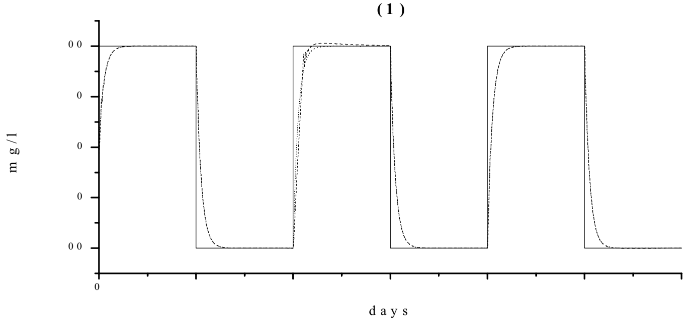


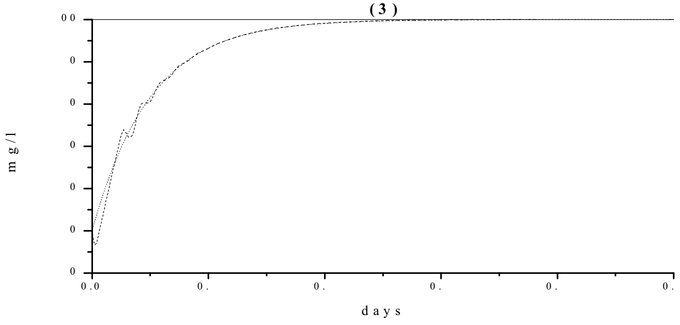
Advanced control example #2: FB & FF

MLSS control by direct model reference adaptive control with PI controller









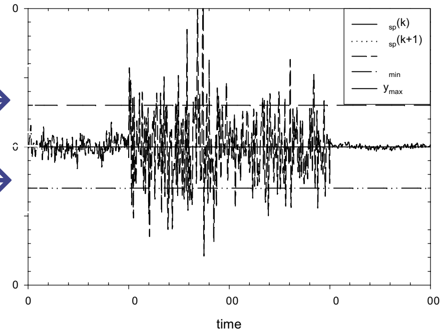
Set-point controller(SPC)

- **Objective**
  - Set-point decision for a feed-back controller
- **Properties**
  - Controlled variables have ranges, e.g. 1<DO<3; 1500<MLSS<3000
  - Controlled process output has Gaussian distribution
  - Disturbances are time-varying
  - Set-point of a controller exists in the process operation range

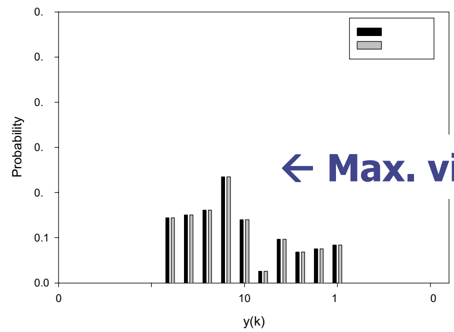
Constant set-point

Max. operation limit→

Min. operation limit →

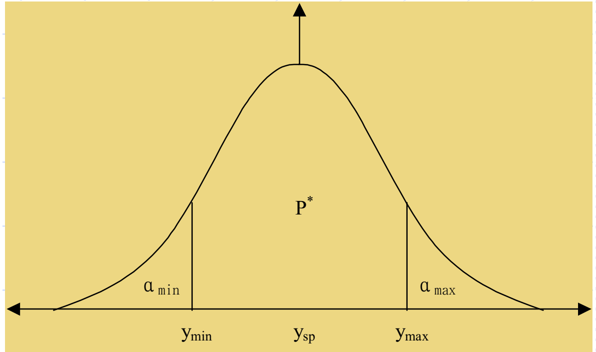


Violation rate



← Max. violation rate: 25%

SPC method



$$(k) \quad (\quad (k), \ \sigma^2_{(k)})$$

$$y_{sp}(k) \ \ni \ P\{y \quad \le Y(k) \le y \quad \} > p^*$$

$$y_{sp}(\ ) \ \ni \ [\ \{ \ (\ ) \le y_{m} \ \} \le \alpha_{m} \ \cap \ \{ \ (\ ) \ge y_{max} \} \le \alpha_{max} \ ]$$

$$y_{sp}(k) \ \ni \ [\ \{ \ (\ ) \le y_{min} \} \le \lambda \cdot \alpha \ \cap \ \{ \ (\ ) \ge y_{max} \} \le (1-\lambda) \cdot \alpha]$$

$$y_{sp \cdot min}(k) \ \ni \ P\{Y(k) \le y_{min}\} < \lambda \cdot \alpha$$

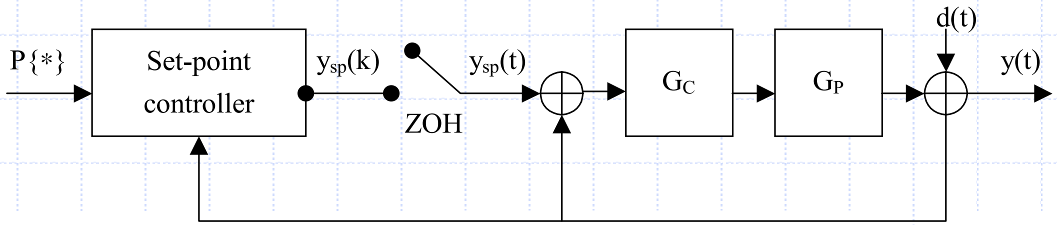
$$y_{sp \cdot max}(k) \ \ni \ P\{Y(k) \ge y_{max}\} \le (1-\lambda) \cdot \alpha$$

$$y_{sp \cdot min}(k) \le y_{sp}(k) \le y_{sp \cdot max}(k)$$

$$T = \frac{Y(k) - y_{sp \cdot miin}(k)}{\sqrt{S^2_{Y(k)}}} \qquad y_{sp \cdot min}(k) \ge \left\{ y_{min} - t^{-1}(\lambda \cdot \alpha, n-1) \cdot \sqrt{S^2_{Y(k)}} \right\}$$

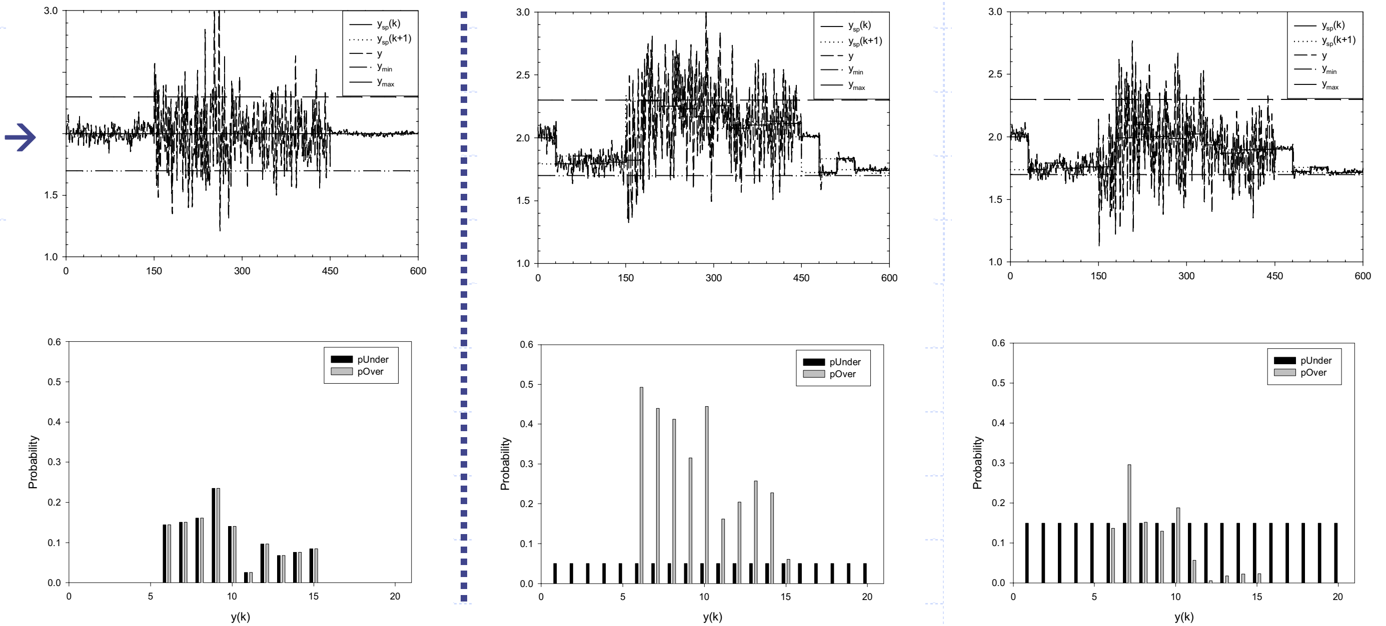
$$T = \frac{Y(k) - y_{sp \cdot max}(k)}{\sqrt{S^2_{Y(k)}}} \qquad y_{sp \cdot max}(k) \le \left\{ y_{max} - t^{-1}(1 - \alpha \cdot (1-\lambda), n-1) \cdot \sqrt{S^2_{Y(k)}} \right\}$$

Case study: SPC on DO process



Controlled process response →

Min/Max violation rate →



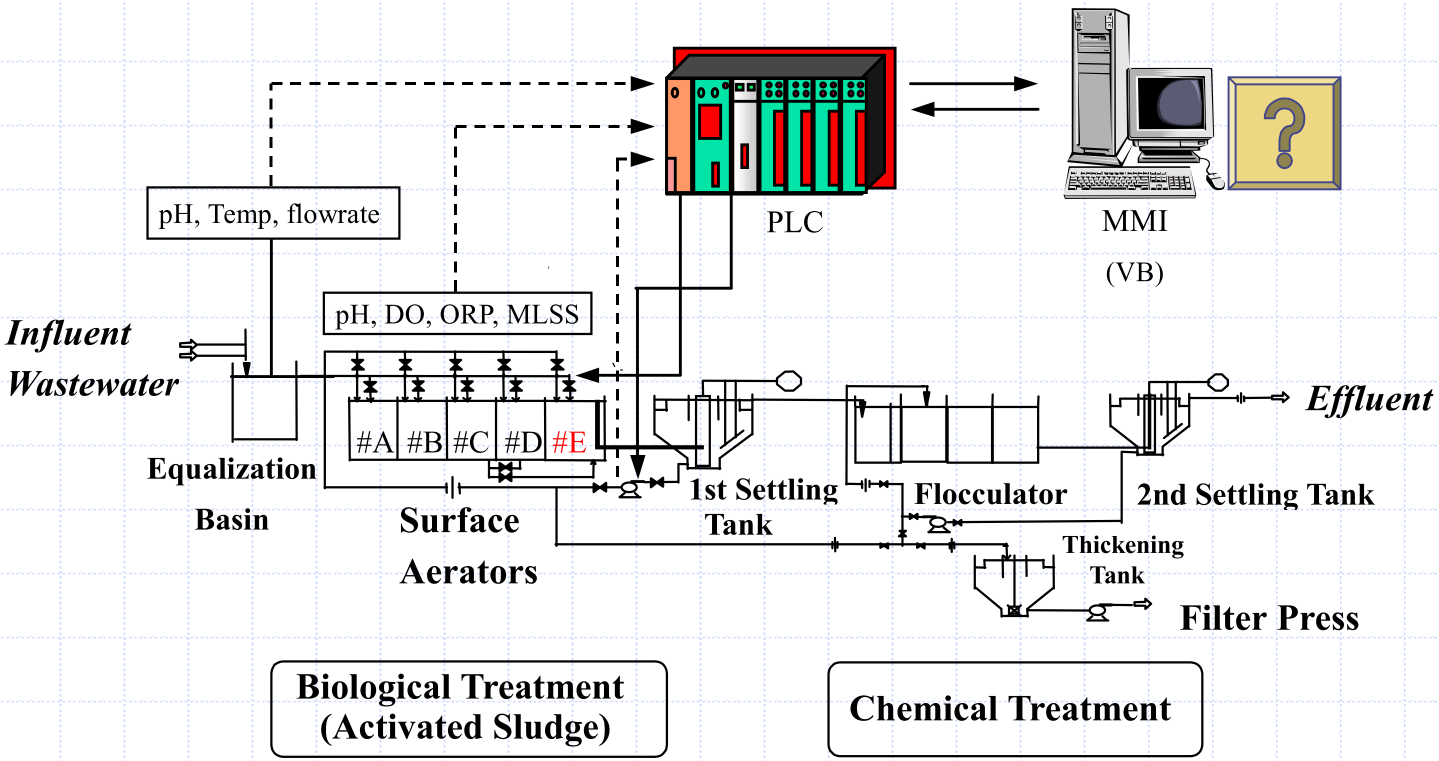
y_{sp}=const **Violation permit 5%** **Violation permit 15%**

Monitoring and Data based DSS

- Face chart monitoring
- Data based DSS
- Field application

WWTP monitoring

Motivation:
On-line data acquisition system makes data rich but information poor situation



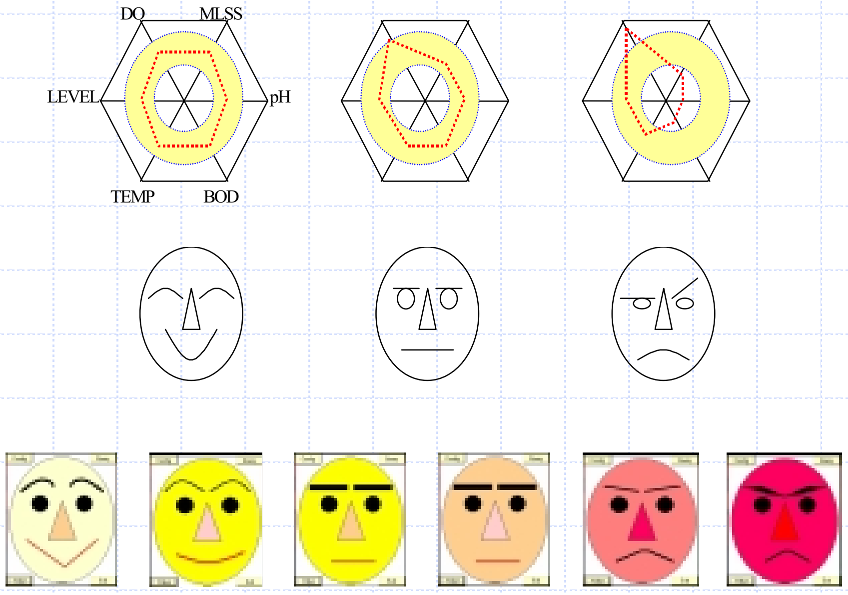
Face chart : Data conceptualize

Objective:

Can huge data are to be mapped to familiar image?

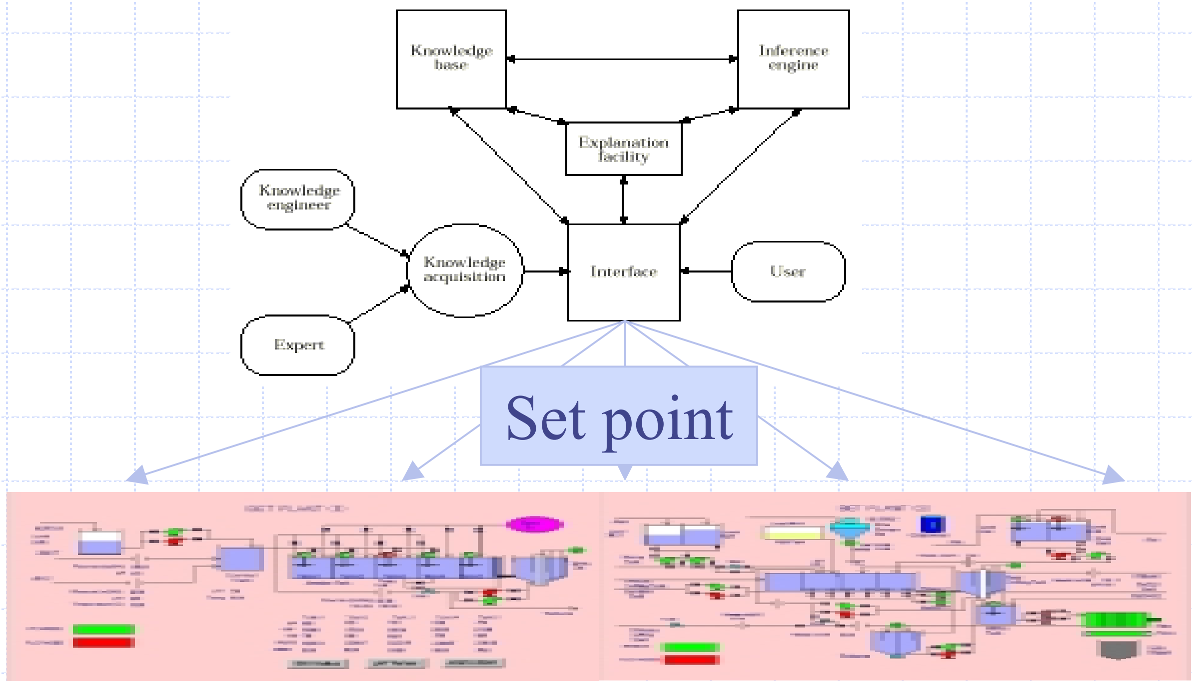
Methodologies:

1. Direct measurements mapping to face chart
2. Scores of latent variables mapping to face chart (Multivariate statistics: T-squares)

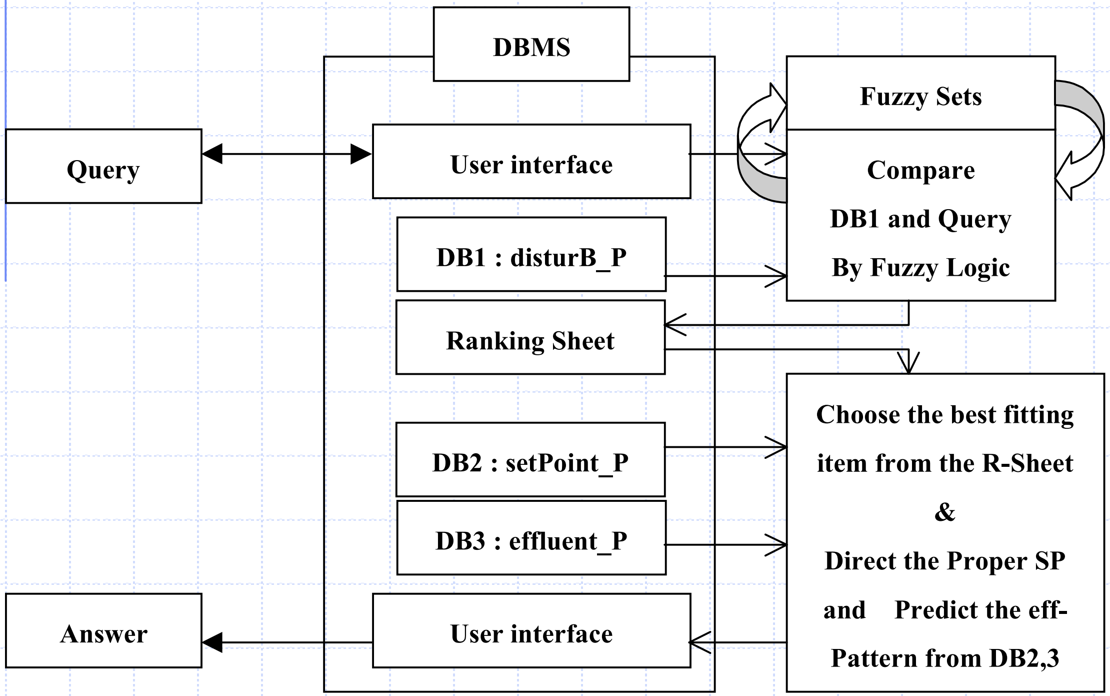


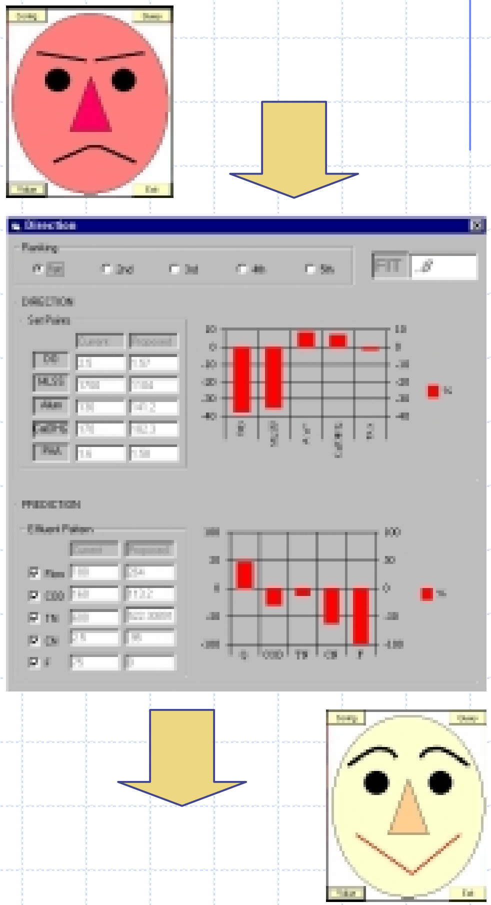
Decision Supporting System

Fuzzy rule based data search engine:
Adjust operating condition by fuzzy rule based knowledge base searching

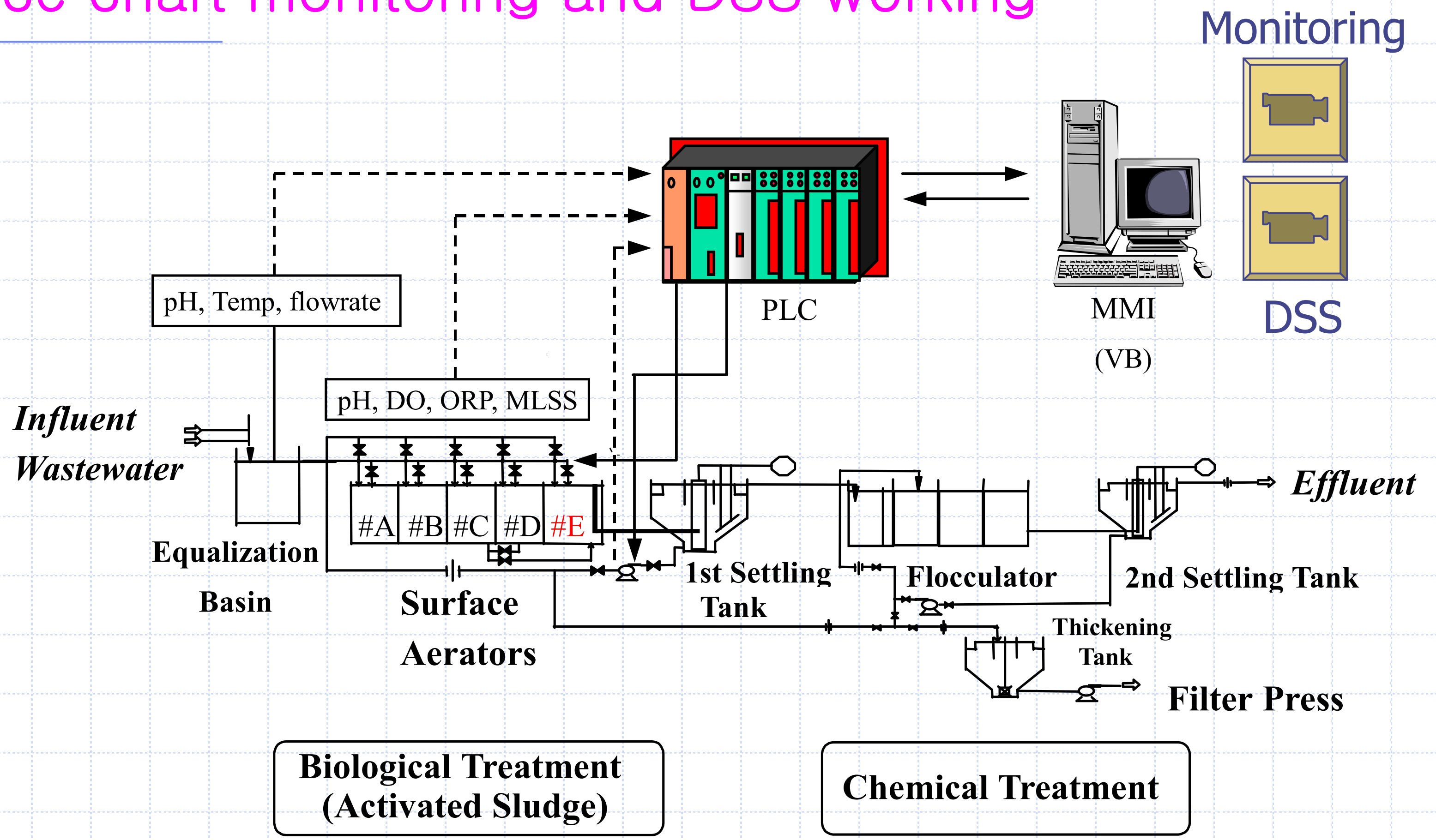


Fuzzy rule based search engine





Face chart monitoring and DSS working



Concluding remarks

◈ Essentials to control WWTP

- Features of the process: Wastewater and WWTP characteristics
- Process model for control: (non)parametric identification
- Measurable, manipulatable, and controllable variables
- Process model for prediction: activated sludge model no.1~3
- Appropriate control methods: On-off, PID, State-feed back, MPC, Adaptive, Optimal,..., etc.

Part 2: Advanced topics

ASM and soft sensor

Multivariate model calibration

Wavelets

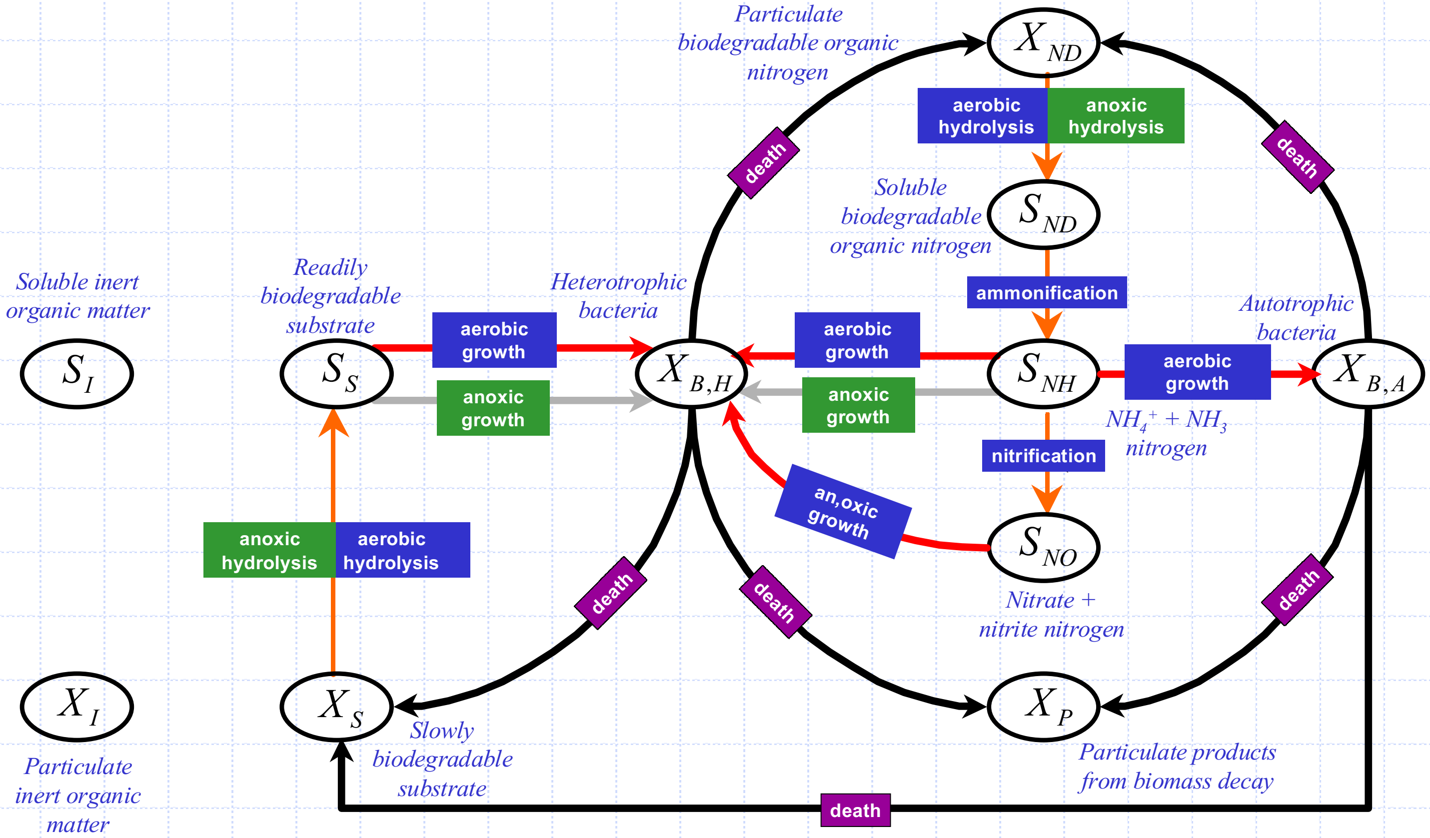
ICA

ASM and soft sensor

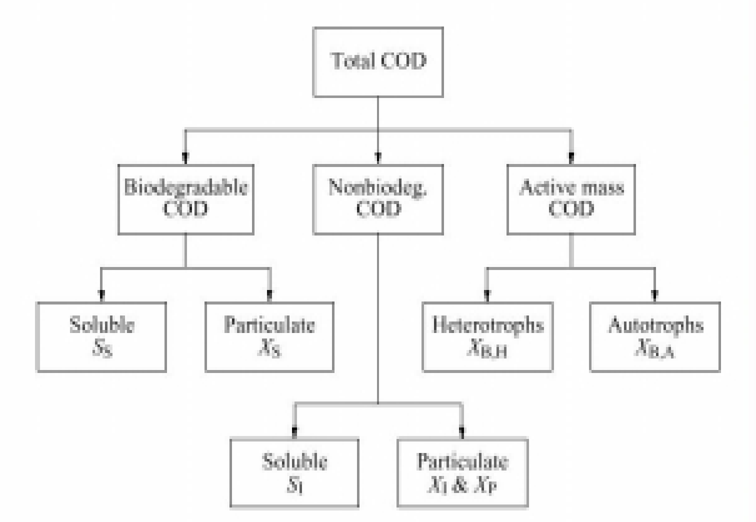
- ➔Activated Sludge Model number 1
- ➔Model based soft sensor: respirometric biosensor

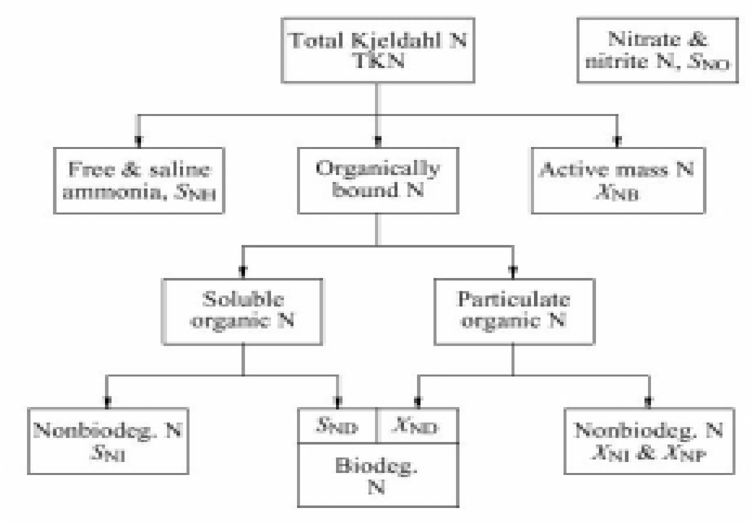
ASM and Respirometry

ASM1: Henz et.al.,1987



Degradation pattern of C and N

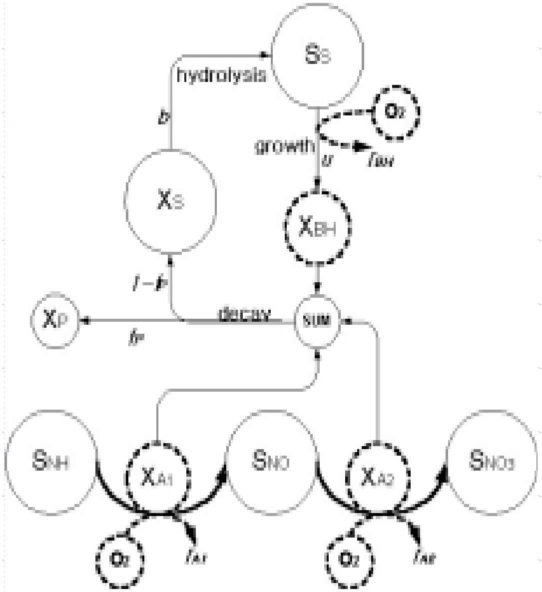




- Carbonaceous compounds
  - XS → [Hydrolysis] → SS → XBH, XBA → [Decay] → XP, XS
- Nitrogenous compounds
  - XND → [Hydrolysis] → SND → [Ammonification] → SNH → [Nitrification] → SNO → [Denitrification] → N2 gas

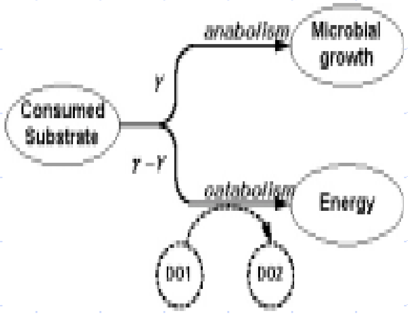
Respirometric biosensor

Simplified ASM1



Anabolism and catabolism

$$(t) = {}_{e}(t) + {}_{end}(t) \qquad {}_{end}(t) \approx const \qquad r\ (t) = \sum_{=1}^{n} r\ (t)$$



$$-\dot{S}_i(t) = \frac{1}{Y_i} \cdot \dot{X}_{Bi}(t)$$

$$-\dot{S}_i(t) = \frac{1}{\gamma_i - Y_i} \cdot r_{ex\,i}(t)$$

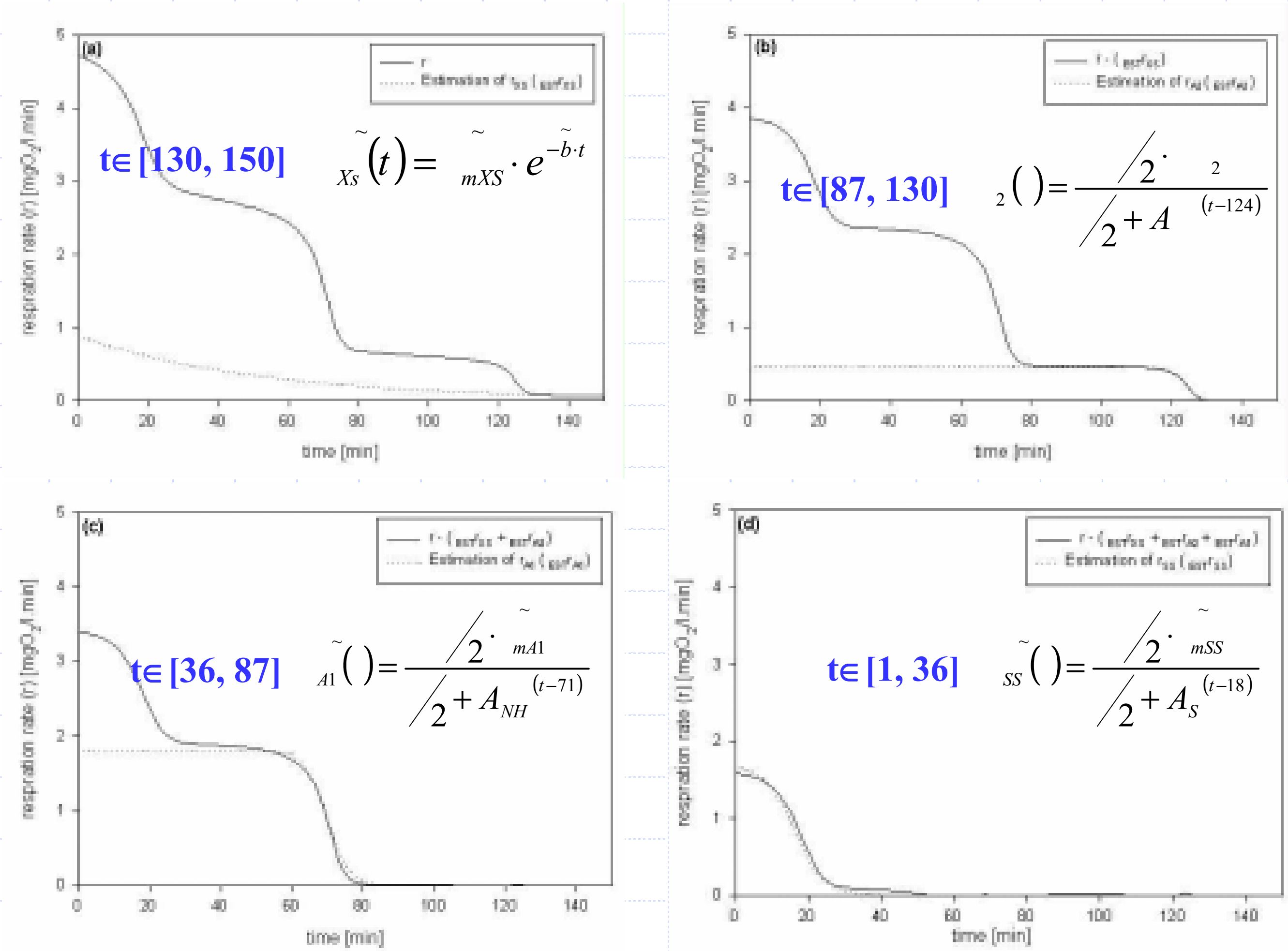
$$\dot{}_i(t) = \mu_i \cdot {}_i(t)$$

$$\mu_i = \mu_{mi} \cdot \frac{S_i(t)}{Ks_i + S_i(t)}$$

$$r\ (t) = \sum_{=1}^{n} \left\{ \frac{\gamma - Y}{Y} \cdot X \cdot \mu \cdot \frac{S\ (t)}{Ks + S\ (t)} \right\} = \sum_{=1}^{n} \left\{ r \cdot \frac{S\ (t)}{Ks + S\ (t)} \right\}$$

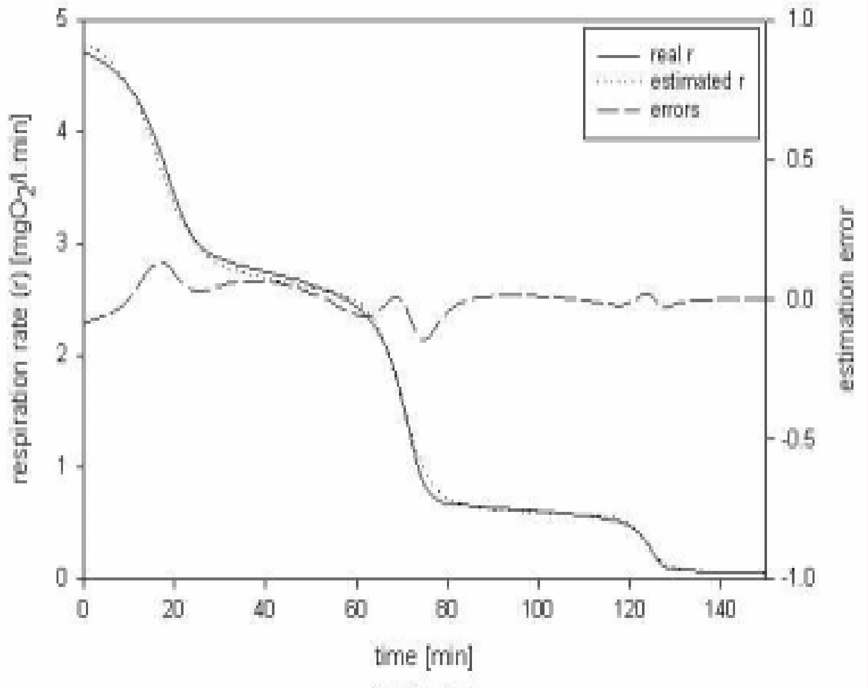
Respirogram evaluation

d) 1st C oxidation(Range4): Ss → CO2
) 1st oxidation(Range): → NO2
) 2nd N oxidation(Range2): NO2 → NO3
a) 2nd C oxidation(Range1): s → Ss → CO2



ASP model calibration results

sti ation rrors



Half saturation o ff

	K_S	K_{NH}	K_{NO}
Real	12.50	1.00	0.50
Est.	18.40	1.30	0.65

a i u r s iration rat

	r_{mXS}	r_{mSS}	r_{mA1}	r_{mA2}
Real	0.73	2.69	2.00	0.50
Est.	0.74	2.66	1.88	0.47
error(%)	1.37	1.12	6.00	6.00

nitial su strat s on ntration

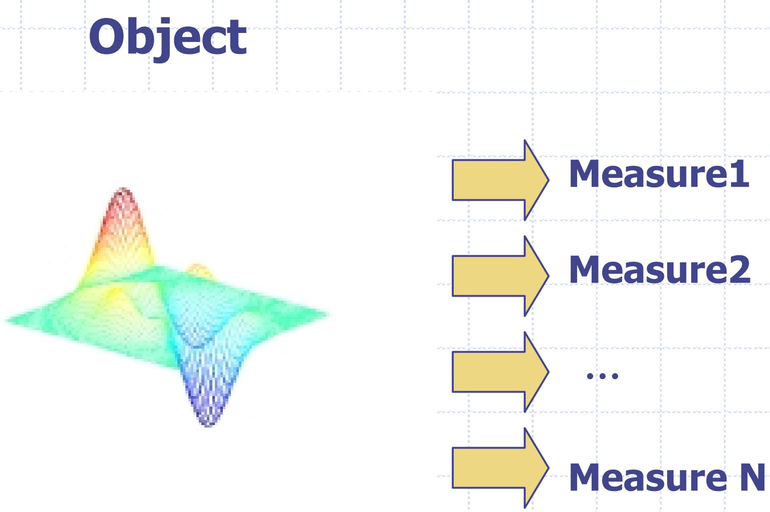
	$X_S(0)$	$S_S(0)$	$S_{NH}(0)$	$S_{NO}(0)$
Real	120	80	40	15
Est.	116	82	39	14

Multivariate model calibration

- ➔Latent variable regression
- ➔Number of factors selection
- ➔NIR spectroscopic data analysis

Latent variable

- Measurements are the shadow of a few factors (latent variables)
- Multivariate process monitoring/control focus on the LVs



Measurements regression vs. Latent variables regression

Ordinary least squares regression model

$$y = X \cdot b + e \qquad X = U \cdot \Sigma \cdot V^T$$

$$= \cdot \cdot {}^T \cdot + e \qquad = {}_* \cdot \phi + e \qquad \phi = \left({}^T_* \cdot {}_* \right)^{-1} \cdot {}^T_* \cdot y$$

$$\hat{b} = \sum_{i=1}^{k} v_i \cdot \phi_i \qquad \hat{b}_{LS} = \sum_{i=1}^{k} v_i \cdot \left(\frac{u_i \cdot y}{\sigma_i} \right) \qquad \hat{b}_{RR} = \sum_{i=1}^{k} v_i \cdot \left(\frac{\sigma_i \cdot u_i^T \cdot y}{\sigma_i^2 + s} \right) = \sum_{i=1}^{k} v_i \cdot \phi_i$$

Dim(y)=[m,1]
Dim(X)=[m,k]
Dim(T,U)=[m,d]
Dim(V,P)=[k,d]
Dim(b)=[k,1]
Dim(Sigma, Q)=[d,d]

Where, k>>d

Latent variable regression model

$$\hat{b}_{PCR} = \sum_{i=1}^{d} v_i \cdot \left(\frac{u_i^T \cdot y}{\sigma_i} \right) = \sum_{i=1}^{d} v_i \cdot \phi_i \qquad \hat{b}_{PCR\_RR} = \sum_{i=1}^{d} v_i \cdot \left(\frac{u_i^T \cdot y}{\sigma_i + s} \right) = \sum_{i=1}^{d} v_i \cdot \phi_i$$

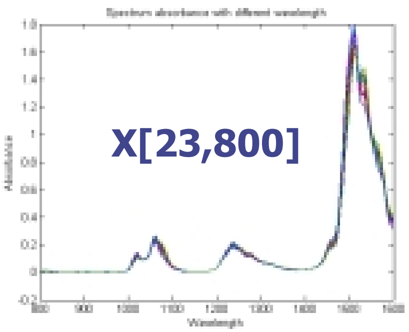
$$\hat{b}_{PLS} = \sum_{i=1}^{d} p_i \cdot \phi_i \qquad X = T \cdot Q \cdot P^T \qquad \phi = \left(Q^T \cdot Q \right)^{-1} \cdot Q^T \cdot T^T \cdot y$$

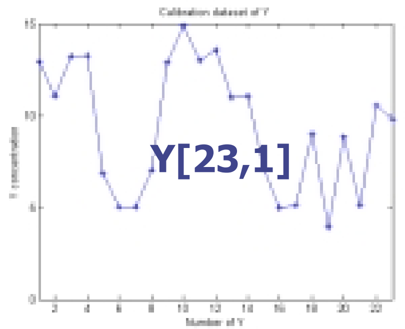
Number of latent variables selection

$$RMSEP = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \qquad PRESS = \sum_{i=1}^{n} \left(y_i - \hat{y}_i(i) \right)^2 \qquad RMSECV = \sqrt{\frac{PRESS}{n}}$$

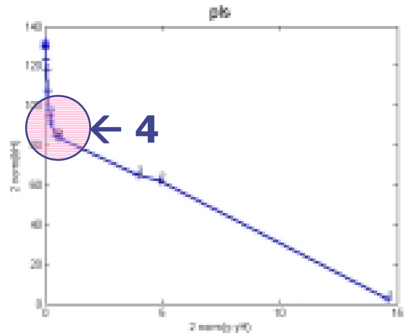
Case study:
Non-infrared spectroscopic data calibration

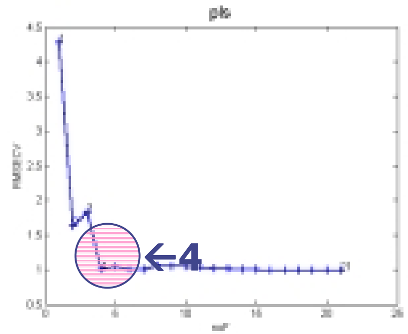
Calibration data set
23x800=18400



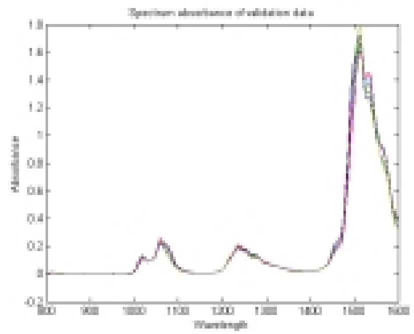


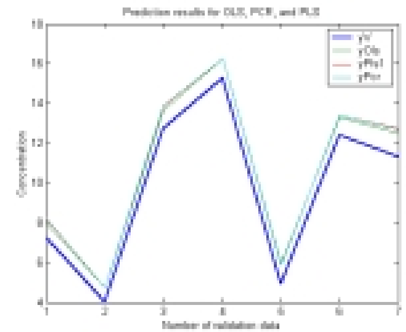
Factor number selection
23x4=92





Validation results
Negligible difference



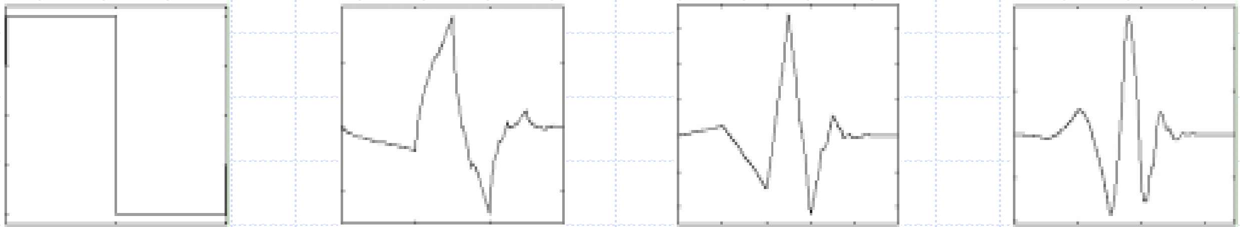


Wavelets and ICA

- Wavelets
- ICA

Wavelets

- Wavelets means small waves



Daubenchies1 **Daubenchies2** **Daubenchies3** **Daubenchies4**

- Popular applications
  - Denoising
    - Contaminated data with noise ➔ robust problem occurrences
    - Filters(exponential, polynomial, median,etc)? Phase shifting problem, Spikes handling problem,...etc. ➔ wavelet denoising!
  - Multi-resolution analysis (MRA):See both tree and forest

Continuous and discrete wavelet transform

Fourier transform: projection of any signal onto sinusoidal function

$$F(w) = \int_{-\infty}^{\infty} x(t) \cdot e^{-iwt} dt$$

Short time Fourier transform:projection of any signal onto windowed sinusoidal function

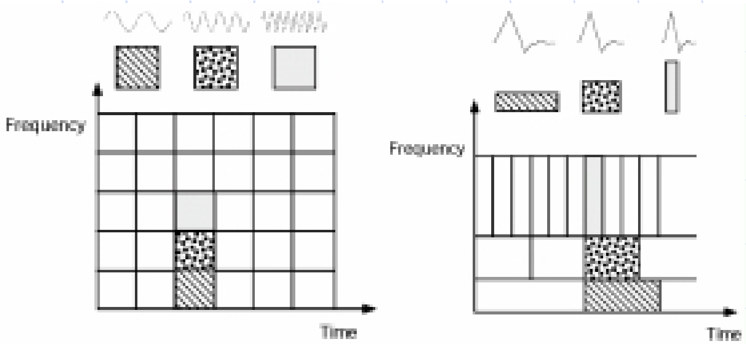
$$STFT(s,w) = \int_{-\infty}^{\infty} x(t) \cdot g(t-s) \cdot e^{-iwt} dt$$

Wavelet transform: projection of any signal onto wavelet basis function

$$CWT(a,b)\{f(t)\} = \int_{-\infty}^{\infty} \psi_{a,b}^{*} \cdot f(t) dt = \langle \psi_{a,b} \mid f(t) \rangle \qquad \psi_{a,b} = \frac{1}{\left|\sqrt{a}\right|} \psi\left(\frac{t-b}{a}\right), \; a,b \in R, \; a \neq 0$$

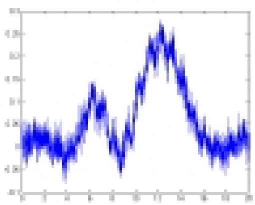
DWT: dyadic dilations and translations

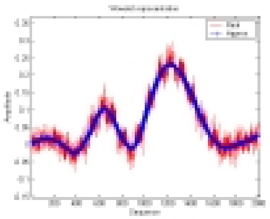
$$a = a_0^j, \; b = k \cdot b_0 \cdot a_0^j; \; k, j \in Z$$



Applications:

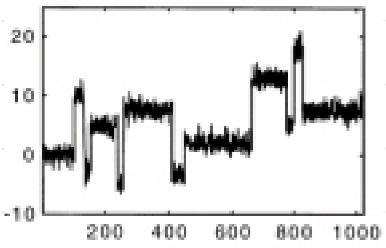
Denoising, Debasing, Zero crossing,
Signal compression, Wavelet regression



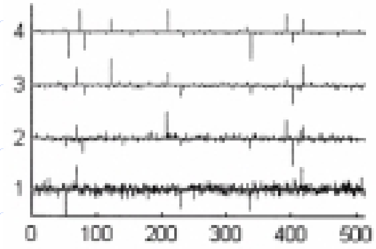


Case study

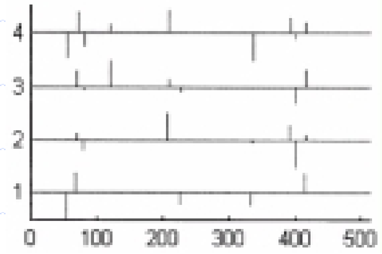
Denoising example: hard thresholding, Daubenchies4 wavelet



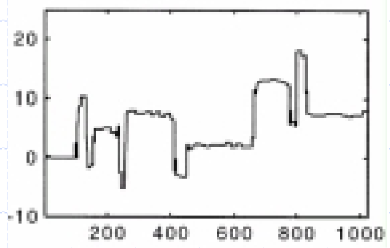
Measurements



Wavelet coefficients

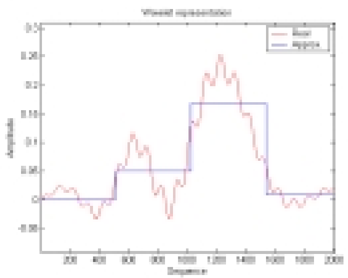


Dominant coefficient

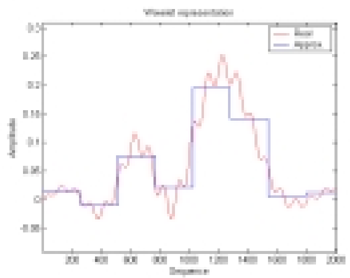


Denoised signal

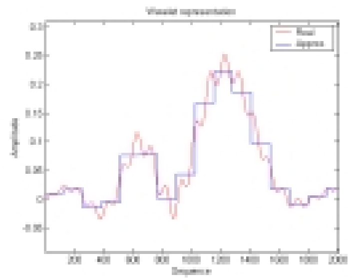
MRA example: altering scales from 1 to 4



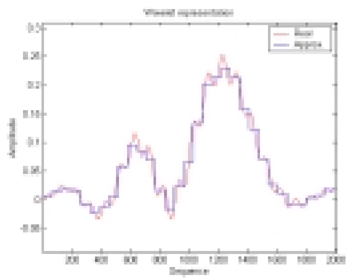
scale4



scale3



scale2

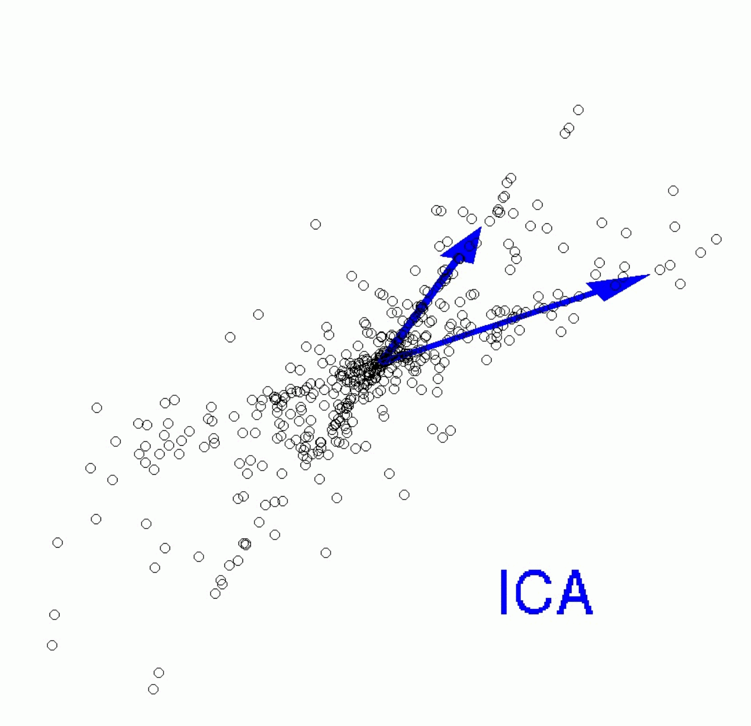


scale1

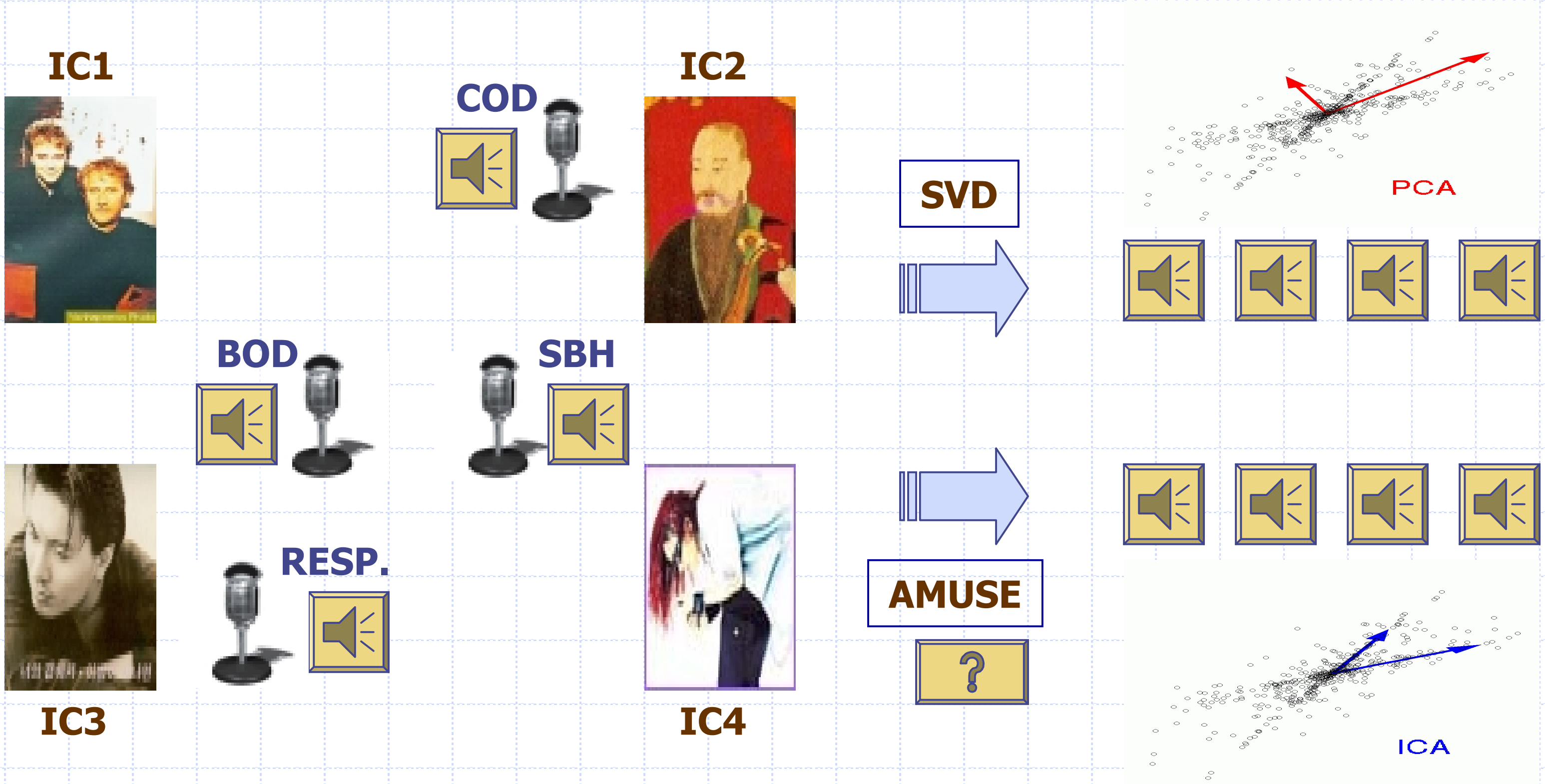
Independent Component Analysis

- Principal Component Analysis (PCA) finds directions of maximal variance in Gaussian data (second-order statistics).

- Independent Component Analysis (ICA) finds directions of maximal independence in non-Gaussian data (higher-order statistics).



Case study: audio decomposition

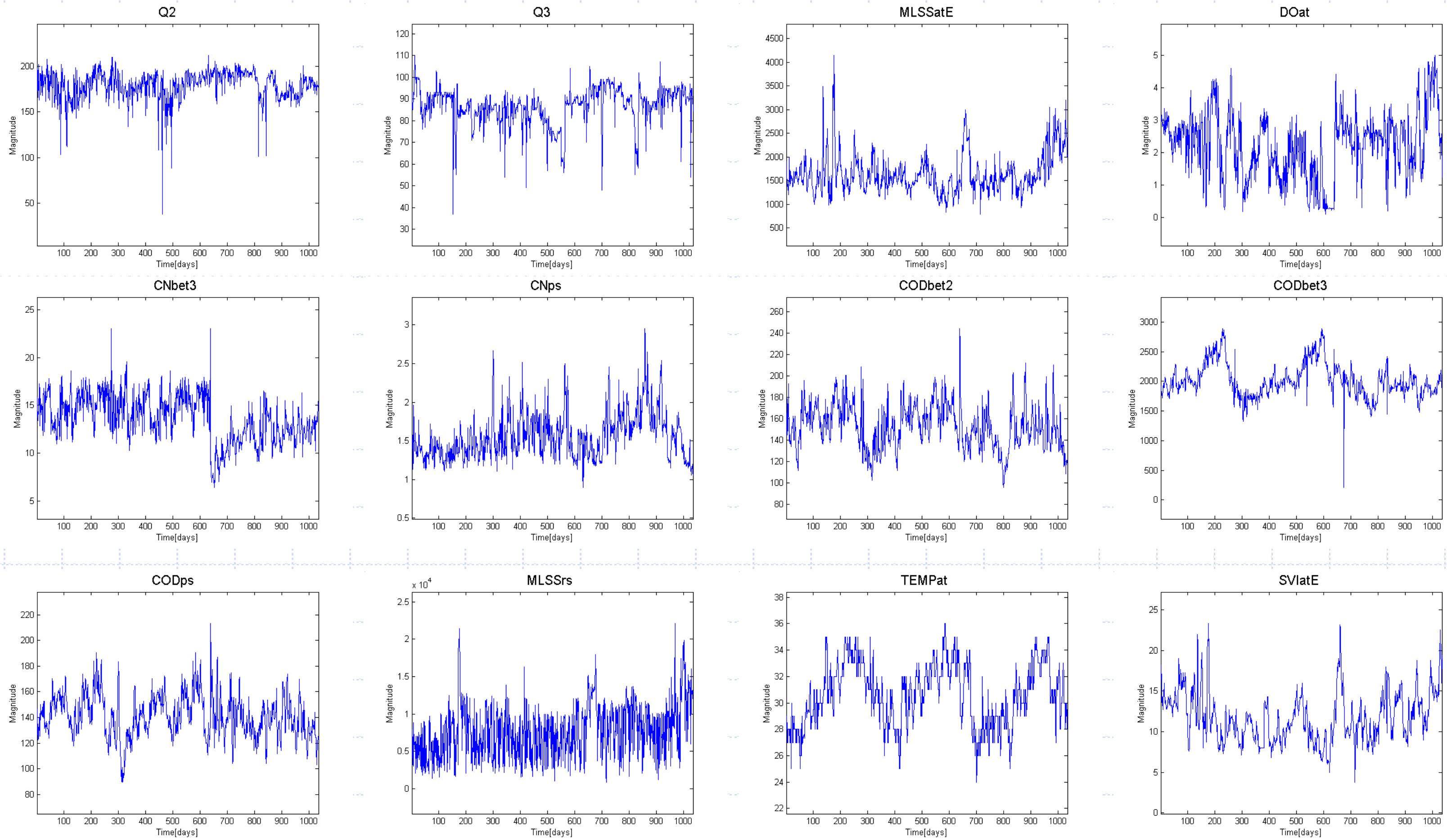


Summary

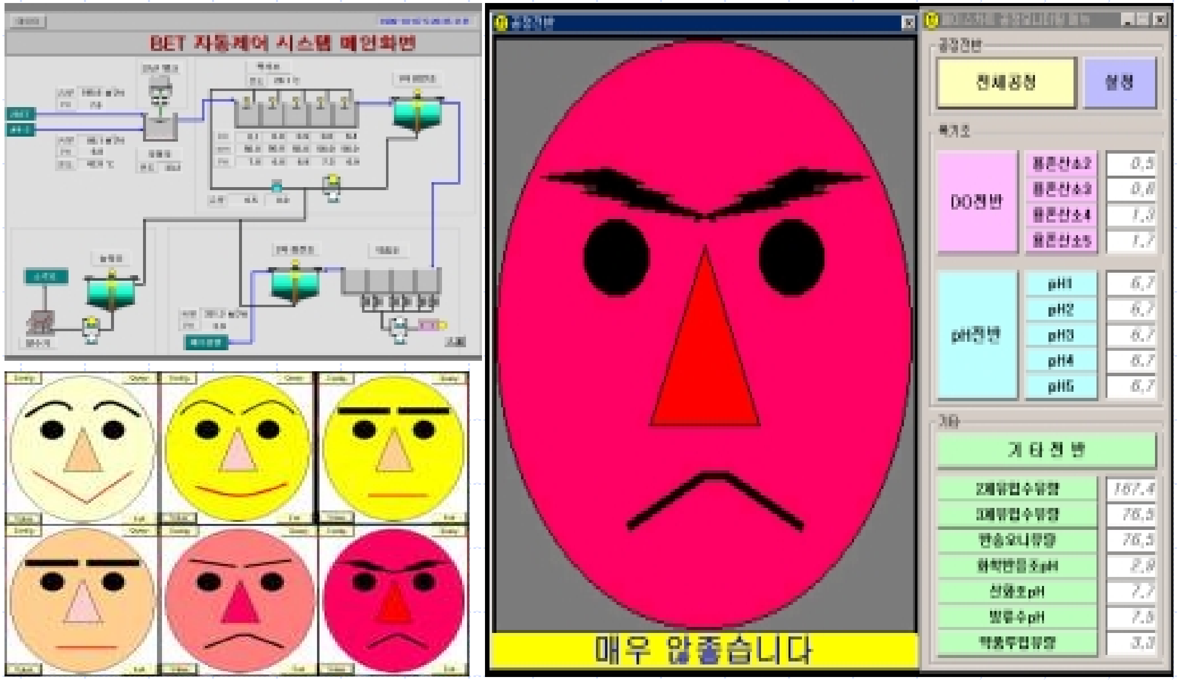
- To set proper WWTP control strategy, we introduced…
  - Features of the process → introduction
  - Control methods → WWTP control
  - Plant wide process management → monitoring and DSS
- In addition to these,
  - WWTP system characteristics → ASM and soft sensor
  - Latent variable analysis → multivariate model calibration
  - Signal processing → Wavelet
  - Hidden factor analysis → ICA

Thanks

On-line WWT data acquisition results



Face chart monitoring method



DSS

퍼지로직의 멤버쉽 함수값을 설정합니다 - 관리자외에는 변경하지 마시오

2BET 유출수

	평균값	표준편차
유량	180	15
COD	160	15
NH3	600	40
CN	2,5	0,3
F	75	2

3BET 유입수

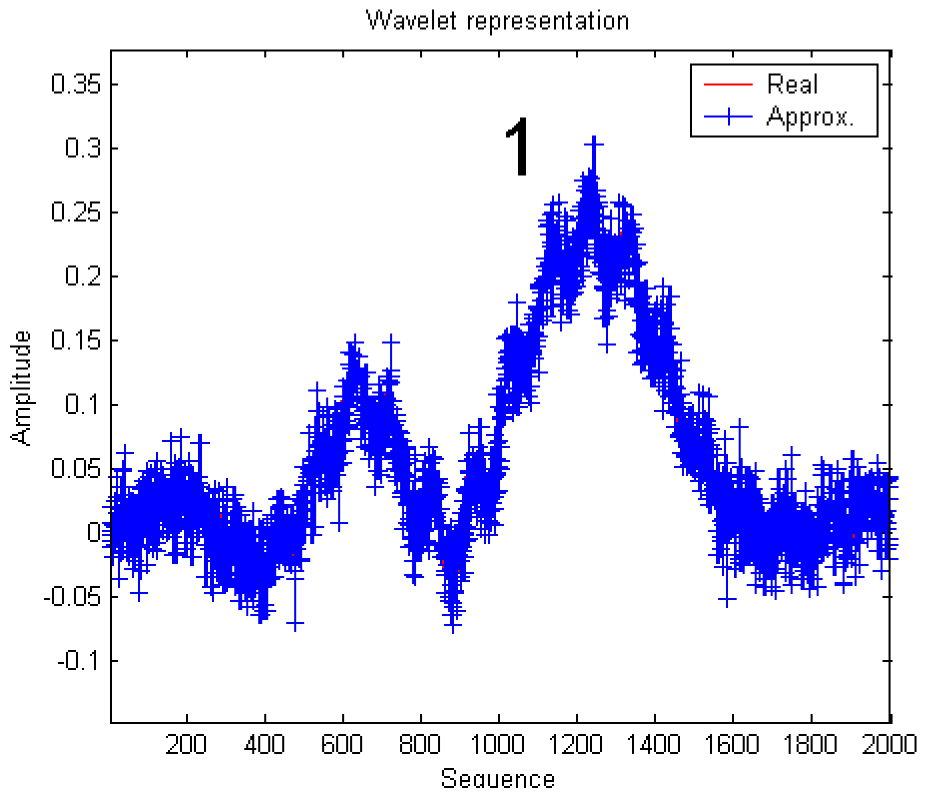
	평균값	표준편차
유량	90	5
COD	2200	280
NH3	600	40
CN	15	1,5
F	75	2

최종 유출수

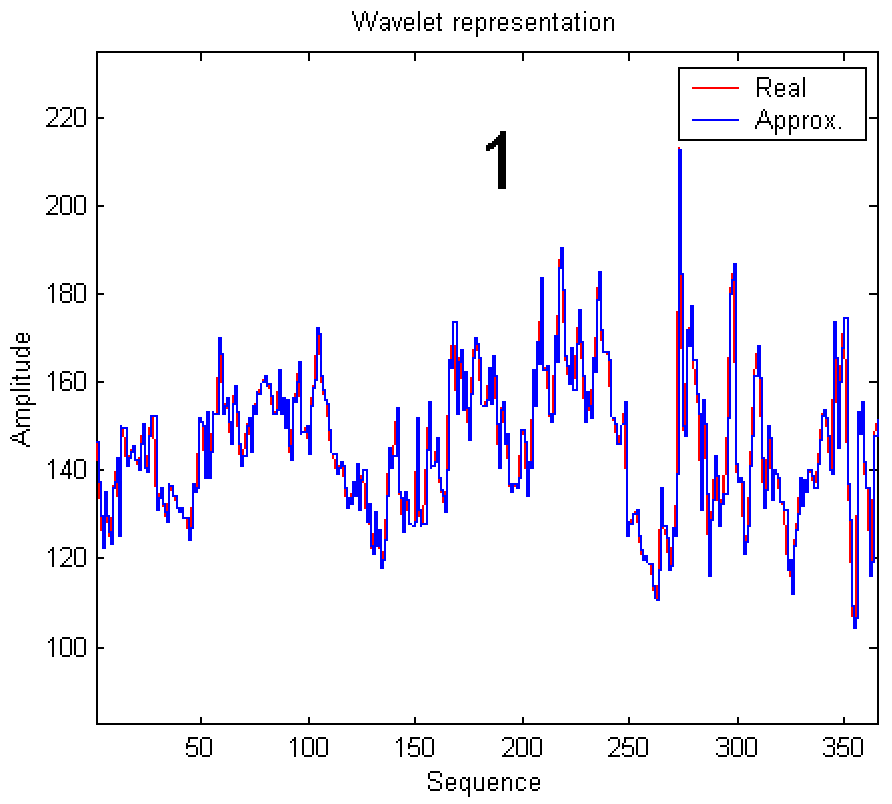
	평균값	표준편차
유량	260	15
COD	95	5
NH3	500	30
CN	0,9	0,005
F	25	5

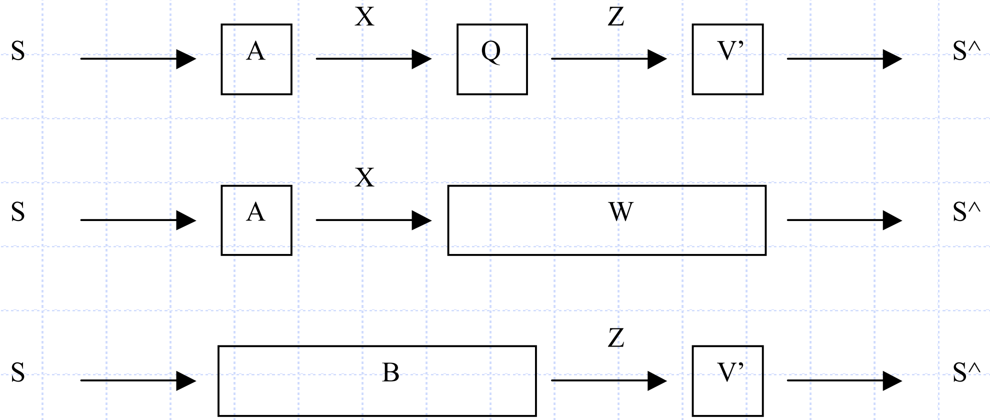
OK | Exit

Wavelets: Artificial signal



Wavelets: Flow rate data





AMUSE: Algorithm for Multiple Unknown Signals Extraction

1. Whitening of X: $Z(t)=Q \cdot X(t)=Q \cdot A \cdot S(t)=B \cdot S(t)$, where $Q=D^{-0.5} \cdot U^T$, $[U,D]=eig\{cov(X)\}$

2. Find the cross-covariance matrix:

- $Rs(\tau) = E[S(t) \cdot S(t-\tau)^T]$ where off-diag($Rs(\tau)$)=0, because $S_i(t)$ and $S_j(t)$ are independent.

- $Rz(\tau) = E[Z(t) \cdot Z(t-\tau)^T] = B \cdot Rs(\tau) \cdot B^T$, where $Rz(\tau)$ is symmetric

- Let $Mz = 0.5 \cdot \{Rz(\tau) + Rz(\tau)^T\}$

3. Unitary transformation of Mz: $Mz = V \cdot d \cdot V^T$, where $[V,d]=eig\{Mz\}$

4. Demixing: $S\hat{} = V^T \cdot Z = V^T \cdot Q \cdot X$