

Advanced Biogas Processes applied in Fuel Cell Systems

ao.Univ.Prof. DI Dr. Peter Holubar

Workshop
Hydrogen and Fuel Cells in a future
sustainable Energy-system

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Institute of Applied Microbiology

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Why Monitoring & Control
The Black Box “Anaerobic Digestion”
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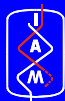
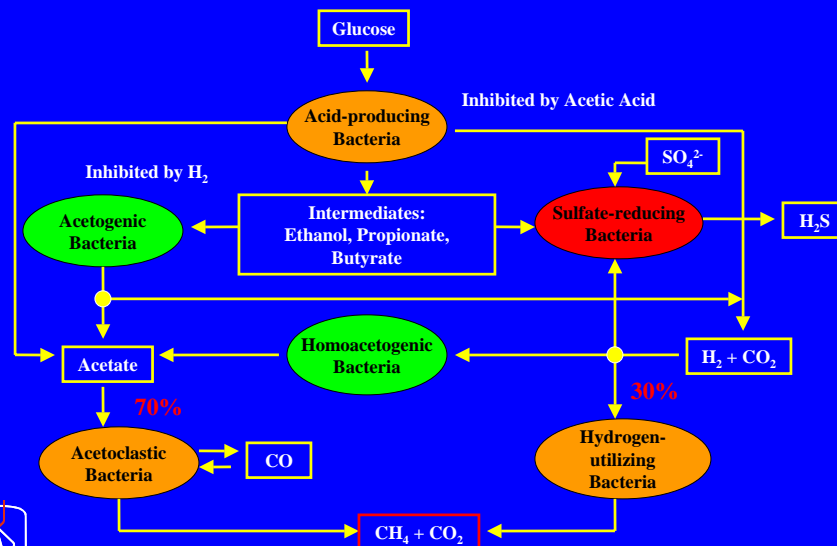
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Why Monitoring and Control?

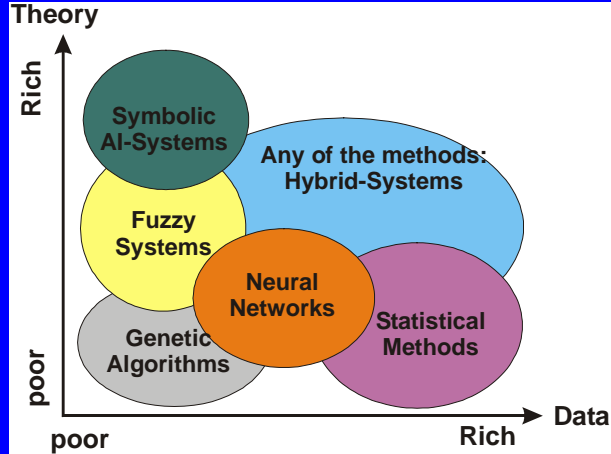
- Proper monitoring and control can prevent the transformation of a minor operational problem into a major disaster.
- As hydraulic- and organic loading rates are pushed upwards in order to reduce the size of the reactor, monitoring and control become more critical to avoid plant failure.
- Instrumental process monitoring and control are small prizes to be paid for higher loading rates, lower alkalinity costs and smaller reactor volumes. Such investments can yield very favorable paybacks.
- Monitoring and control can increase the biogas-yield in AD and improve the waste water treatments plant's overall energy balance.



Black Box Anaerobic Digestion

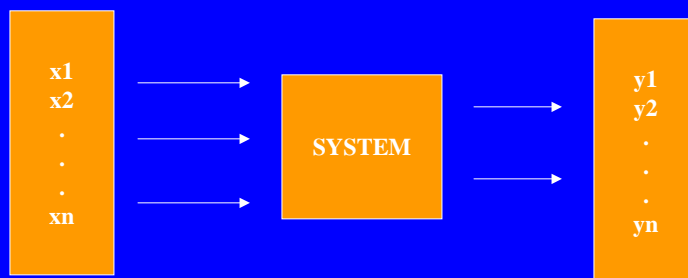


Use of Neural Networks



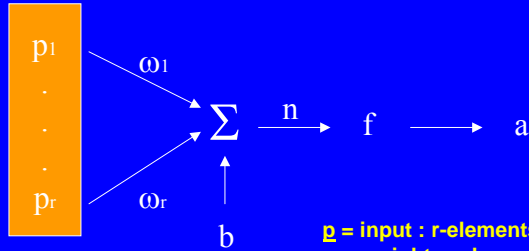
Neural Networks are

- mathematical models inspired by biological nervous systems.
- composed of simple interconnected elements operating in parallel.
- basically a method for handling multivariate - multiresponse data.



Single-Neuron Model

Vector input



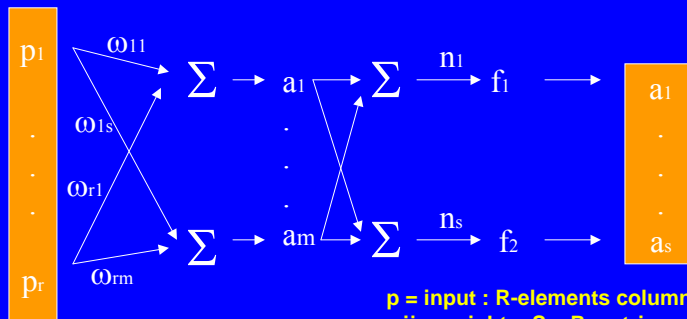
$$a = f(\underline{w} \times \underline{p} + b)$$

\underline{p} = input : r-elements column vector
 \underline{w} = weight: r-elements row vector
 b = bias
 n = net input to the transfer function = $\underline{w}\underline{p} + b$
 f = transfer function
 a = output (scalar)



Multi-Neuron Model

Multiple layers of neurons

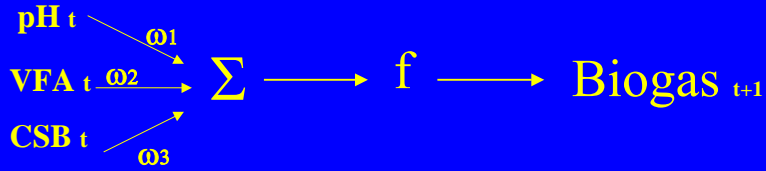


\underline{p} = input : R-elements column vector
 w_{ij} = weights: S x R matrix
 \underline{b} = bias: S-elements column vector
 $\underline{n} = \underline{W} \times \underline{p} + \underline{b}$
 f = transfer functions
 \underline{a} = output: S-elements vector



Neuronal Network

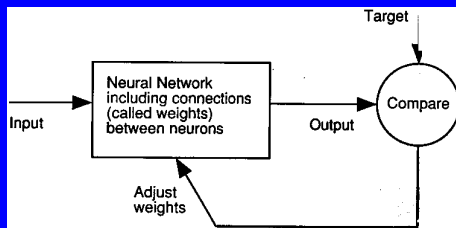
- A neural network consists of several calculator units
- Each unit is called neuron



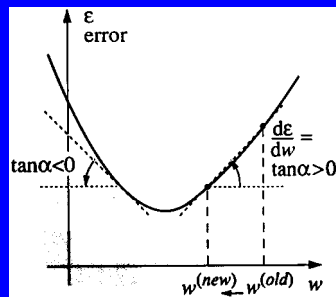
$$\text{Biogas}_{t+1} = f(\omega_1 \text{pH}_t + \omega_2 \text{VFA}_t + \omega_3 \text{CSB}_t)$$



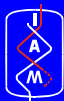
Feed Forward Back-propagation Network



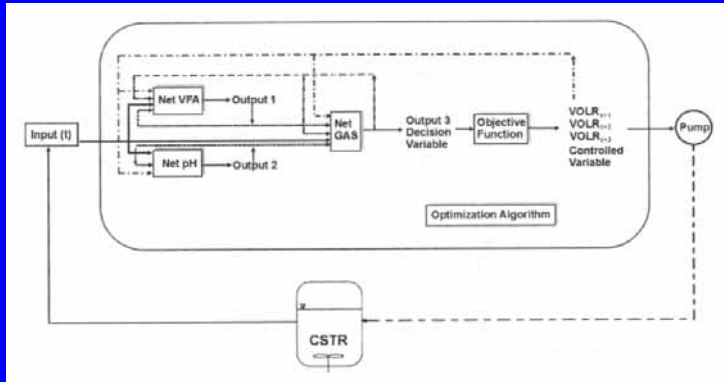
Learning due to adjustment of weights



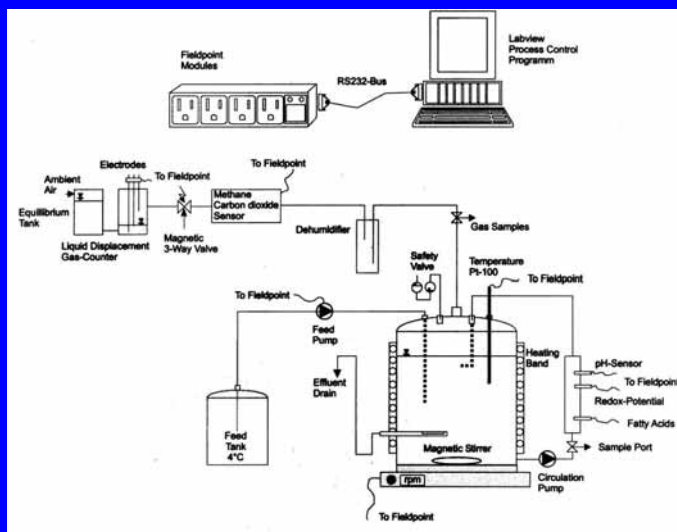
Adjustment of weights to search for a minimum in the error-function



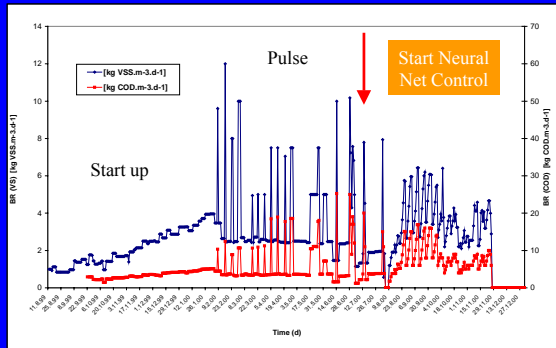
Neural Network-based Decision Support System



Lab-scale anaerobic CSTR



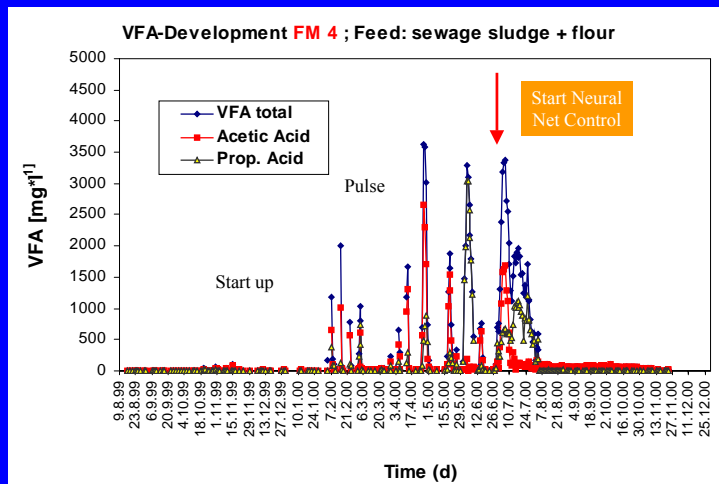
Pulse Experiments I



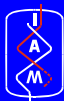
Organic Loading Rate



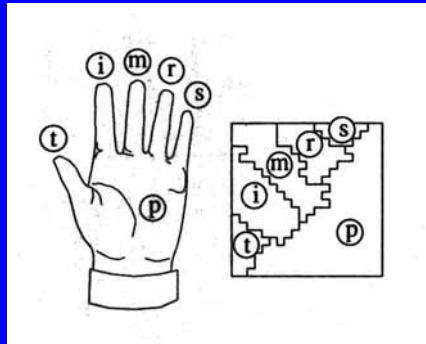
Pulse Experiments II



Volatile Fatty Acids



Kohonen SOMs - Self Organizing Maps

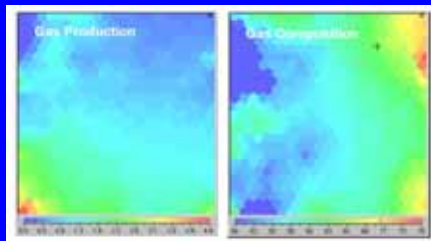


Transformation of
n-dimensional data sets
into a 2-dimensional
map.

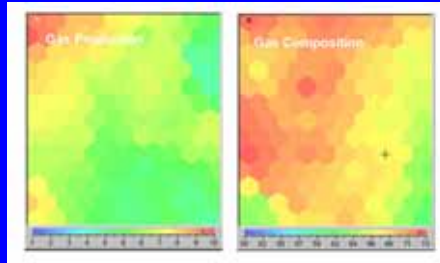


Visualization of Operational Space

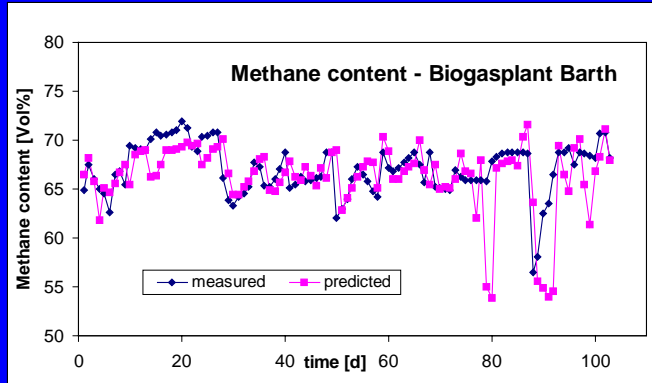
Without NN-control



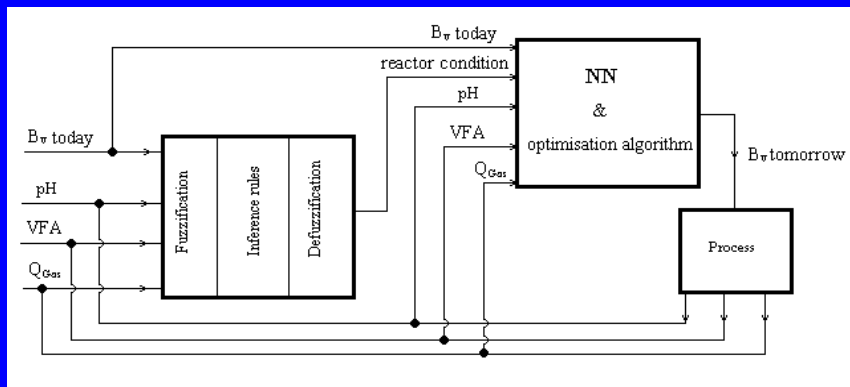
With NN-control



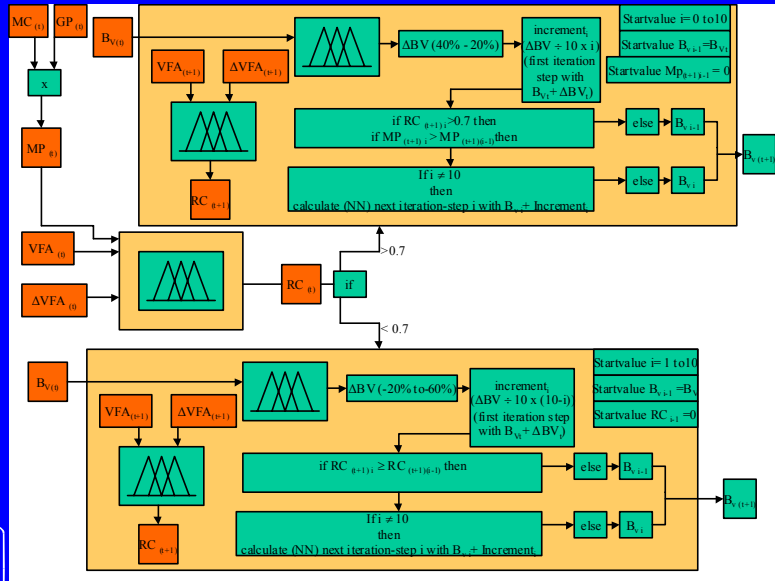
Test of Tool on Biogas-plants



Fuzzy Control - reactor condition parameter

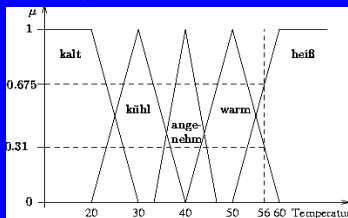


Fuzzy Control - reactor condition parameter



Fuzzy Logic

1. Fuzzyfication

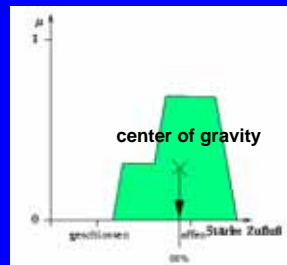
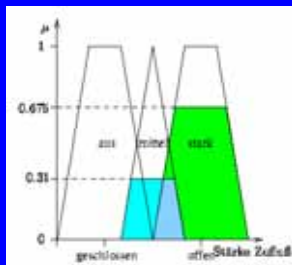


2. Inference-Rules

1. IF temperature = „hot“, THEN cold water flow = „high“ AND warm water flow = „off“
2. IF temperature = „warm“, THEN cold water flow = „medium“ AND warm water flow = „off“

3. Defuzzyfication

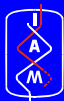
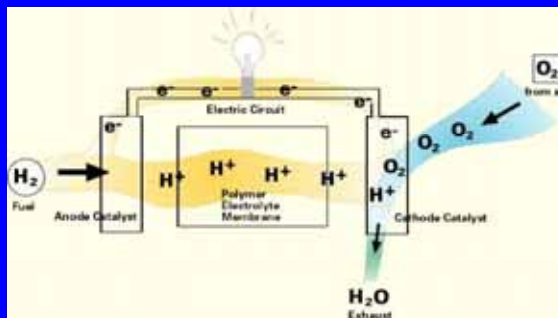
Cold water



The Problem of Trace Gases



Use of Biogas in Fuel Cells



Fuel Cell - Effect of Trace Gases

Fuel cell	PEFC	PAFC	MCFC	SOFC
Operating T. (°C)	70-90	160-210	600-700	800-1000
H2	Fuel	Fuel	Fuel	Fuel
CO2	Diluent	Diluent	Re-circulated	Diluent
CO	Toxic	Toxic	With water shifted to H2	With water shifted to H2
C2-C6		Toxic	Fuel, plugging & coking	Fuel, plugging & coking
Sulfur		Toxic	Toxic (< 1 ppm H2S)	Toxic (1 ppm H2S)
NH3		Toxic	Fuel or inert?	Fuel (< 5000 ppm)
Halogens		Toxic	Toxic (< 0,1-1 ppm)	Toxic (1 ppm)
Alkali metals			Electrolyte loss (1-10 ppm)	



Modeling Sulfate-Reduction by ADM1 Parameters

4 types of metabolic reactions (X5-X8)

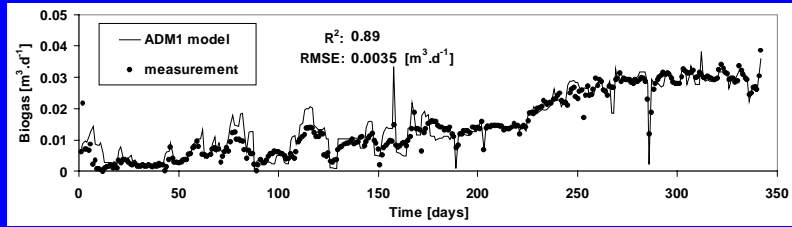
$\rho_{20} X_5$:	$C_3H_7COOH + 0.5 SO_4^{2-} \rightarrow 2 CH_3COOH + 0.5 S^{2-}$ 100% butyrate COD \rightarrow 80% acetic COD + 20% sulfide COD
$\rho_{21} X_6$:	$C_2H_5COOH + 0.75 SO_4^{2-} \rightarrow CH_3COOH + CO_2 + H_2O + 0.75 S^{2-}$ 100% propionate COD \rightarrow 57% acetate COD + 43% sulfide COD
$\rho_{22} X_7$:	$CH_3COOH + SO_4^{2-} \rightarrow 2 CO_2 + 2 H_2O + S^{2-}$ 100% acetate COD \rightarrow 100% sulfide COD
$\rho_{23} X_8$:	$4 H_2 + SO_4^{2-} \rightarrow S^{2-} + 4 H_2O$ 100% hydrogen COD \rightarrow 100% sulfide COD

Parameter	Value	Range from literature*
$k_{m,ac}$ (COD.COD ⁻¹ .d. ⁻¹)	35	0.14 – 52 ¹
$K_{S,ac}$ (kg COD.m ⁻³)	0.03	0.011 – 0.93 ¹
Y_{X5} (COD.COD ⁻¹)	0.12	0.0329 ²
Y_{X6} (COD.COD ⁻¹)	0.12	0.0329 ²
Y_{X7} (COD.COD ⁻¹)	0.12	0.0342 ²
Y_{X8} (COD.COD ⁻¹)	0.12	0.0366 (COD.COD ⁻¹) ² – 13 (g cell mat.mol H ₂ ⁻¹) ³
K_{H,H_2S} (M.bar ⁻¹)	0.04	0.0952 ⁴ Can differ a factor 2 or 3 ⁵

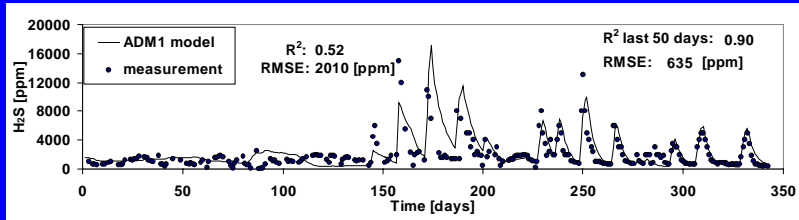
(1) Batstone et al., 2002; (2) Fedorovich et al., 2003; (3) Badzioz and Thauer, 1978; (4) Stumm and Morgan, 1996; (5) Mackay and Shiu, 1981



Modeling Sulfate-Reduction by ADM1



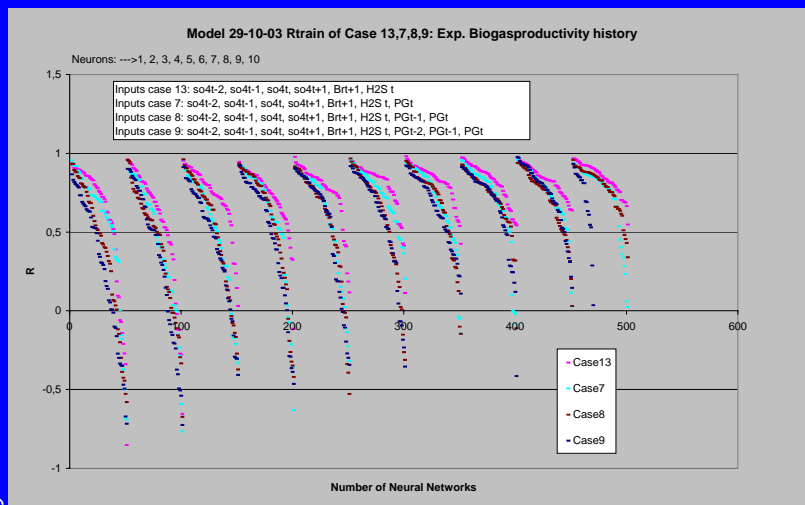
biogas-production



hydrogen sulfide-production



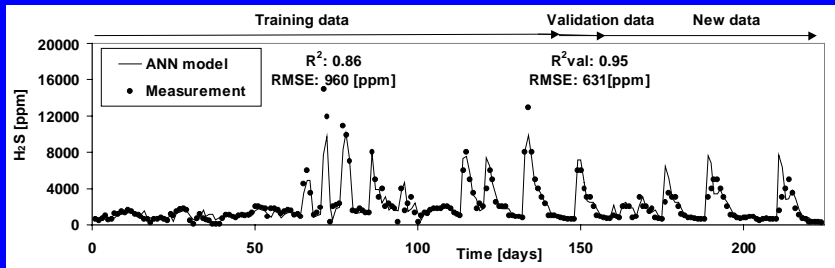
Finding the best Neural Network



Modeling Sulfate-Reduction by Neural Networks

Inputs	Hidden layer	Output
1. Sulfate loading rate $t+1$ [g $\text{SO}_4\text{-S}\cdot\text{m}^{-3}\cdot\text{d}^{-1}$]	Six neurons	1. Hydrogen sulfide $t+1$ [ppm]
2. Sulfate loading rate t [g $\text{SO}_4\text{-S}\cdot\text{m}^{-3}\cdot\text{d}^{-1}$]		
3. Sulfate loading rate $t-1$ [g $\text{SO}_4\text{-S}\cdot\text{m}^{-3}\cdot\text{d}^{-1}$]		
4. Sulfate loading rate $t-2$ [g $\text{SO}_4\text{-S}\cdot\text{m}^{-3}\cdot\text{d}^{-1}$]		
5. Organic loading rate $t+1$ [kg COD $\cdot\text{m}^{-3}\cdot\text{d}^{-1}$]		
6. Hydrogen sulfide t [ppm]		

hydrogen sulfide-production



Financial Balance of Monitoring & Control of AD

Basic assumption				
Reactor volume	300 m ³			
Investment expenses	200 €m ⁻³			
Operation expenses	18.000 €	(includes depreciation, insurance, servicing, wages, energy cost)		
Energy content of biogas	6 kWhm ⁻³			
Electricity output	1.92 kWh _{el} m ⁻³			
Market price electricity	16 Cent kWh ⁻¹			
Revenues				
Monitoring		No	VFA (Lange)	external laboratory
Control		minimal	optimized	Optimized
Biogas yield	m ³ m ⁻³ reactor d ⁻¹	1.2	2.5	2.5
Biogas yield	m ³ a ⁻¹	131.400	273.750	273.750
Energy content	kWh a ⁻¹	788.400	1.642.500	1.642.500
Electricity output	kWh _{el} a ⁻¹	252.288	525.600	525.600
Sales revenues	€a ⁻¹	40.366	84.096	84.096
Costs				
Working hours	h d ⁻¹	-	0.6	0.5
Person hours	h a ⁻¹	-	219	182
Wages (15 €h ⁻¹)	€a ⁻¹	-	3.285	2.730
Consumables	€a ⁻¹	-	3.281	20.440
Depreciation for lab- equipment	€a ⁻¹	-	1.335	750
Σ Operation expenses	€a ⁻¹	18.000	18.000	18.000
Σ costs per year	€a ⁻¹	18.000	25.900	41.920
Profit & loss account	€a ⁻¹	22.366	58.196	42.176



***“When you think that everything is under control,
you don't drive fast enough.”***

Alain Prost



Thank you for your attention.

