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Summer School on Mathematical Control Theory

(3 - 28 September 2001)

Experimental illustrations of on-line control of wastewater treatment processes

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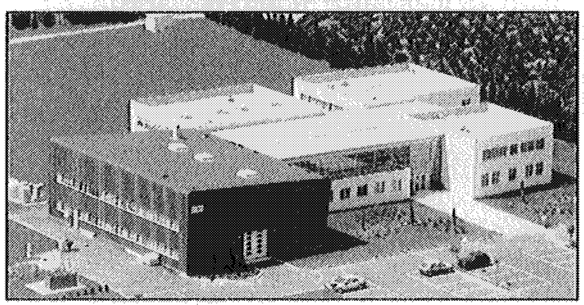
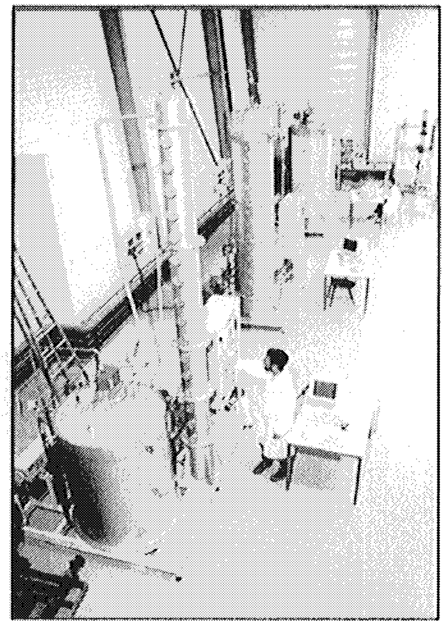




Contents

Requirements for the control system (1)

1 - Insensitivity to unmodeled phenomena

- Neglected kinetics,
- Hydrodynamics in the reactor,
- Spatial distribution of the components.

2 - Insensitivity to parameter variations

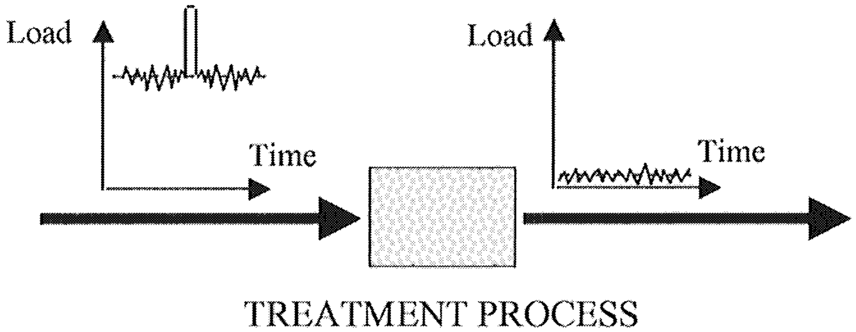
- Kinetic constants for nitrifying bacteria

Organism	Max. growth rate (μ_{max} d^{-1})	Cellular yield (Y_{obs} gVSS/gN)	K_S (g/m^3)	K_{O2} (g/m^3)	Reference
Nitrosomonas	0.46-1.86 (30 °C)	0.06	10 (30 °C) 3.5 (25 °C) 1.2 (20 °C)	0.5 (30 °C) 0.3 (20 °C)	(Painter 1977)
	0.46-2.20	0.03-0.13	0.06-5.6 (15-32 °C)	0.3 - 1.3	(Charley et al., 1980)
Nitrobacter	1.39 (32 °C)	0.02	8 (32 °C) 5 (25 °C)	1.00 (30 °C) 0.50 (32 °C) 0.25 (18 °C)	(Painter 1977)
	0.28-1.44	0.02-0.08	0.07-8.4 (15-32 °C)	0.25-1.3	(Sharma 1977)

Requirements for the control system (2)

3 - Disturbance rejection

- Short time scale events (e.g., cleaning of a tank),
- Long time scale events (e.g., domestic wastewater in sea resorts, wine distillery wastewater, ...).

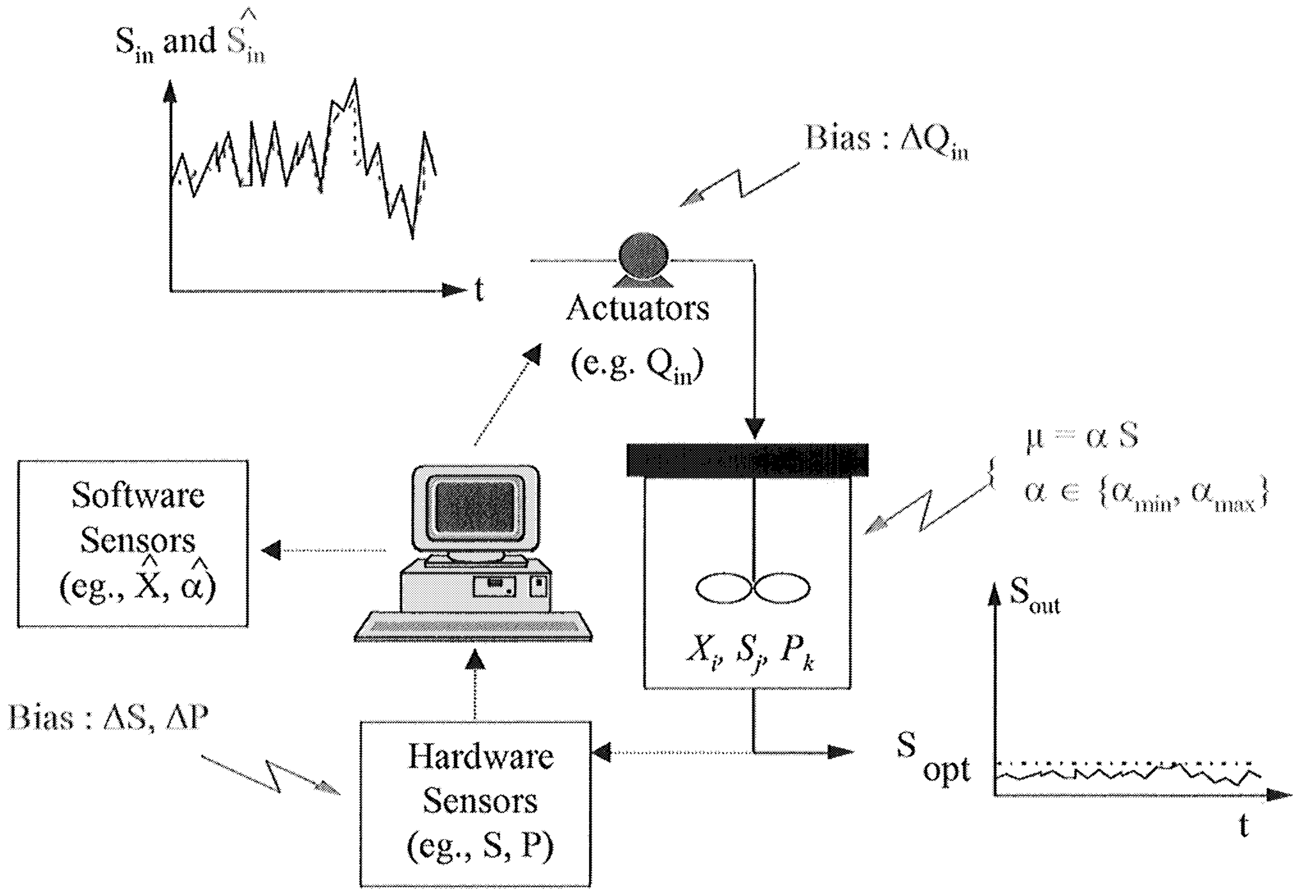


4 - System constraints

- State constraints (e.g., oxygen tranfer),
- Physical limitations of the actuators (e.g., pump capacity).

Main Requirements for Process Control

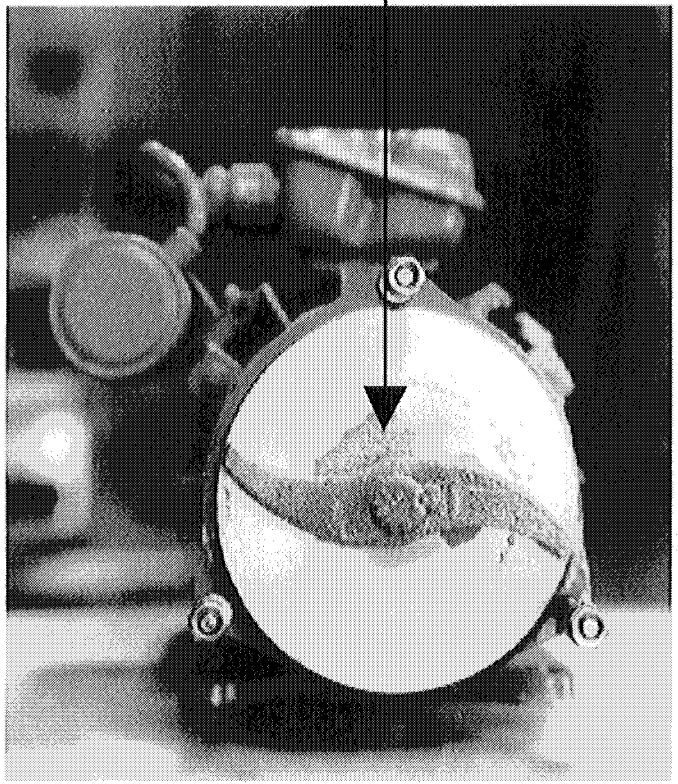
Objectives : Process regulation in the presence of internal/external disturbances and uncertainty

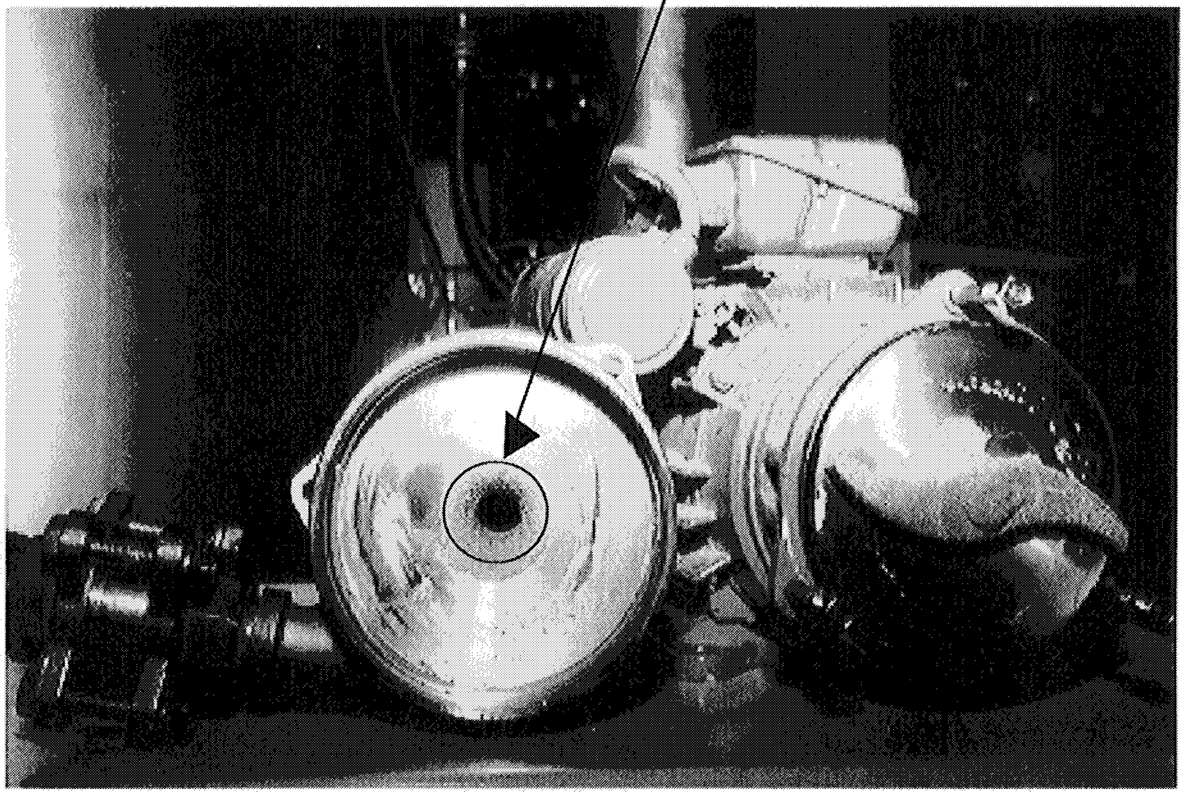


Pipe Clogging due to Struvite Formation

Pure Struvite appears on the pump

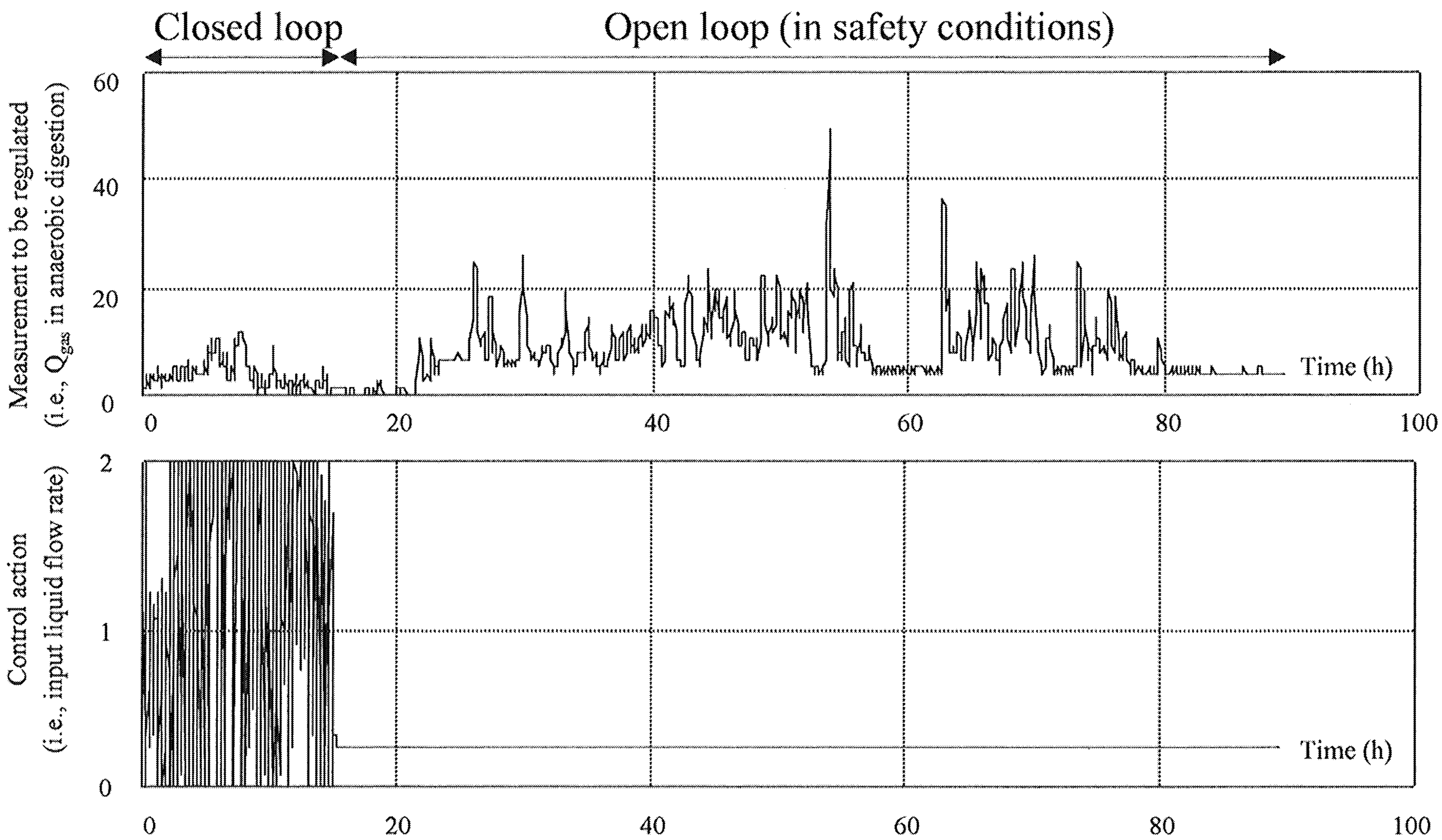
Original hole for the pipe





Pumps are very often used as main actuators

Consequences of the Unappropriate Tuning of a Control Law



It took more than a week for the process to recover
(i.e., during this time, the wastewater was not treated !...)

Motivations for Benchmarking

Among PID, adaptive control, optimal control, robust control, fuzzy control, neural control, ... what are the most appropriate strategies (according to our control objectives) ?

Contents

The nitrification process

Nitrification is the biological process in which ammonia (NH_4^+) is aerobically converted first to nitrite (NO_2^-) and then to nitrate (NO_3^-).

⇒ Two-step process with two genera of microorganisms involved :

Nitrosomonas $NH_4^+ + 1.5O_2 \rightarrow NO_2 + H_2O + 2H^+$

and *Nitrobacter* $NO_2^- + 0.5O_2 \rightarrow NO_3^-$

Objective : Regulation of ammonia concentration in the output

Application : Piggery waste treatment

Mass balance modeling of nitrification

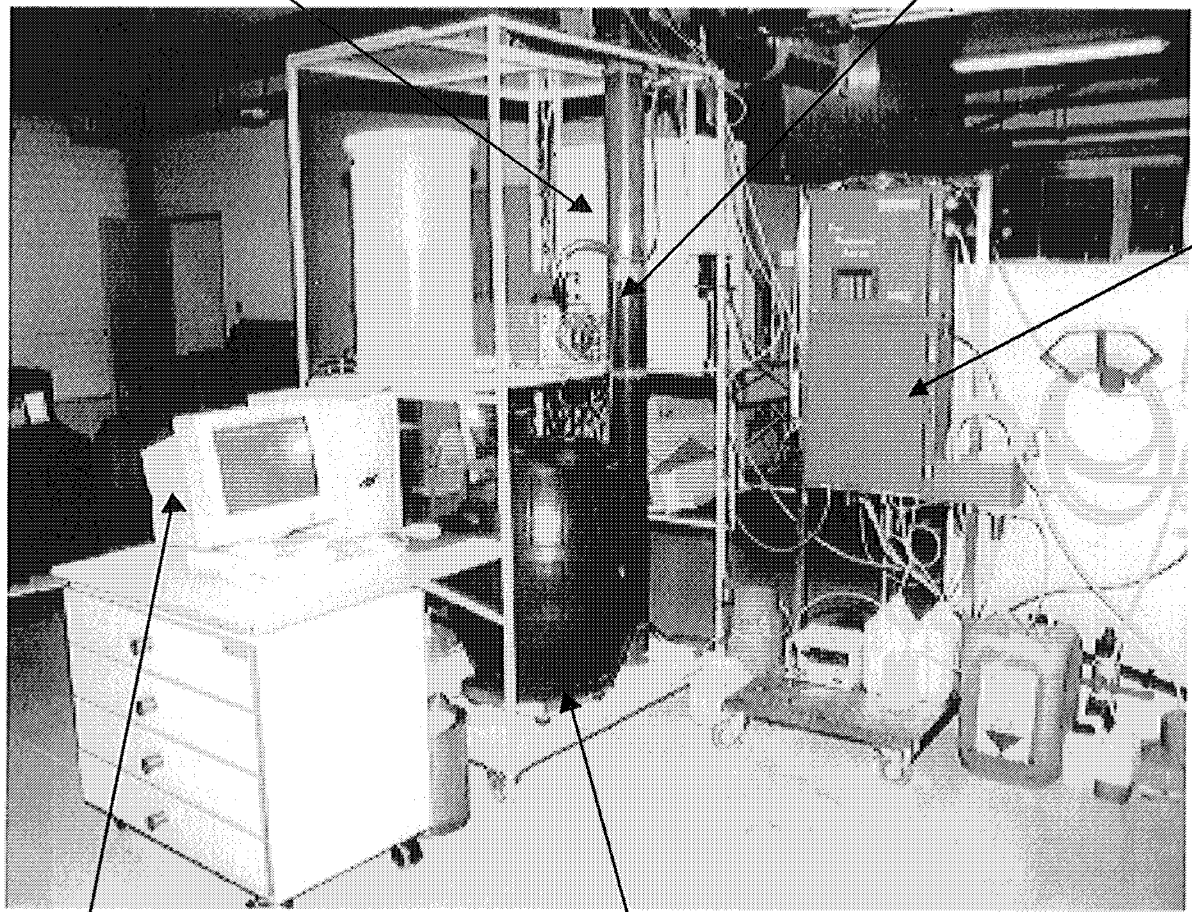
Organism	μ_{max} (d^{-1})	Y_{obs} (gVSS/gN)	K_S (g/m^3)	K_{O2} (g/m^3)	Reference
Nitrosomonas	0.46-1.86 (30 °C)	0.06	10 (30 °C) 3.5 (25 °C) 1.2 (20 °C)	0.5 (30 °C) 0.3 (20 °C)	[Painter 1977]
	0.46-2.20	0.03-0.13	0.06-5.6 (15-32 °C)	0.3 - 1.3	[Charley *et al.*, 1980]
Nitrobacter	1.39 (32 °C)	0.02	8 (32 °C) 5 (25 °C)	1.00 (30 °C) 0.50 (32 °C) 0.25 (18 °C)	[Painter 1977]
	0.28-1.44	0.02-0.08	0.07-8.4 (15-32 °C)	0.25-1.3	[Sharma 1977]

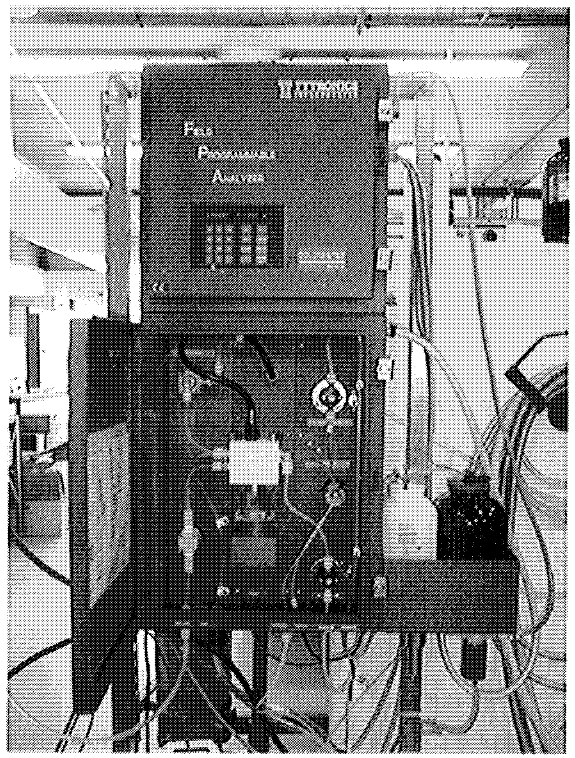
The Process at the LBE-INRA

Input-Ouput Device

Fluidized Bed Reator
(20 liters)

On-Line
Ammonia
Sensor

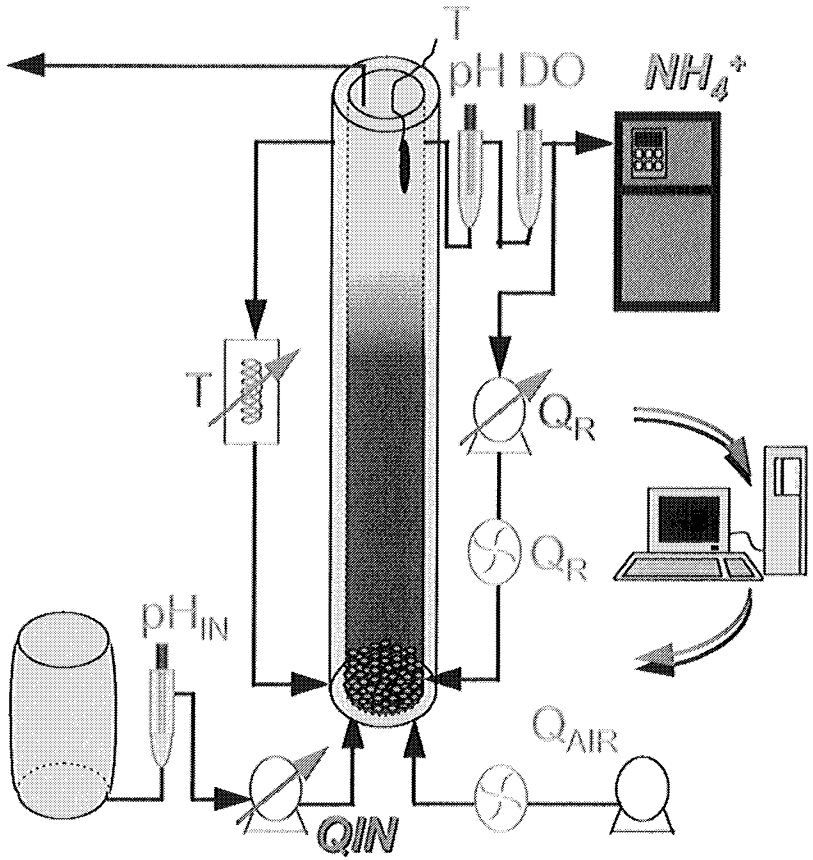




Personal
Computer

Feeding Tank

The Process at the LBE-INRA



On-line measurements:

- Recirculation flow rate
- Air flow rate
- Influent pH
- Reactor temperature
- Recirculation pH
- Recirculation DO
- Recirculation NH_4^+

Actuator:

- Influent flow rate

Off-line adjustments:

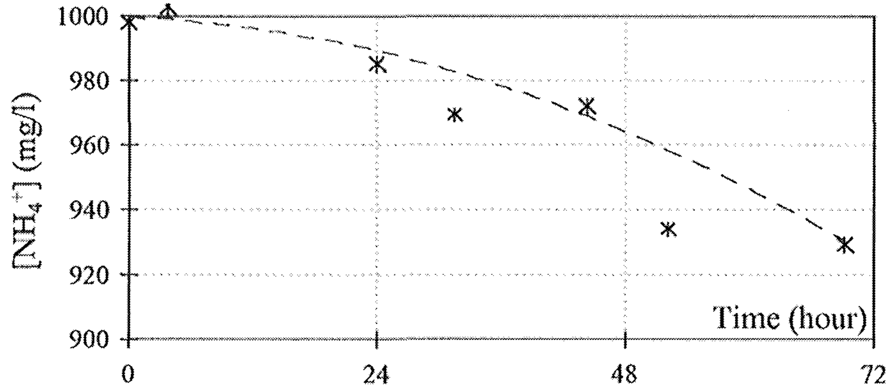
- Temperature
- Recirculation flow rate

Objective : *To control the effluent ammonia concentration at a certain setpoint, using the influent flow rate as the manipulated variable*

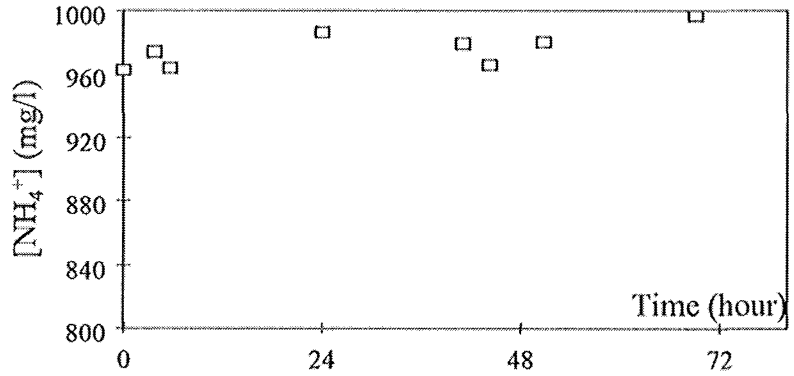
Some technical problems faced with the process

CHANGES IN INFLUENT NH_4^+ CONCENTRATION

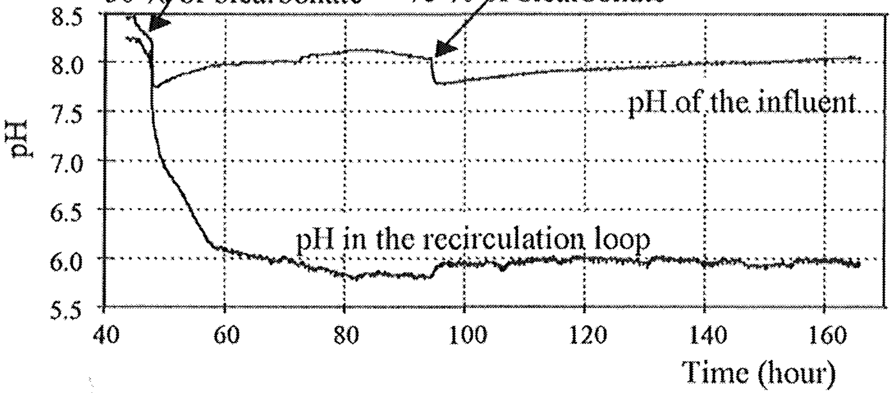
Influent at ambient temperature

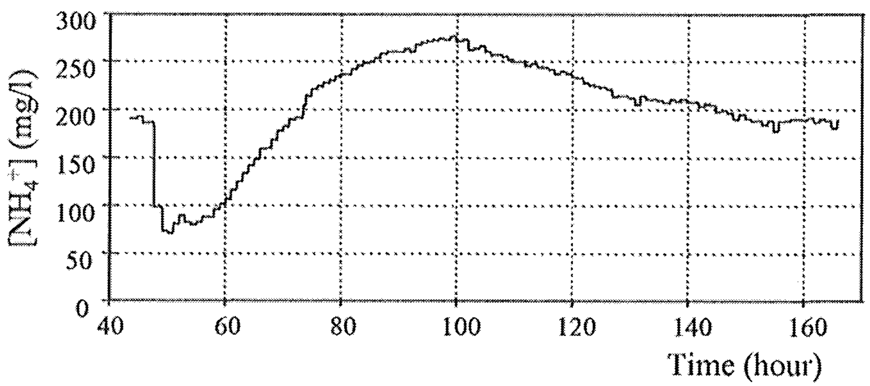


Influent at 7 °C



INFLUENT CARBONATE PRECIPITATION

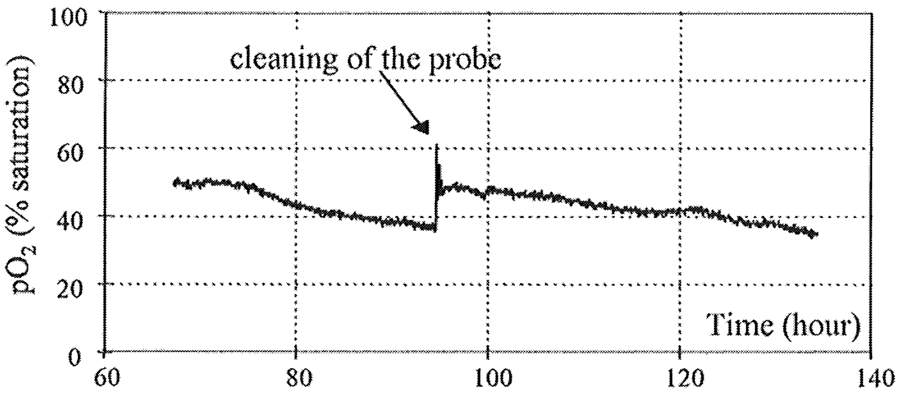




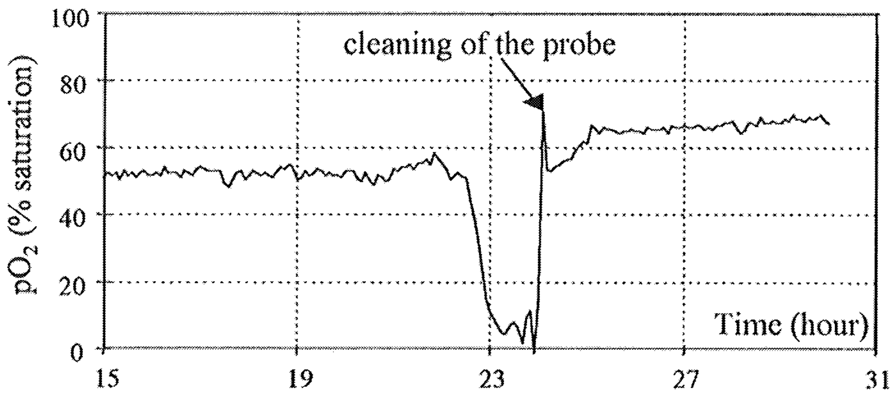
Some technical problems faced with the process

PROBE CLOGGING

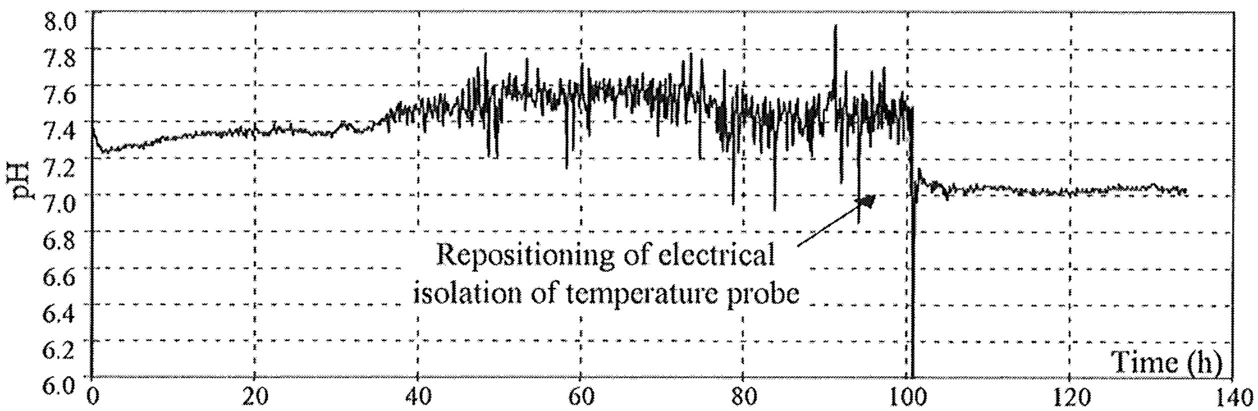
Slow clogging



Fast clogging



ELECTRICAL INTERFERENCES BETWEEN PROBES



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Hypothesis

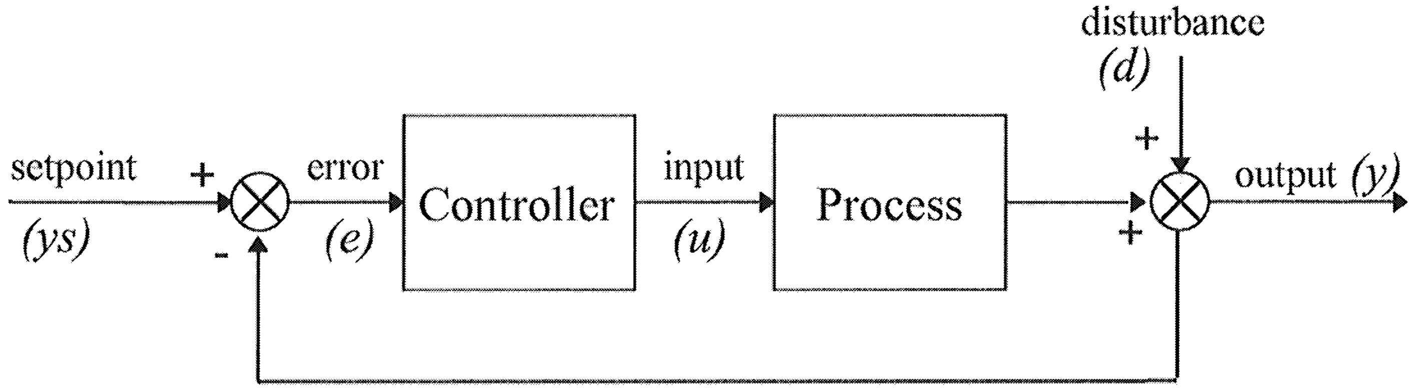
We do not have any reliable model…
We do not know how exactely the process works ...

But we do have a large amount of available on-line data !

↳ *Artificial neural networks could be a solution*

The PID controller

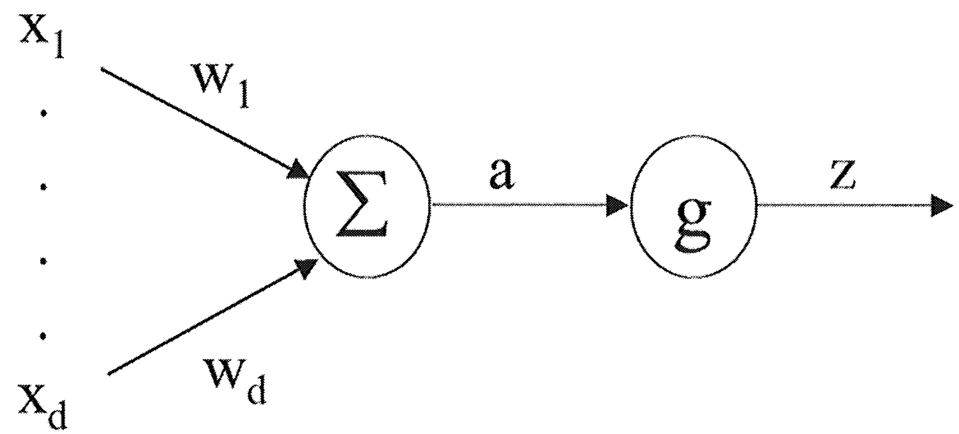
A PID (*i.e.*, Proportional Integral Derivative) controller is an example of a feedback controller. It determines the action *(u)* to be applied to the process in order to minimize the deviation *(e)* of the output *(y)* from the setpoint *(ys)*, in the presence of disturbances *(d)*.



$$u(t) = K_C\left[e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}\right] + u_0$$

Artificial Neural Networks

An ***artificial*** **neuron** is a **non linear function** which transforms a set of input variables x_i into an output variable z.

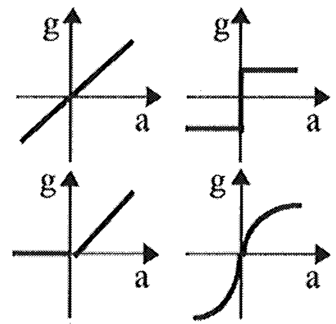


inputs

output

$$a = \sum_{i=1}^{d} w_i x_i + w_0$$

$$z = g(a)$$



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Some Vocabulary

- The transformation of the x_i variables into the z variable is governed by a set of parameters called ***weights*** (i.e., the w_i parameters).

- The process of determining the w_i parameters is often called the ***training*** or ***learning procedure***.

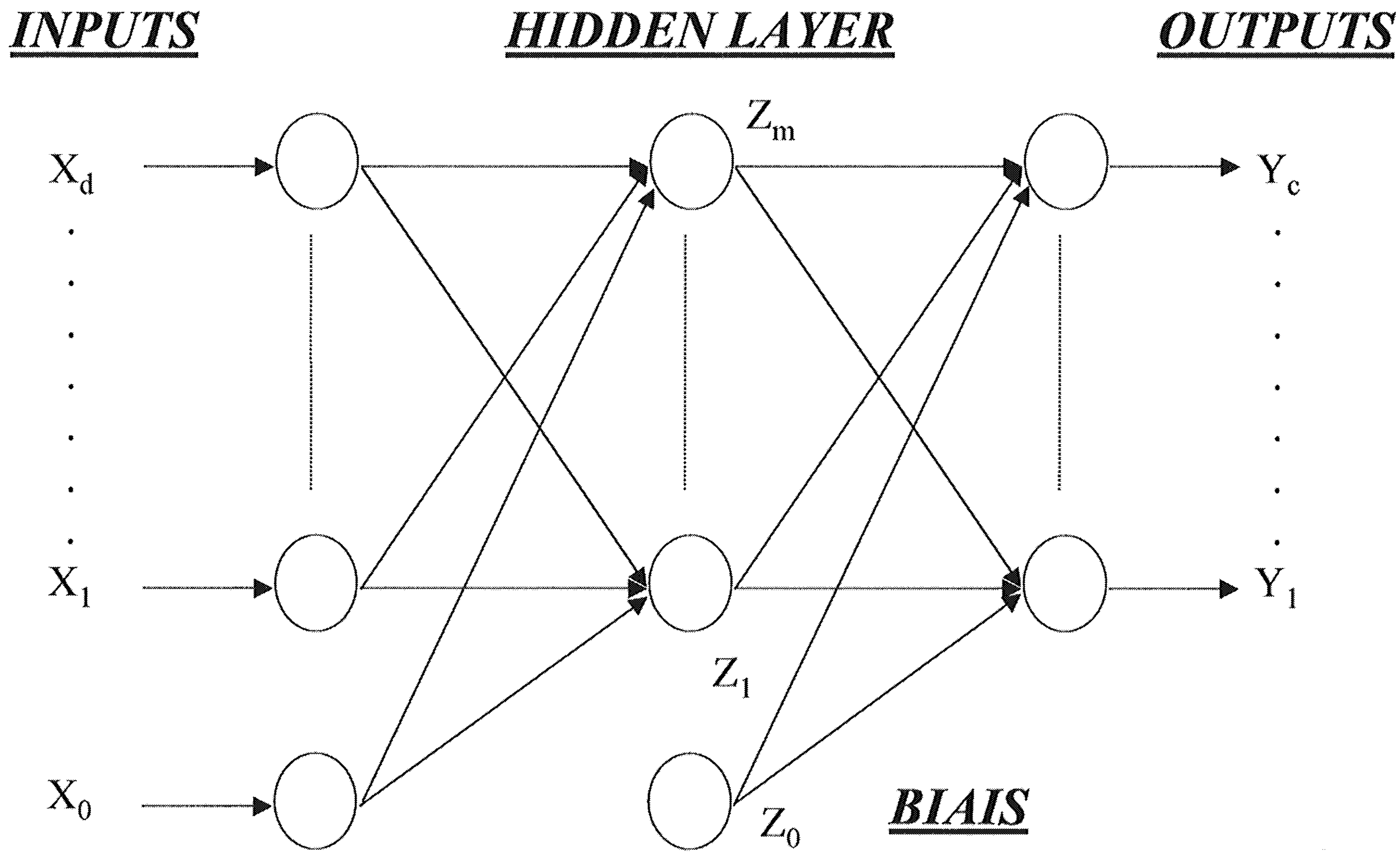
- Learning can be a computationally intensive undertaking. However, once the weights have been fixed, new data can be processed by the network very rapidly.

Field of applications for ANN

Broadly speaking, neural networks should be considered as possible candidates to solve problems which have some, or all, of the following characteristics :

- There is ample data for network training.
- It is difficult to provide a first-principle model which is adequate.
- New data must be processed at high speed.
- The data processing methods need to be robust to modest levels of noise on the input data.

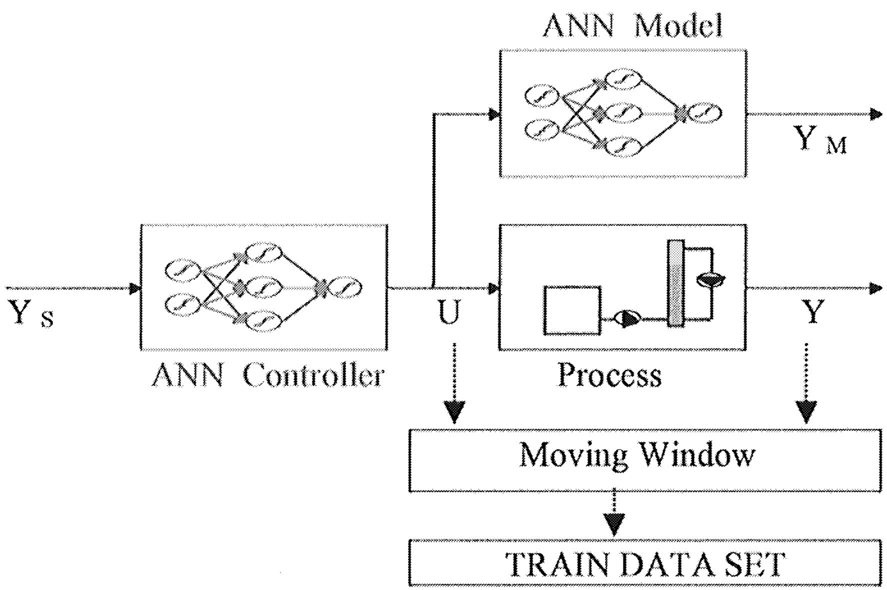
Architecture of a multilayer perceptron



Structure of the neural network based controller

Two different artificial neural networks are used :

- one to model the process and to account for variations (i.e., the ANN model)
- one to decide about the best action to perform on the process (i.e., the ANN controller)



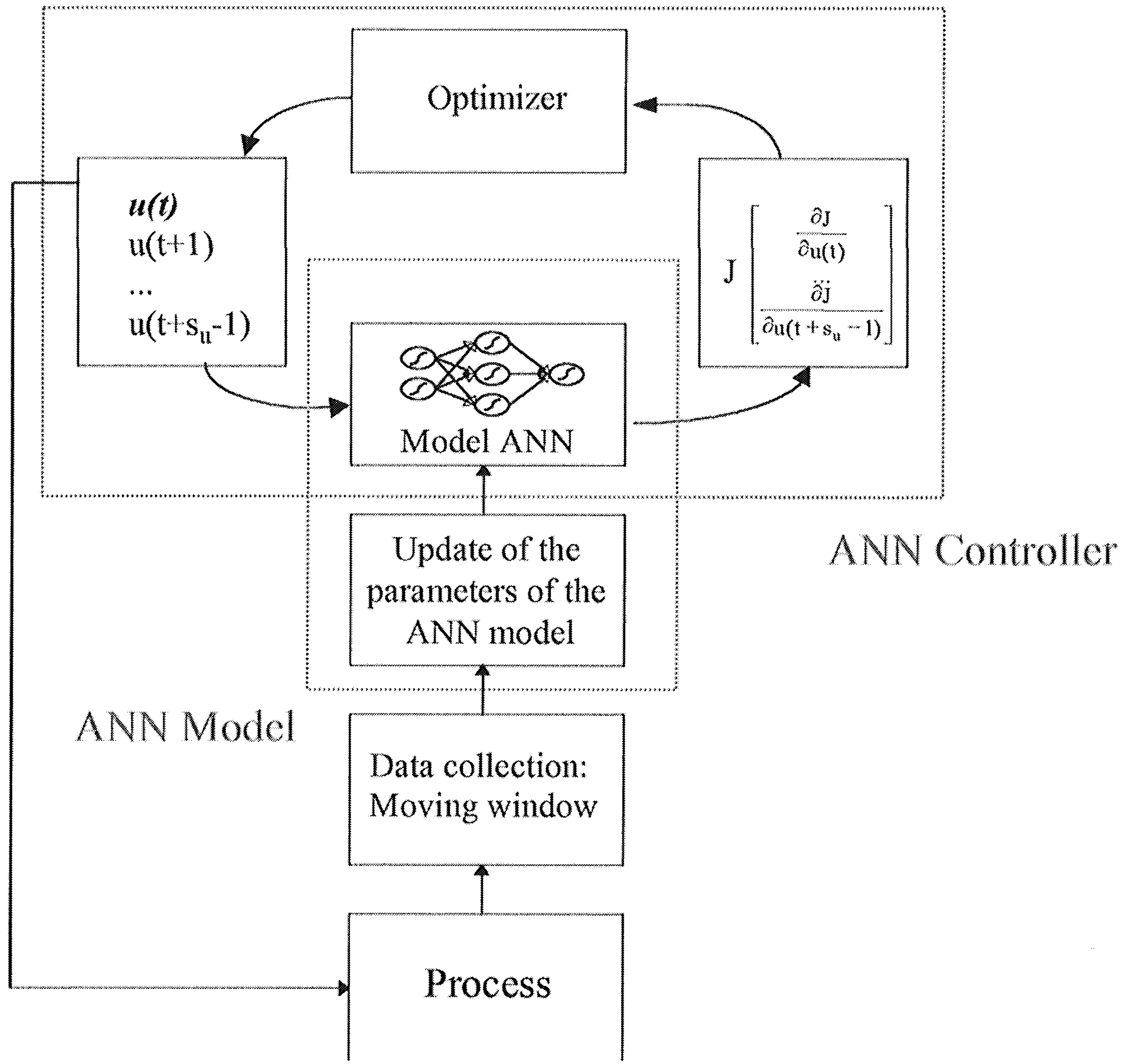
ANN Model

$$\left.\begin{array}{l} Y(t-n) \\ \ldots \\ Y(t) \\ U(t-m) \\ \ldots \\ U(t) \end{array}\right\} Y(t+\theta)$$

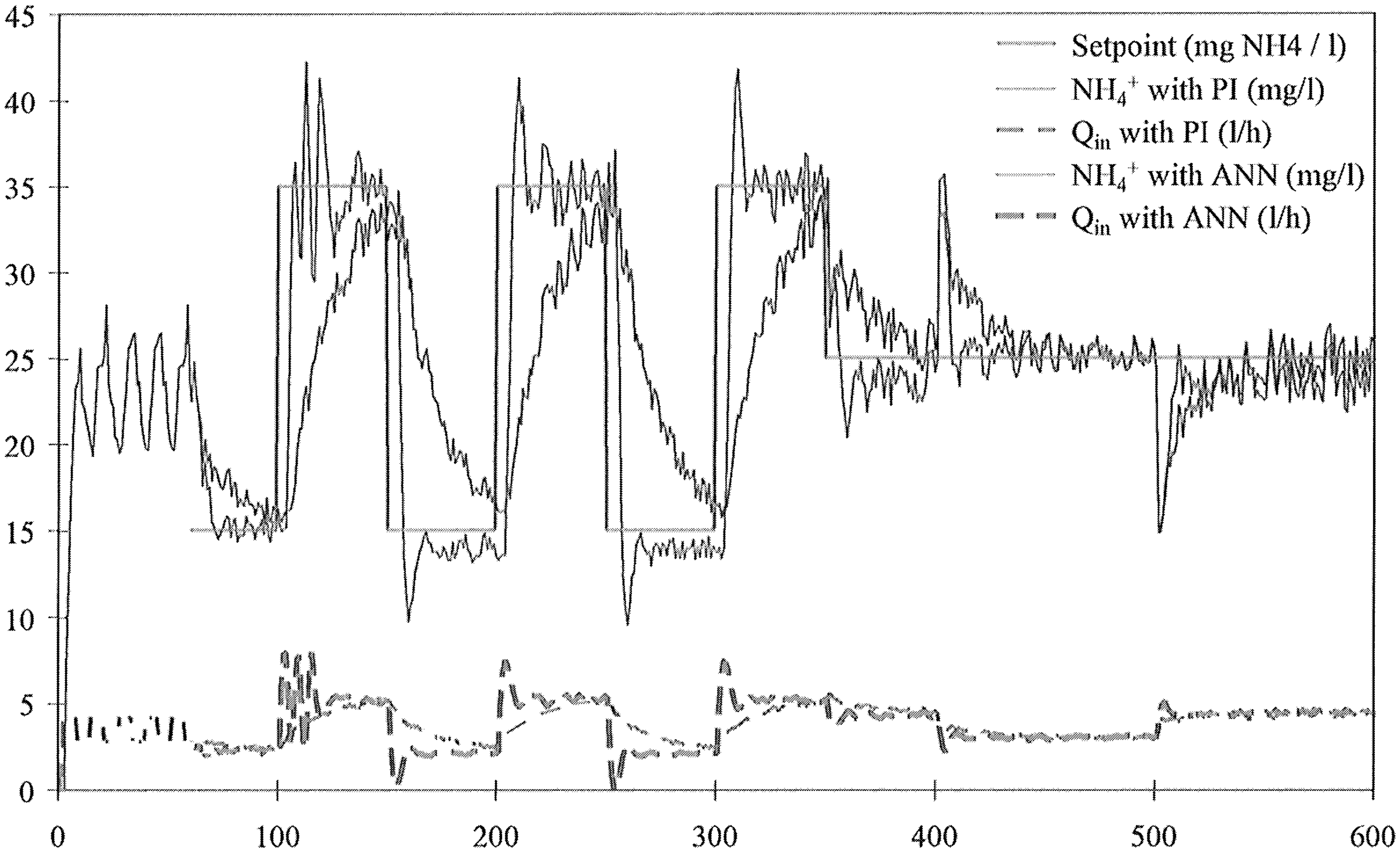
ANN Controller

$$\left.\begin{array}{l} Y(t-n) \\ \ldots \\ Y(t) \\ U(t-m) \\ \ldots \\ U(t-1) \\ Y_S(t+\theta) \end{array}\right\} U(t)$$

Scheme of the predictive controller using an adaptive neural model

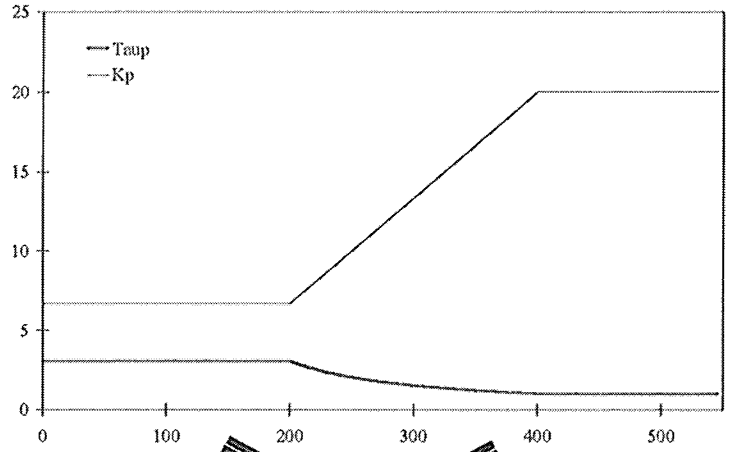


Comparison (simulation) between a PI controller and a MPC using an adaptive ANN model

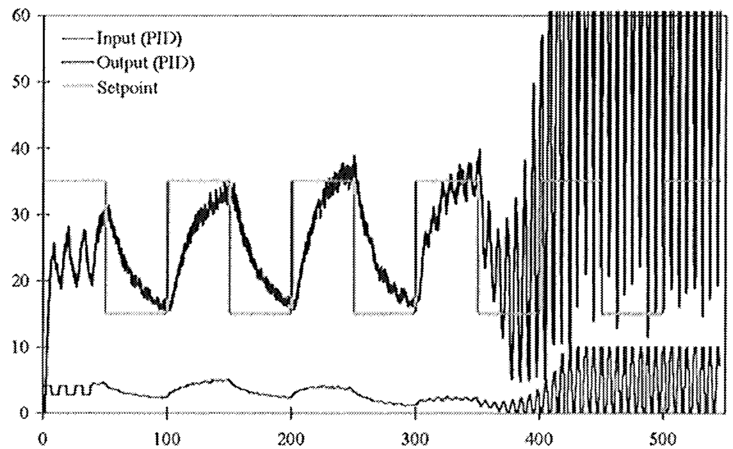


Simulation results to illustrate the ability to control processes with time varying dynamics

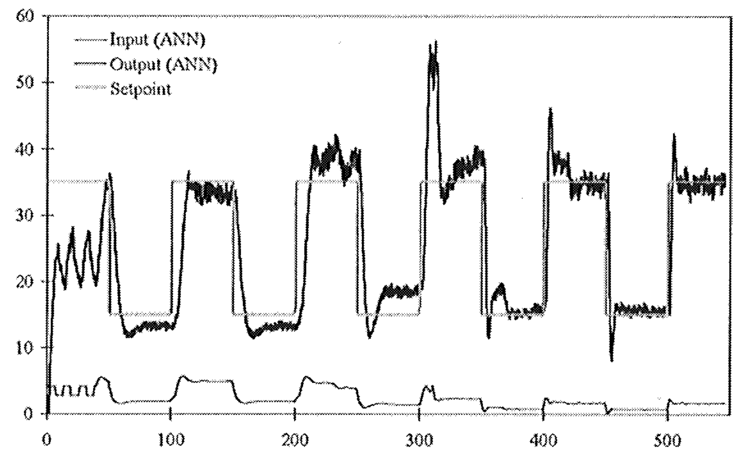
Variation of the first order model parameters



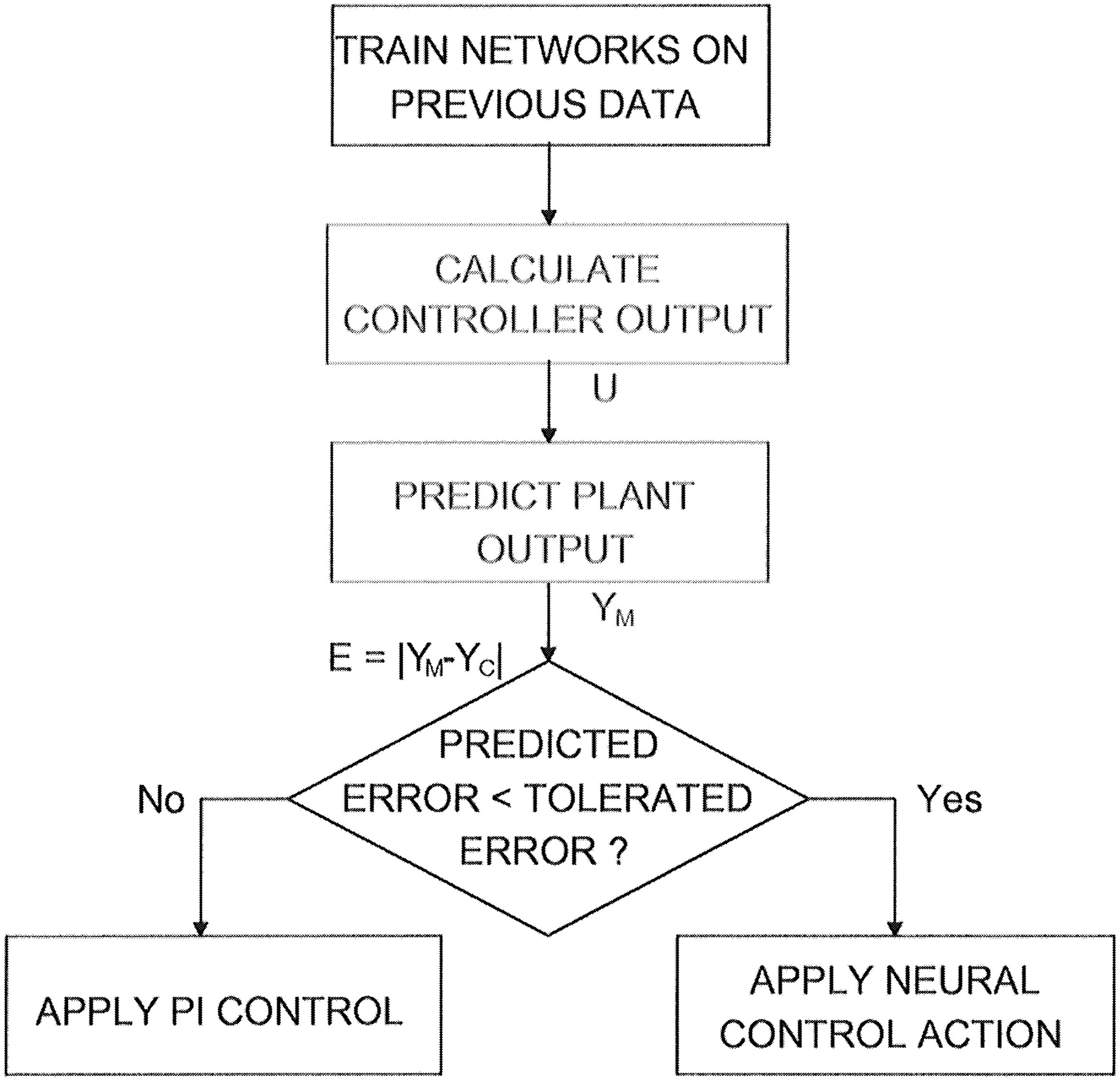
PI controller



ANN based controller

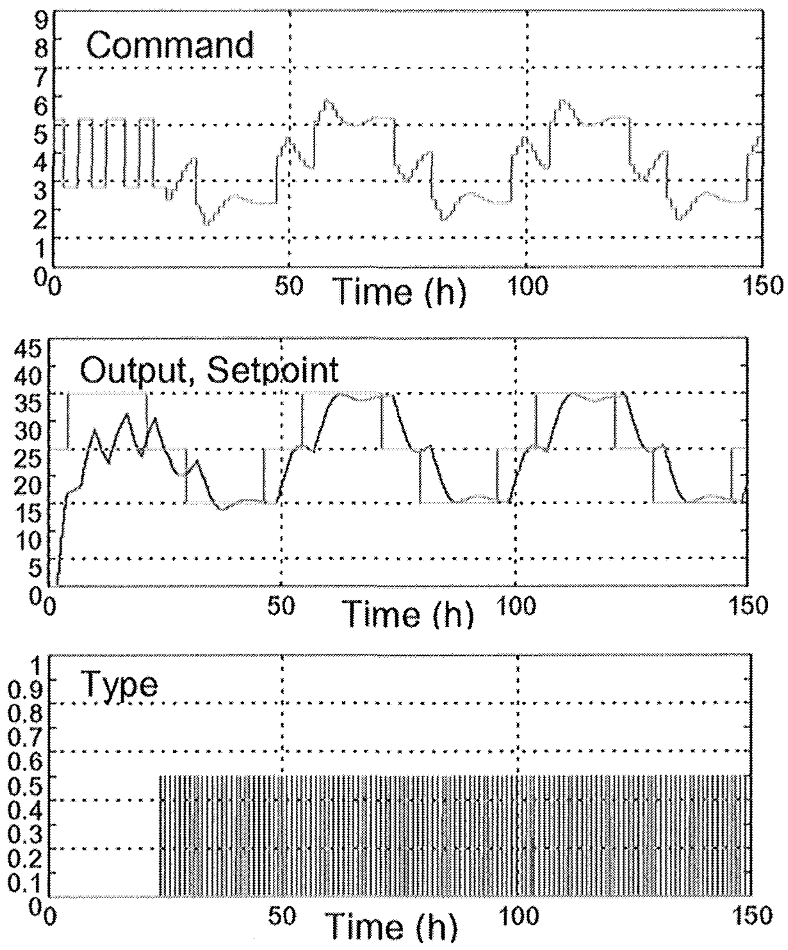


Practical implementation of the controller

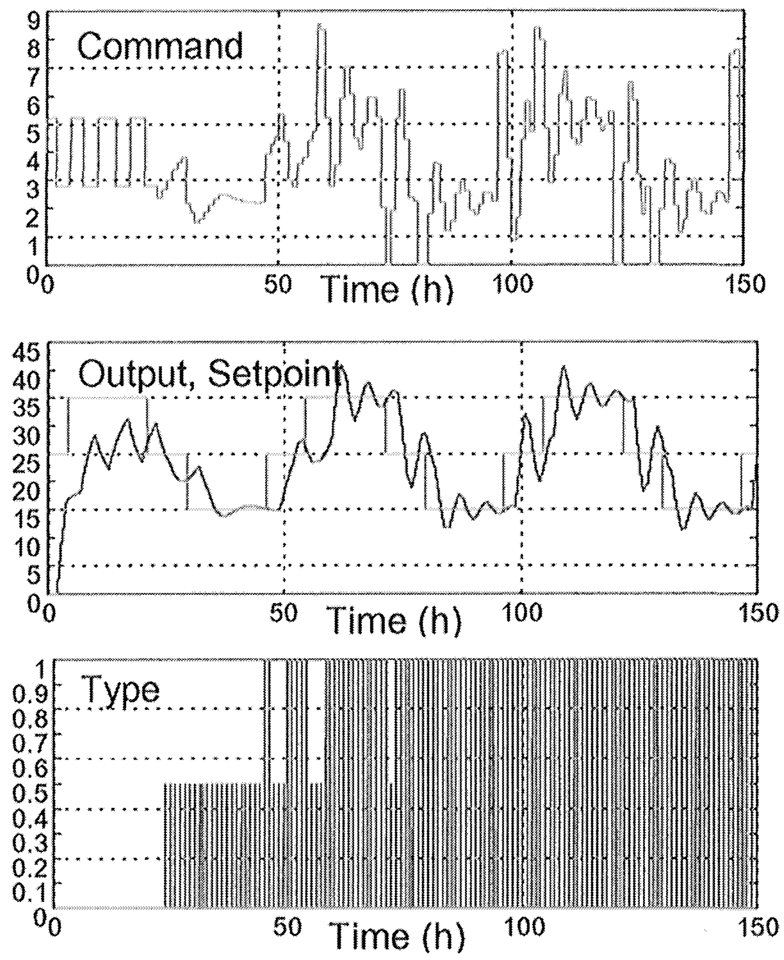


Comparison between a PI and an ANN controller (simulation results)

PI control



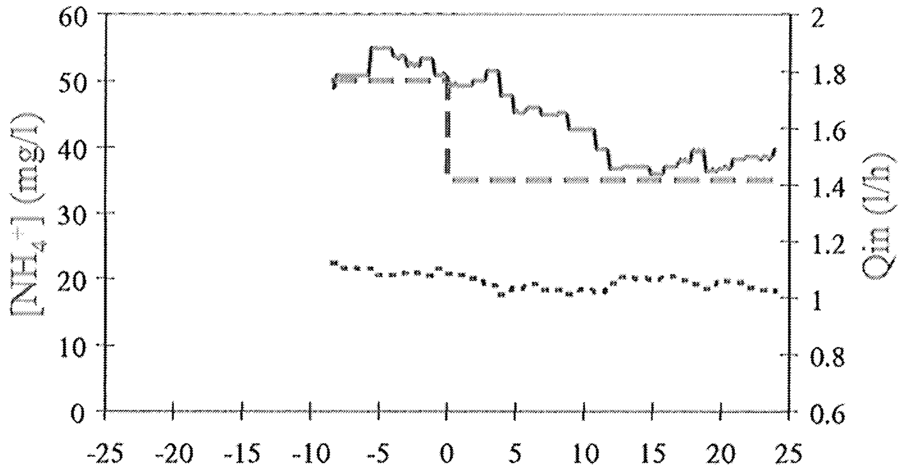
Neural control

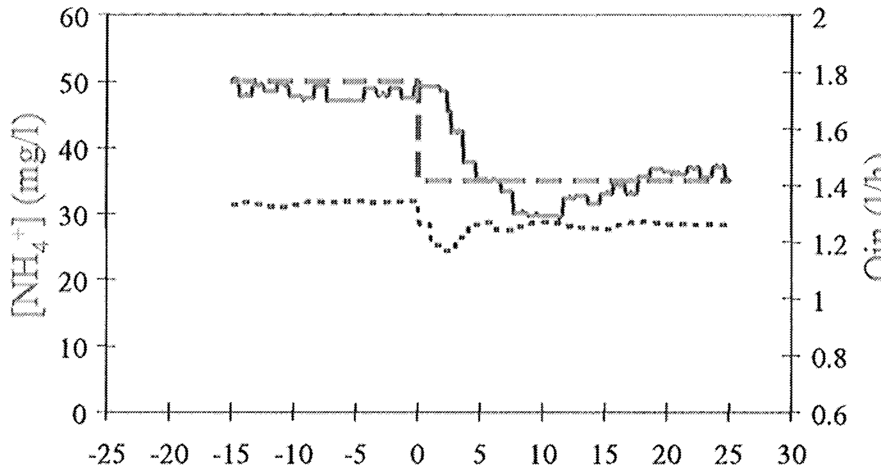


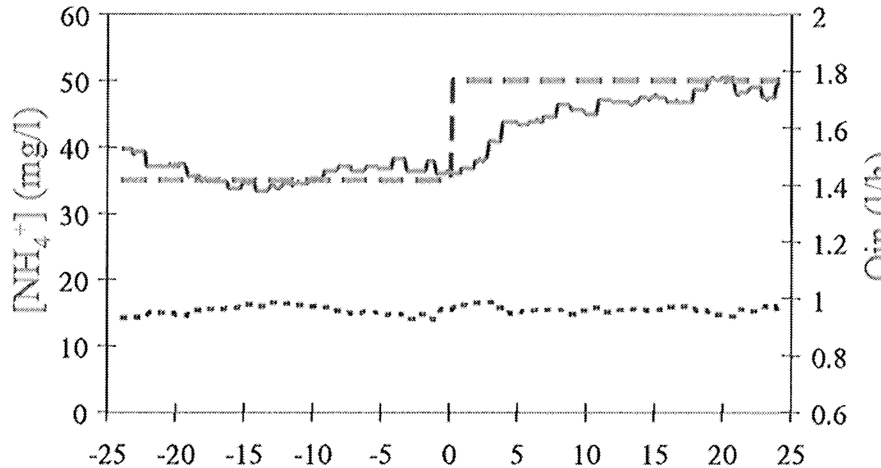
Setpoint changes (Experimental results)

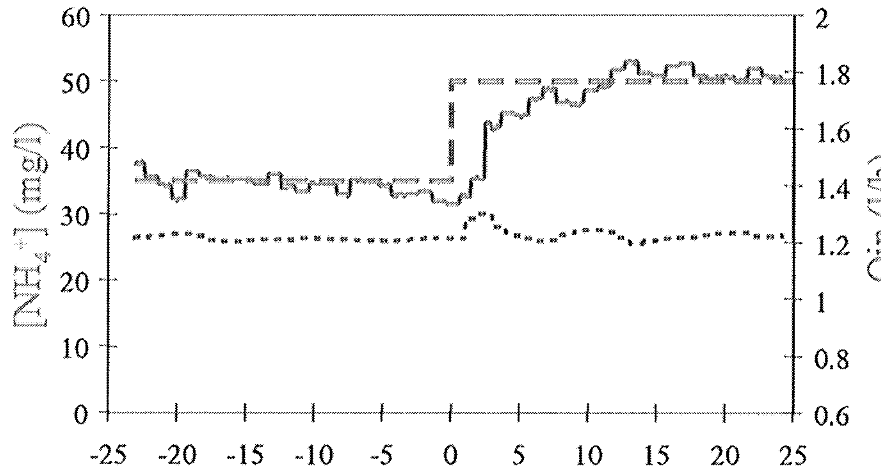
PI control

ANN based control



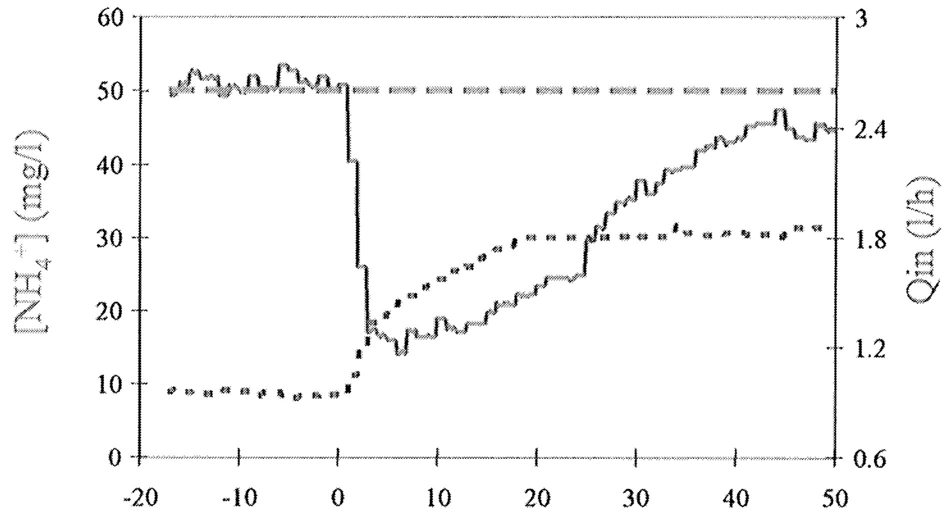




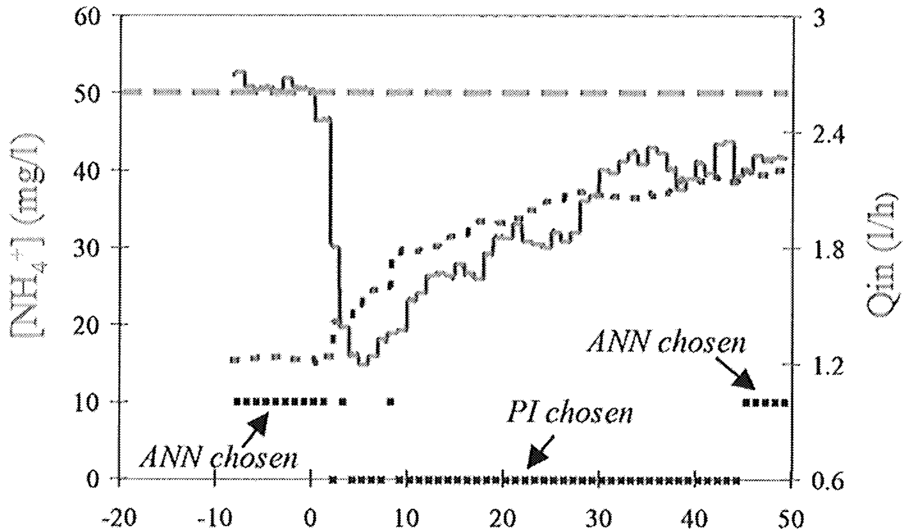


For a 40 % dilution of the influent (Experimental results)

PI control



ANN based control



Concluding remarks on ANN

Artificial Neural Networks
have been ***successfully applied*** to biological processes
both for ***Modeling, Control and Diagnosis***

Advantages	*Disadvantages*
Fast results Nonlinear properties No need of explicit model Robustness, fault tolerance Learning (adaptation) capabilities	Data needed Meaningless parameters Stability not always guaranteed

Contents

INRA

Hypothesis

We do not have any reliable model…
We do not have large amount of on-line data ...

But we know how the process works
(i.e., some expertise is available !)

↳ *Fuzzy Logic could be a solution*

History of Fuzzy Logic

1965 Seminal paper "Fuzzy Logic" by Prof. Lotfi Zadeh, Faculty in Electrical Engineering, U.C. Berkeley. Sets the foundation of the "Fuzzy Set Theory"

1970 First application of Fuzzy Logic in Control Engineering (Europe)

1975 Introduction of Fuzzy Logic in Japan

1980 Empirical verification of Fuzzy Logic in Europe

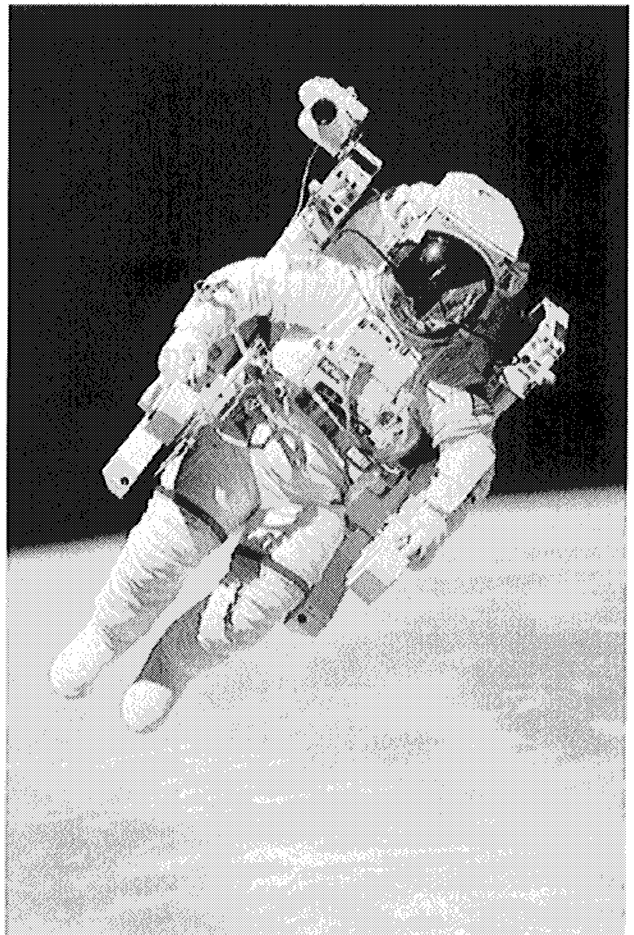
1985 Broad application of Fuzzy Logic in Japan

1990 Broad application of Fuzzy Logic in Europe

1995 Broad application of Fuzzy Logic in the U.S.

2000 Fuzzy Logic becomes a standard technology. Main applications in data and sensor signal analysis as well as multi-variable control.

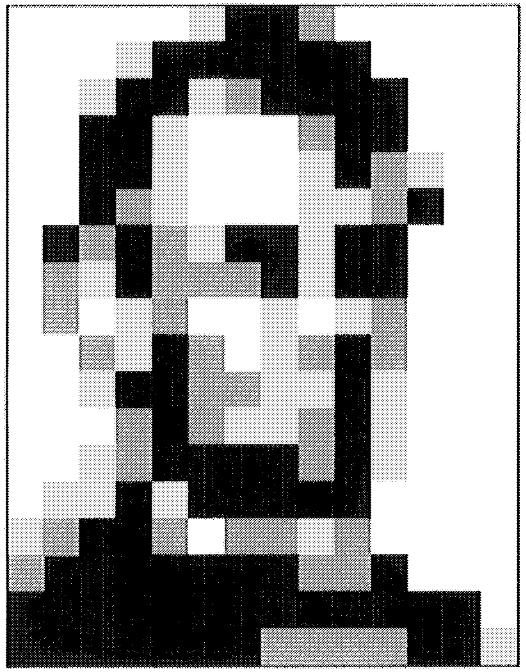
Applications Study of the IEEE in 1996



- ✓ About 1100 successful Fuzzy Logic applications have been published (an estimated 5% of those in existence)
- ✓ Almost all applications have not involved the replacement of a standard type controller (PID,..) but rather multi-variable supervisory control
- ✓ Applications range from embedded control (28%), industrial automation (62%) to process control (10%)
- ✓ Of 311 authors that answered a questionnaire, about 90% state that Fuzzy Logic has slashed design time by more than half
- ✓ In this questionnaire, 97.5% of the designers stated that they will use Fuzzy Logic again in future applications, if Fuzzy Logic is applicable

Fuzzy Logic will play a major role in Control Engineering !

Types of Uncertainty



Stochastic Uncertainty

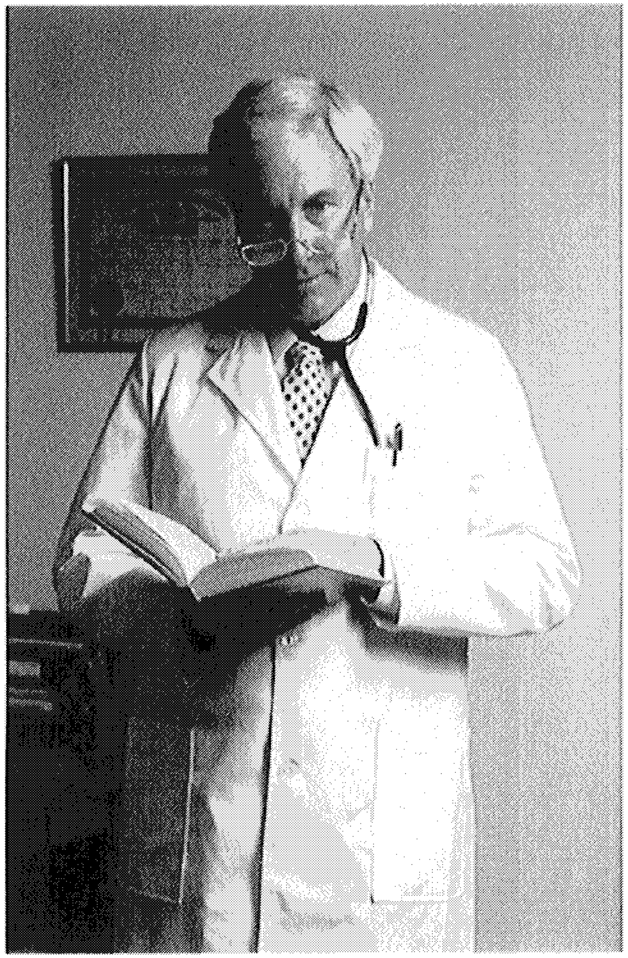
- ✓ "The probability of hitting the target is 0.8"

Lexical Uncertainty

- ✓ "Tall men", "Hot days", ...
- ✓ We will probably have an overloading of the process.
- ✓ The experience of Expert A shows that B Is likely to occur. However, Expert C is convinced this is not true.

Most words and evaluations we use in our daily reasoning are not clearly defined in a mathematical manner. This allows humans to reason on an abstract level.

Probability and Uncertainty



"... a person suffering from hepatitis shows in 60% of all cases a strong fever, in 45% of all cases yellowish colored skin, and in 30% of all cases suffers from nausea ..."

Stochastics and Fuzzy Logic complement each other !

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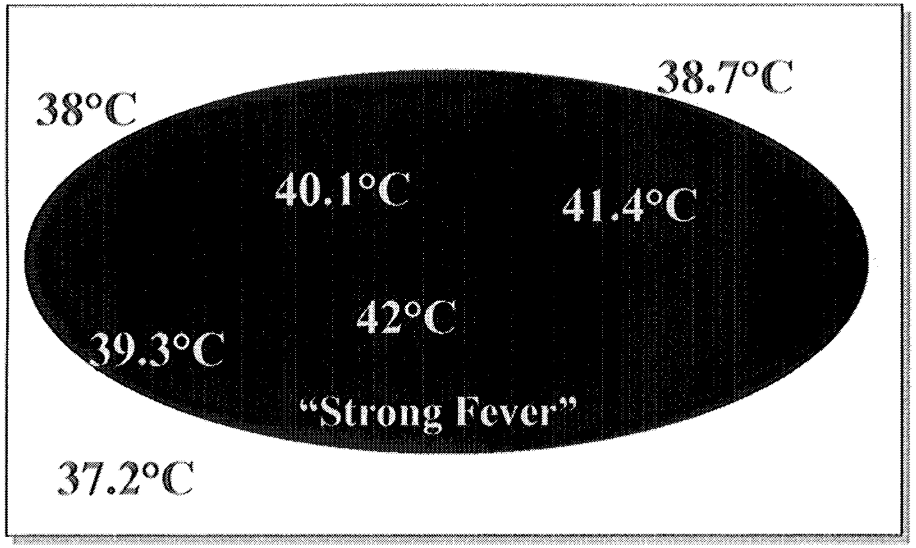
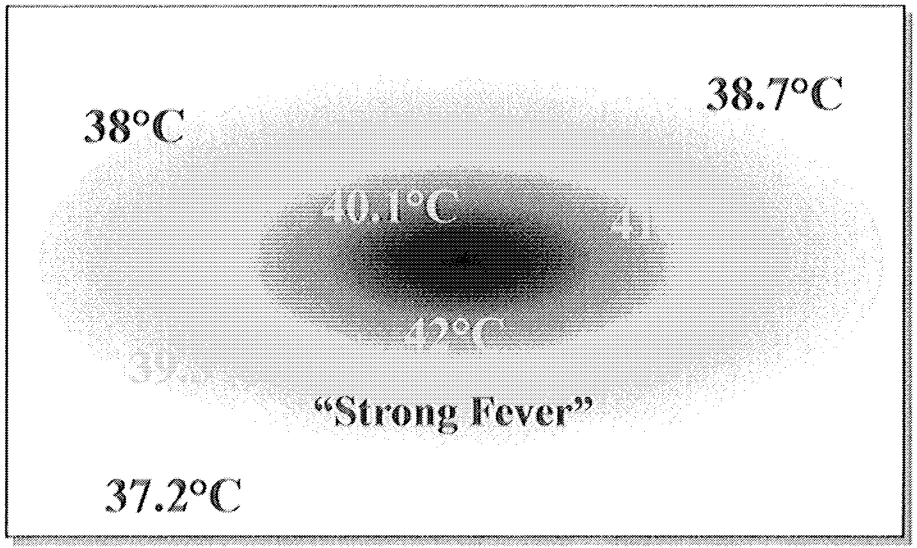
Fuzzy Set Theory

Conventional (Boolean) Set Theory



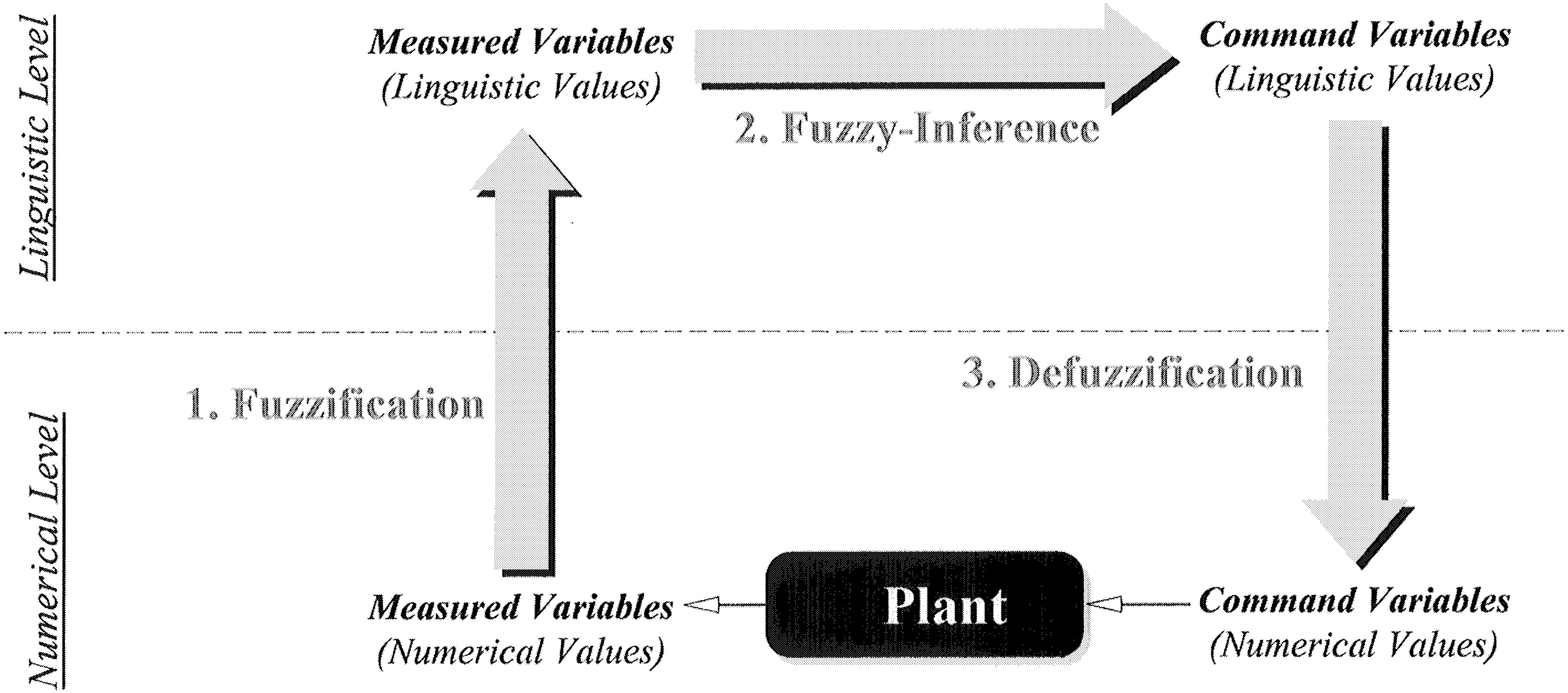
Fuzzy Set Theory



"More-or-Less" rather than "Either-Or" !

Basic Elements of a Fuzzy Logic System

Fuzzification, Fuzzy Inference and Defuzzification

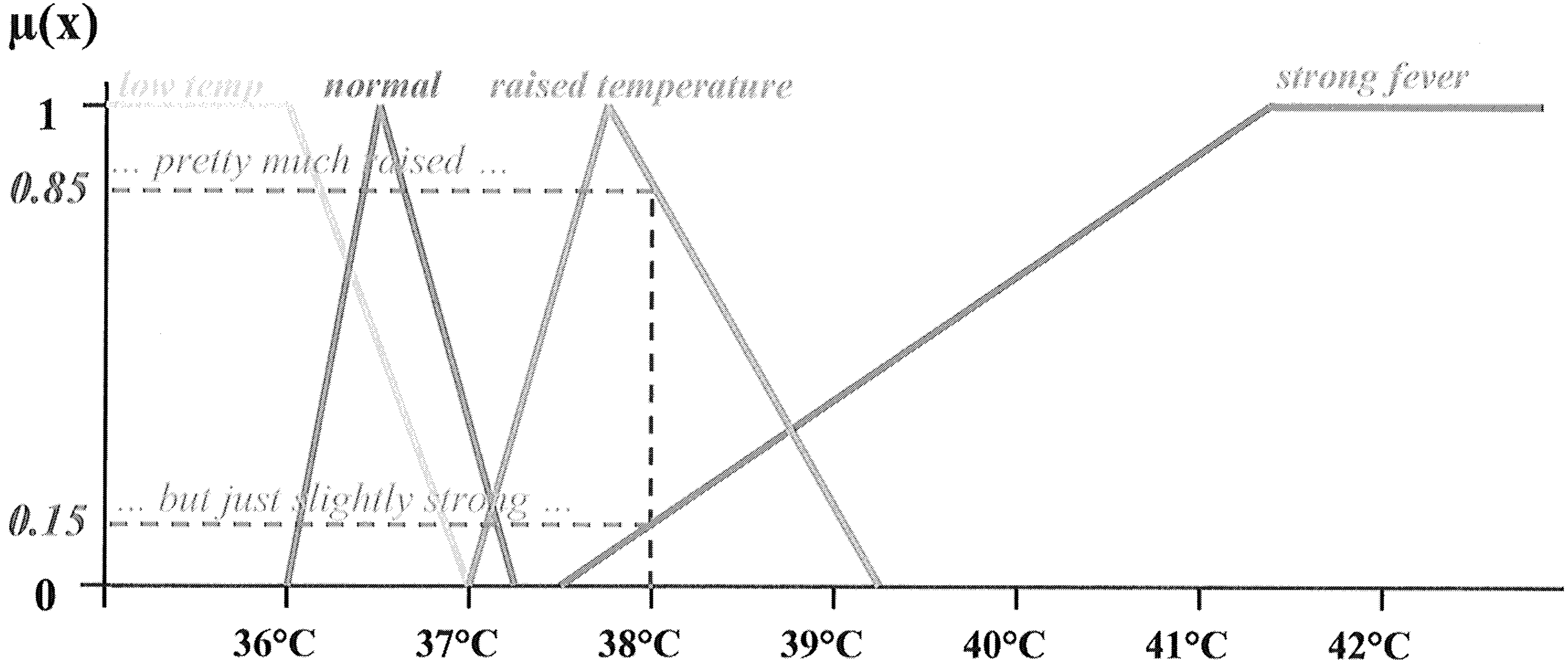


Fuzzy Logic defines the control strategy on a linguistic level

1) Fuzzyfication

From numerical to linguistic values

Example : if my temperature is 38 °C ...



A linguistic variable defines a concept of our everyday language

2) Fuzzy inference

"IF-THEN" Rules

Examples :

#1: IF *temperature* is *medium* AND *pH* is *low* THEN *feed_flow* is *low*

#2: IF *oxygen* is *medium* AND *pH* is *normal* THEN *feed_flow* is *normal*

#3: IF *oxygen* is *high* OR *pH* is *high* THEN *feed_flow* is *high*

Boolean logic only defines operators for 0/1

A	B	A∧B
0	0	0
0	1	0
1	0	0
1	1	1

Fuzzy Logic delivers a continuous extension

✓ **AND** : $\mu_{A \wedge B} = \min\{ \mu_A ; \mu_B \}$

✓ **OR** : $\mu_{A \vee B} = \max\{ \mu_A ; \mu_B \}$

✓ **NOT** : $\mu_{A^-} = 1 - \mu_A$

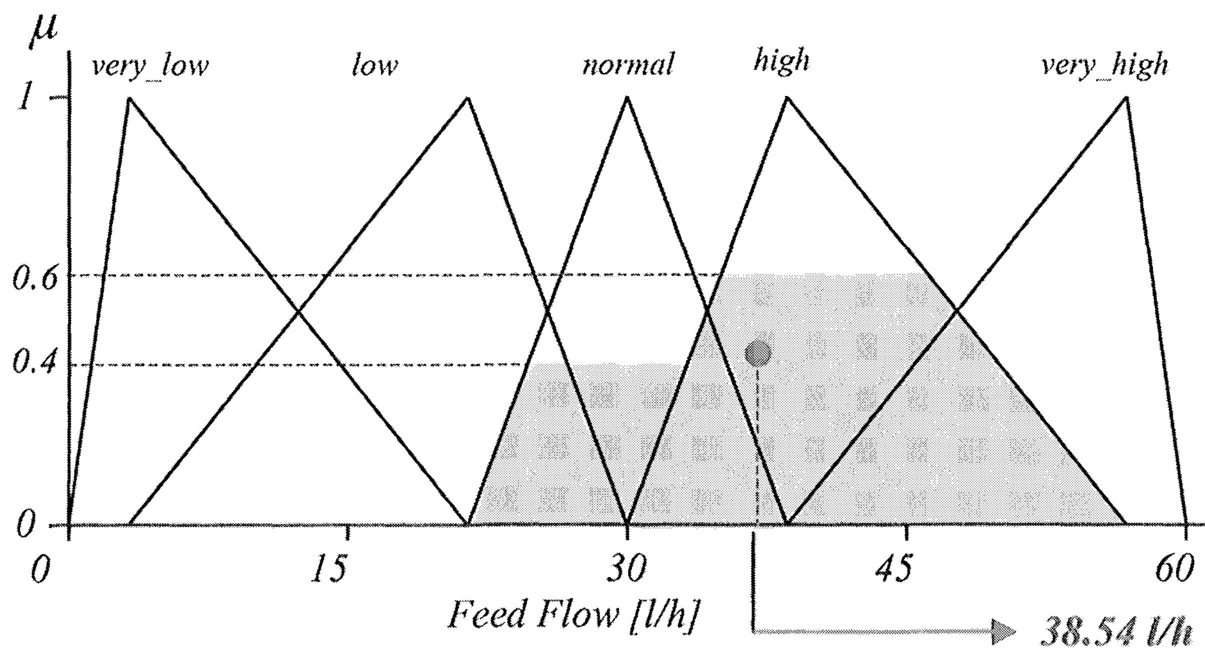
The rules of the Fuzzy Logic system are the "laws" it executes

3) Defuzzyfication

From linguistic to numerical values while "balancing" out the result

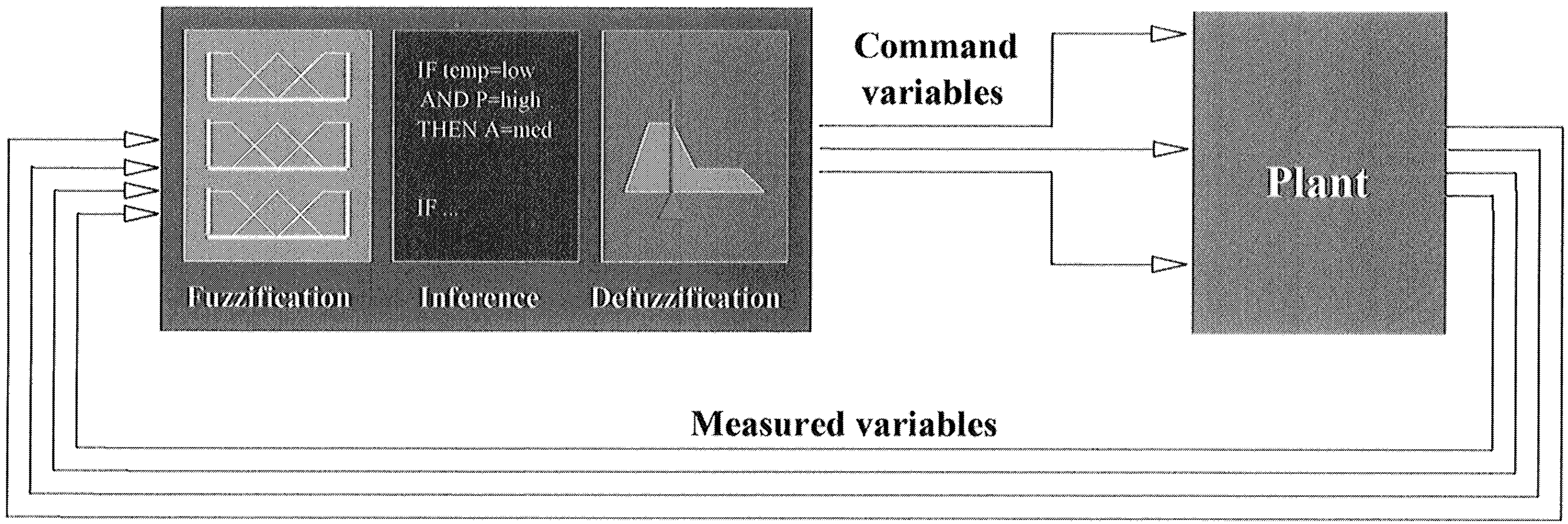
Finding a compromise using the "center of gravity"

Example : Rule #i ⇒ feed_flow is high (*0.6*)
Rule #j ⇒ feed_flow is normal (*0.4*)



Application #1 : Direct Controller

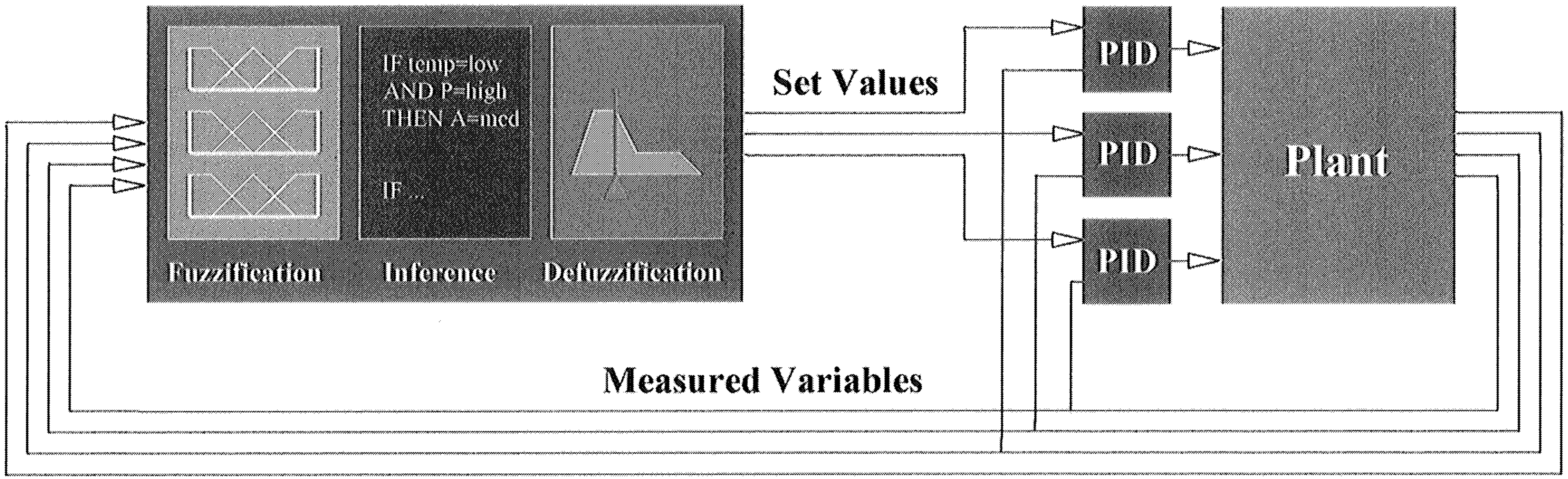
The outputs of the Fuzzy Logic system are the command variables of the plant



Fuzzy rules induce absolute values

Application #2 : Supervisory Control

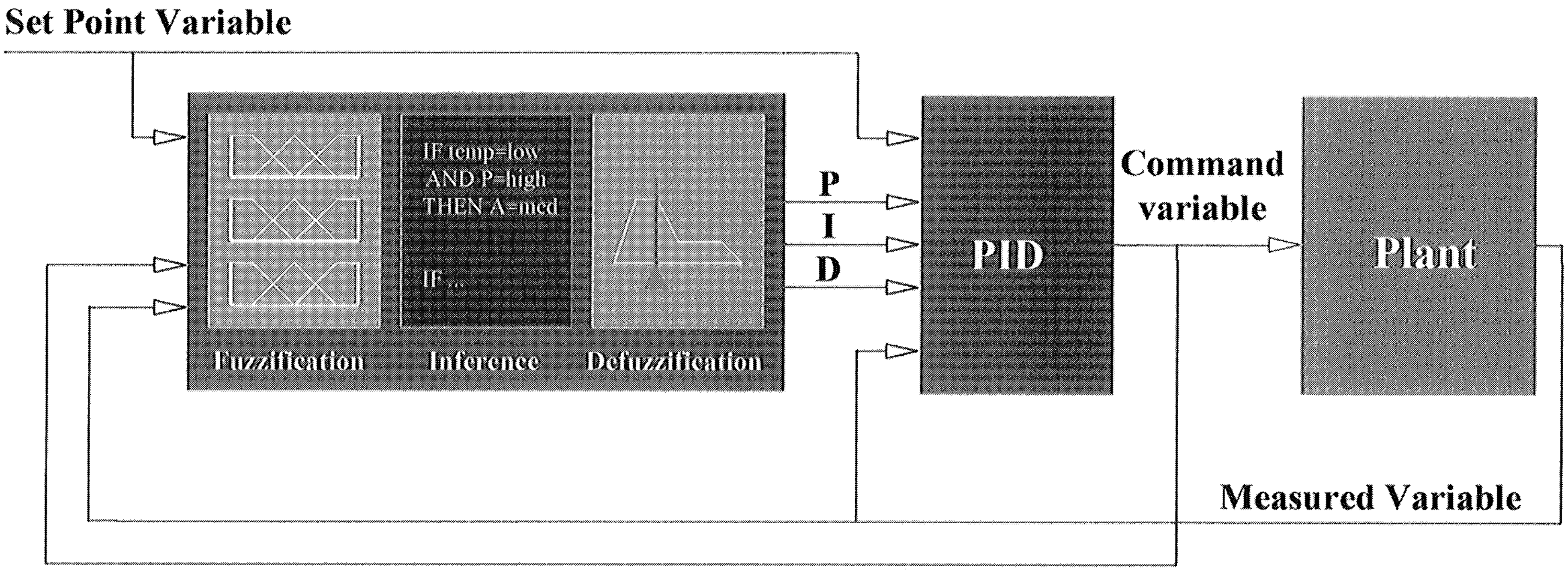
Fuzzy Logic controller outputs set values for underlying PID controllers



Human Operator Type Control

Application #3 : PID Adaptation

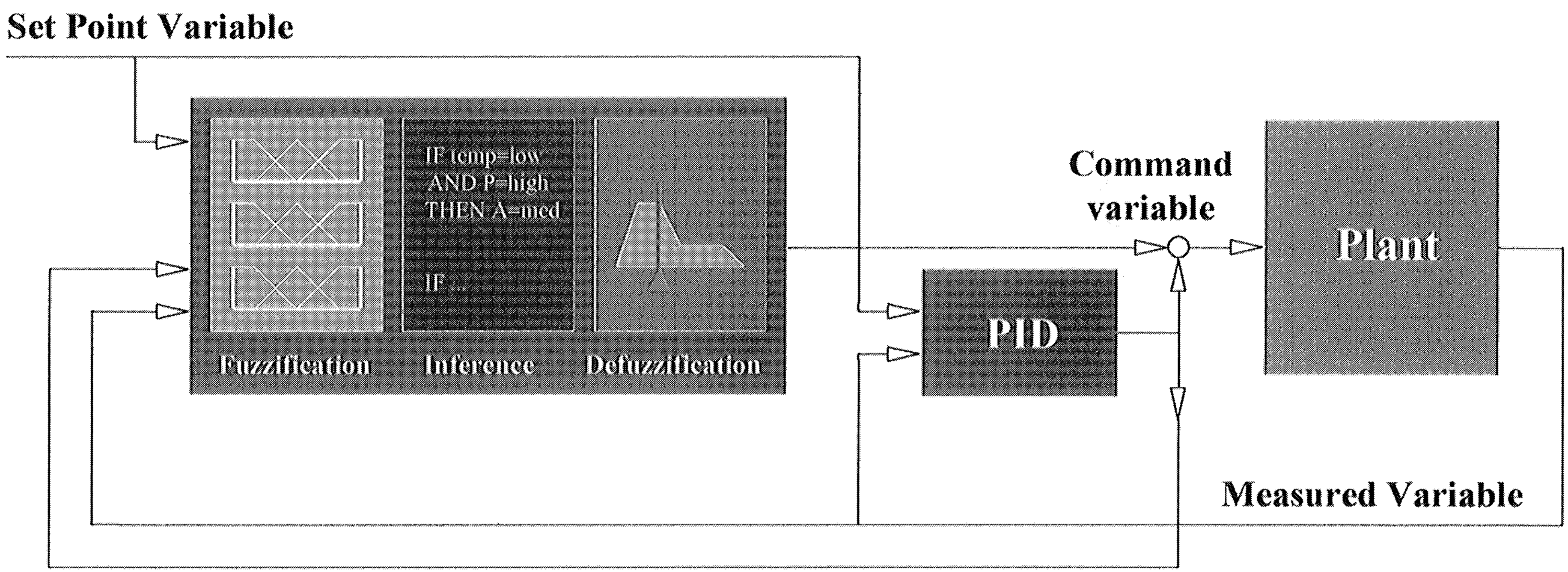
Fuzzy Logic controller adapts the P, I, and D parameters of a conventional PID controller



The Fuzzy Logic system analyzes the performance of the PID controller and optimizes it

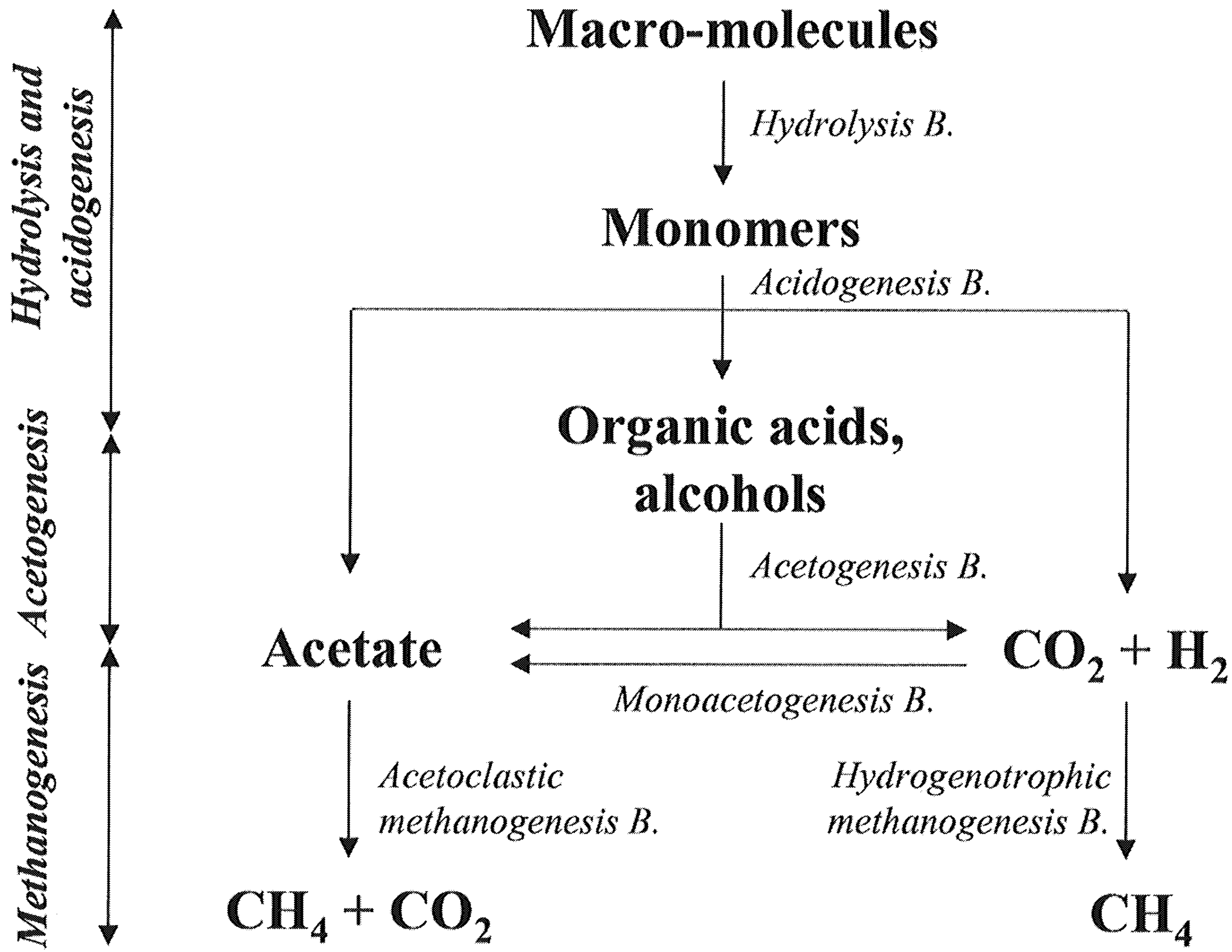
Application #4 : Fuzzy Intervention

Fuzzy Logic controller and PID controller in parallel



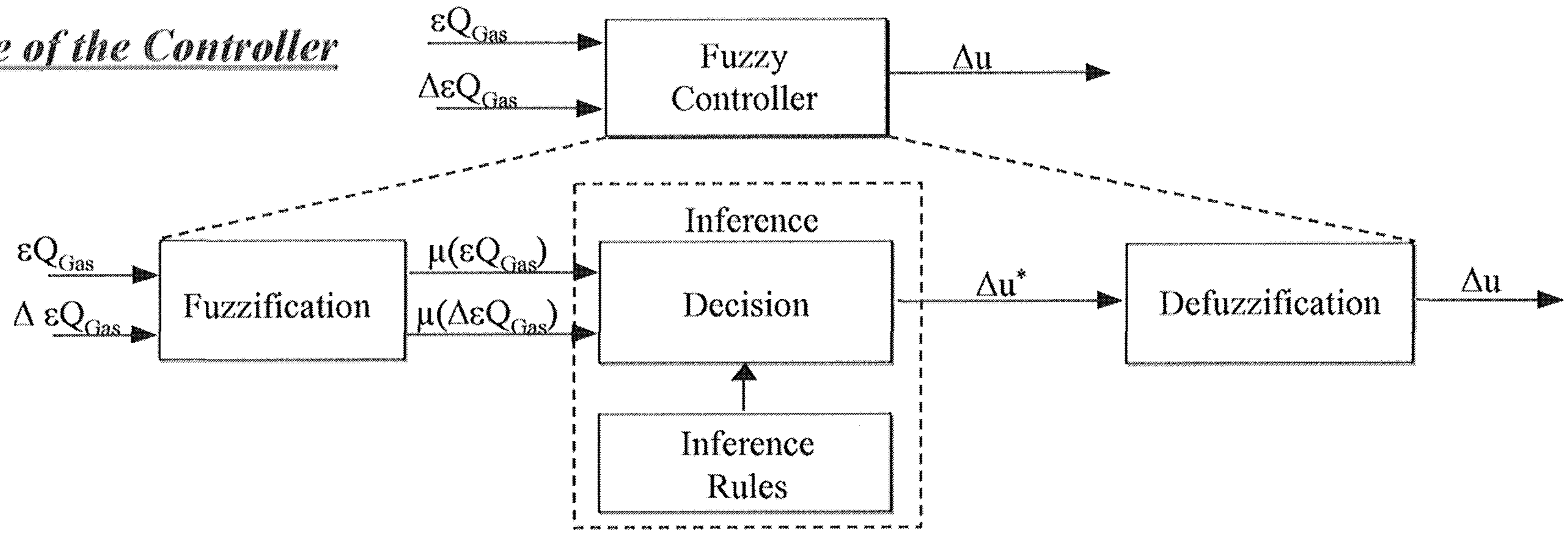
Intervention of the Fuzzy Logic Controller into large disturbances

Application : Biogas regulation in AD processes



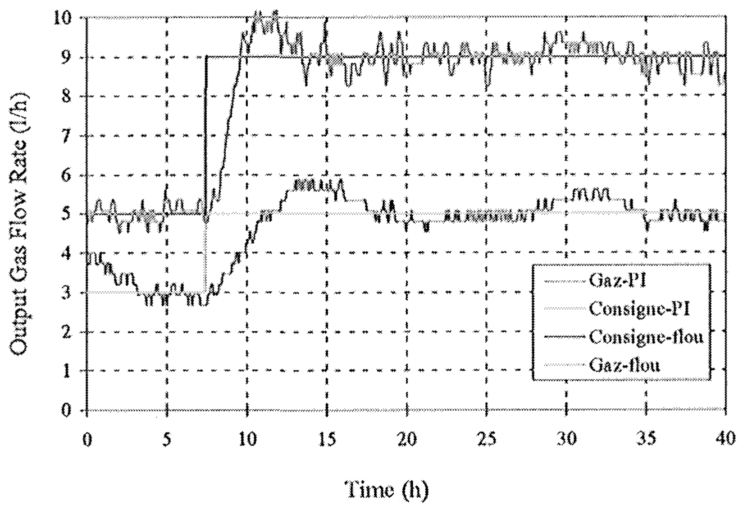
Direct Fuzzy Control of the Biogas Flow Rate

1) Structure of the Controller

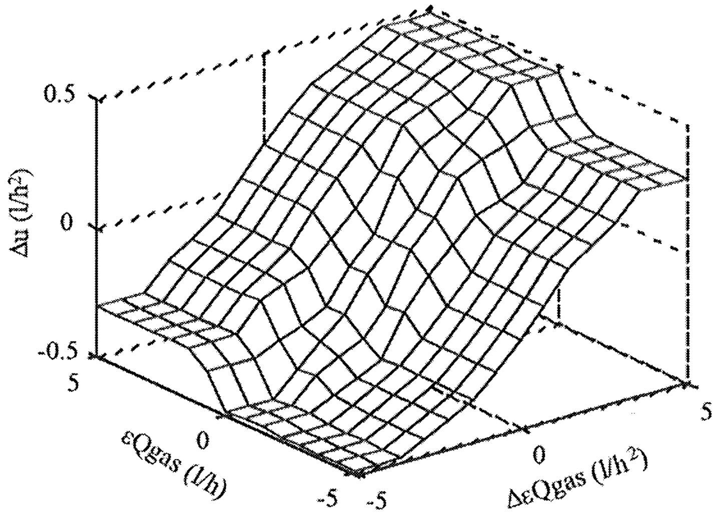


2) Comparison with a PI controller

Experimental Results

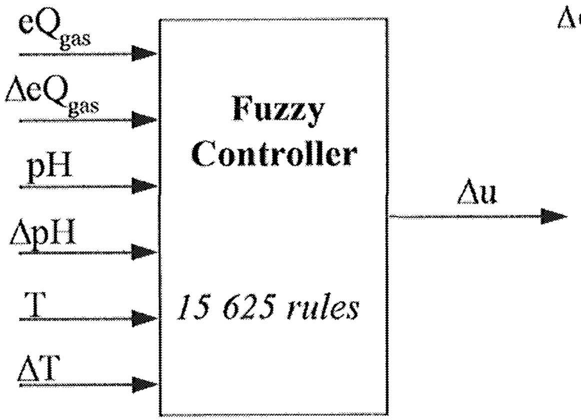


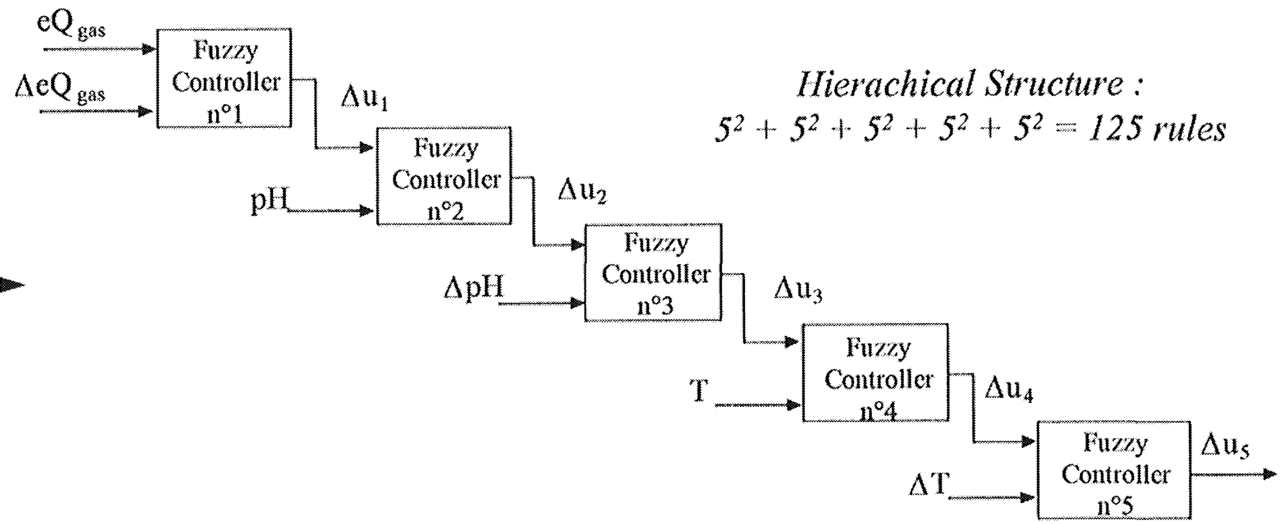
Control Surface



Hierarchical Fuzzy Direct Controller

1) It allows to account for additional variables

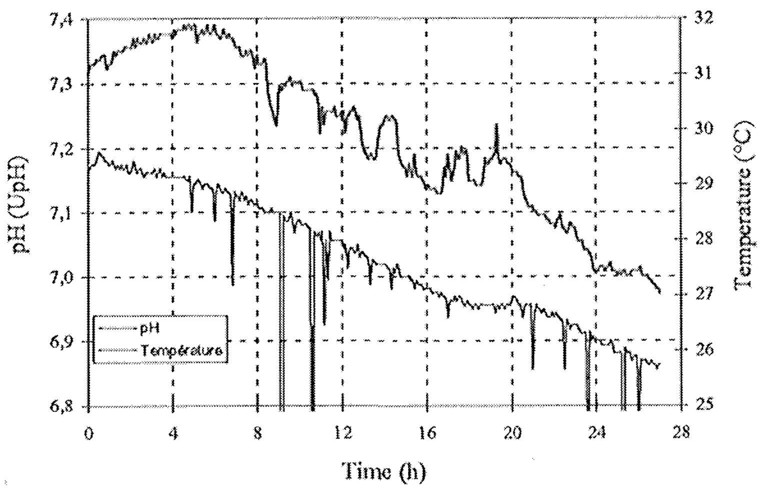


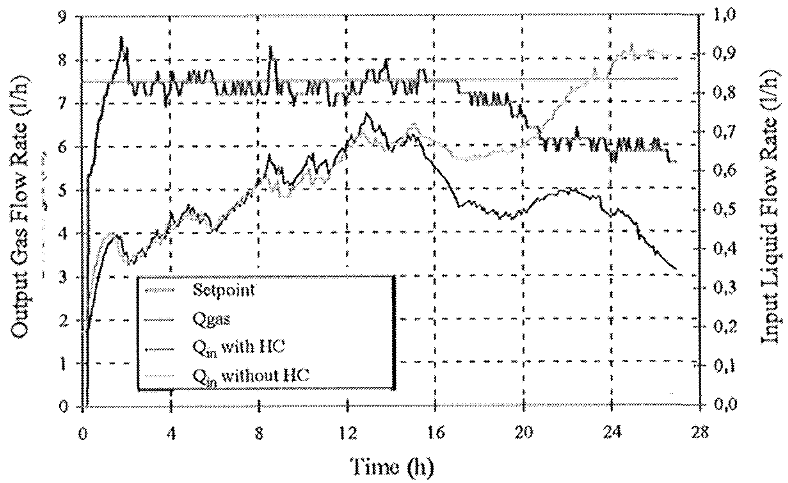


Hierachical Structure :

$5^2 + 5^2 + 5^2 + 5^2 + 5^2 = 125$ rules

2) In the case of an organic overloading (made on purpose)

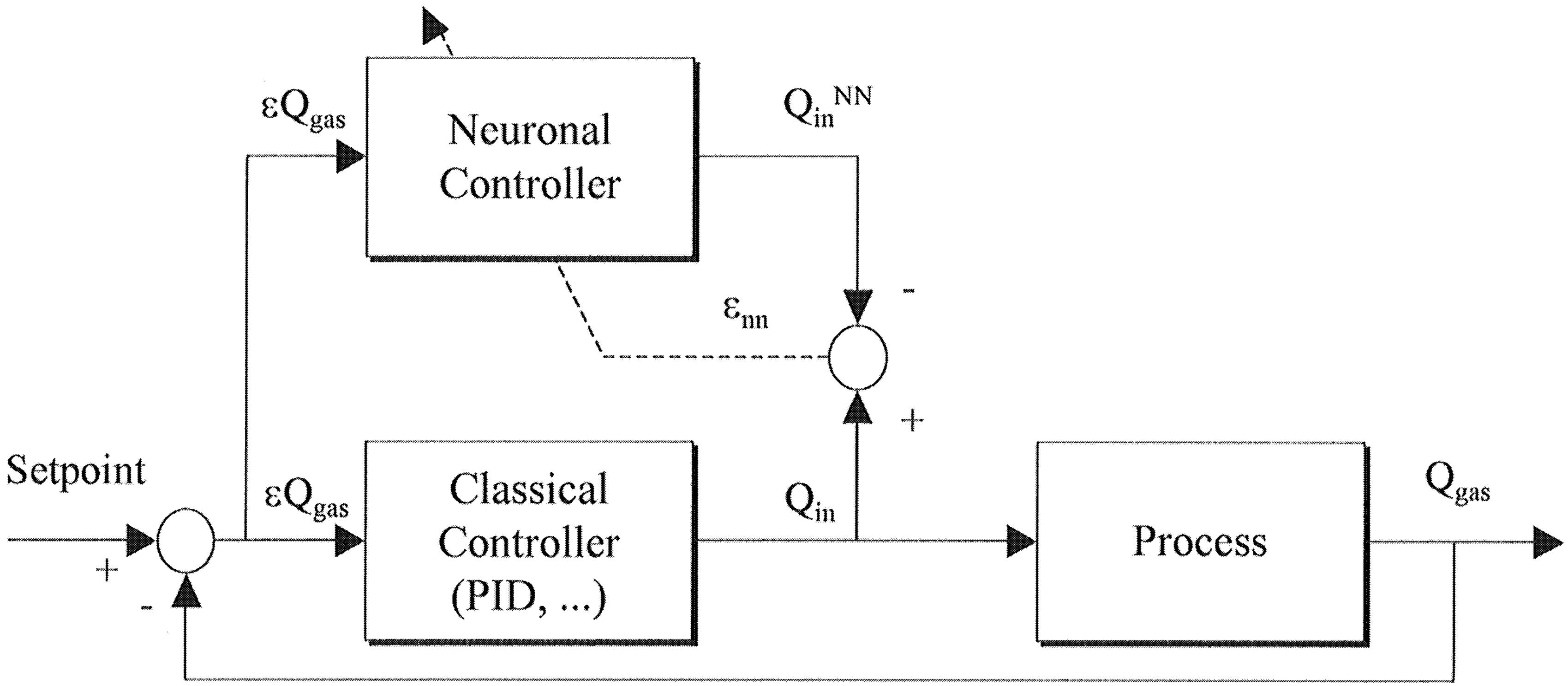




Direct Neuronal Controller

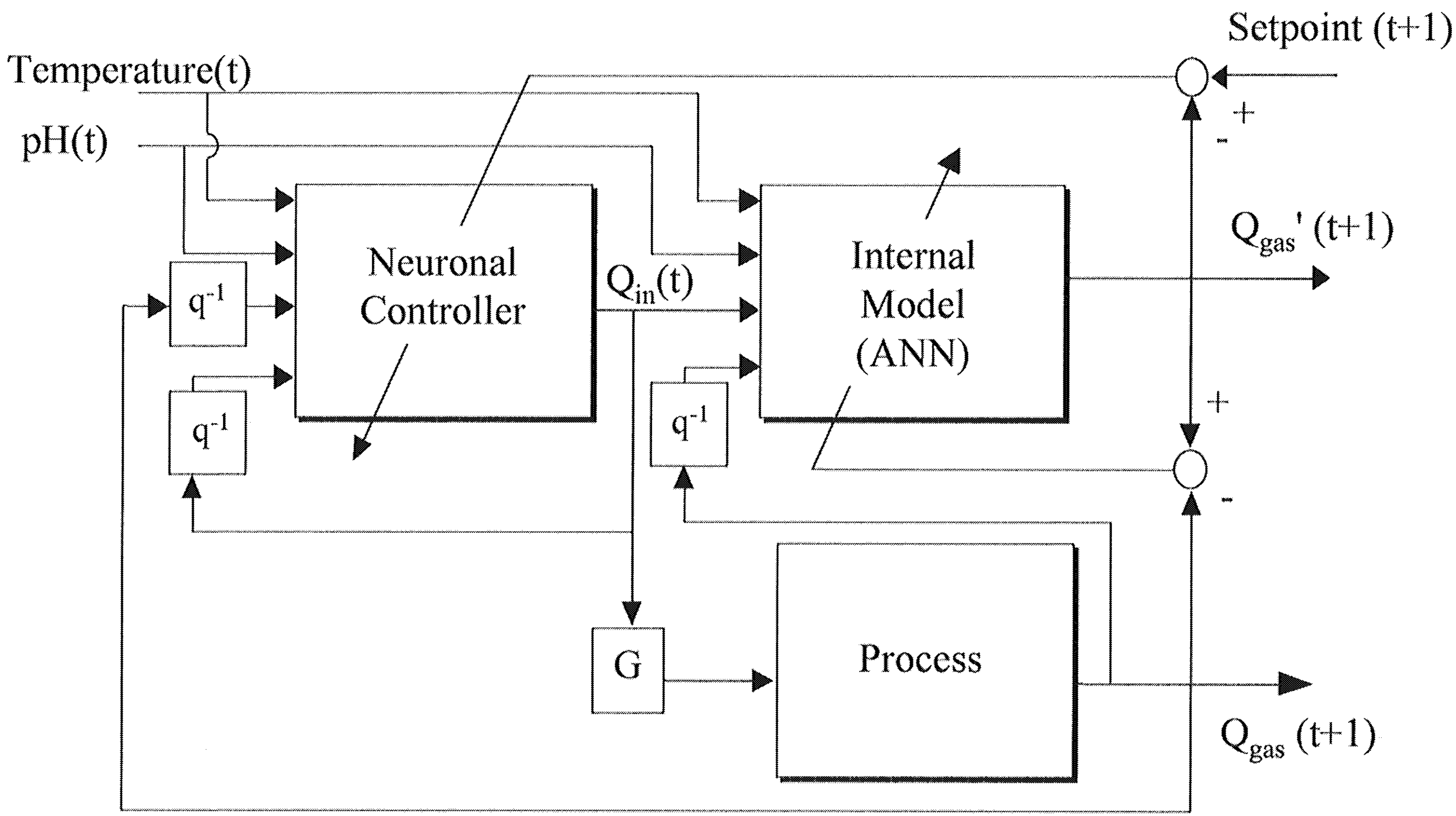
Objective : To replace a classical controller by a neural network based controller

2 phases : ✓ Learning from the classical controller
✓ Switching on of the neural controller



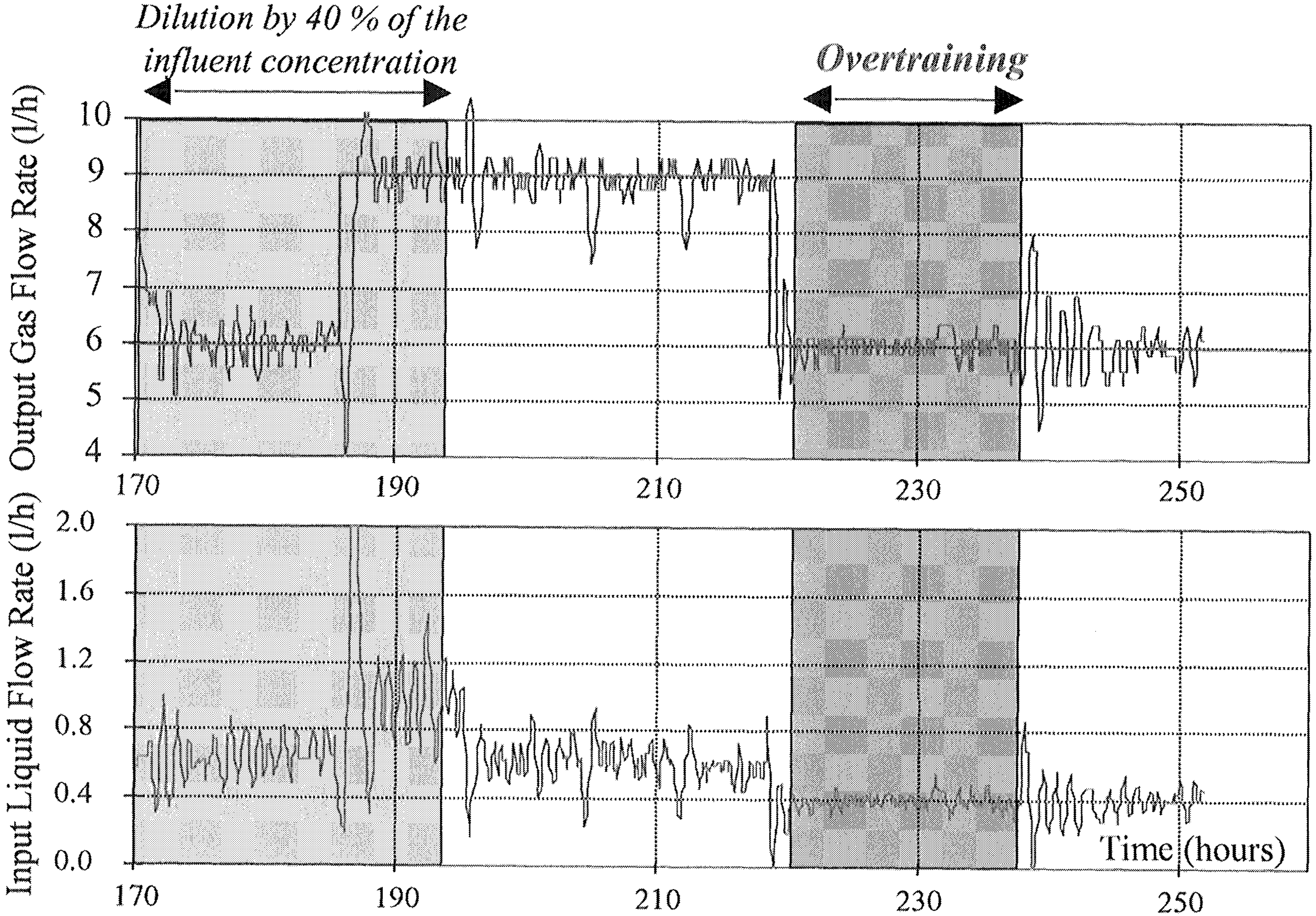
Internal Model Neuronal Controller

Objective : To build a neural network based controller from "scratch"



Adaptive Internal Model Neuronal Controller

Weights adaptation every 2 hours



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Contents

Hypothesis

We have a "reliable" model at our disposal ...

So we should use it !

Hypothesis

In case a *linear* model is available ...

Disturbance Accomodating Controller

✓ ***Identification of the model***

- ARMAX model

$$A(q)y(t) = B(q)u(t) + C(q)e(t)$$

- ARMAX to state space form

- Introduction of the dynamic of the disturbance considered (actuator bias = constant)

✓ ***Synthesis of an OVC Controller***

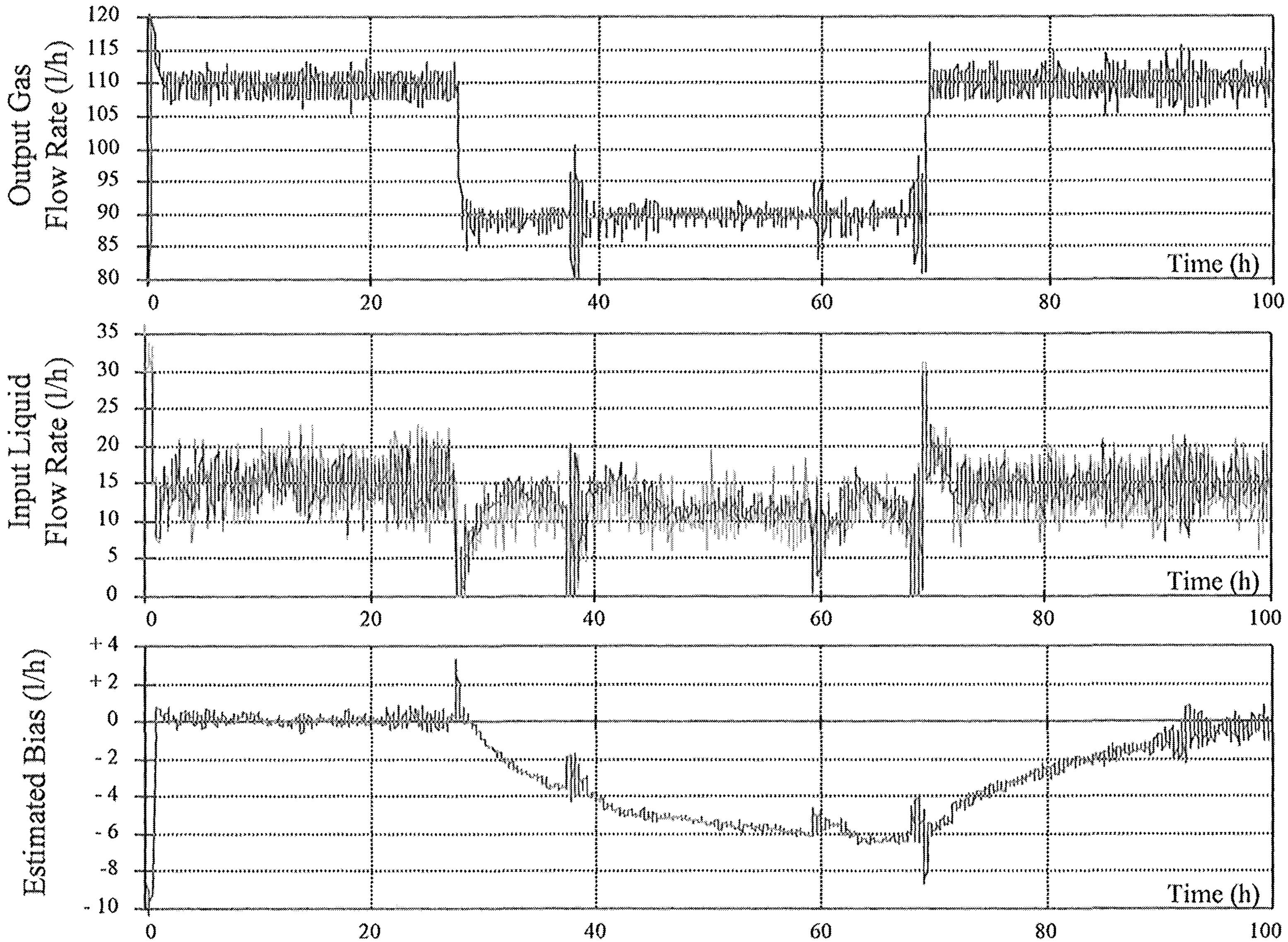
- Principle

$$\begin{cases} \min\limits_{F,\,G} \sum\limits_{k=0}^{\infty} u^T(k)Ru(k) \\ \text{under the constrainsts } \varepsilon_{\infty} y_i^2(k) \le \varphi_i \end{cases}$$

✓ ***Implementation on the Anaerobic Digestion Process***

Disturbance Accomodating Controller

Bias (- 1 l/h) on the Input Liquid Flow Rate between $29 < t < 69.1$ h



Hypothesis

In case a *non linear* model is available ...

The "AMOCO" Anaerobic Digestion Model
(EU FAIR Project CT 1198)

From Mass Balance

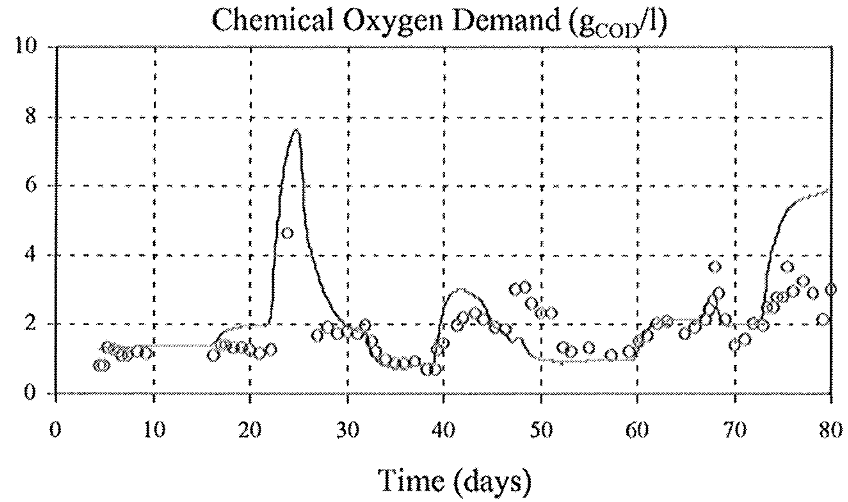
$$
\begin{cases}
\dot{X}_1 = (\mu_1 - \alpha D) X_1 \\
\dot{X}_2 = (\mu_2 - \alpha D) X_2 \\
\dot{Z} = D(Z^i - Z) \\
\dot{S}_1 = D(S_1^i - S_1) - k_1 \mu_1 X_1 \\
\dot{S}_2 = D(S_2^i - S_2) + k_2 \mu_1 X_1 - k_3 \mu_2 X_2 \\
\dot{C}_{TI} = D(C_{TI}^i - C_{TI}) + k_7 (k_8 P_{CO_2} + Z - C_{TI} - S_2) + k_4 \mu_1 X_1 + k_5 \mu_2 X_2
\end{cases}
$$

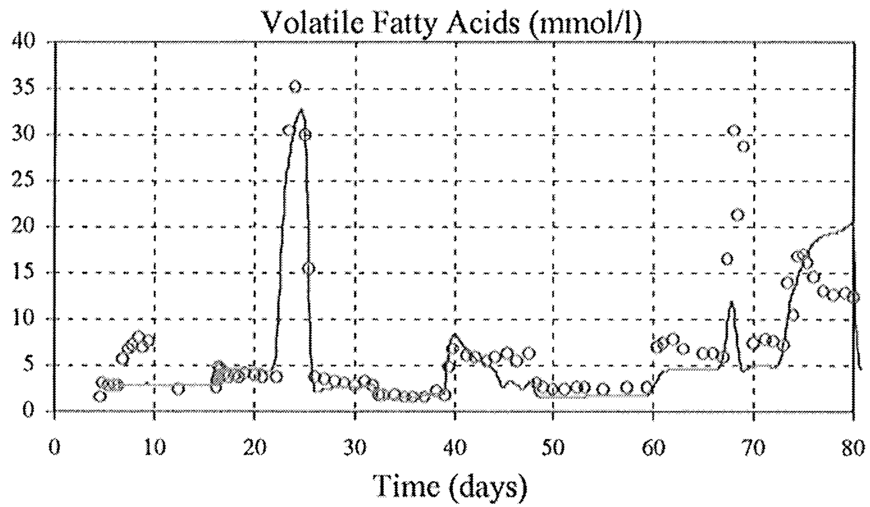
With $\mu_1 = \mu_{\max 1} \dfrac{S_1}{K_{S_1} + S_1}$ (*i.e.*, limitation by organic matter)

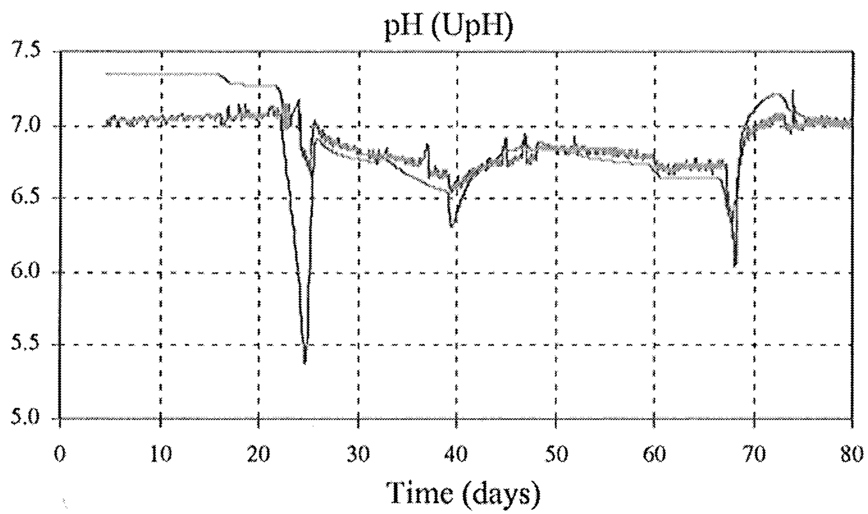
and $\mu_2 = \mu_{\max 2} \dfrac{S_2}{K_{S_2} + S_2 + \left(\dfrac{S_2}{K_{I_2}}\right)^2}$ (*i.e.*, limitation and inhibition by VFA)

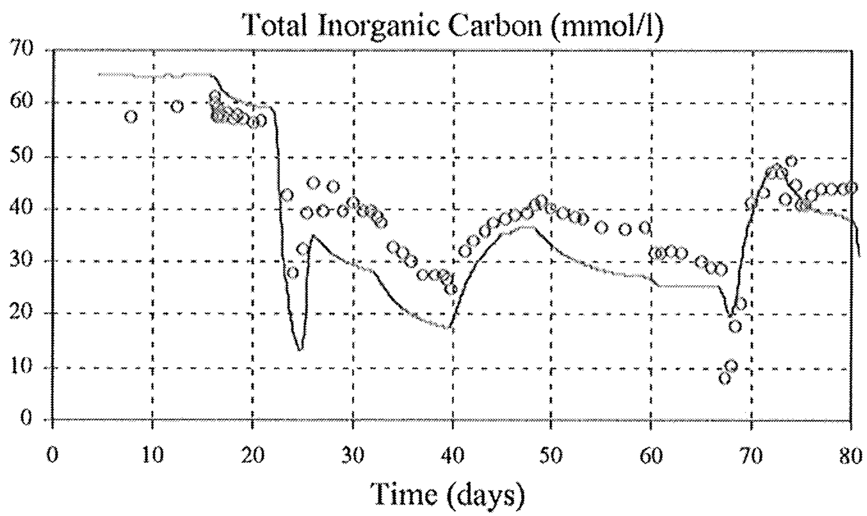
Dynamical Model of the Anaerobic Digestion

The "AMOCO" Model (EU FAIR Project CT 1198)









Dynamical Model of the Anaerobic Digestion

From the initial model developped in 1997, 6 distinct sets of parameters have been identified. Their range of variation is represented in the following table :

Name	Meaning	Min	Max	Unit
k_1	Yield coefficient for COD degradation	6.60	86.11	g COD/g X_1
k_2	Yield coefficient for fatty acid production	7.80	181.2	mmol VFA/g X_1
k_3	Yield coefficient for fatty acid consumption	268	1814	mmol VFA/g X_2
k_4	Yield coefficient for CO_2 production due to X_1	12.4	230	mmol CO_2/g X_1
k_5	Yield coefficient for CO_2 production due to X_2	273	1924	mmol CO_2/g X_2
k_6	Yield coefficient for CH_4 production	315	2696	mmol CH_4/g X
k_7	Liquid/gas transfer rate	19.8	500	day^{-1}
k_8	Henry's constant	16.0	26.7	mmol CO_2/l-atm
α	Proportion of dilution rate for bacteria	0.30	0.50	
μ_{max1}	Maximum acidogenic biomass growth rate	1.20	1.40	day^{-1}
μ_{max2}	Maximum methanogenic biomass growth rate	0.50	0.85	day^{-1}
K_{S1}	Saturation parameter associated with S_1	3.72	10.7	g COD/l
K_{S2}	Saturation parameter associated with S_2	5.28	18.0	mmol VFA/l
K_{I2}	Inhibition constant associated with S_2	16.0	25.0	mmol VFA/l

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Problem Statement

How to regulate a measured state in presence of :

- *perturbations in the unknown process inputs*
- *uncertainties in the process kinetics*
- *and using partial information on the non-measured state variables (provided by an Interval Observer)*

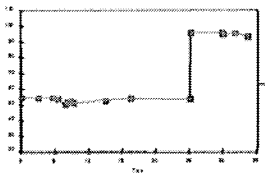
Software sensors in Biotechnology

In WWTPs, the time-varying inputs of the process are unknown !

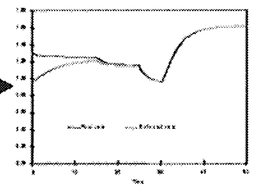
The system is not observable and classical approaches cannot be applied

One solution : interval observers

Known inputs

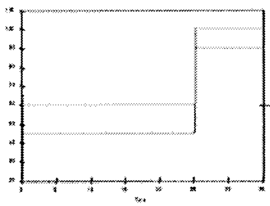


Classical observers
(eg. exponential observers)

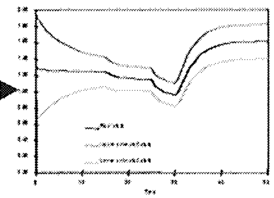


Estimated state

Known boundary input region



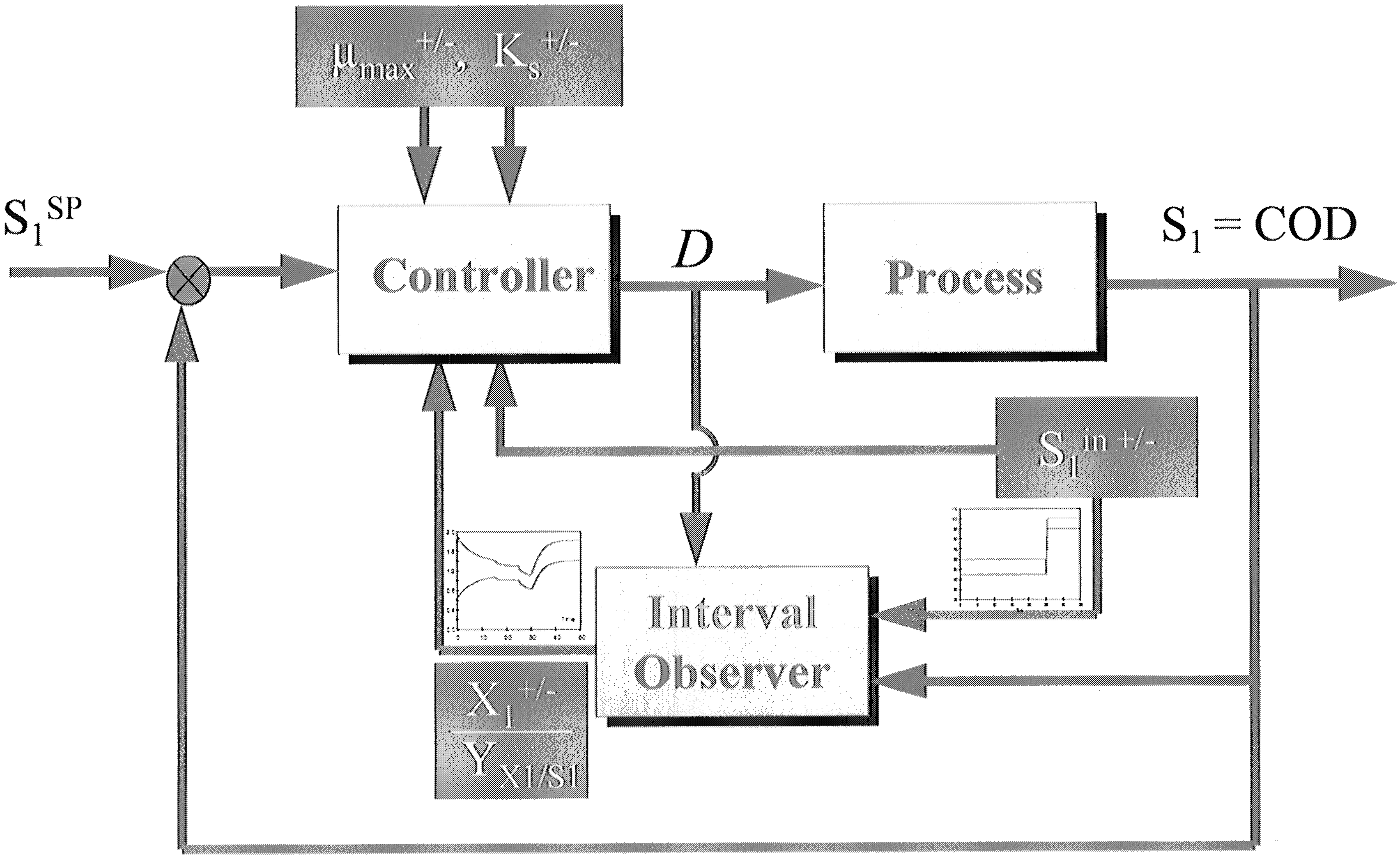
Interval observer
(the system's cooperativity property is required)



Guaranteed state interval

If the observer is cooperative, the estimated state are guaranteed to live within the estimated bounds

Controller Design



Controller Design

The regulated variable $S_1(t) = COD(t)$ having the dynamics :

$$\frac{dS_1}{dt} = -\frac{\mu_1(t)X_1(t)}{Y_{x_1/s_1}} - D(t)\left(S_1(t) - S_1^{in}(t)\right)$$

the following regulation law :

$$D(t) \equiv D^*(t) = \frac{\left(\dfrac{X_1}{Y_{x_1/s_1}}\right)^* \dfrac{\mu^*_{max_1} S_1(t)}{K^*_{s_1} + S_1(t)} - \lambda\left(S_1(t) - S_1^{SP}\right)}{S_1^{in*}(t) - S_1(t)}$$

with

$$\left(\mu^*_{max_1}, \left(\frac{X_1}{Y_{x_1/s_1}}\right)^*, K^*_{s_1}, S_1^{in*}(t)\right) = \begin{cases} \left(\mu^-_{max_1}, \left(\dfrac{X_1}{Y_{x_1/s_1}}\right)^-, K^+_{s_1}, S_1^{in+}(t)\right) & \text{if } S_1(t) > S_1^{SP} \\ \left(\mu^+_{max_1}, \left(\dfrac{X_1}{Y_{x_1/s_1}}\right)^+, K^-_{s_1}, S_1^{in-}(t)\right) & \text{if } S_1(t) < S_1^{SP} \end{cases}$$

exponentially stabilizes $S_1(t)$ around S_1^{SP} for any $\lambda > 0$ sufficiently small.

Controller Design

Moreover, the following λ and δ:

$$\lambda \leq \frac{\left(\dfrac{X_1}{Y_{x_1/s_1}}\right)^{-}_{t=0} \dfrac{\mu_{max_1}^{-} S_1^{SP}}{K_{s_1}^{+} + S_1^{SP}} - \delta}{\left(S_1^{in+}\right)_{t=0} - S_1^{SP}} \qquad \delta < \left(\frac{X_1}{Y_{x_1/s_1}}\right)^{-}_{t=0} \frac{\mu_{max_1}^{-} S_1^{SP}}{K_{s_1}^{-} + S_1^{SP}}$$

ensure that $D(t) > \delta > 0 \;\; \forall t$

Practical stability :

$$D_{\varepsilon}^{*}(t) = \begin{cases} D^{*1}(t) & \text{if } S_1(t) > S_1^{SP} + \varepsilon \\ D^{*1}(t)\dfrac{\left(S_1(t) - S_1^{SP} + \varepsilon\right)}{2\varepsilon} + D^{*2}(t)\dfrac{\left(S_1^{SP} + \varepsilon - S_1(t)\right)}{2\varepsilon} & \text{if } \left|S_1(t) - S_1^{SP}\right| \leq \varepsilon \\ D^{*2}(t) & \text{if } S_1(t) < S_1^{SP} - \varepsilon \end{cases}$$

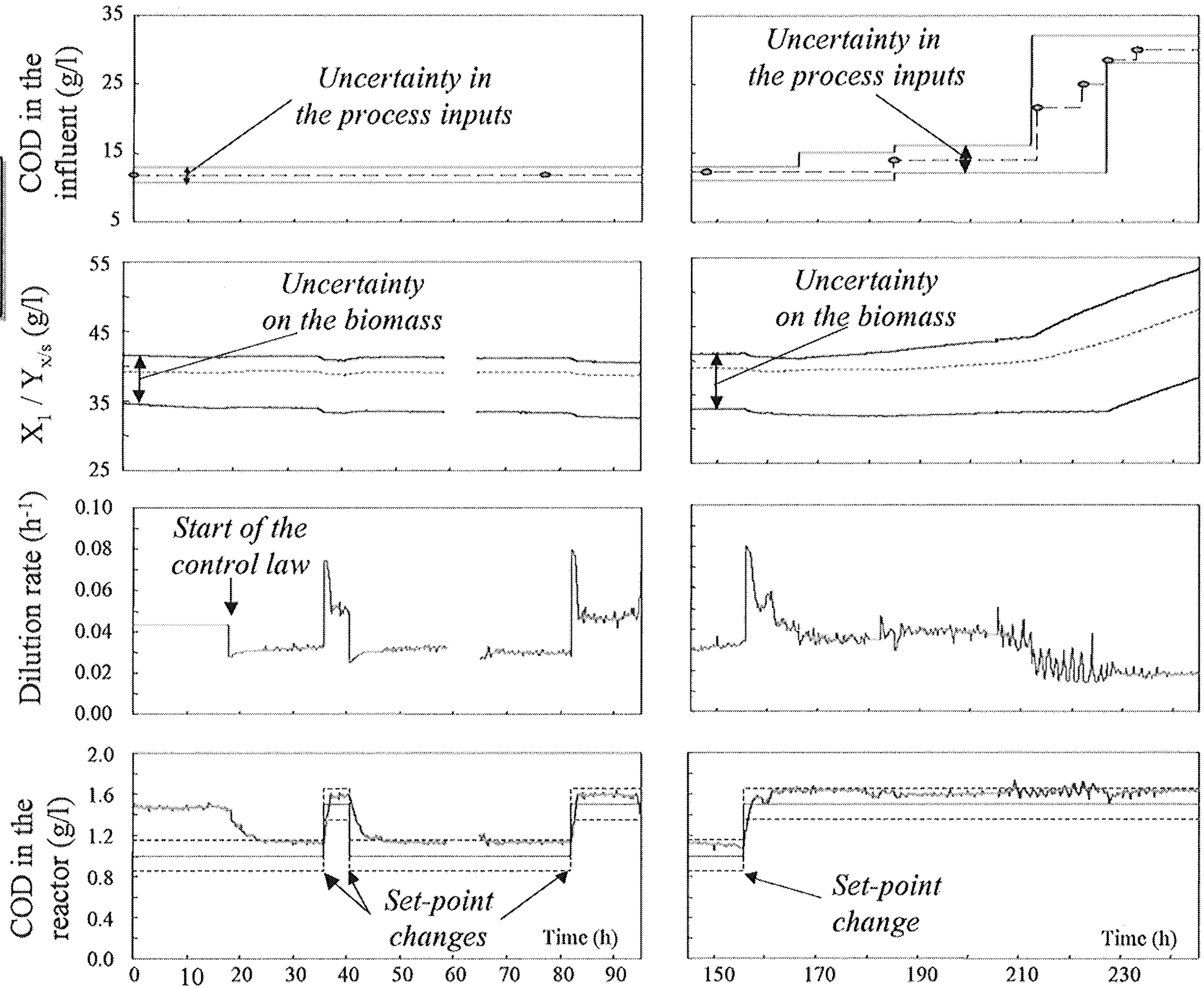
The regulated variable is driven into a pipe

Experimental Results

$$0.054 \leq \mu_{max1} \leq 0.058$$

$$3.6 \leq K_{s1} \leq 3.8$$

Uncertainty on the kinetics



Conclusions on Interval Based Control

- A robust set-valued SISO regulation law has been proposed for a biological wastewater treatment process whose behavior is described by a highly nonlinear dynamic model.
- This regulation law presented an excellent performance keeping the regulated variable to its setpoint even under a highly uncertain environment.
- This regulation law allows us to consider strong disturbances (i.e., unknown inputs) for which the system might be not observable together with uncertainties on the kinetics and on the biomass activity.
- Logical extensions of this approach (i.e., to the SIMO and MIMO cases) are now under study based upon the same philosophy.

Conclusions (1)

It is very difficult to compare control approaches with only one criteria since *there is NO one best solution !* It is mainly a question of the nature of the perturbations that are to be accounted for and of the efforts (in terms of model, control energy, money, ...) that are needed to solve the control problem.

However, from our experience in "real life" processes, we would like to point out that :

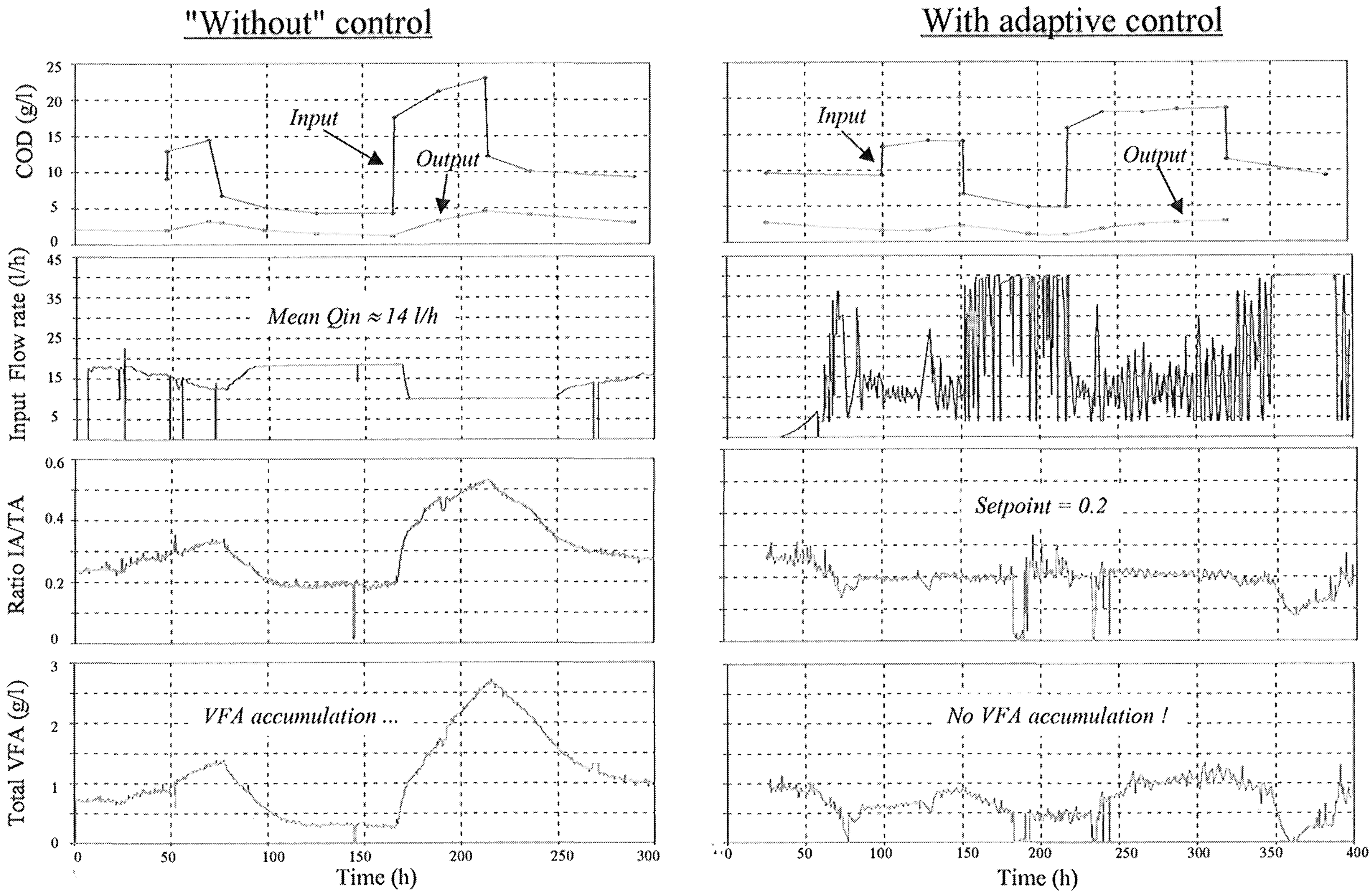
- If the **PID Controller** is satisfactory, it is the best solution,
- The **Fuzzy Logic** allows one to obtain very good results without specific efforts for the model,
- The **Artificial Neural Networks** are promising tools but it is important to have an efficient training,
- The **Disturbance Accommodating Controller** is particularly attractive since it makes the link between control and diagnosis,
- The **Non Linear Interval Based Controller** is very well adapted to WWTPs since it uses minimal information and since it is very robust.

Note : It is important to keep in mind that the sensors are all not yet available

Conclusions (2)

Feedback control is mandatory ...

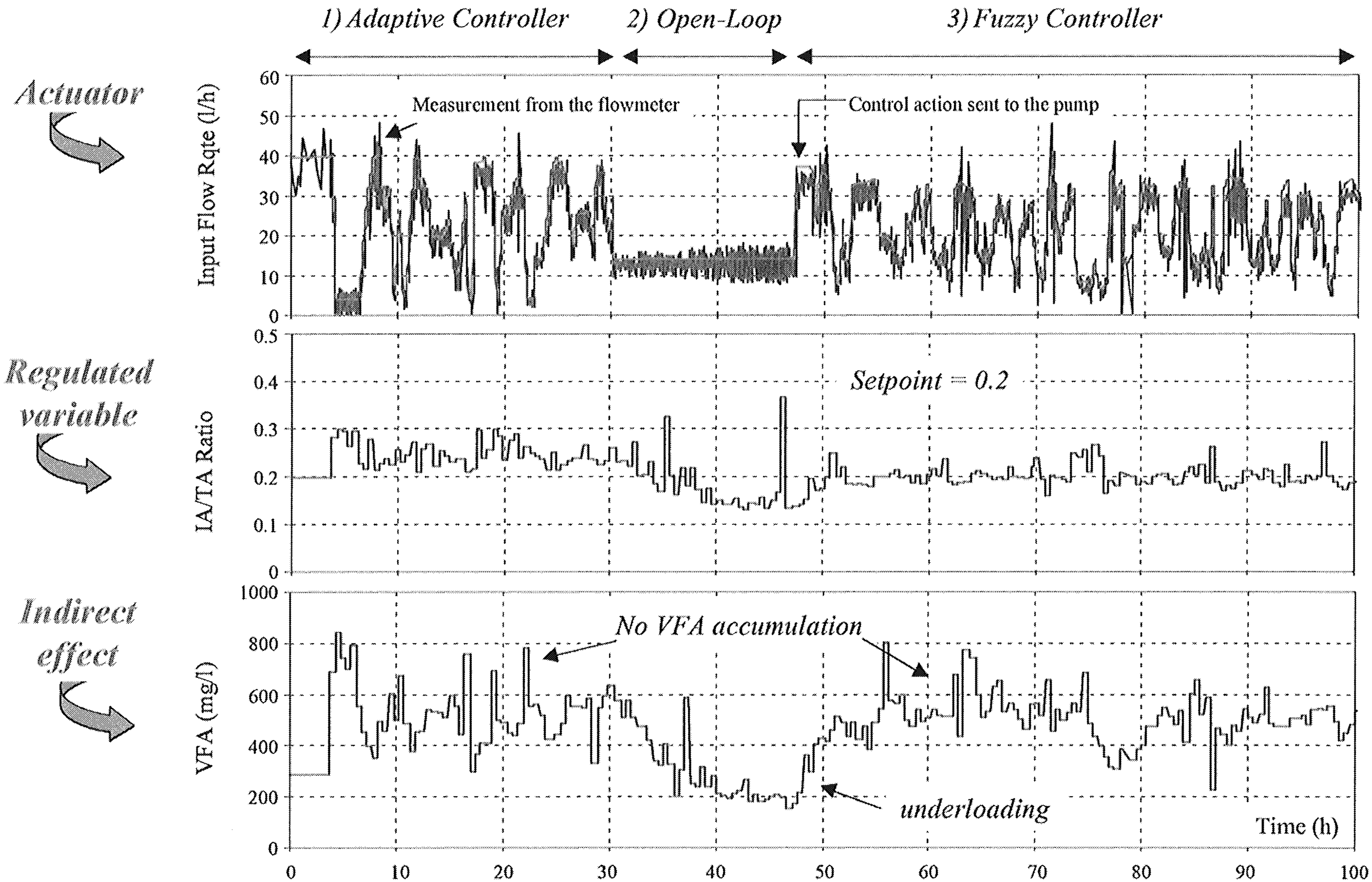
Comparison with/without control



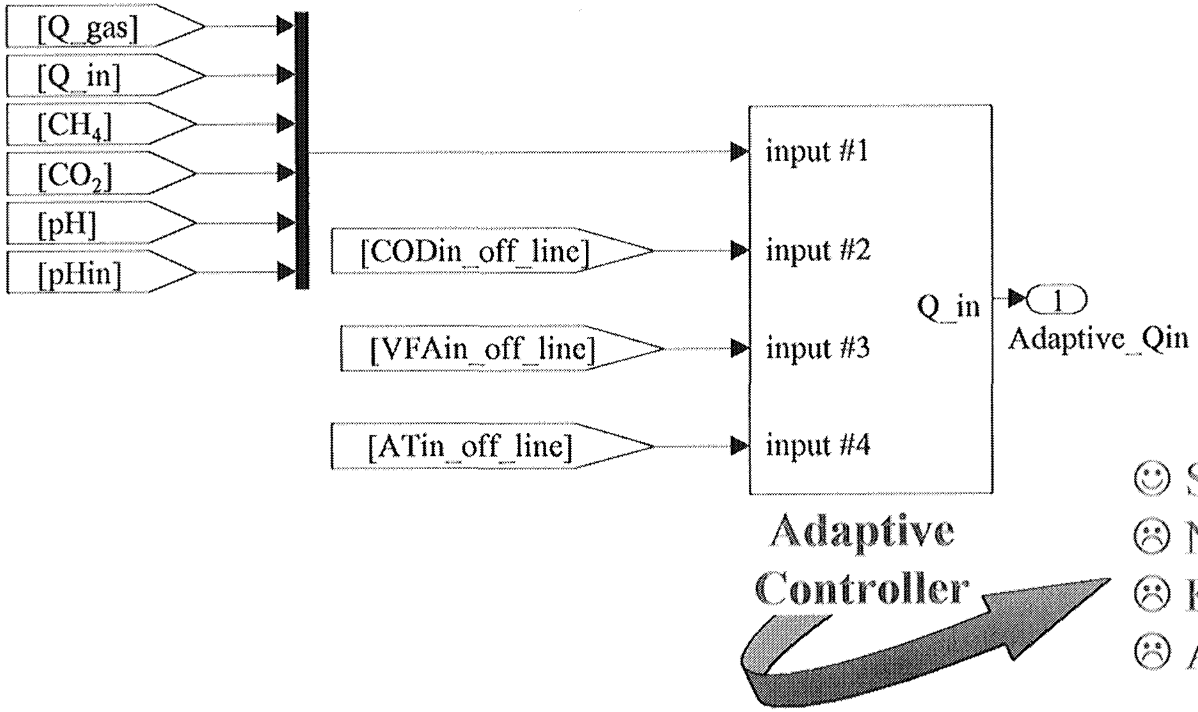
Conclusions (2)

But "Keep It Simple" !!!

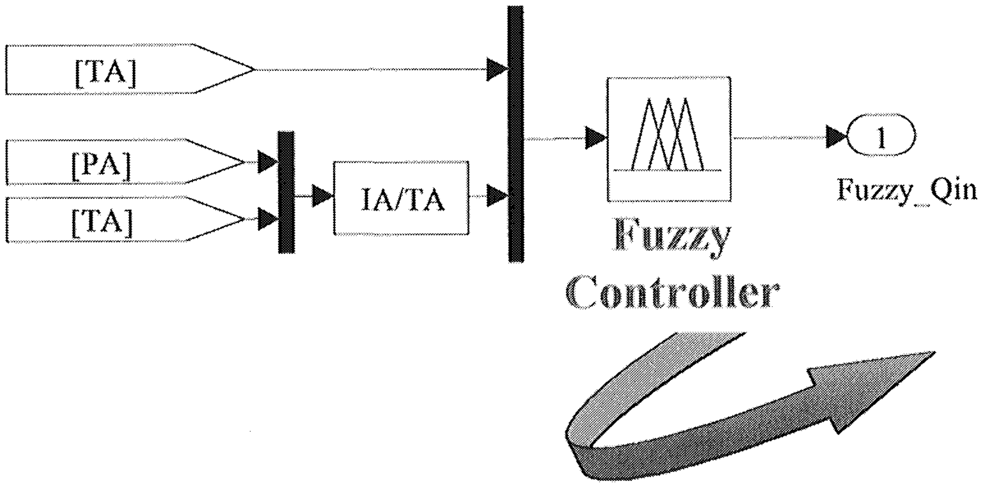
Advanced Control and/or Advanced Instrumentation ?



Advanced Control and/or Advanced Instrumentation ?



- ☺ Simple sensors
- ☹ Need of a model
- ☹ Knowledge of the input
- ☹ Advanced mathematical calculations



- ☹ Advanced sensor
- ☺ No need of a model
- ☺ No knowledge of the input
- ☺ Simple calculations

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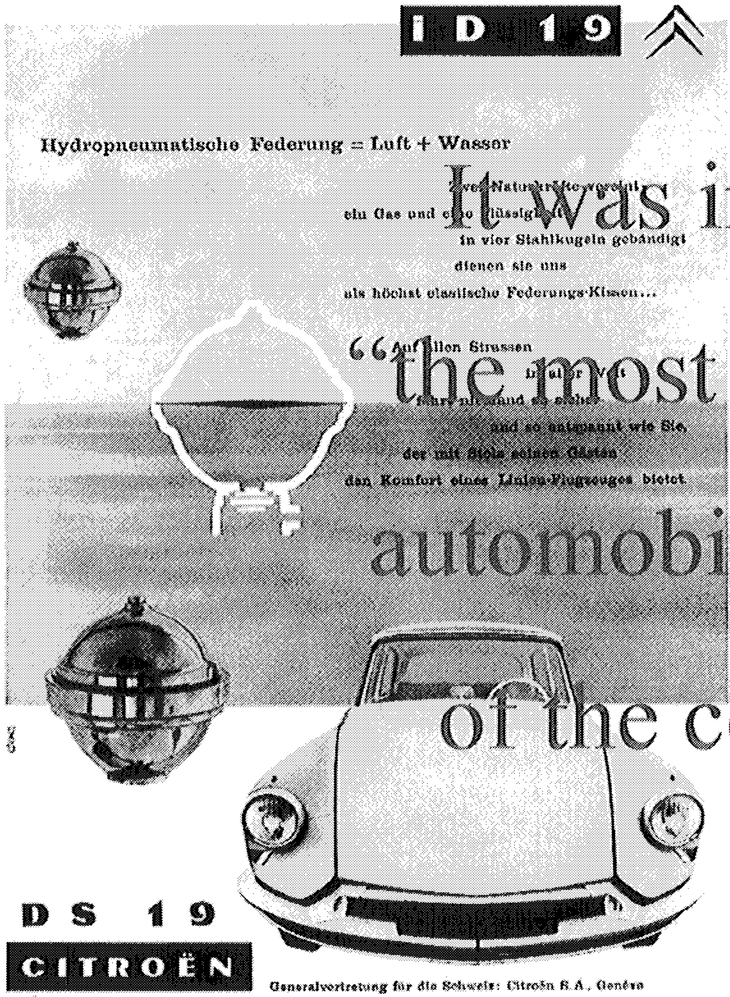
Conclusion

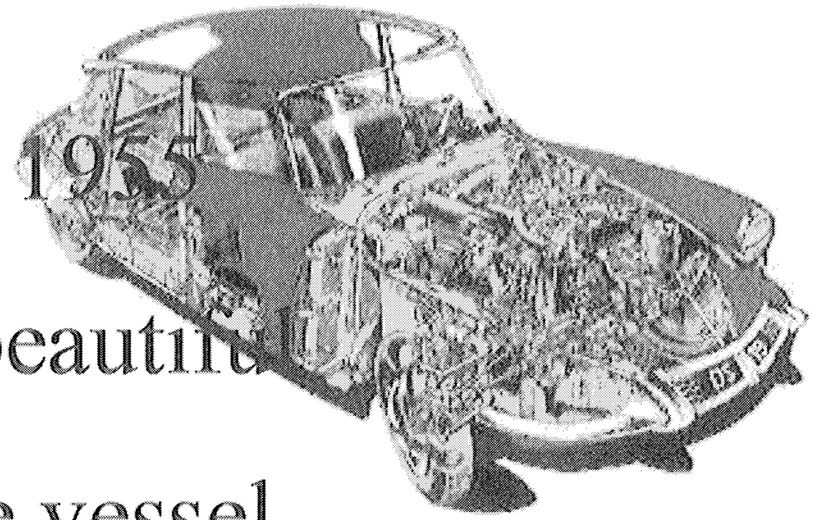


It was in 1955

“the most beautiful

automobile vessel

of the century”



Too many innovations !

Not reliable !

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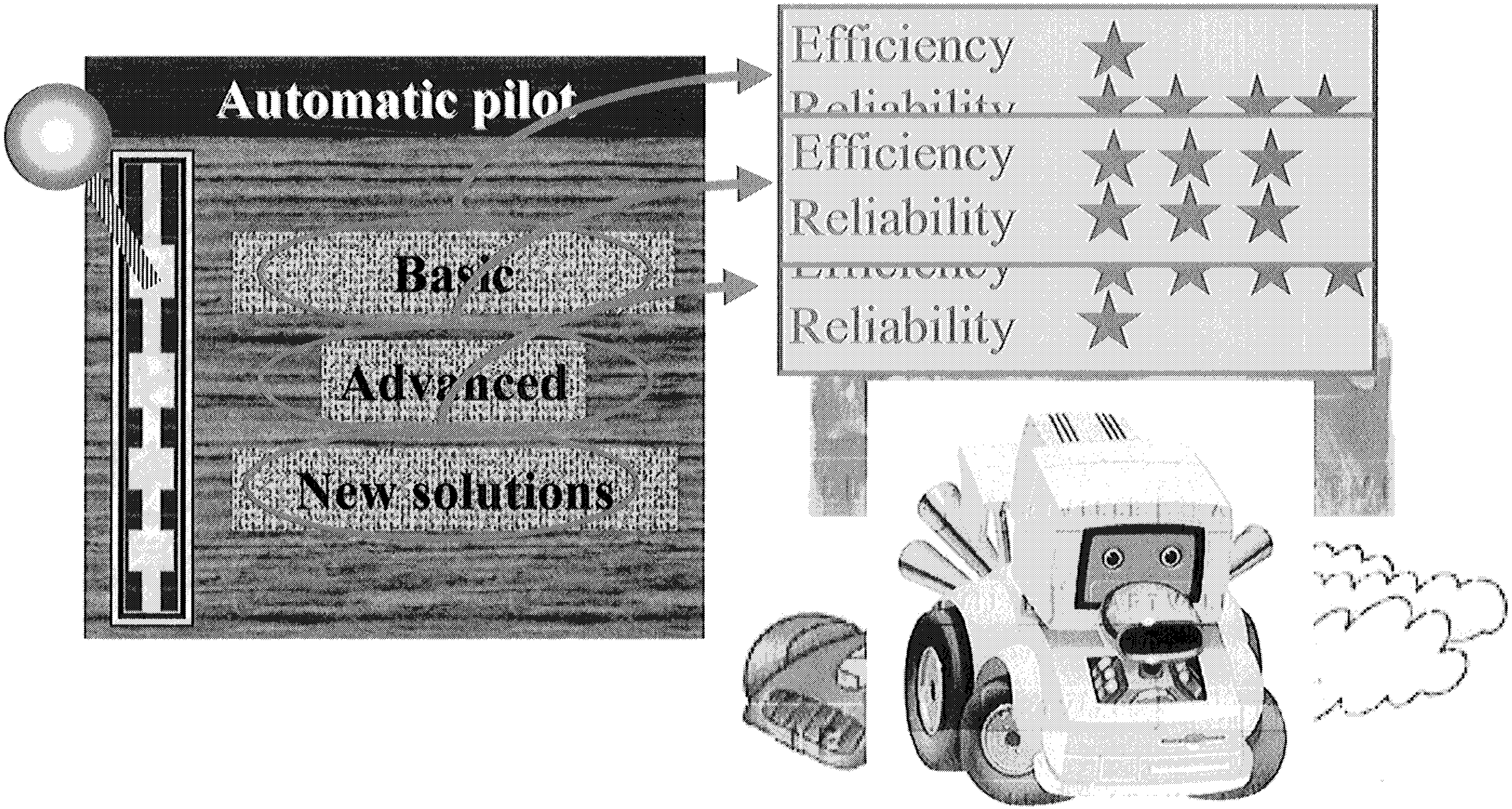
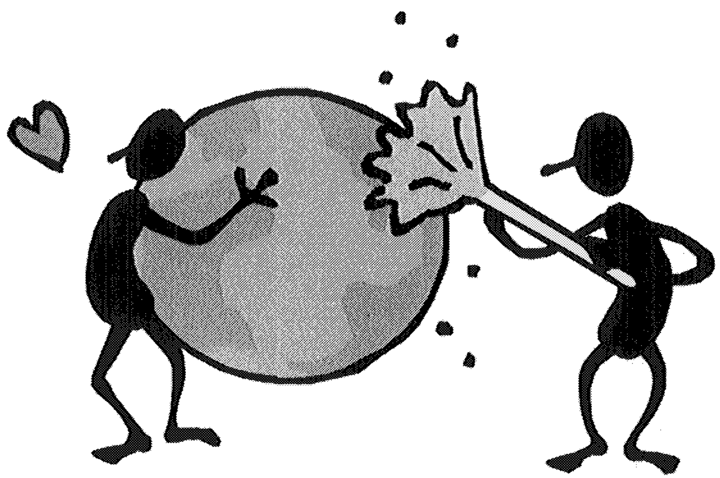
Conclusion



Thank you very much for your attention !



I will be very happy to answer your questions