Neuro-Fuzzy Control for Anaerobic Wastewater Treatment

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Abstract: The aim is to develop a simple adaptive neuro-fuzzy controller for control of the biogas production rate in the anaerobic digestion of organic waste in waters. The main contributions concern the design of a two-level Mamdani fuzzy system for control and tuning of the scaling coefficients and its further implementation for training of a neural network to yield an adaptive Sugeno fuzzy controller. The fuzzy systems are simulated in MATLAB and compared with an ordinary control system with a PI controller.

Key-Words: - Anaerobic biological wastewater treatment, Fuzzy controller, ANFIS, Simulation, MATLAB

1 Introduction

The anaerobic digestion of organic waste in waters has recently gained popularity over the aerobic for its efficiently treating of higher organic load, production of less sludge and energy recovery through the biogas produced. It is a multistage process that takes place in presence of microorganisms of several diverse groups and can be viewed upon as a three-phase conversion of organic waste into biogas (mainly methane and carbon dioxide) [1]-[4] – hydrolysis, acidogenesis and methanogenesis.

The models used are nonlinear both in terms of parameters and variables, making the classical control theory inapplicable. The parameters cannot be precisely determined [1]-[3] because of the specific features of living organisms (dependence on physiological state and environment, complex interactions between different microorganisms, slow growth, etc.) that often makes the system ill-defined or unstable, the experiments are practically irreproducible, very slow and expensive with few measurements, interfered with noise and accumulation of error from sequential processes.

The control of anaerobic digestion may attempt different goals: to maintain a constant concentration of organic matter at the output of the reactor, according to legislation; to optimise biogas production for further energy exploitation; to ensure a stable operation of systems treating high organic loading rates, exposed to input concentration and/or flow rate variations.

Since Zadeh introduced the theory of fuzzy sets in constituting an easy way to represent heuristic expert knowledge by linguistic labels, implemented in linguistic rules, and thus to deal simply with uncertainties, the fuzzy approach has been successfully applied to many complex, time-varying and nonlinear processes [5], [6], including anaerobic and mostly aerobic processes modelling, prediction and control [7]-[11]. Nowadays the tuning of the fuzzy controller is related with the advantages of the neural networks to learn and adapt [5], [12], [13].

The aim of this paper is to combine the fuzzy and neural network approach in the design of an adaptive neuro-fuzzy controller (NFC), trained on the base of a developed two-level fuzzy system for control of the biogas production rate and supervisory tuning. The NFC simplifies the control configuration, ensuring adaptability to all signal and plant parameter changes accounted for in the training of NFC. As the anaerobic wastewater treatment process is very slow, particular importance is attached to modelling and simulations in MATLAB using Fuzzy Logic Toolbox, ANFIS (Adaptive Neuro-Fuzzy Inference System) and Simulink [13], [14].

2 Problem Formulation

In recent years more and more complex mathematical models were introduced in order to better present the biodegradable processes [1]-[3]. Here the fifth order Barth-Hill nonlinear model is accepted to investigate and control the biogas production using fuzzy rules, which reflects the multistage character and the diverse groups of microorganisms by considering the process as a three-phase:

$$
\begin{cases}
\dfrac{dS_o}{dt} = -DS_o - \beta X_1 S_o + DY_p S_{oi} \\
\dfrac{dX_1}{dt} = (\mu_2 - k_1 - D)X_1 \\
\dfrac{dS_1}{dt} = -DS_1 + \beta X_1 S_1 - \dfrac{\mu_1 X_1}{Y_1} \\
\dfrac{dX_2}{dt} = (\mu_2 - k_2 - D)X_2 \\
\dfrac{dS_2}{dt} = -DS_2 + Y_b \mu_1 X_1 - \dfrac{\mu_2 X_2}{Y_2} \\
Q = Y_g \mu_2 X_2 \\
\mu_1 = \dfrac{\mu_{1\max} S_1}{k_{s1} + S_1}, \mu_2 = \dfrac{\mu_{2\max} S_2}{k_{s2} + S_2}
\end{cases}, \qquad (1)
$$

where the state space vector $X^T = [S_o X_1 S_1 X_2 S_2]$ is comprised of the concentrations of: soluble organics S_o, mg/l; acidogenic bacteria X_1, mg/l; substrate for acidogenic bacteria S_1, mg/l; methanogenic bacteria X_2, mg/l; substrate for methanogenic bacteria S_2, mg/l. The initial conditions for the state space vector are:

$$
X(0)^T = [S_o(0)\, X_1(0)\, S_1(0)\, X_2(0)\, S_2(0)\,] =
$$
$$
= [10\;\; 0.36\;\; 0.18\;\; 15.66\;\; 0.18\;\;]
$$

The measurable and controlled output is the specific biogas production rate $y = [Q]$, l/l.d, $Q(0)$=0.04. The inputs are the dilution rate D, d^{-1} ($D \in [0,0.3]$), which is the control variable, and the influent organic concentration S_{oi}, g/l, which is the disturbance ($S_{oi} \in [30,70]$). The vector of the parameters

$$
q^T = [\beta\, Y_p \mu_{1\max}\; k_{s1}\; k_1\; Y_1\; \mu_{2\max}\; k_{s2}\; k_2\; Y_1\; Y_b\; Y_g\,]
$$

consists of the coefficients β, d^{-1}, Y_p,mg/l, Y_b, mg/g and Y_g, l/mg, the maximal specific growth rate of acidogenic $\mu_{1\max}$, d^{-1} and methanogenic $\mu_{2\max}$, d^{-1} bacteria respectively, the yield coefficients Y_1, mg/mg and Y_2, mg/mg, the saturation k_{s1}, k_{s2}, mg/l and the decay k_1, k_2, d^{-1} coefficients for the corresponding bacteria. Its nominal value for Q=0.94 and $S_{oi} = 50$ is:

$$
q^{oT} = [1\;\; 2\;\; 0.4\;\; 1\;\; 0.02\;\; 0.006\;\; 0.4\;\; 1\;\; 0.02\;\; 1.1\;\; 40\;\; 1].
$$

The model is studied by simulation in [7], its nonlinear characteristic is confirmed for different step input D and the influence of S_{oi} obtained for $S_{oi} = 30,40,50,60$, g/l is shown in Fig.1.

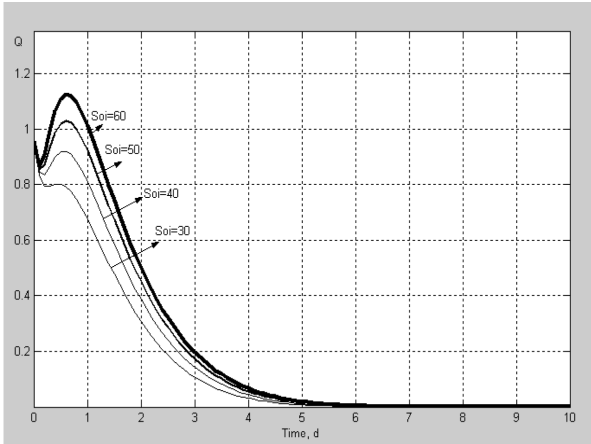

Fig.1. Plant output Q for different input S_{oi}

The problem is to design and tune a simple adaptive and robust fuzzy controller using the neuro-fuzzy approach to ensure desired performance of the overall system at plant uncertainties due to the change of the operation point along the nonlinear characteristic as a result of variations in the organic load S_{oi}, in the reference Q_r, in the plant parameters, related with the state of the microorganisms, etc.

The solution of the problem requires the accomplishment of the following tasks:

- development of a composite two-level Mamdani fuzzy controller, built of two units - one for the biogas production flow rate control and the other - for the tuning of its scaling coefficients for the inputs and the output;
- optimal design of an equivalent simple Sugeno fuzzy controller using a neural network that is trained on the base of the input-output data collected from the developed two-level fuzzy system to achieve adaptability and robustness;
- simulation investigations and comparison with an ordinary system with conventional PI controller.

3 Design of a Composite Mamdani Controller

The proposed composite two-level Mamdani controller is shown in Fig.2. The fuzzy controller 1 has two inputs – the error e - $e = Q - Q_r$ and its derivative de obtained at the output of a differentiator with transfer function $\dfrac{2s}{0.1s+1}$, both

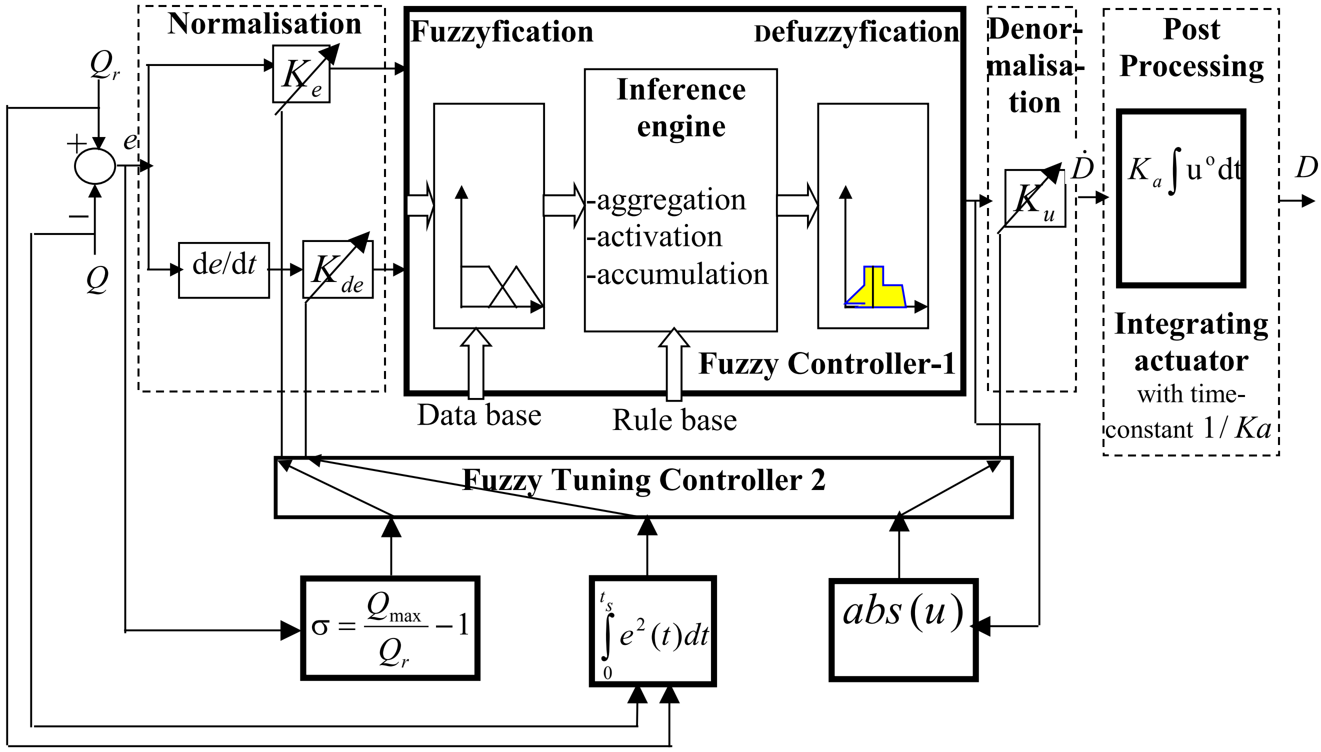

Fig.2. A Two-level Mamdani fuzzy controller

normalized in the range [-0.5,0.5] by K_e and K_{de}. The output of the controller u is in the range [-1,1] and after denormalisation with K_u it yields $\dot{D}$. The dilution rate D is obtained at the output of the integrating actuator that controls the opening of the valve for pure water. The integrating time-constant is 20, s ($1/T_a = K_a = 0.05,\%/s$).

The membership functions for e, de and u are shown in Fig.3. The linguistic variables take the following terms:

e = “great negative”(gn), “negative” (n), “zero” (z), “positive” (p), “great positive” (gp)
de = “ negative”, “ zero”, “ positive”
u = “great negative”, “negative”, “zero”, “positive”, “great positive”

The fuzzy rules are given in Table 1.

The Mamdani fuzzy controller 2 is introduced for tuning of K_e, K_{de} and K_u. It is based on the following rules:

If input is **z** then K is **bk**
If input is **m** then K is **mk**
If input is **b** then K is **zk**,

where the linguistic terms for the input are **z** – for zero, **m** – for medium and **b** – for big, while **zk**, **mk** and **bk** are the same linguistic values but related to

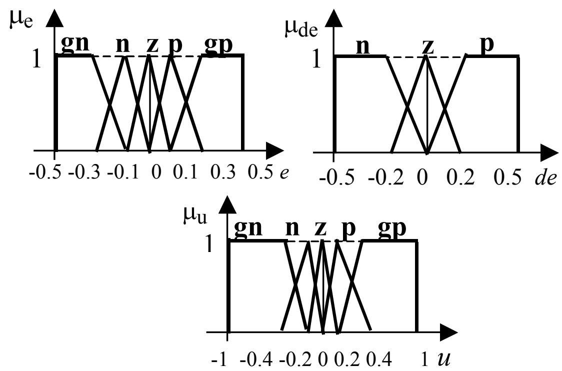

Fig.3. Membership functions for fuzzy controller 1

Table 1 Rules for level I controller

de	e				
	gn	n	z	p	gp
n	gn	gn	n	p	p
z	gn	n	z	p	gp
p	n	n	p	gp	gp

the scaling coefficients K_e, K_{de} and K_u. Thus this controller is composed of three fuzzy units – the first with input the integral squared error $I = \int_0^{t_s} e^2(t)dt$ and output K_{de}, the second – with input the overshoot in the system $\sigma = \frac{Q_{max}}{Q_r} - 1$ and output K_e and the third – with input $abs(u)$ and output K_u. The membership functions are shown in Fig.4.

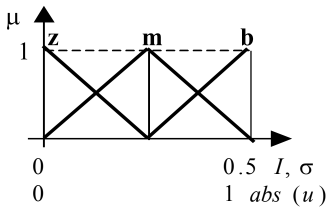

Fig.4. Membership functions for fuzzy controller 2

The two fuzzy controllers use the min operator for **and**, the max operator for **or**, the Mamdani implication and the centroid method for defuzzyfication. The design is carried out with the Fuzzy Logic Toolbox of MATLAB [14].

4 Design of an Adaptive Sugeno Fuzzy Controller by Training of a Neural Network

The fuzzy inference system for Sugeno fuzzy models is of network type similar in structure to a neural network. ANFIS [22] in MATLAB provides a technique for automatic generation of Sugeno-type models based on training of a neural network to fit a given input-output data.

Here ANFIS is used to develop, train and validate a neural network that corresponds to a Sugeno fuzzy controller. First the input and output space is partitioned according to the detected clusters in the corresponding input (output) data. Then the parameters of the membership functions are tuned during training. The input membership functions are gaussian with tuning parameters the standard deviation and the mean value. The output membership functions are first order functions of the inputs with tuning coefficients.

The training algorithm is based on a combination of the backpropagation of the error method for the tuning of the membership functions of the input and the least square error method for the tuning of the output membership functions.

The number of the output membership functions is equal to the number of the rules:

1. If e is A_1 and de is B_1, then $f_1=p_1e+q_1de+r_1$
2. If e is A_2 and de is B_2, then $f_2=p_2e+q_2de+r_2$, etc.,

where A_i, B_i , i=1,2,… are the corresponding fuzzy sets for the terms.

The defuzzyfication method used is the weighted average $\dot{D} = \frac{\sum_i w_i f_i}{\sum_i w_i}$, where w_i is the strength with which the i-th rule is fired.

Thus ANFIS automatically takes the expert decision on the optimal number and location of the membership functions as well as on the generation of the fuzzy rules. For the training of the neural network and after that for the validation of the model two different sets of training and checking input-output data are used to produce fuzzy models that adapt to variable signals. The training data should include all possible experimental data for e, de and u [20]-[22] and is collected from the simulated two-level Mamdani fuzzy control system at different disturbances and plant uncertainties.

The structure and parameters of the neural network after training are shown in Fig.5. In Fig.6 is given the Sugeno fuzzy controller, which is very simple compared to the two-level Mamdani fuzzy controller from Fig.2. By FLC is denoted the fuzzy logic controller that carries out fuzzyfication inference and defuzzyfication. There is no need to tune parameters. Besides, the number of the membership functions and hence the number of the rules is considerably reduced. The subjective decisions on construction of the membership functions and the fuzzy rules are substituted by optimization procedures.

5 Simulation Investigations

The closed loop systems with the designed Mamdani two-level and Sugeno fuzzy controllers are simulated in Simulink. For comparison an ordinary system is designed and simulated – the parameters of the PI conventional controller, tuned in order to ensure stability index ξ=0.7 for the worst possible plant parameters, are $K_p = 0.019, T_i = 1.723$.

The simulation experiments are the following.

1. At moment t=0s the reference for $Q - Q_r$ changes from 1.174 to 0.94. The organic load, which is the main disturbance, is S_{oi}=50. During this first step response K_e and K_{de} take minimal possible values. At the end of the transient response they are tuned

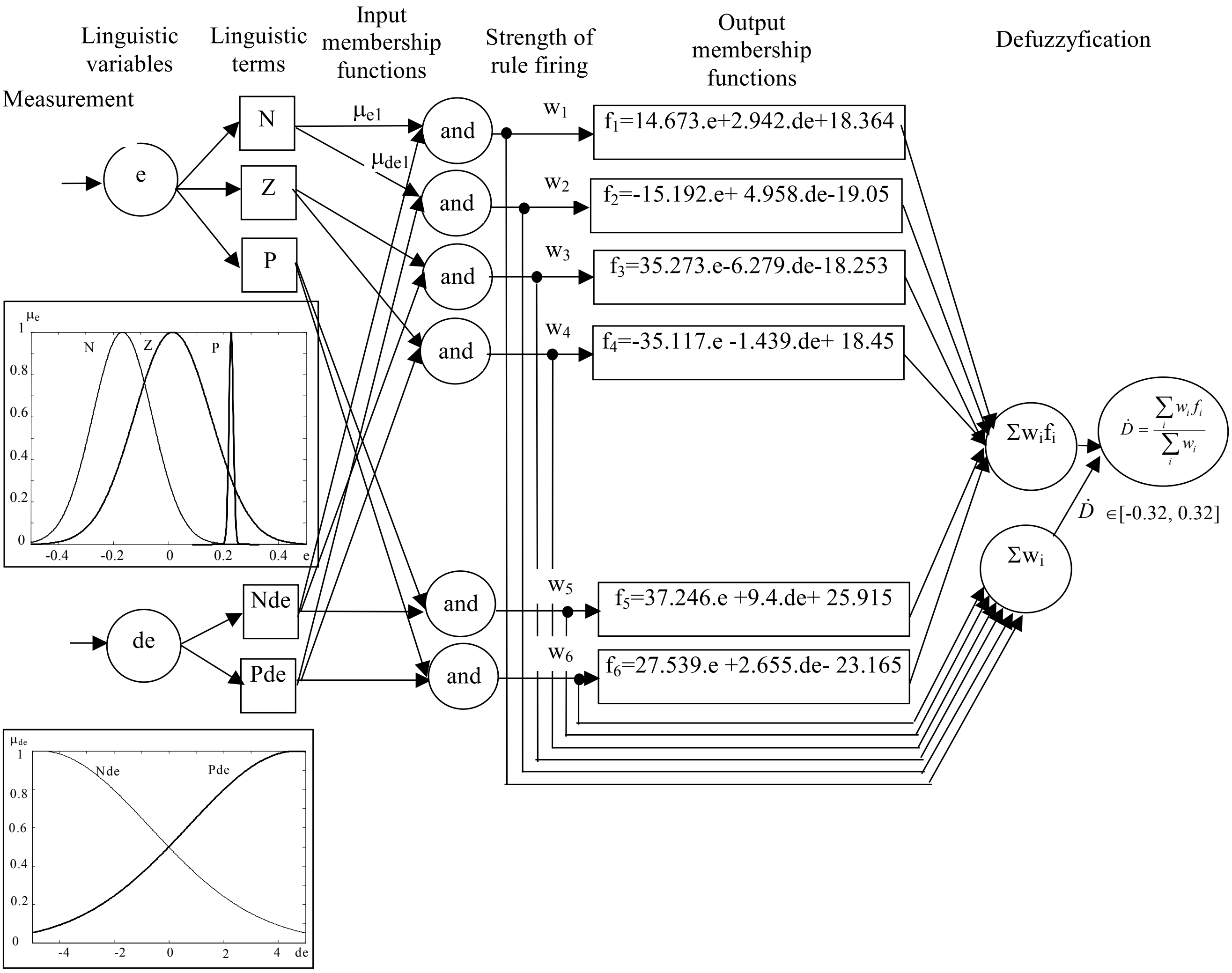

Fig.5. Neural network structure for Sugeno fuzzy controller

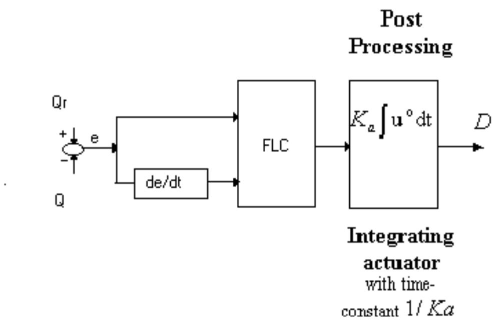

Fig.6. Sugeno fuzzy controller

and remain unchanged for the rest of the experiments. K_u is constantly being adjusted.

2. At t=30s the organic load S_{oi} rises from 50 to 70.

3. At t=65s Q_r changes from 1.174 to 0.94 at S_{oi}=70.

4. At t=90s the organic load S_{oi} changes from 70 to 50 at Q_r =0.94 and already tuned gains K_e and K_{de}

The step responses of biogas flow rate Q for the system with the Mamdani controller and for the ordinary system are shown in Fig.7, where can be observed as well the scaling coefficients, the integral of the squared error, the control D and the normalised input $Ke*e$. The step responses of Q of the system with the Sugeno controller and of the ordinary system as well as the control and the error are depicted in Fig.8.

6 Conclusion

The main contributions of this paper can be systemised in the following way.

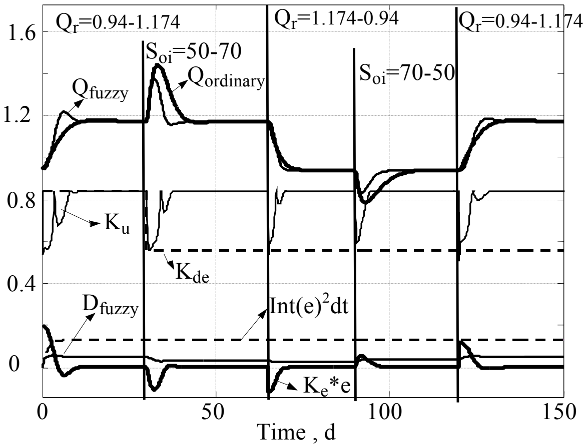

Fig.7. Step responses of system with Mamdani controller and of ordinary system

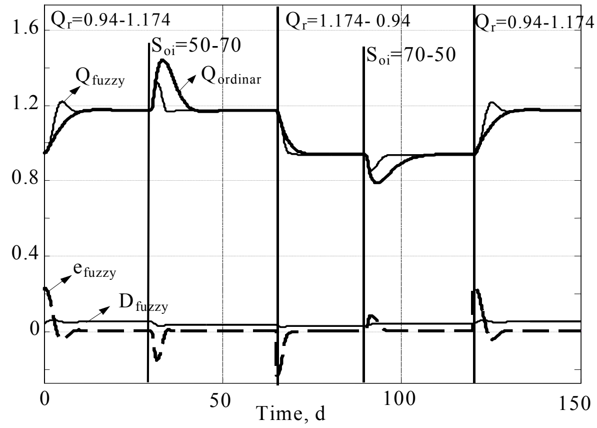

Fig.8. Step responses of system with Sugeno controller and of ordinary system

- A Mamdani fuzzy controller is proposed for the control of the biogas flow rate in the anaerobic wastewater treatment processes, whose scaling coefficients of the input and output variables are tuned by a second Mamdani fuzzy controller in order to achieve desired transient responses at disturbances and plant uncertainties.
- A Sugeno fuzzy controller is developed using neural network model in ANFIS environment and the data from the system with the Mamdani controllers for training, which results in simplified control configuration, design procedure and fuzzy controller.
- Simulink models are developed for simulation of the systems with the fuzzy controllers.
- The transient responses are compared with the responses of a properly designed ordinary system and the advantages of the fuzzy control estimated.

The designed fuzzy controllers ensure several times faster transient responses at different operating points, more smooth, economic and effective control. The precise control is of crucial importance because the two types of bacteria that perform the digestion are quite sensitive to the environment media.

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