Decentralized Adaptive Fuzzy-Neural Control of an Anaerobic Digestion Bioprocess Plant

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Abstract— *The paper proposed to use recurrent Fuzzy-Neural Multi-Model (FNMM) identifier for decentralized identification of a distributed parameter anaerobic wastewater treatment digestion bioprocess, carried out in a fixed bed and a recirculation tank. The distributed parameter analytical model of the digestion bioprocess is used as a plant data generator. It is reduced to a lumped system using the orthogonal collocation method, applied in three collocation points (plus the recirculation tank), which are used as centers of the membership functions of the fuzzyfied plant output variables with respect to the space variable. The local and global weight parameters and states of the proposed FNMM identifier are used to design hierarchical FNMM direct and indirect controllers. The comparative graphical simulation results of the digestion system direct and indirect control, obtained via learning, exhibited a good convergence, and precise reference tracking. The comparative numerical results, giving the final means squared error of control of each output variable showed that the indirect adaptive decentralized fuzzy-neural control outperformed the direct one, and the it outperformed the linearized proportional optimal control too.*

Keywords— Decentralized control, direct adaptive control, indirect adaptive control, distributed parameter digestion bioprocess system, recurrent neural network model, hierarchical fuzzy neural identification and control.

1 Introduction

The Distributed Parameter Systems (DPS) are distinguished by the fact that the states, controls, and outputs may depend on spatial position, [1]. Thus the natural form of the system description is by Partial Differential Equations (PDE), integral equations, or transcendental transfer functions, [1]. On the other side, in the last two decades, a new identification and control tools like Neural Networks (NN), used for biotechnological plants, [2], rose fame. Among several possible network architectures the ones most widely used are the Feedforward NN (FFNN) and the Recurrent NN (RNN), [3]. The main NN property namely the ability to approximate complex non-linear relationships without prior knowledge of the model structure makes them a very attractive alternative to the classical modeling and control techniques. This property has been proved for both types of NNs by the universal approximation theorem [3]. The preference given to NN identification with respect to the classical methods of process identification is clearly demonstrated in the solution of the "bias-variance dilemma" [3]. The FFNN and the RNN have been applied for DPS identification and control too. In [4], a RNN is used for system identification and process prediction of a DPS dynamics - an adsorption column for wastewater treatment of water contaminated with toxic chemicals. In [5, 6], a spectral-approximation-based intelligent modeling approach is proposed for the distributed thermal processing of the snap curing oven DPS that is used in semiconductor packaging industry. In [7], it is presented a new methodology for the identification of DPS, based on NN architectures, motivated by standard numerical discretization techniques used for the solution of PDE. In [8], an attempt is made to use the philosophy of the NN adaptive-critic design to the optimal control of distributed parameter systems. In [9] the concept of proper orthogonal decomposition is used for the model reduction of DPS to form a reduced order lumped parameter problem. In [10], measurement data of an industrial process are generated by solving the PDE numerically using the finite differences method. Both centralized and decentralized NN models are introduced and constructed based on this data. The models are implemented on FFNN using Backpropagation (BP) and Levenberg-Marquardt learning algorithms. In [11, 12, 13, 14], Baruch et al. defined direct and indirect Fuzzy Neural Multi-Model (FNMM) control system, based on Takagi-Sugeno (T-S) fuzzy rules, [15], containing in its consequent parts computational procedure of a Backpropagation Learning (BP) of a Recurrent Trainable NN (RTNN), [14]. In the present paper, the direct and indirect FNMM control system are modified and used for decentralized identification and control of a digestion anaerobic DPS of wastewater treatment, [16]. The anaerobic bioprocess plant model, used as an input/output plant data generator, is described by PDE/ODE, and simplified using the orthogonal collocation technique in three collocation points and a recirculation tank, [16], [17].

2 Analytical Model of the Anaerobic Digestion Bioprocess

The anaerobic digestion systems conformed by a fixed bed reactor and a recirculation tank is depicted on Fig. 1. It contained a fixed bed bioreactor and a recirculation tank. The anaerobic digestion process is modeled using PDE, [16]:

$$\frac{\partial X_1}{\partial t} = (\mu_1 - \varepsilon D) X_1, \quad \mu_1 = \mu_{1\max} \frac{S_1}{K'_{s_1} X_1 + S_1}, \tag{1}$$

$$\frac{\partial X_2}{\partial t} = (\mu_2 - \varepsilon D) X_2, \quad \mu_2 = \mu_{2s} \frac{S_2}{K'_{s_2} X_2 + S_2 + \frac{S_2^2}{K_{I_2}}}, \tag{2}$$

Where: X_1 is concentration of acidogenic bacteria; X_2-

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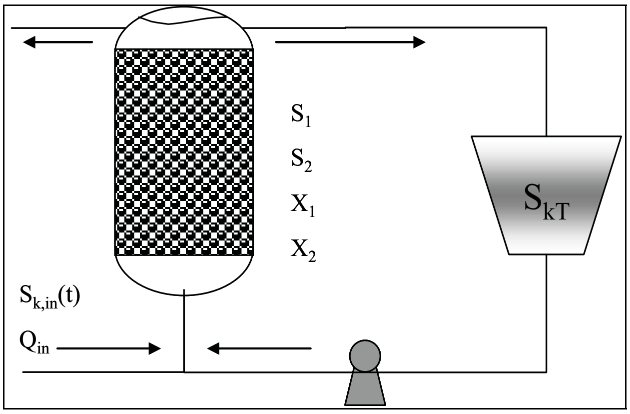

Figure 1: Block-Diagram of Anaerobic Digestion Bioreactor

concentration of methanogenic bacteria; S_1 - chemical oxygen demand; S_2 - volatile fatty acids; μ_1, μ_2- Monod functions, representing the acidogenesis and methanogenesis growth rate; D - dilution rate; ε - bacteria fraction in the liquid phase. The next equations of the bioprocess model are:

$$\frac{\partial S_1}{\partial t} = \frac{E_z}{H^2}\frac{\partial^2 S_1}{\partial z^2} - D\frac{\partial S_1}{\partial t} - k_1\mu_1 X_1 \,, \tag{3}$$

$$\frac{\partial S_2}{\partial t} = \frac{E_z}{H^2}\frac{\partial^2 S_2}{\partial z^2} - D\frac{\partial S_2}{\partial t} + k_2\mu_1 X_1 \,, \tag{4}$$

$$S_1(0,t) = \frac{S_{1,in}(t) + RS_{1T}}{R+1}, \quad S_2(0,t) = \frac{S_{2,in}(t) + RS_{2T}}{R+1}, \quad R = \frac{Q_T}{DV_{eff}} \tag{5}$$

$$\frac{\partial S_1}{\partial z}(1,t) = 0 \,, \quad \frac{\partial S_2}{\partial z}(1,t) = 0 \,. \tag{6}$$

$$\frac{dS_{1T}}{dt} = \frac{Q_T}{V_T}\left(S_1(1,t) - S_{1T}\right), \quad \frac{dS_{2T}}{dt} = \frac{Q_T}{V_T}\left(S_2(1,t) - S_{2T}\right). \tag{7}$$

Where: S_{1T} , S_{2T} are concentrations of the chemical oxygen demand and the volatile fatty acids in the recirculation tank, respectively; H - fixed bed length; Q_T - recycle flow rate; V_T - volume of the recirculation tank. The physical meaning of the other constants and initial values of the variables of the process model are given in [16]. For practical purpose, the full PDE process model, [16], could be reduced to an ODE system using an early lumping technique and the Orthogonal Collocation Method (OCM), [16], [17]. The precision of the OCM approximation of the PDE model depended on the number of measurement (collocation) points, but the approximation is always exact in that points. If the number of points is very high and the point positions are chosen inappropriately, the ODE model could loose identifiability. Furthermore the ODE plant model here is used as a plant data generator for neural identification and control of PDE system and the number of point not need to be too high. So to fulfill this objective we need a reduced order model having only three points, (0.25H, 0.5 H, 0.75H), but generating 14 measured variables. The reference set points generated for all that variables keep the form but differ in amplification due to its position. The plant ODE system model, obtained by OCM is taken from [16] and used as a plant process input/output data generator so to obtain identification and control simulation results.

3 Description of the Direct and Indirect Fuzzy-Neural Multi-Model Control System

3.1 Direct Adaptive FNMM Control System Design

The block-diagrams of the complete control system and its identification and control parts are schematically depicted in Fig. 2, Fig. 3 and Fig. 4.

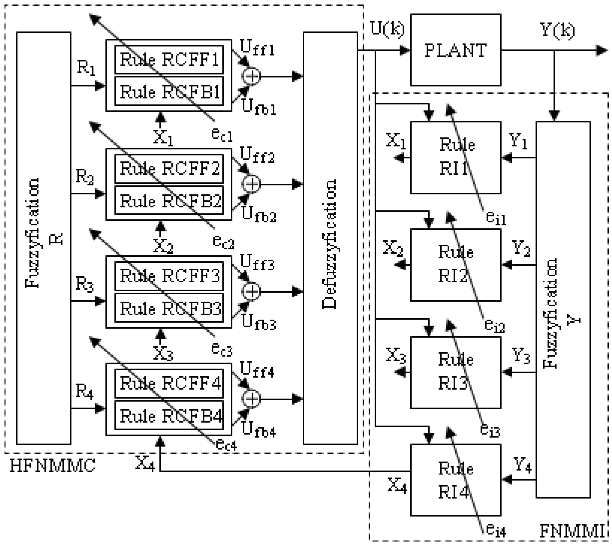

Figure .2: Block-Diagram of the FNMM Control System.

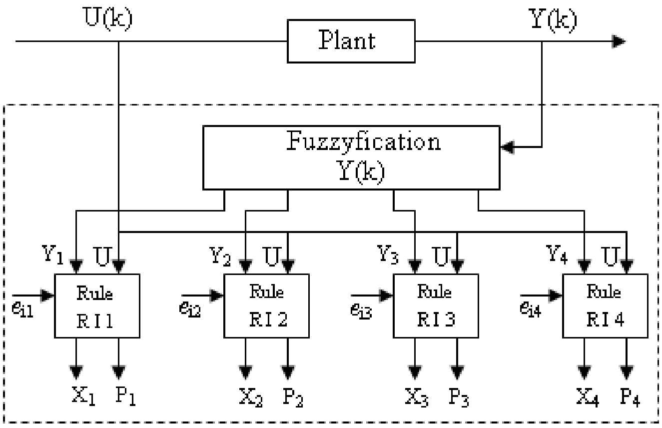

Figure 3: Detailed block-diagram of the FNMM identifier

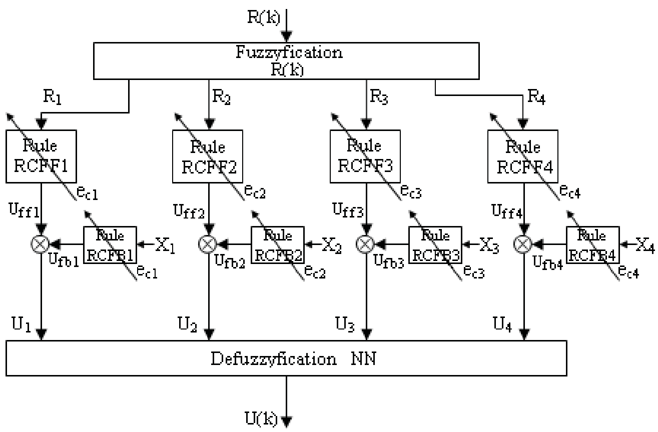

Figure 4: Detailed block-diagram of the HFNMM controller

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The structure of the entire control system, [12, 14], contained Fuzzyfier, Fuzzy Rule-Based Inference System (FRBIS), containing four identification, four feedback control and four feedforward control T-S rules (RI_i, $RCfb_i$, $RCff_i$) and a Defuzzyfier. The plant output variable and its correspondent reference variable depended on space and time, and they are fuzzyfied on space. The membership functions of the fixed-bed output variables are triangular/trapezoidal ones and that belonging to the output variables of the recirculation tank are singletons. The centers of the membership functions are the respective collocation points of the plant. The main objective of the Fuzzy-Neural Multi-Model Identifier (FNMMI), containing four rules, is to issue states for the direct adaptive Fuzzy-Neural Multi-Model Feedback Controller (FNMMFBC) when the FNMMI outputs follows the outputs of the plant in the four measurement (collocation) points with minimum Means Squared Error (MSE) of approximation. The direct fuzzy neural controller has also a direct adaptive Fuzzy-Neural Multi-Model Feedforward Controller (FNMMFFC). The objective of the direct adaptive FNMM controller, containing four Feedback (FB) and four Feedforward (FF) T-S control rules is to reduce the error of control. The upper hierarchical level of the FNMM control system is one layer perceptron which represented the defuzzyfier, [12, 14]. The hierarchical FNMM controller has two levels – Lower Level of Control (LLC), and Upper Level of Control (ULC). It is composed of three parts: 1) Fuzzyfication, where the normalized reference vector signal contained reference components of four measurement points; 2) Lower Level Inference Engine, which contains twelve T-S fuzzy rules (four rules for identification and eight rules for control- four in the feedback part and four in the feedforward part), operating in the corresponding measurement points; 3) Upper Hierarchical Level of neural defuzzification.

The detailed block-diagram of the FNMMI, given on Fig. 3, contained a space plant output fuzzyfier and four identification T-S fuzzy rules, labeled as RI_i, which consequent parts are RTNN learning procedures, [14]. The identification T-S fuzzy rules have the form:

$$RI_i\text{: } \textbf{\textit{If}}\ x(k)\ \textbf{\textit{is}}\ A_i\ \textbf{\textit{and}}\ u(k)\ \textbf{\textit{is}}\ B_i\ \textbf{\textit{then}}\quad Y_i = \Pi_i\,(L,M,N_i,Y_{di},U,X_i,A_i,B_i,C_i,E_i),\ i=1,2,..,4 \tag{8}$$

The detailed block-diagram of the FNMMC, given on Fig. 4, contained a spaced plant reference fuzzyfier and eight control T-S fuzzy rules (four FB and four FF), which consequent parts are also RTNN learning procedures, [12, 14], using the state information, issued by the corresponding identification rules. The consequent part of each feedforward control rule (the consequent learning procedure) has the M, L, N_i RTNN model dimensions, R_i, Y_{di}, E_{ci} inputs and U_{ffi}, outputs used to form the total control. The T-S fuzzy rule has the form:

$$RCFF_i\text{: } \textbf{\textit{If}}\ R(k)\ \textbf{\textit{is}}\ B_i\ \textbf{\textit{then}}\ Uff_i = \Pi_i\,(M, L, N_i, R_i, Y_{di}, X_i, J_i, B_i, C_i, E_{ci}),\ i=1,2,..,4 \tag{9}$$

The consequent part of each feedback control rule (the consequent learning procedure) has the M, L, N_i RTNN model dimensions, Y_{di}, X_i, E_{ci} inputs and U_{fbi}, outputs used to form the total control. The T-S fuzzy rule has the form:

$$RCFB_i\text{: } \textbf{\textit{If}}\ Y_{di}\ \textbf{\textit{is}}\ A_i\ \textbf{\textit{then}}\ Ufb_i = \Pi_i\,(M, L, N_i, Y_{di}, X_i, X_{ci}, J_i, B_i, C_i, E_{ci}),\ i=1,2,..,4 \tag{10}$$

The total control corresponding to each of the four measurement points is a sum of its corresponding feedforward and feedback parts:

$$U_i\,(k) = -U_{ffi}\,(k) + U_{fbi}\,(k) \tag{11}$$

The defuzzyfication learning procedure, which correspond to the single layer perceptron learning, performed a weighted sum of the control variables Ui, [15]. It is described by:

$$U = \Pi\ (M, L, N, Y_d, Uo, X, A, B, C, E) \tag{12}$$

3.1 Indirect Adaptive FNMM Control System Design

The block-diagram of this control system is schematically depicted in Fig.5. The structure of the entire control system, [14, 15], contained Fuzzyfier, Fuzzy Rule-Based Inference System (FRBIS), containing four identification and four control T-S rules (RI_i, RC_i), and a Defuzzyfier. The plant output variable and its correspondent reference variable depended on space and time, and they are fuzzyfied on space. The membership functions and the Identifier (FNMMI) are the same used in the direct controller. The objective of the indirect adaptive FNMM controller is equivalent to that of the direct controller. The hierarchical FNMM controller has two levels – Lower Level of Control (LLC), and Upper Level of Control (ULC). It is composed of three parts: 1) Fuzzyfication, where the normalized reference vector signal contained reference components of four measurement points; 2) Lower Level Inference Engine, which contains eight T-S fuzzy rules (four rules for identification and four rules for control), operating in the corresponding measurement points; 3) Upper Hierarchical Level of neural defuzzification. The detailed block-diagram of the FNMMC is given on Fig. 6. It contained a spaced plant reference fuzzyfier and four sliding mode control T-S fuzzy rules, which consequent parts are SMC procedures, [13, 14], using the state, and parameter information, issued by the corresponding identification rules. The control T-S fuzzy rules have the form:

$$RC_i\text{: } \textbf{\textit{If}}\ R(k)\ \textbf{\textit{is}}\ C_i\ \textbf{\textit{then}}\ U_i = \Pi_i\,(M, L, N_i, R_i, Y_{di}, X_i, A_i, B_i, C_i, E_{ci}),\ i=1, 2,\dots, 4 \tag{13}$$

The defuzzyfication of the control variable is a learning procedure, which correspond to the single layer perceptron learning. It is described by:

$$U = \Pi\ (M, L, N, Y_d, Uo, X, A, B, C, E) \tag{14}$$

The T-S rule and the defuzzification of the plant output of the fixed bed with respect to the space variable z ($\lambda i,z$ is the correspondent membership function), [14, 15], are given by:

$$RO_i\text{: } \textbf{\textit{If}}\ Y_{i,t}\ \textbf{\textit{is}}\ A_i\ \textbf{\textit{then}}\ Y_{i,t} = a_i^T Y_t + b_i,\ i=1,2,3 \tag{15}$$

$$Y_z=[\Sigma_i\,\gamma_{i,z}\,a_i^T]\ Y_t + \Sigma_i\,\gamma_{i,z}\,b_i\ ;\ \gamma_{i,z} = \lambda_{i,z} / (\Sigma_j\,\lambda_{j,z}) \tag{16}$$

The indirect adaptive neural control algorithm, which is the consequent part of the local fuzzy control rule RCi (13) is viewed as a Sliding Mode Control (SMC), [13, 14], using the

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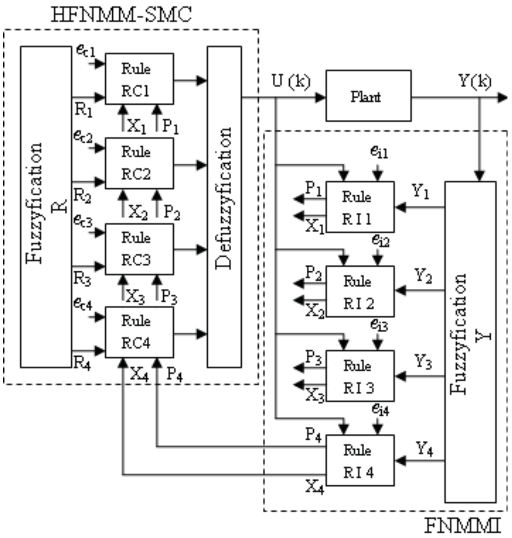

Figure 5: Block-diagram of the FNMM Control system.

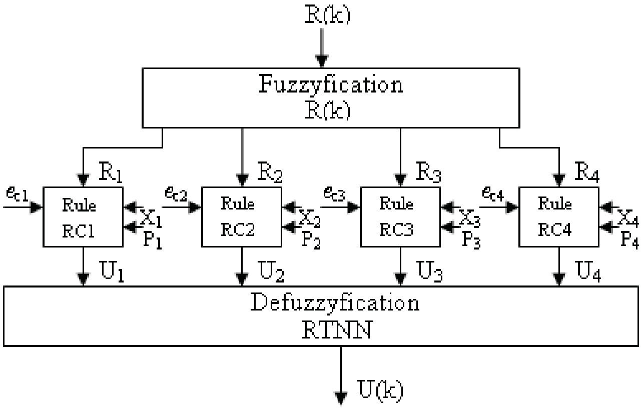

Figure 6: Detailed block-diagram of the HFNMM controller

parameters and states issued by the correspondent identification local fuzzy rule RIi (8). The equivalent control capable to lead the system to the sliding surface in the case when L>M is given by the equations:

$$U_{eq}(k) = (CB)^{+}\left[-CAX(k) + R(k+1) + \sum_{i=1}^{P} \gamma_i E(k-i+1)\right] + Of$$
$$(CB)^{+} = [(CB)^{T}(CB)]^{-1}(CB)^{T} \quad (17)$$

Here the added offset Of is a learnable M-dimensional constant vector which is learnt using a simple delta rule (see [3]), where the error of the plant input is obtained backpropagating the output error through the adjoint RTNN model (see [18, 14]). The SMC avoiding chattering is taken using a saturation function inside a bounded control level Uo, taking into account plant uncertainties. So the SMC takes the form:

$$U(k) = \begin{cases} U_{eq}(k), & if \ \left\|U_{eq}(k)\right\| < U_0 \\ -U_0 U_{eq}(k)/\left\|U_{eq}(k)\right\|, & if \ \left\|U_{eq}(k)\right\| \geq U_0 \end{cases} \quad (18)$$

The proposed SMC cope with the characteristics of the wide class of plant model reduction neural control with reference model, and represents an indirect adaptive neural control, given by [11, 13, 14].

3.1 Description of the RTNN and its Learning Algorithm

The RTNN topology, including thresholds in both layers, and its learning algorithm, which appeared in the consequent part of the identification fuzzy rule as a learning procedure, are described in vector-matrix form as:

$X(k+1) = AX(k) + BU(k);\ B = [B_1 ; B_0];\ U^T = [U_1 ; U_2]$ (19)
$Z_1(k) = G[X(k)]$ (20)
$V(k) = CZ(k);\ C = [C_1 ; C_0];\ Z^T = [Z_1 ; Z_2]$ (21)
$Y(k) = F[V(k)];\ A = \text{block-diag}(A_i),\ |A_i| < 1$ (22)
$W(k+1) = W(k) + \eta\, \Delta W(k) + \alpha\, \Delta W_{ij}(k-1)$ (23)
$E(k) = T(k)-Y(k);\ E_1(k) = F'[Y(k)]\, E(k)$ (24)
$\Delta C(k) = E_1(k)\, Z^T(k);\ F'[Y(k)] = [1-Y^2(k)]$ (25)
$E_3(k) = G'[Z(k)]\, E_2(k);\ E_2(k) = C^T(k)\, E_1(k)$ (26)
$\Delta B(k) = E_3(k)\, U^T(k);\ G'[Z(k)] = [1-Z^2(k)]$ (27)
$\Delta A(k) = E_3(k)\, X^T(k);\ Vec(\Delta A(k)) = E_3(k) \square X(k)$ (28)

Where: X, Y, U are vectors of state, output, and augmented input with dimensions N, L, (M+1), respectively, Z is an (L+1) –dimensional input of the feedforward output layer, where Z_1 and U_1 are the (Nx1) output and (Mx1) input of the hidden layer; the constant scalar threshold entries are $Z_2 = -1$, $U_2 = -1$, respectively; V is a (Lx1) pre-synaptic activity of the output layer; T is the (Lx1) plant output vector, considered as a RNN reference; A is (NxN) block-diagonal weight matrix; B and C are [Nx(M+1)] and [Lx(N+1)]-augmented weight matrices; B_0 and C_0 are (Nx1) and (Lx1) threshold weights of the hidden and output layers; F[.], G[.] are vector-valued tanh(.)-activation functions with corresponding dimensions; F'[.], G'[.] are the derivatives of these tanh(.) functions; W is a general weight, denoting each weight matrix (C, A, B) in the RTNN model, to be updated; ΔW (ΔC, ΔA, ΔB), is the weight correction of W; η, α are learning rate parameters; ΔC is an weight correction of the learned matrix C; ΔB, ΔA are weight corrections of the learned matrices B, A; the diagonal of the matrix A is denoted by Vec (.) where (28) represents its learning as an element-by-element vector product; E, E_1, E_2, E_3, are error vectors with appropriate dimensions. The stability of the RTNN model is assured by the activation functions [-1, 1] bounds and by the local stability weight bound condition, given by (22). The learning procedure having forward and backward steps (19)-(28), could be denoted by Y(k) = Π (L, M, N, Y_d, U, X, A, B, C, E). The defuzzyfication learning procedure, corresponding to the single layer perceptron, denoted by (14) is a simple delta rule (see [3]), where the error of the plant controlled input is obtained backpropagating the output error through the adjoint RTNN model, [18].

4 Simulation Results

The decentralized FNMM identifier used a set of four T-S fuzzy rules containing in its consequent part RTNN learning procedures (see Fig. 3). The topology of the first three RTNNs is (2-6-4) (2 inputs, 6 neurons in the hidden layer, 4 outputs) and the last one has topology (2-6-2) corresponding to the fixed bed plant behavior in each collocation point and the recirculation tank. The RTNNs identified the following fixed bed variables: X_1 (acidogenic bacteria), X_2

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(methanogenic bacteria), S_1 (chemical oxygen demand) and S_2 (volatile fatty acids), in the following collocation points, z=0.25H, z=0.5H, z=0.75H, and the following variables in the recirculation tank: S_{1T} (chemical oxygen demand) and S_{2T} (volatile fatty acids). The graphical simulation results of RTNNs learning are obtained on-line during 100 days with a step of 0.1 day (To=0.1 sec.; Nt=1000 iterations). The learning rate parameters of RTNN have small values which are different for the different measurement point variables. The Fig. 7, Fig.8, Fig. 9, Fig. 10 showed similar three dimensional and two dimensional graphical simulation results of the direct and indirect decentralized FNMM control of X_1, X_2, where the outputs of the plant are compared with the reference signals at the collocation points. The reference signals for all variables are proportional train of pulses with uniform duration and random amplitude. The Means Squared Error (MSE%) of identification, direct, indirect and optimal control for each output signal and each measurement point are given on Table 1, 2, 3, 4, respectively. The comparison showed a slight preference of the indirect FNMM-SMC control over the direct FNMM control, due to the better adaptation of the first low.

Table 1: MSE% of the decentralized FNMM approximation of the bioprocess output variables

Coll. point	X_1	X_2	S_1 / S_{1T}	S_2 / S_{2T}
z=0.25H	1.2524e-8	6.5791e-8	2.9615e-5	4.3302e-4
z=0.5H	5.0180e-9	2.9067e-8	1.1840e-8	2.7851e-6
z=0.75H	1.0487e-9	2.7977e-9	9.3562e-5	2.8941e-4
Recir Tank	-	-	8.6967e-7	2.0205e-6

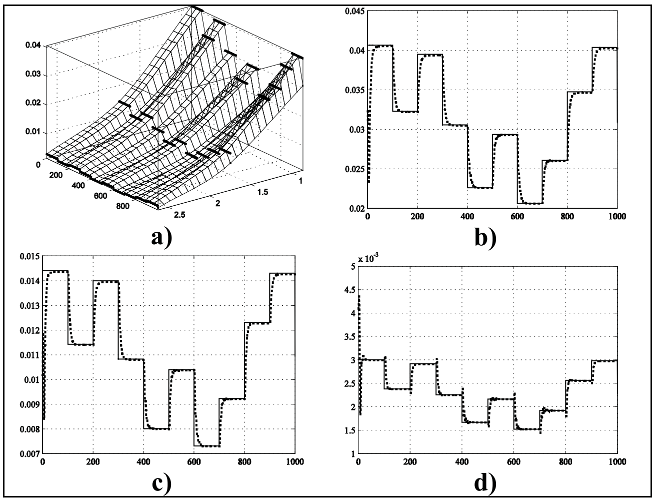

Figure 7: Results of the direct decentralized FNMM control of X_1 (acidogenic bacteria in the fixed bed) (dotted line-plant output, continuous-reference); a) 3d view of X_1 ; b) Ref vs X_1 in z=0.25H; c) Ref vs X_1 in z=0.5H; d) Ref vs X_1 in z=0.75H.

Table 2: MSE% of the direct decentralized FNMM control of the bioprocess output variables

Coll. point	X_1	X_2	S_1 / S_{1T}	S_2 / S_{2T}
z=0.25H	1.2524e-8	6.5791e-8	2.9615e-5	4.3302e-4
z=0.5H	5.0180e-9	2.9067e-8	1.1840e-8	2.7851e-6
z=0.75H	1.0487e-9	2.7977e-9	9.3562e-5	2.8941e-4
Recir Tank	-	-	8.6967e-5	2.0205e-4

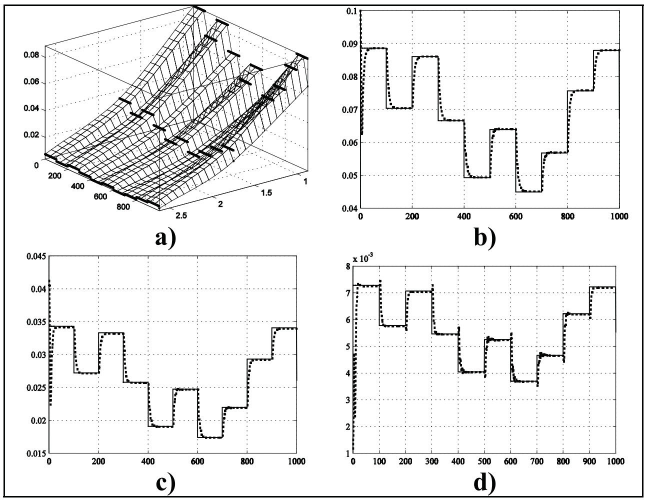

Figure 8: Results of the direct decentralized FNMM control of X_2 (methanogenic bacteria in the fixed bed) (dotted line-plant output, continuous-reference); a) 3d view of X_2 ; b) Ref vs X_2 in z=0.25H; c) Ref vs X_2 in z=0.5H; d) Ref vs X_2 in z=0.75H.

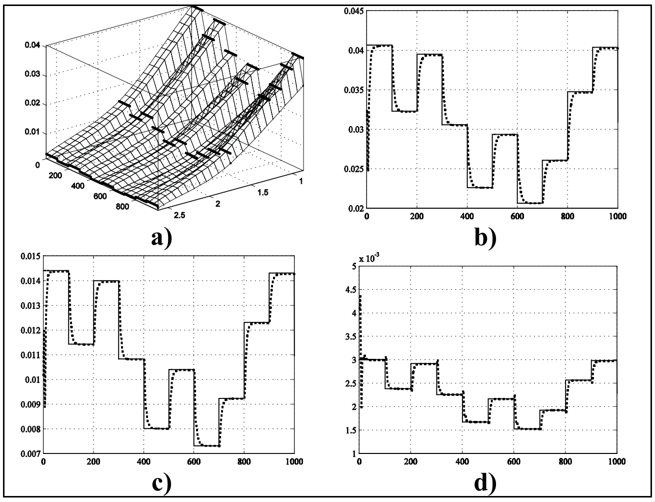

Figure 9: Results of the decentralized FNMM-SMC of X_1 (acidogenic bacteria in the fixed bed) (dotted line-plant output, continuous-reference); a) 3d view of X_1; b) SMC of X_1 in z=0.25H; c) SMC of X_1 in z=0.5H; d) SMC of X_1 in z=0.75H.

Table 3: MSE% of the decentralized FNMM–SMC of the bioprocess output variables

Coll. point	X_1	X_2	S_1 / S_{1T}	S_2 / S_{2T}
z=0.25H	1.7494E-8	3.0157E-9	3.9538E-6	7.9391E-9
z=0.5H	2.2131E-9	1.9669E-8	4.8951E-7	2.1116E-6
z=0.75H	1.0415E-10	1.3238E-9	2.3548E-8	1.3095E-7
Recir Tank			8.4352E-8	5.8734E-9

Table 4: MSE% of the proportional optimal control of the bioprocess output variables

Coll. point	X_1	X_2	S_1 / S_{1T}	S_2 / S_{2T}
z=0.25H	5.3057E-8	1.7632E-7	1.1978E-5	2.1078E-5
z=0.5H	6.6925E-9	4.2626E-8	1.4922E-6	4.4276E-6
z=0.75H	3.0440E-10	2.0501E-9	6.8737E-8	2.0178E-7
Recir Tank			2.7323E-7	6.0146E-7

The comparison also showed a slight preference of the FNMM-SMC control over the linearized optimal control, due to the adaptation of the FNMM-SMC control low.

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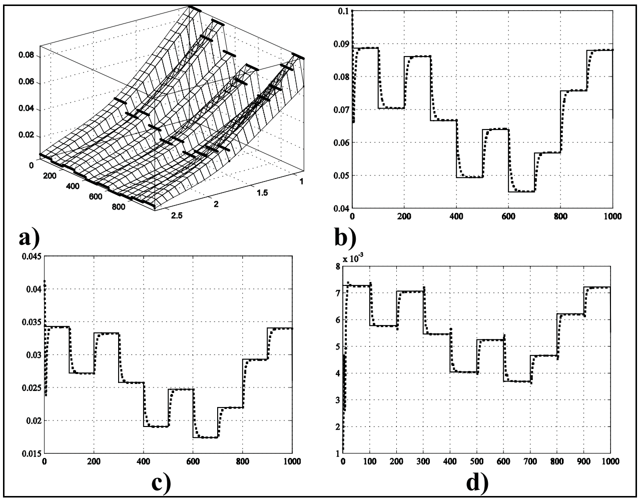

Figure 10: Results of the decentralized FNMM-SMC of X_2 (methanogenic bacteria in the fixed bed) (dotted line-plant output, continuous-reference); a) 3d view of X_2; b) SMC of X_2 in z=0.25H; c) SMC of X_2 in z=0.5H; d) SMC of X_2 in z=0.75H.

5 Conclusions

The paper performed decentralized recurrent fuzzy-neural identification, direct and indirect control of an anaerobic digestion wastewater treatment bioprocess, composed by a fixed bed and a recirculation tank represented a DPS. The simplification of the PDE process model by ODE is realized using the orthogonal collocation method in three collocation points (plus the recirculation tank) represented centers of membership functions of the space fuzzyfied output variables. The obtained from the FNMMI state and parameter information is used by a HFNMM direct and indirect control. All graphical control results exhibited good convergence and precise reference tracking. All obtained comparative numerical identification and control results (final MSE%) exhibited a high precision and showed that the indirect decentralized FNMM control is the better one outperforming the linearized optimal control and the direct decentralized fuzzy-neural control.

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