COMPARATIVE RESEARCH ON NEURO-FUZZY ALGORITHMS

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Abstract

Present research deals with the comparison of neuro-fuzzy algorithms theoretical and application aspects. The compared algorithms are applied for a non-linear MISO system predictive model design. The modelled system is an unstudied continuous biotechnological process for protein biosynthesis. Simulative research is carried out in Fuzzy Toolbox of Matlab 5.2. Experimental approvement of the models is realized from experts in the Institute of Microbiology - Bulgarian Academy of Sciences.

Key words**:** neuro-fuzzy algorithms, knowledge-based modeling, predictive control, biotechnology, protein synthesis.

1. INTRODUCTION

Universal approximation using neuro-fuzzy reasoning is an efficient approach for unstudied non-linear systems modeling, where the expert knowledge implementation plays a leading role. A characteristic class of non-linear systems are biotechnological processes (Vassileva et al., 2000). The automatic adjustment of linguistic variables and extraction of fuzzy rules is one of the most important tasks when neuro-fuzzy algorithms are implemented for modeling of real processes. For this reason our goal is to compare and choose for technological applications one of two neuro-fuzzy algorithms for predictive modeling of an new biotechnological process. Neuro-fuzzy algorithms are applied because they "holds great potential benefit in reducing computing time and optimizing results "(Tsoukalas, 1997).

2. PROBLEM FORMULATION

Present paper investigates the efficiency of adaptive neuro-fuzzy modeling techniques by using well-known ANFIS (Jang, 1993) and its modification, based on a compensatory algorithm for fuzzy reasoning (Zhang et al., 1998).

The m fuzzy IF-THEN rules of the n-input-one-output compensatory fuzzy logic system are described below:

$$FR^{(k)} : IF.x_1.is.A_1^k and...and.x_n.is.A_n^k.THEN.y.is.B^k \qquad (1)$$

where A_i^k and B^k are fuzzy sets in $U_i \subset R$ and $V \subset R$, respectively, and $x_i \in U_i$ and $y \in V$ are linguistic variables for I=1,2,…,n and k=1,2,…,m.

The fuzzy membership functions of A_i^k and B^k are defined by (2) and (3), respectively:

$$\mu_{A_i}{}^k(x_i) = \exp\left[-\left(\frac{x_i - a_i^k}{\sigma_i^k}\right)^2\right] \qquad (2)$$

$$\mu_B{}^k(y) = \exp\left[-\left(\frac{y - b^k}{\delta^k}\right)^2\right] \qquad (3)$$

Suppose $\underline{x}$ = (x_1, x_2,…,x_n), $U=U_1 x U_2 x \ldots x U_n$.

For an input fuzzy set A' in U, the k^{-th} fuzzy rule (1) can generate an output fuzzy set B_k in V by using the sup-dot composition (4)

$$\mu_{B^k} = \sup_{\underline{x} \in U} \left[\mu_{A_1^k x \ldots x A_n^k \to B^k} (\underline{x}, y) \bullet \mu_{A'}(\underline{x}) \right] \tag{4}$$

In connection with neuro-fuzzy adaptation of Sugeno-fuzzy inference systems, equation (4) could be presented with the help of following equation (5) - the compensatory form:

$$\mu_{A_1^k x \ldots x A_n^k} (\underline{x}) = \left(u^k\right)^{1-\gamma} \left(\nu^k\right)^{\gamma} \tag{5}$$

Using pessimistic operation (6) and optimistic operation (7) with a compensatory degree $\gamma \in [0,1]$

$$u^k = \prod_{i=1}^{n} \mu_{A_i^k}(x_i) \tag{6}$$

$$\nu^k = \left[\prod_{i=1}^{n} \mu_{A_i^k}(x_i) \right]^{\frac{1}{n}} \tag{7}$$

as a result and for simplicity it can be used expression:

$$\mu_{A_1^k \times \ldots \times A_n^k} (\underline{x}) = \left[\prod_{i=1}^{n} \mu_{A_i^k}(x) \right]^{1-\gamma+\gamma/n} \tag{8}$$

The product-operation is defined as follows:

$$\mu_{A \to B}(x, y) = \mu_A(x) \mu_B(y) \tag{9}$$

Substituting equations (8)-(10) in the equation (4) it is obtained:

$$\mu_B{}^{rk}(y) = \sup_{x \in U} \left\{ \mu_{B^k}(y) \mu_{A'}(\underline{x}) \left[\prod_{j=1}^{n} \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n} \right\} \tag{10}$$

Defuzzifier is defined as follows:

$$f(\underline{x}) = \frac{\sum_{k=1}^{m} b^k \delta^k \mu_{B^{rk}}\left(b^k\right)}{\sum_{k=1}^{m} \delta^k \mu_{B^{rk}}\left(b^k\right)} \tag{11}$$

According equation (10), since membership functions for input variables and output equal to 1, for the singleton fuzzifier follows:

$$\mu_{B^{rk}}\left(b^k\right) = \left[\prod_{i=1}^{n} \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n} \tag{12}$$

The desired fuzzified output is:

$$f(\underline{x}) = \frac{\sum b^k \delta^k \left[\prod_{i=1}^{n} \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n}}{\sum \delta^k \left[\prod_{i=1}^{n} \mu_{A_i^k}(x_i) \right]^{1-\gamma+\gamma/n}} \tag{13}$$

The fuzzy membership functions of A_i^k and B_k are defined by (14) and (15), respectively:

$$\mu_{A_i}{}^k(x_i^p) = \exp\left[-\left(\frac{x_i^p - a_i^k}{\sigma_i^k} \right)^2 \right] \tag{14}$$

$$\mu_B{}^k(y^p) = \exp\left[-\left(\frac{y^p - b^k}{\delta^k}\right)^2\right] \tag{15}$$

Replacing in (14) z^k

$$z^k = \left[\prod_{i=1}^{n} \mu_{A_i^k}\left(x_i^p\right)\right]^{1-\gamma+\gamma/n} \tag{16}$$

it is obtained

$$f\left(x^p\right) = \frac{\sum_{k=1}^{m} b^k \delta^k z^k}{\sum_{k=1}^{m} \delta^k z^k} \tag{17}$$

Implementing γ we obtain an adaptive structure of our neuro-fuzzy system in the dynamics of the learning procedure (Zhang at all, 1998).

The objective function J is defined as

$$J^p = \frac{1}{2}\left[f\left(x^p\right) - y^p\right]^2 \to \min \tag{18}$$

The compensatory neural fuzzy network with n-dimensional input-data vector x_p and one-dimensional output-data vector, y_p, similarly to ANFIS, has 5 functional layers - input layer, fuzzification layer, pessimistic-optimistic operation layer, compensatory operation layer (fuzzy reasoning method), defuzzification layer (Fig.3.).

Fuzzy prediction problem statement, presented as a collection of IF-THEN rules, is as follows:

$$FR^{(k)}: \text{IF.}y(k)\text{.is.}A_1^k\text{and...and.}y(k-n_y+1)\text{..and..IF.}x(k)\text{.is.}B_n\text{.and.}x(k-n_u+1)\text{..is.}B_i^n\text{.THEN.}y.(k+1)\text{..is}$$

$$y(k+1) = \sum_{j=1}^{n_y} a_{ij} y(k-j+1) + \sum_{j=1}^{n_u} b_{ij} x(k-j+1) + c_i, \quad i = 1, K, k \tag{19}$$

where a_{ij}, b_{ij} and c_i are crisp consequent parameters. The weighted means predicted output y(k+1) of the model is:

$$y(k+1) = \frac{\sum_{i=1}^{K} \lambda_i\left(y(k), K, x\left(k-n_u+1\right)\right) y_i(k+1)}{\sum_{i=1}^{K} \lambda_i\left(y(k), K, x\left(k-n_u+1\right)\right)} \tag{20}$$

where the normalized form of the fulfillment degree is presented by:

$$\lambda_i\left(y(k), K, x\left(k-n_u+1\right)\right) = \frac{\lambda_i\left(y(k), K, x\left(k-n_u+1\right)\right)}{\sum_{i=1}^{K} \lambda_i\left(y(k), K, x\left(k-n_u+1\right)\right)} \tag{21}$$

3. SIMULATION RESULTS AND EXPERT APPROVEMENT

Bioprocesses are highly non-linear and non-stationary MIMO systems. There are a lot of interconnected relationships and mutual impacts between different by nature and dynamics bioprocess variables, time-varying properties of the microorganisms and unknown effects (Vassileva et al., 2000). Due to the process uncertainty, inherent in biotechnological applications, and real need to process heterogeneous information (numeric and linguistic, as well as expert knowledge), original results in the fuzzy model-based prediction for dilution rate influence on protein continuous biosynthesis are presented.

The influence of five dilution rates (D=0.1; 0.2; 0.3; 0.4, 0.5h^{-1}) at carbon limitation on the yields of protein, protein synthesizing ability and bioproductivity of the microbial strain *C.pseudotropicalis 11* continuous fermentation is modeled comparing above mentioned neuro-fuzzy algorithms.

Data instances from the microbiological experiments are shown in Table 1. The stable tendency to augmentation of RNA, [%] content was found with the increase of the dilution rateD, [h^{-1}]. That leads to increase of the protein content PR, [%]. It was observed a decrease of the protein yield Ypr, [%], due to the biomass yield reduce. The studied microbila strain *C.pseudotropicalis 11* showed a high sensibility to RNA synthesis with the change of the dilution rate in the conditions of carbon limitation. The protein synthesizing ability A, [%] of the cells increased with the growth of D and it reached the maximal value at 0.4 h^{-1}. Illustrative 3-D optimal surfaces in Fig.6 for ANFIS-based models and Fig.7 for compensatory algorithm-based models, confirm the experimental results.

As is known from the literature and our previous investigations, fuzzy membership functions (FMF's) influence model accuracy and rule realism (Vassileva et al., 2000). Linguistic variables presentation is shown in Fig.1 and Fig.2, where it is able to compare used in both cases FMF's before (Fig.1a and b, Fig.2a and b) and after training (Fig.1c and d, Fig.2c and d). Our simulation results show that the implemented neuro-fuzzy algorithms fulfill the requests for high model accuracy (Table 2.) In addition, Fig.4 and Fig.5 illustrates decrease of the training and checking errors with the increasing number of epochs for one of the models A=*FM*(D,PR). The optimal number of epochs for all fuzzy models obtaining by using both algorithms is approximately 250.

The optimal 3D-surfaces are smoothed and assures fluent movement from one to the other point, which is significant in the automation control.

The model appliance and rules realism of the extracted automatically rule-bases were tested also from experts in the laboratory conditions in the Institute of microbiology-BAS in control points (D=0.1, 0.2, 0.3, 0.4, 0.5 h^{-1}). The derived fuzzy models satisfy the requirements of biotechnologist as a human-expert, which yields missing information about relevant process variables.

4. CONCLUSIONS

The obtained in our paper results shows that neuro-fuzzy algorithms qives opportunity to adjust membership functions, automatically extract fuzzy rules and these algorithms are suitable for solving tasks as well as biotechnological processes predictive modeling.

Obtained fuzzy models can be used for manual control assistance or for expert control – direct or supervisory (Brown M. and al, 1994). In manual control mode fuzzy model serves as assistant process-operator, which determines changes in the output if the operator attempts to execute certain control action. In the expert mode fuzzy model replaces conventional controller.

Obtained in this research fuzzy models are capable of assisting in a manual mode of control of the dilution rate of continuously operated fermentation process for protein biosynthesis.

Table 1 Data instances from microbiological experiments

Dilution rate, D[h-1];	Protein, PR [%]	Ribonucleic acid, RNA[%]	Protein yield, Ypr [%]	Protein-synthesizing ability, A [%]
0.1	40.9	5.86	19.00	0.697
0.2	43.1	6.47	18.06	1.332
0.3	45.5	7.53	18.38	1.812
0.4	47.6	9.43	17.65	2.019
0.5	47.1	13.50	15.11	1.744

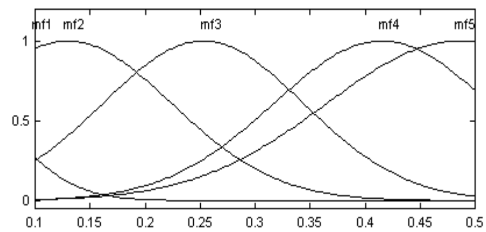


Fig.1 a) D-MF's before training

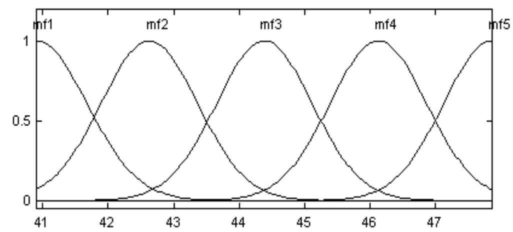


Fig.1 b) PR-MF's before training

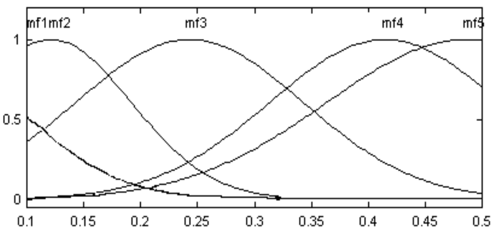


Fig.1 c) D-MF's after training

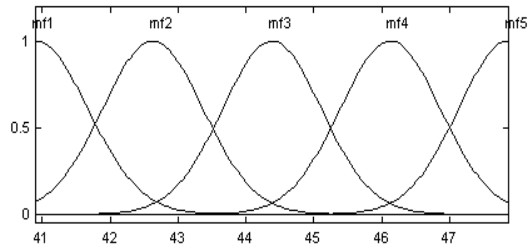
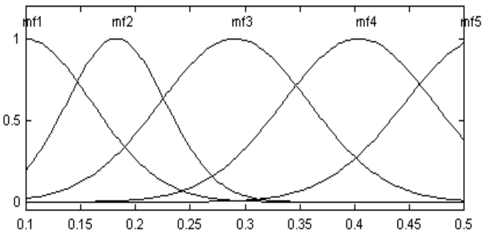


Fig.1 d) PR-MF's after training

Fig.1 Fuzzy membership functions (FM's) for input variables linguistic

presentation in ANFIS-based model Y_{pr}=*FM*(D,PR)



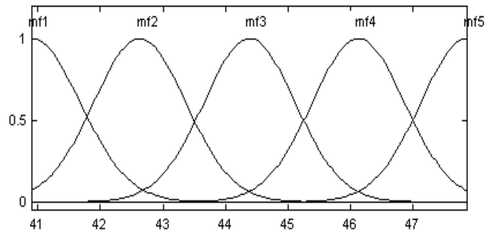
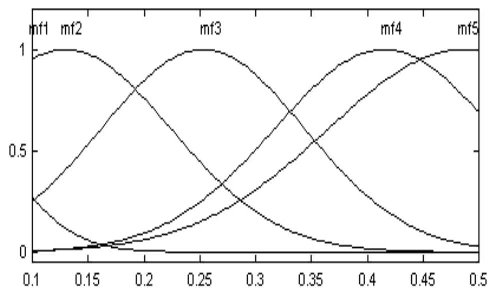


Fig.2 a) D-MF's before training Fig.2 b) PR-MF's before training



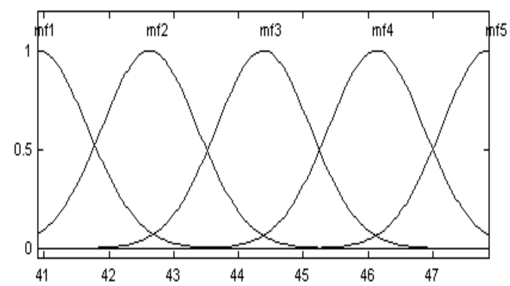


Fig.2 a) D-MF's after training Fig.2 b) PR-MF's after training

Fig.2 Fuzzy membership functions (FM's) for input variables linguistic

presentation in the compensatory algorithm -based model Ypr=FM(D,PR)

Table 2 Fuzzy models accuracy

No	Fuzzy Model, FM	ANFIS-errors		Compensatory FIS-errors	
		Training error	Checking error	Training error	Checking error
1	Y_{PR} =FM(D, PR)	0.0006	0.0008	0.0000	0.0001
2	Y_{PR} =FM (D,RNA)	0.0002	0.0003	0.0015	0.0006
3	A= FM(D, PR)	0.036 x1.E-3	0.0001	0.0268	0.0000
4	A = FM(D, RNA)	0.073 **x**1.E-3	0.0001	0.0362	0.0001

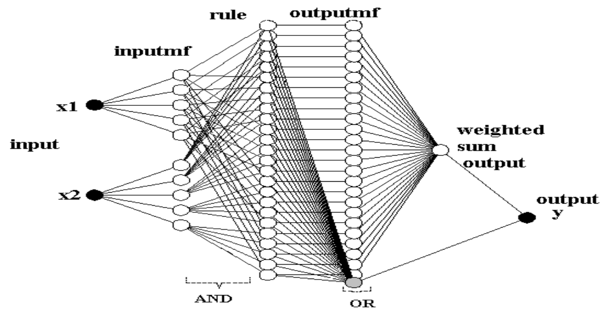


Fig. 3 Structure of two-input-one-output adaptive neuro-fuzzy inference system

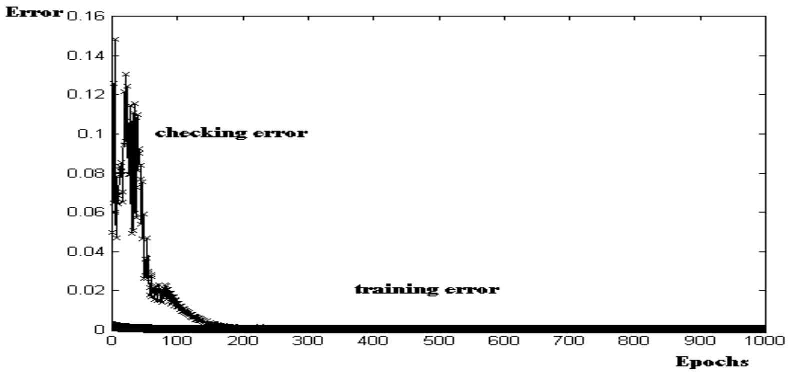


Fig.4 Training and checking errors change for

ANFIS -based model A = *FM* (D, PR)

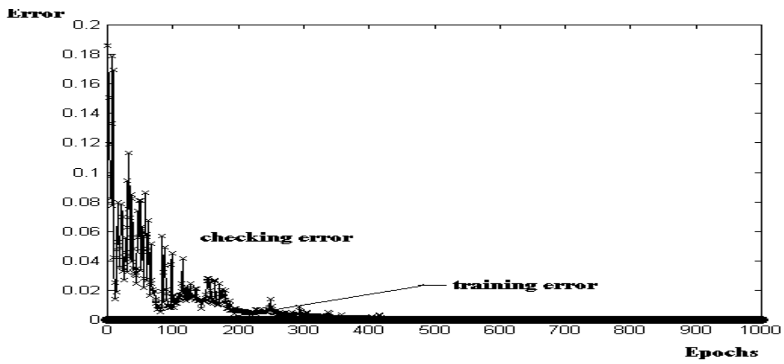


Fig.5 Training and checking errors change for compensatory

algorithm -based model A= FM (D, PR)

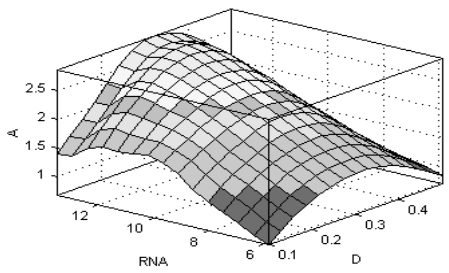


Fig.6a) A= *FM*(D, RNA)

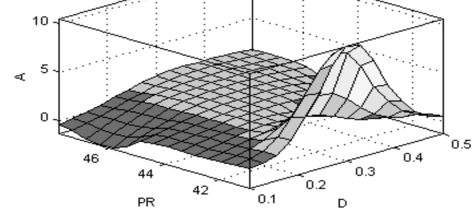


Fig.6b) A = *FM*(D, PR)

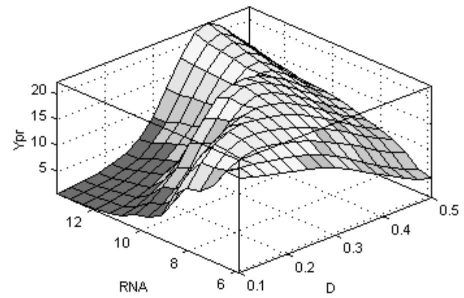


Fig.6c) Ypr = *FM*(D, RNA)

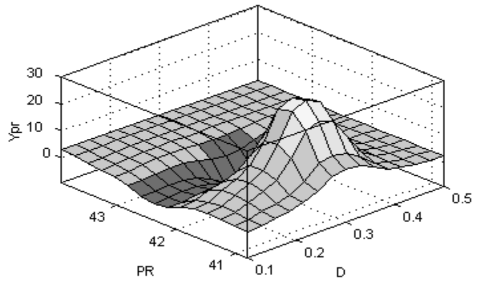


Fig.6d) Ypr = *FM* (D, PR)

Fig.6 3-D optimal surface of the ANFIS-based models

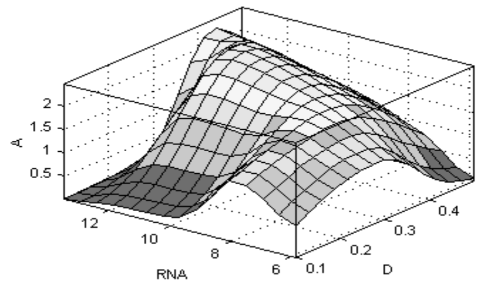


Fig.7a) A = FM (D, RNA)

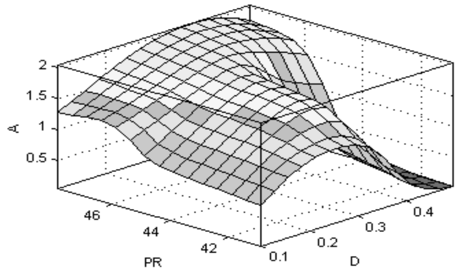


Fig.7a) A = FM (D, PR)

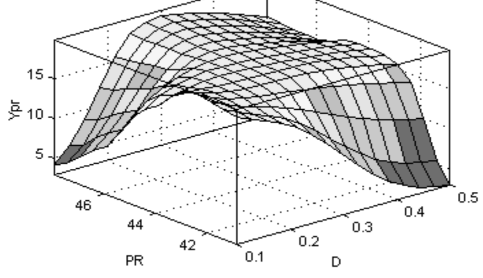


Fig.7a) Ypr = *FM* (D, RNA)

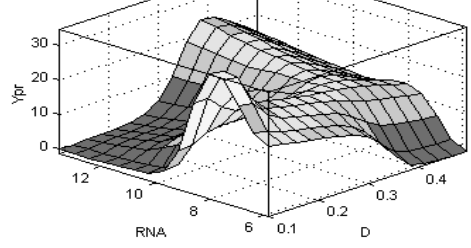


Fig.7a) Ypr = *FM* (D, PR)

Fig.7 3-D optimal surface of the compensatory -algorithm based models

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