Type-2 Fuzzy Control of a Bioreactor

Cosenza Bartolomeo, Galluzzo Mosè
Dipartimento di Ingegneria Chimica dei Processi e dei Materiali
Università degli Studi di Palermo
Viale delle Scienze, ed. 6, 90128 Palermo, Italy
galluzzo@unipa.it

Abstract—**In this paper the control of a bioprocess using an adaptive type-2 fuzzy logic controller is proposed. The process is concerned with the aerobic alcoholic fermentation for the growth of *Saccharomyces Cerevisiae* and is characterized by nonlinearity and parameter uncertainty. Three type-2 fuzzy controllers heve been developed and tested by simulation: a simple type-2 fuzzy logic controller with 49 rules; a type-2 fuzzy-neuro-predictive controller (T2FNPC); a type-2 self-tuning fuzzy controller (T2STFC). The T2FNPC combines the capability of the type-2 fuzzy logic to handle uncertainties, with the ability of predictive control to predict future plant performance making use of a neural network model of the non linear system. In the T2STFC the output scaling factor is adjusted on-line by fuzzy rules according to the current trend of the controlled process. The advantage of the proposed adaptive algorithms is to greatly decrease the number of rules needed for the control reducing the computational load and at same time assuring a robust control.**

Keywords: adaptive control, type-2 fuzzy control, non-linear system, uncertainty

I. Introduction

It is well known that many traditional control design techniques require restrictive assumptions for the plant model and for the control to be designed. This is particularly true for systems characterized by multiple steady states. For all non linear systems dependent from one or more parameters the operative conditions remain stable only if the values of these parameters remain in a limited range. If the system parameters go out of this range, the system may also reach new equilibrium points that may be stable but unacceptable for the plant operation. Many chemical process exhibit similar behaviour that makes their control problematic. The use of nonlinear controllers like fuzzy logic controllers is justified by their robustness and by their ability to handle changes in the system parameters as well. In addition to traditional fuzzy logic systems based on type-1 fuzzy sets more recently other fuzzy logic systems based on type-2 fuzzy sets have been proposed [1]. Despite their popularity type-1 fuzzy logic control show some weakness in particular when the systems to control are characterized by uncertainties.Type-2 fuzzy sets in fact can handle the uncertainties in a better way than type-1 fuzzy sets because they are characterized by a larger number of parameters and more design freedom degrees. The few applications in the field of process control regard the control of: marine diesel engines [2], liquid level process [3], autonomous mobile robots [4], [5], vehicle active suspensions [6], biochemical reactor [7], CSTR [8].

The system here considered is a biochemical process for the aerobic growth of *Saccharomyces Cerevisiae* on glucose and ethanol. A dynamic analysis of the process model showed that multiple steady states occur depending on the feed concentration and kinetic parameters as well. The control objective for the biochemical reactor under study is to keep the concentration value of the substrate concentration at desired value taking into account all the disturbances and all the uncertainties, corresponding to small variations of the model kinetic parameter values.

In some cases, in systems where parameters are time varying and affected by uncertainty and strong nonlinearities are present, the use of type-2 fuzzy logic controllers might not allow to reach good control results. The introduction of an adaptive algorithm, that changes some controller parameters depending on the system condition, can improve the control action enormously reducing the number of rules necessary for the control and considerably decreasing the computational load as consequence.

II. Type-2 Fuzzy Logic

A. *Interval type-2 fuzzy set*

The type-2 fuzzy set, denoted with the symbol $\tilde{A}$, is characterized by a type-2 membership function $\mu_{\tilde{A}}(x,u) \in [0,1]$ as follows:

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x} \mu_{\tilde{A}}(x,u)/(x,u) \qquad (1)$$

where $x \in X$ and $u \in J_x \subseteq [0,1]$.

Type-2 fuzzy logic operations are very prohibitive, therefore at the moment only a particular sub case of type-2 fuzzy logic is treated in research field: the interval type-2 fuzzy logic.

An interval fuzzy set $\tilde{A}_I$ (Fig. 1) is defined as:

$$\tilde{A}_I = \int_{x\in X}\int_{u\in J_x\subseteq[0,1]} 1/(x,u) \qquad (2)$$

The secondary grade of interval set can assume only two values: 0 or 1.

B. Footprint of Uncertainty

Type-2 fuzzy logic shows all its potential only in environments characterized by uncertainty. The Footprint of Uncertainty [9] consists of a bounded region that can be considered as a measure of dispersion of the system input The FOU is bounded by a lower (LMF) and a upper membership function (UMF) (Fig. 2).

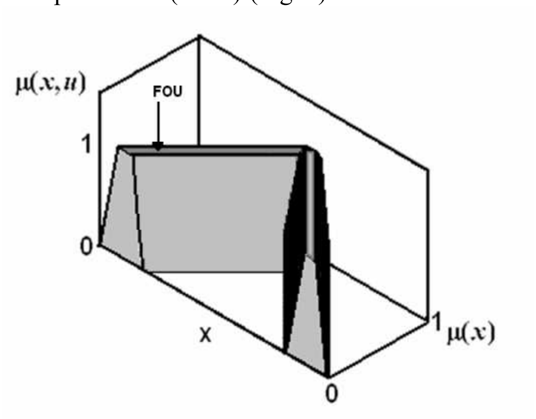

Figure 1. Type-2 fuzzy set

All the uncertainties present in a system can be taking in to account by opportune use of FOU (Fig. 2) and their negative effects can be minimize as well consequently.

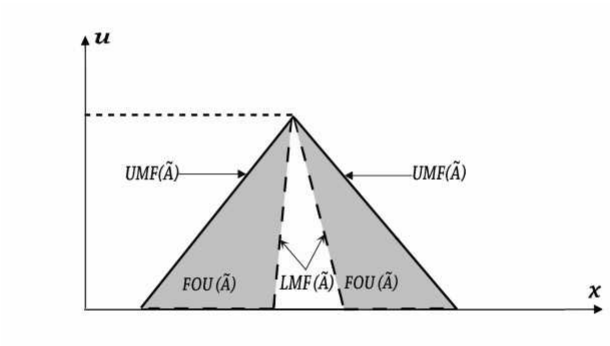

Figure 2. FOU (shaded), LMF (dashed), UMF (solid) for interval type-2 fuzzy logic.

The main difference between type-2 and type-1 FLSs is the output-processor. The output-processor in fact for a type-1 FLS is a simple defuzzifier, while, for a type-2 FLS it is composed by two components: the first component is a type-reducer which maps a type-2 fuzzy set into a type-1 fuzzy set. The second component is just a normal defuzzifier that transforms a fuzzy output in a crisp output.

C. Type-reduction

One of the most used type-reduction methods is the *center of sets* type reducer [10], which can be expressed as:

$$Y_{\cos}(\mathrm{x})=[y_l,y_r]=\int_{\mathrm{y}^1\in\left[\mathrm{y}_l^1,\mathrm{y}_r^1\right]}\cdots\int_{\mathrm{y}^M\in\left[\mathrm{y}_l^M,\mathrm{y}_r^M\right]}\int_{\mathrm{f}^1\in\left[\underline{\mathrm{f}}^1,\overline{\mathrm{f}}^1\right]}\cdots\cdots\cdots$$

$$\cdots\int_{\mathrm{f}^M\in\left[\underline{\mathrm{f}}^M,\overline{\mathrm{f}}^M\right]} 1\Bigg/\left(\frac{\sum_{i=1}^{M}\mathrm{f}^i\mathrm{y}^i}{\sum_{i=1}^{M}\mathrm{f}^i}\right) \tag{3}$$

In (2) $Y_{\cos}(\mathbf{x})$ is an interval set while y_l and y_r are its end-points, $\left[\underline{f}^i,\overline{f}_i\right]$ and $\left[y_l^i,y_r^i\right]$ are respectively the interval firing level of the *i*th rule and the centroid of the type-2 interval consequent set. With the Karnik-Mendel iterative method [10] it is possible to compute $Y_{\cos}(\mathrm{x})$ using the equation (2). The defuzzification of $Y_{\cos}(\mathrm{x})$ is a simple operation. $Y_{\cos}(\mathrm{x})$ is in fact an interval type-2 fuzzy set and the defuzzified output is a simple average of y_l and y_r:

$$y(x)=\frac{y_l+y_r}{2} \tag{4}$$

III. TYPE-2 FUZZY CONTROLLERS STRUCTURE

A. Type-2 FuzzyLogic Controller

Three different type-2 fuzzy controllers were designed, two of which adaptive. All the controllers use the Sugeno inference (zero order for the simple type-2 fuzzy controller and first order for the adaptive type-2 fuzzy controllers); the input variables are the error and the integral of the error; and the output variable is the control variable, i.e. the dilution rate.

The simple type-2 FLC is characterized by a set of 49 rules. For each input variable, seven Gaussian membership functions were chosen. Although the type-2 fuzzy controller with a large number of rules shows to be a very robust controller, the choice of adaptive control represents a better alternative in terms of efficiency above all when the parameters of the controlled process are time varying as in this case [11].

B. Type-2 Fuzzy Neuro Predictive Controller

The first adaptive controller has a hybrid type-2 fuzzy predictive-neural-control structure (T2FNPC) that is shown in Fig. 3. The predictive neural algorithm can be divided in two parts: a predictive part and a neural network part. The first part uses the receding horizon technique, the prediction is carried out by a numerical optimization program that determines the control signal that minimizes a performance criterion over a specified horizon. The neural network) provides, after a training stage, the model of the system from which the prediction of the plant response is obtained. The measured output of the control system also represents the input signal of the predictive-neural controller. The control signal of the predictive-neural network controller is combined with the control signal of the type-2 feedback fuzzy controller and constitutes the input of the process. The rule set of the type-2 fuzzy controller is formed by only two rules with Gaussian membership functions.

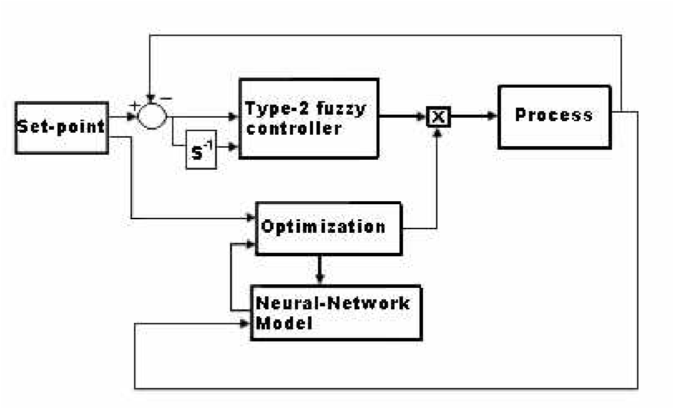

Figure 3. Type-2 neuro-predictive fuzzy controller structure.

C. *Type-2 Self Tuning Controller*

The second adaptive fuzzy controller is a type-2 self-tuning fuzzy controller (T2STFC), designed taking into account the fuzzy controller structure proposed by Mudi and Pal [12]. The adaptive controller, shown in Fig. 4, is based on a control hierarchical structure constituted on two fuzzy controllers. The fuzzy rules of the secondary fuzzy controller adjust online the output scaling factor (SF) of the main fuzzy controller, according to the current trend of the controlled process. The main controller is a normal type-2 fuzzy controller with 2 rules (Gaussian membership functions) while the adaptive secondary controller is a type-1 fuzzy controller with 2 rules as well. The control variable of the type-2 fuzzy controller is updated by the signal that comes from the type-1 fuzzy controller and sent to the final control element.

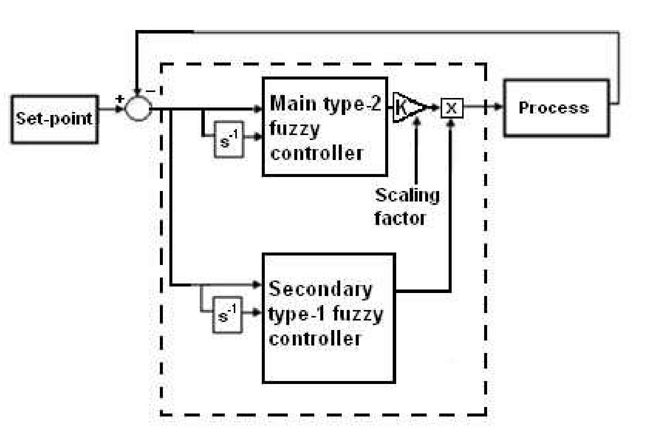

Figure 4. Type-2 self tuning fuzzy controller structure.

IV. MODEL DYNAMICS ANALYSIS

An accurate and detailed analysis of the bioreactor model used in the simulation study can be found in Lei et al. [13]. In the model all reactions are modelled assuming a Michaelis-Menten kinetics with respect to a given substrate and a first order dependency on the active biomass concentration X_a. The reactor volume and all physical-chemical properties are assumed constant. The control of glucose concentration inside the bioreactor using the dilution rate as manipulation variable is the control objective. The glucose concentration is used as carbon and energy source and strongly influences the *Saccharomyces Cerevisiae* growth. Generally, to avoid the Crabtree effect [14] an efficient control of glucose concentration is required. In all simulations carried out, an initial value of dilution rate was imposed at instant t=0 hr. This value (in accordance with the equilibrium conditions of the system) corresponds to the steady state value of the dilution rate for given values of the substrate and biomass concentrations in the bioreactor. Suppose to work (without control) with a constant value of the substrate concentration equal to 0.065 gl^{-1}. The corresponding equilibrium value of the dilution rate and biomass concentration are 0.38 h^{-1} and 6.9 gl^{-1} respectively.

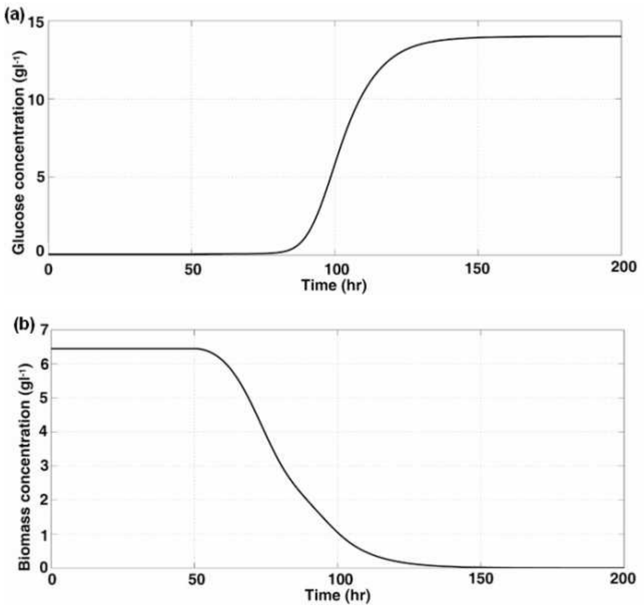

Figure 5. Glucose concentration (a) and biomass concentration (b) for a linear change of k_7 from 1.203 to 0.953 in 50 hours

Let us suppose that the value of the system kinetic parameter k_7 decreases for 50 hours from the initial value 1.203 with a ramp change (slope = - 0.005 h^{-1}).

From Fig. 5 it can be seen that a small change of a particular kinetic parameter, can cause a large decrease in the biomass product. The new operative condition corresponding to the steady state values reached by the glucose substrate concentration (15 gl^{-1}) and the biomass concentration ($\cong 0$ gl^{-1}), although stable, is obviously unacceptable.

Also a change in the feed substrate concentration may modify the steady state of the bioreactor with undesirable effects on biomass concentration, although the negative effects are not so significant if compared with the previous simulation results. Fig. 6 shows the effects of a disturbance in the substrate feed concentration respectively on glucose concentration (a) and on biomass concentration (b) for the uncontrolled system.

The objective of the bioreactor control is therefore to keep the system in the chosen initial equilibrium point, with a glucose concentration equal to 0.065 gl^{-1} even in the presence of disturbances and parameter changes by suitably modifying the value of the manipulation variable. The previously performance of the simple type-2 fuzzy controller with 49 rules described was compared by simulation with the performance of the T2FNPC and with that of the T

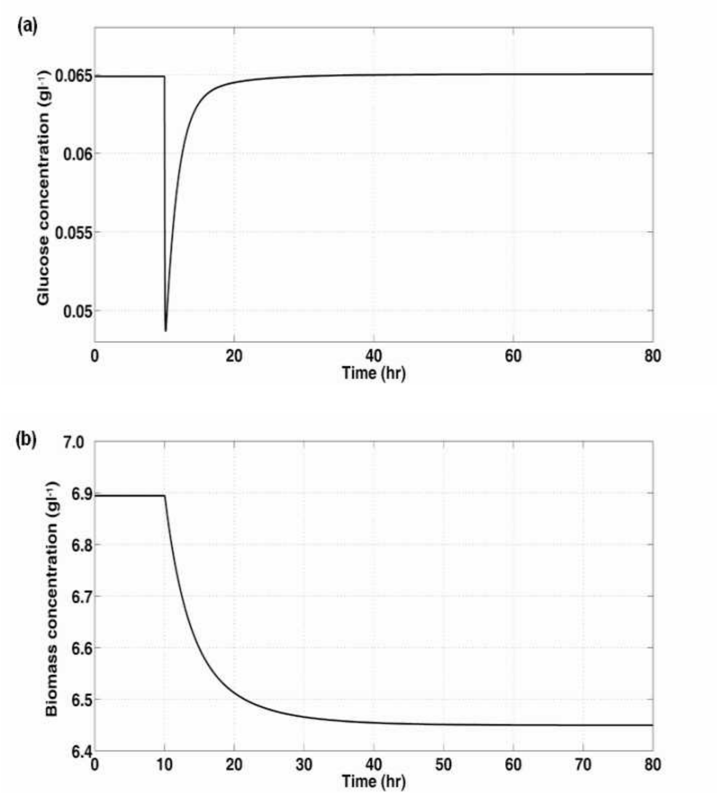

Figure 6. Glucose concentration (a) and biomass concentration (b) for a step change of S_f from an initial value of 15 to 14 (gl^{-1}) at t = 20 hr.

V. SIMULATION RESULTS

Fig. 7 shows the simulation results obtained introducing at t =10 hr a disturbance in the system with a negative step in S_f, from 15 to 14 gl^{-1}. The system in each three cases reaches the set-point value imposed, removing the effects of the disturbance. The two adaptive fuzzy controllers perform better than the simple type-2 fuzzy controllers with the T2STFC showing the best performance for the fastest control action and the lowest deviation amplitude after the disturbance.

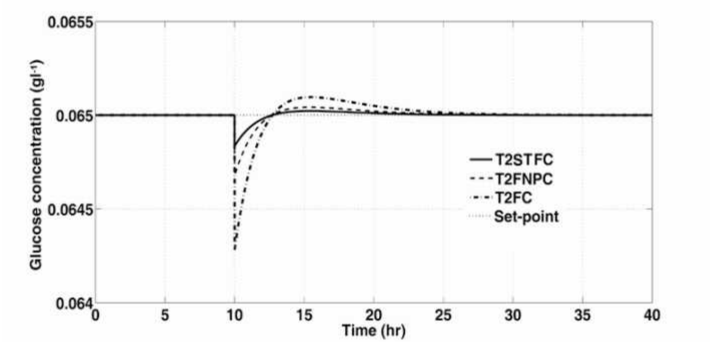

Figure 7. Response of the controlled system to a S_f disturbance (step from 15 to 14 gl^{-1} at t =10 hr).

Fig. 8 shows instead the simulation results obtained imposing two disturbances to the system: the first as a ramp change to the k_7 kinetic parameter value (starting at time 10 hr and lasting until the end of the simulation time) and the second as a step change to S_f value (step from 15 to 14 gl^{-1} at t =30 hr). In this case all three type-2 fuzzy controller are not able to remove the negative effects of this parameter drift k_7. Although in each case an off set appears it is more accentuated in the case of the simple type-2 fuzzy controller and the T2STFC results to be the controllers that minimize in the best ways the effects of the kinetic parameter disturbance.

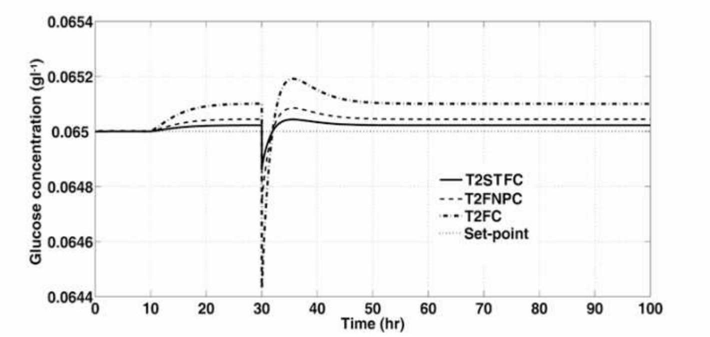

Figure 8. Response of the controlled system to a k_7 disturbance (ramp disturbance starting at t =10 hr) and to a S_f disturbance (step from 15 to 14 gl^{-1} at t =30 hr).

Fig. 9 shows the simulation result obtained imposing a random variation of the k_7 kinetic parameter throughout simulation, confirming again the best behavior of the T2STFC.

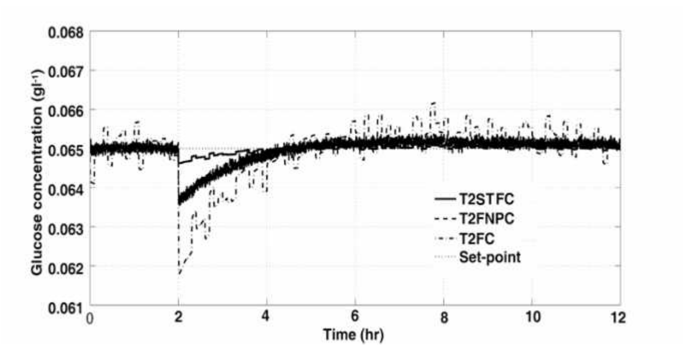

Figure 9. Response of the controlled system to a random variation of k_7 and to a S_{f1} disturbance (step from 15 to 13 gl^{-1} at t =2 hr).

The last simulation results shown in Fig. 10 is obtained imposing a step to S_f from 15 to 14 gl^{-1} at t = 5 hr; a second step to k_7 from 1.203 to 1.1 at t =25 hr; a third step to kinetic parameters k_{il1} from 0.94 to 1 at t =45 hr and a fourth step k_3 from 0.501 to 0.48 at t =45 hr as well.

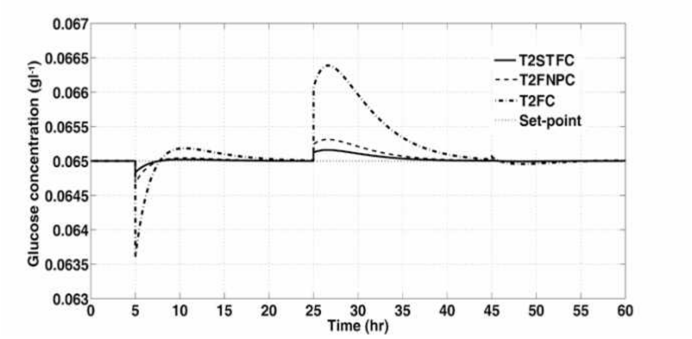

Figure 10. Response of the controlled system to disturbances in S_f of (step from 15 to 14 gl^{-1} at t =5 hr), in k_7 step from 1.203 to 1.1at t =25 hr), in k_{il1} (step from 0.94 to 1) and in k_3 (step from 0.501 to 0.48 at t = 45 hr).

From Fig. 10 it can be seen that the change of the two kinetic parameters k_{il1} and k_3 seems to have no effects on the bioreactor controlled by adaptive fuzzy controllers. In particular the T2STFC is very fast and robust for changes of the feed substrate concentration and the kinetic parameters, in comparison with the other two fuzzy controllers.

VI. CONCLUSIONS

In this paper, the control of a bioreactor for the aerobic growth of *Saccharomyces Cerevisiae*, characterized by time varying parameters, was studied by use of three type-2 fuzzy controllers: a simple T2FC with 49 rules and two adaptive type-2 fuzzy controllers: a T2FNPC and a T2STFC, both with only two rules. The simulation results confirm that despite the reduced rule set, compared with the simple T2FC, the two adaptive fuzzy controllers, in particular the T2STFC, allow to reach very efficient control of the bioreactor in presence of parameter changes of different type with a very fast response and very low overshoot. The adaptive fuzzy algorithm of the T2STFC, that operates on the output scaling factor allows to minimize all the negative effects of all system parameters with a minimum computational load

VII. REFERENCES

[1] J. M. Mendel, “Uncertainty, Type-2 fuzzy Sets, and Footprints of Uncertainty,” Proceeding of 9th Int’l. Conf. on Information Processing and Management of Uncertainty in Knowledge Based Systems, Annecy, France, pp. 325-331, 2002.

[2] Lynch C., Hagras H., Callaghan V., 2006. Using Uncertainty Bounds in the Design of an Embedded Real-Time Type-2 Neuro-Fuzzy Speed Controller for Marine Diesel Engines. Proc. FUZZ-IEEE, 7217-7224, Vancouver, Canada.

[3] D. Wu, W.W. Tan, “Genetic learning and performance evaluation of interval type-2 fuzzy logic controllers,” Engineering Applications of artificial Intelligence vol. 19, pp. 829-841, 2006.

[4] H., Hagras, “A type-2 fuzzy logic controller for autonomous mobile robots,” Proceedings of the IEEE International Conference on Fuzzy Systems, Budapest, Hungary, pp. 965-970, 2004.

[5] R. Martinez, O. Castillo, L. T.,Aguilar, “Optimization of interval type-2 fuzzy logic controllers for a perturbed autonomous wheeled mobile robot using genetic algorithms,” Journal of Information Sciences vol. 179 (13), pp. 2158-2174, June 2009.

[6] J. Cao, H. Liu, P. Li, D. Brown, “Adaptive Fuzzy Logic Controller for Vehicle Active Suspension with Interval Type-2 Fuzzy Membership Functions,” FUZZ-IEEE, Hong Kong, vol. 222, pp.1361-1373, 2008.

[7] M. Galluzzo, B. Cosenza, “Control of the biodegradation of mixed wastes in a continuous bioreactor by a type-2 fuzzy logic controller,” Computers & Chemical Engineering,vol.33 pp. 1475-1483, 2009.

[8] M. Galluzzo, B. Cosenza, “Control of a Non-isothermal CSTR by Type-2 Fuzzy logic Controllers,” Lecture notes in computer science (5571), pp. 295-302, 2009.

[9] N. N. Karnik, J. M. Mendel, “Operations on Type-2 Fuzzy Sets, Fuzzy Sets and Systems,” vol. 122, pp. 327-348, 2000.

[10] N. N. Karnik, J. M. Mendel, “Type-2 reduction,” Proceedings IEEE Conference of systems, man and Cybernetics, San diego, CA, vol. 10 2046-2051, 1998.

[11] R. Striezel, H. Töpfer, “Feedforward adaption to control processes in chemical engineering,”Proceeding of the IFAC Workshop, Frankfurt/Main, pp.115-120, 1985.

[12] R. K. Mudi, N. R.., Pal, “A self-tuning fuzzy PI controller,” vol. 115 (2), Fuzzy Sets and Systems 327-338, 2000.

[13] F. Lei, M. Rotboll, S.B. Jorgensen, “A biochemically structured model for Saccharomyces cerevisiae,” Journal of Biotechnology vol. 88, pp. 205-221, 2001.

[14] E. Postma, C. Verduyn, A. Scheffers, J. Van Dijken, “Enzimatic analysis of the Crabtree effect in glucose-limited chemostat cultures of Saccharomyces cerevisiae,” Appl. Env. Microbiol. vol. 55, 468-ì