The Egyption Int. J. of Eng. Sci. and Technology
Vol. 15 No. 1 (Jan. 2012)

EIJEST

A HYBRID NEURO -FUZZY (ANFIS) APPROACH TO THE CONTROL SYSTEM OF BENFIELD SOLUTION STAGE IN UREA PLANT*

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ABSTRACT

A nonlinear model for the chemical process Benfield Solution (B.S.) stage in urea plant system is presented .This stage in a closed loop chemical process to a chive certain range of values for the concentration of that (B.S.). Different types of controllers such as PID, fuzzy and Neuro-fuzzy are proposed to achieve the required performance. Comparison study was made to select the best controller from point of view of transient response parameters (over shoot percentage, settling time ,steady state error) . Therefore, the proposed design confirms the fact that fuzzy control is relevant to the fast control of non-linear processes such as system drives where quantitative methods are not always appropriate.

KEY WORDS: Fuzzy control, Neuro-Fuzzy Techniques, Adaptive Neuro-Fuzzy Inference system (ANFIS),Fuzzy Subtractive Clustering, Membership Functions. Benfield Solution (B.S.), PID Control.

UN HYBRIDE NEURO-FLOUE (ANFIS) APPROCHE DE LE SYSTÈME DE CONTRÔLE DE LA PHASE SOLUTION DANS BENFIELD USINE D'URÉE

RÉSUMÉ

Un modèle non linéaire pour le processus chimique de solutions Benfield (BS) dans le système phase usine d'urée est présente. Cette étape dans un procédé chimique en boucle fermée à une gamme de valeurs de ciboulette certaine pour la concentration de ce (BS). Différents types de contrôleurs tels que PID, logique floue et neuro-floue sont proposées pour atteindre les performances requises. Etude comparative a été faite pour sélectionner le meilleur contrôleur à partir du point de vue des paramètres de réponse transitoire (plus de pourcentage tournage, le temps de stabilisation, erreur en régime permanent). Par conséquent, la conception proposée confirme le fait que la commande floue est pertinent pour le contrôle rapide des processus non linéaires tels que les lecteurs du système où les méthodes quantitatives ne sont pas toujours approprié.

MOTS CLÉS: contrôle Fuzzy, neuro-flous Techniques, Adaptive système d'inférence neuro-floue (ANFIS), Fuzzy Clustering soustractif, fonctions d'appartenance. Benfield Solution (b.s.), le contrôle PID.

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* Received: 18 / 9 / 2011, Accepted: 25/ 12 / 201? (Original Paper)
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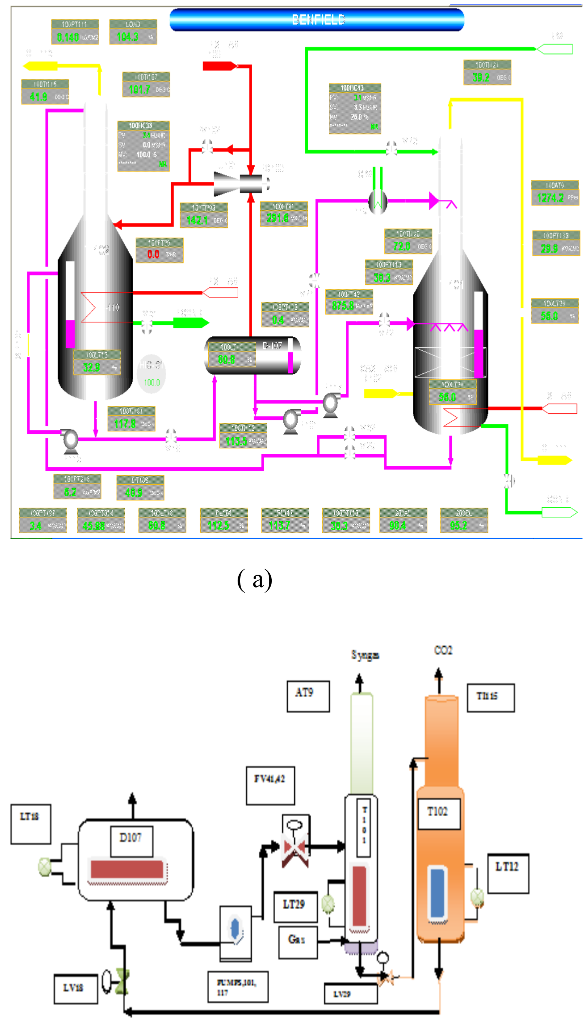
1-INTRODUCTION

In our presents Urea plant, some chemical processes is offered to the present system, in the stage of carbon dioxide removal, nature gas reforming and the singers shift conversion produce a large amount of carbon dioxide that shall be removed to make syngass suitable for Ammonia unit. A Benfield hot carbonate system is used for carbon dioxide removal and recovery as by - prooduct for use in Urea manufacture. Benfield solution. The Raw synthesized gas which contains carbon dioxide is reduced in the present system by the Benfield activated (potassium - carbonate solution) carbonate process. In the absorption at elevanted pressure, the Co_2 is removed (T102) by an aqueous solution of potassium carbonate .The present system under study is simplified as shown in Figure (1).Figure (1) illustrates the drum (D107),feeding Benfield solution through valve (18) from tower (T102) under the pressure system .The pumps(117&101) take from (D107) to (T101) through valves(41 &42) .The flow to (T 102) from (T101) through valves (29&62).The transmitters (29,12&18) measure the level in the tower (T101), tower (T102) and drum (D107) respectively[1] .In this paper we targeted to construct a simulation model of that system in order to develop a fuzzy logic controller instead of the PID controller conventionally used in Fertilizing industry and also new design controller for concentration of B.S.in tower (T102) .

Fuzzy logic design is not based on the mathematical model of the process. The controller designed using fuzzy logic implements human reasoning that has been programmed into fuzzy logic language (member ship function, rules and the rule interpretation). Closed loop control adding PI mode and select optimal parameters to minimize error between measured point and reference point is compared. Design of control systems using the classical s-plane methods is difficult for non experts because of the nature of the design methods which require iterations and visual inspection of the root locus. Expertise and experience often play a major role in a accomplishing a design [2]. Forming the design and building an operational real- time knowledge based system for process control [3].



(b)

Fig. 1: (a) A typical industrial diagram of (B.S) stage in urea plant ; (b) Schematic diagram of (B.S.) stage in urea plant

2. MODEL DEVELOPMENT

The industrial installation shown in Fig. 1 is more complicated because a number of effects are additionally interconnected in series. Examination of a typical installation, suggests that the configuration and parameter values may differ widely from one effect to another, but the form of the dynamic equations for each component of the system remains the same .The B.S process tends to exhibit long time delay and significant response time, due mainly to container numbers and their capacities, piping, flow ratio, local level controllers and heat transfer dynamics. Model order reduction can be obtained by assuming the action of local level controllers for the Benfield level effect allows neglecting the variations of the hold-up masses ,and developing the model relationships directly from mass balances . Consequently, the physical model consists of a number of linear and non linear differential equations and can be written as follows:

$$\dot{x}_1 = a_1 q_1(t) - a_2\sqrt{x_1}$$

$$\dot{x}_2 = a_3\sqrt{x_1} - a_4\sqrt{x_2} \qquad (1)$$

$$\dot{x}_3 = a_5\sqrt{x_2} - a_6\sqrt{x_3}$$

where
x_1 (t), is the level of the Benfield solution liquid in D (107), (m),
x_2(t), is the level of Benfield solution in the tower, (T101),(m).
x_3(t), is the level of Benfield solution in the tower (T102), (m).
q_1 (t), is the inlet flow, m^3/min.
According to the last equations (1), a Simulink model has been developed for B.S system. On the other hand, in order to carry out a performance comparison between the results of our case study and the results obtained by application of advanced control approaches, we adopted the same operating parameters

Table 1: Model parameters

symbol variable	value	unit
a1	0.02659	$1/m^2$
a2	0.1535	m/min
a3	0.60104	m/min
a4	0.6198	m/min
a5	0.o936	m/min
a6	0.09074	m/min

Table 1, shows the values of model parameters above list all the variables in the complete process model, and their nominal steady state values. In order to validate the developed model, whether all outputs variables take on the respective steady-state values when the inputs are given the nominal steady-state values, we replaced the imports by either Constant blocks or Step Input blocks, with the appropriate amplitudes. The correct steady state values of these parameters have been obtained after transients have finished. This leads to the following expressions can be obtained

This models (NLM) non linear model and linear model are obtained in detail in [5].The linear model can be obtained from the nonlinear model at the nominal steady state variables and can be rewritten inform transfer function as :

$$G_p(s) = \frac{H_3(s)}{Q_i(s)} = \frac{K_1 K_2 k_3}{(\tau_1 s+1)(\tau_2 s+1)(\tau_3 s+1)} \qquad (2)$$

where

$G_p(s)$, is the system transfer function model.The block diagram for this system can be represented as shown in Fig. 2.

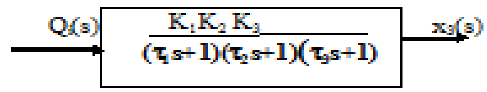


Fig. 2: Block diagram of the system

Taking in consideration the values of different parameter at normal operation this process transfer function can be written as:

$$G_p(s) = \frac{0.091}{15.543\,s^3 + 24.538\,s^2 + 9.558\,s + 1} \qquad (3)$$

Also we can be put in the form of state variable representation.

Table 1 model parameters

$$\dot{x} = Ax + Bu$$
$$y = CX + du$$

As the following

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -\frac{1}{\tau 1} & 0 & 0 \\ \frac{k2}{\tau 2} & -\frac{1}{\tau 2} & 0 \\ 0 & \frac{k3}{\tau 3} & -\frac{1}{\tau 3} \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} + \begin{bmatrix} \frac{k_1}{\tau_1} \\ 0 \\ 0 \end{bmatrix} Q_i(t) \qquad (4)$$

Where the matrix A can be obtained and the matrix B

$$A = \begin{bmatrix} -0.3534 & 0 & 0 \\ 1.3789 & -1.0526 & 0 \\ 0 & 0.15928 & -0.17322 \end{bmatrix} \qquad (5)$$

$$B = \begin{bmatrix} 0.02661 \\ 0 \\ 0 \end{bmatrix} \qquad (6)$$

$$Y = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} \qquad (7)$$

Where the matrix C:

$$\begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$$

3. CONVENTION CONTROL

The PID controller may be implemented in continuous or discrete time, in a number of controller structures. The ideal continuous time PID controller is expressed in Laplace form as follows:

$$G_C(s) = K_C\left(1 + \frac{1}{T_I s} + T_D s\right)$$

with K_c = proportional gain, T_i = integral time constant and T_d = derivative time constant. If $T_i = \infty$ and $T_d = 0$ (i.e. P control), then the closed loop measured value will always be less than the desired value for processes without an integrator term, as a positive error is necessary to keep the measured value constant, and less than the desired value. The introduction of integral action facilitates the achievement of equality between the measured value and the desired value, as a constant error produces an increasing controller output.

The introduction of derivative action means that changes in the desired value may be anticipated, and thus an appropriate correction may be added prior to the actual change. Thus, in simplified terms, the PID controller allows contributions from present, past and future controller inputs. In many cases, the design of PID controllers for delayed processes is based on methods that were originally used for the controller design of delay-free processes. However, there is general agreement that PID controllers are not well suited for the control of dominant delay processes. It has been suggested that the PID implementation is recommended for the control of processes of low to medium order, with small delays, when controller parameter setting must be done using tuning rules and when controller synthesis may be performed a number of times (Isermann 1989). [22].Ziegler-Nichols method (the process reaction method) is used for tanning PI (proportional gain, 78.66 and integral time constant, 26.66, s) controller, also trial and error method for these parameters is used.

4. FUZZY LOGIC CONTROLLER OF THE SYSTEM METHODOLOGY

4-1 Design Steps of Fuzzy Controller (FC) of Present System

The general fuzzy logic controller design procedures consist of the following steps [8, 9, 10, 14, 15, 16]:

1) **Definition** of the inputs and outputs (linguistic variables), in terms of fuzzy sets, the number of linguistic labels, and the respective membership functions for each labels.
2) **Construction** of fuzzy control rules based upon the knowledge and experience of process operation.
3) **Selection** of the model of fuzzy inference system FIS (e.g. Mamdani, Sugeno .. Types); and the compositional rule of inference (e.g. Min-Max method)
4) **Choosing** the method of defuzzification (e.g., COG , MOM ..) , i.e., transformation of the fuzzy control statement into specific control actions since the controlled process takes only crisp values as inputs . In this section, the design procedures of fuzzy PI controller for the present system, based on Fuzzy Inference System FIS- Editor in MATLAB7.0.4 / Simulink , is discussed . Conceptually , FLC can be derived from the original classical (proportional - integral differential) PID mathematical model [11, 12]:

$$\mathbf{u(t)=K_P\, e(t)+K_i \int e(t)dt + K_d\, de/dt} \qquad \mathbf{(8)}$$

$$\mathbf{u(k) =K_P\, e(k)+K_i\, \Sigma e(m) + K_d\, \Delta e(k),\ m = 0,..,k} \qquad \mathbf{(9)}$$

The increment of the output signal is:

$$\mathbf{\Delta u(k)=u(k)-u(k-1)} \qquad \mathbf{(10)}$$

$$\mathbf{\Delta u(k) = K_P\, \Delta e(k)+K_i\, e(k)+ K_d\Delta_2\, e(k)} \qquad \mathbf{(11)}$$

Depending on the choice made in the design phase we can have different types of FLCs: P, PI, PD, or PID.

In our (system) the FC is a two-input single-output PI-fuzzy controller:

$$\mathbf{\Delta U_S(k)=K_P\Delta E_c(k)+K_iE_c(k)} \qquad \mathbf{(12)}$$

The inputs of the FC are: Ec(k) the Benfield level error which is given by :

$$\mathbf{E_c(k)=h_{ref.}(k)-h(k)} \qquad \mathbf{(13)}$$

where $h_{ref.}$(k) is the level set- point , h (k) is the actual Benfield level at sample k .
The second input signal is $\Delta E_c(k)$ the change of Benfield level error :

$$\mathbf{\Delta E_c(k)=E_c(k)-E_c(k-1),} \qquad \mathbf{(14)}$$

The output of the fuzzy control part is the the incremental control action

$$\mathbf{\Delta U_S(k)=U_S(k)-U_S(k-1)\ ,} \qquad \mathbf{(15)}$$

Finally, we have (*Us*) signal as integrated control action which will be imposed on the level valve . The input and output membership functions (labels: NEGATIVE, POSITIVE) for the E_c , ΔE_c , and (labels : NEGATIVE , ZERO , POSITIVE)for ΔU_S.Using the aforementioned membership functions, the following control rules are established for the fuzzy logic control part:

(R1) If $E_c(k)$ is NEG AND $\Delta E_c(k)$ is NEG Then ΔU_S (k) is NEG.
(R2) If $E_c(k)$ is NEG AND $\Delta E_c(k)$ is POS Then ΔU_S (k) is ZERO.
(R3) If $E_c(k)$ is POS AND Δ $E_c(k)$ is NEG Then ΔU_S (k) is ZERO.
(R4) If $E_c(k)$ is POS AND $\Delta E_c(k)$ is POS Then ΔU_S (k) is POS.
The formulation of these rules can be understood as follows: For Rule 1 (R1): if we look at this rule for the controller, condition $E_c(k)$ (the error is negative) implies that the system's output, h(k), is above the reference $h_{ref.}(k)$, and Δ $E_c(k)$ (rate of error negative) implies h(k)>0 (meaning that the controller at the previous step is driving the system output upward, leaving the reference). Hence, we set $\Delta U_S(k)$ to negative to turn the motion of the stem valve around to the opposite direction. Similarly, for Rule 2 (R2), since the output is above the reference but moving downwards, we set term ΔU_S (k) = 0 (no control action is needed in this case since the output trajectory is moving toward the reference) .Rules 3 and 4 are similarly determined. The final step in the fuzzy logic controller design is to combine the fuzzy outputs into a crisp output. The commonly used Center of gravity "COG" formula is employed to defuzzify the incremental control ΔUS (k) of the fuzzy logic part:

$$\Delta Us_{COG} = \frac{\int_{us} \mu_A(u_s).u_s.du_s}{\int_{us} \mu_A(u_s).du_s} \qquad (16)$$

where the finally tuned values of the scaling factors , associated to each variable are used . The scaling factors enable the use of normalized universes of discourse in the [-1, 0, +1] domain, and play a role similar to that of the gain coefficient in conventional controllers [10, 13]. For more details of FC tuning, see [16].
In our study the Mamdani type of FIS, and Min-Max method for the rule evaluation process, were selected. Fig. (3) shows a Fuzzy Feedback Control System

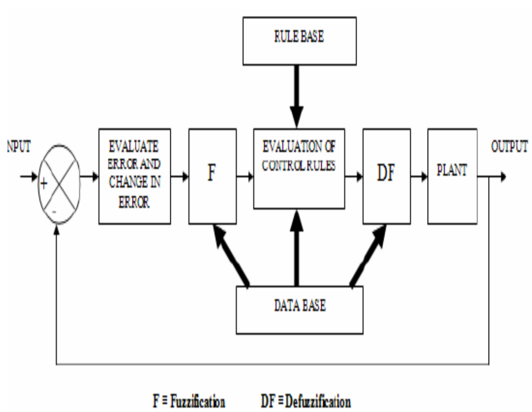


Figure 3: General Structure of a Fuzzy Feedback Control System

4.2. Fuzzy Logic Controller of System Using ANFIS Methodology

The fuzzy logic controller provides an algorithm, which converts the linguistic control, based on expert knowledge into an automatic control strategy [14]. [Therefore, the fuzzy logic algorithm is much closer in spirit to human thinking than traditional logical systems [6, 15]. The main problem with fuzzy logic controller generation is related to the choice of the regulator parameters [12]. For this reason, we apply the ANFIS methodology to adapt the parameters of the fuzzy controller according to real data about the system [13, 23].
Two control applications that require system for success and make use of hierarchical architecture of the control system are described and the control result is provided.

Using the GENFIS2 function (which is based on the subtractive clustering algorithm in the SUBCLUST function) in mat lab, we generate a fuzzy inference system that calculates the output based on the actual data for {Δe, e} for control inputs B.S. level. Actual data are given in Table(2)

4.2.1. Takagi-Sugeno controller for the B.S stage level

Sugeno-type fuzzy inference system was generated using subtractive clustering in the form:

$$e \text{ is } A_i \text{ and } de \text{ is } B_i \quad \text{then } u = p_i e + q_i de + r_i,\ i=1, ... \qquad (17)$$

where *e* is the control error, *de* is the derivation of the control error, *u* is the calculated control and p_i, q_i, r_i are consequent parameters[4,6]. The symmetric Gaussian function (gaussmf in MATLAB) was chosen as the membership function and it depends on two parameters σ and *c* as it is seen in (18)

$$f(x;\sigma,c) = e^{\frac{-(x-c)^2}{2\sigma^2}} \qquad (18)$$

where c, σ are the center and the width of the Gaussian function respectively. The parameters σ and *c* for gauss mf are listed in Table 3. For obtaining of these parameters, it was necessary to have the data sets of *e*, *de* and *u* at first. These data were obtained as in Table (2) by simulation of PID control of the system.

The consequent parameters in the control input rule (17) are listed in Table 4 and the resulting plot of the output surface of a described fuzzy inference system is presented in Fig. 4.

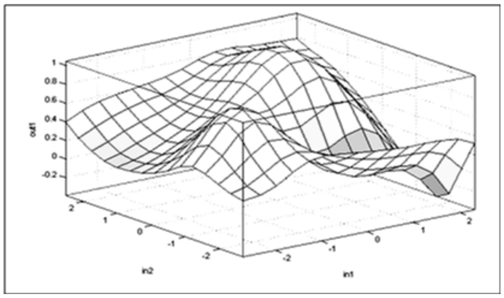


Fig. 4. Takagi-Sugeno controller - control signal *u* *(out)* as function of control error *e(*in1*)* and its derivation *De*.(in^2) .

***Table 2 Experimental error e, derivative Δe and* control action u**

e	0.66	-.08	0.27	-0.69	1.82	1.67	2.32	-0.22	-2.7	-2.5	-0.8	-0.08
Δe	0.59	-0.74	0.35	-0.96	2.51	-0.18	0.65	-2.54	-2.64	0.2	1.7	0.72
u	4.02	4.8	5.9	5.89	6.36	4.4	2.08	4.4	2.08	1.71	2.9	3.42

Table3: Parameters of the Gaussian curve membership function

e		Δ e	
σi	ci	σi	ci
0.8874	0.66	0.9192	-2.69
0.8874	-0.69	0.9192	-0.96
0.8874	-0.86	0.9192	1.7
0.8874	-2.77	0.9192	-2.69
0.8874	1.82	0.9192	2.51
0.8874	-0.22	0.9192	2.89
0.8874	-2.5	0.9192	0.2
0.8874	2.32	0.9192	0.62

Table 4: Consequent parameters

Pi	qi	ri
0	0	1.497
-1.013	0	-0.157
0	0.24	0
-0.06346	0	0
0	0.2906	0
0	-0.2026	0
-0.0148	0	0
-0.2667	0.4995	0

Figure 5(a ,b, c, d) (a)shows the FIS Editor is the fuzzy design tool ,(b) :Membership functions of Benfield level error e inputs with 8 Gaussian fuzzy sets, (c)Fuzzy Rules Viewer and (d) Fuzzy Logic Controller Surface. For inputs (e, Δe) numbers of rules (8) as mentioned and for using N-F to obtain adaptive rules (4) for actual data of (e, Δe) .Using the block diagram of fuzzy logic (eg=5 , u_g= 5) based on the simulated models of the (B.S) and FLC, obtained in previous sections a complete fuzzy control FCS for system was developed .The simulation is conducted using MATLAB SIMULINK AND FUZZY LOGIC TOOLBOX Figure 6 presents the simulation results of (FLC)

of B.S level .These results are compared with those obtained by PID control of B.S level**.**

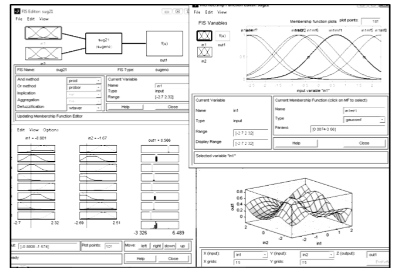


**Fig. 5: (a) The FIS Editor is the fuzzy design tool
(b) Membership functions of Benfield level error E_C ,
(c) Fuzzy Rules Viewer
(d) Fuzzy Logic Controller Surface**

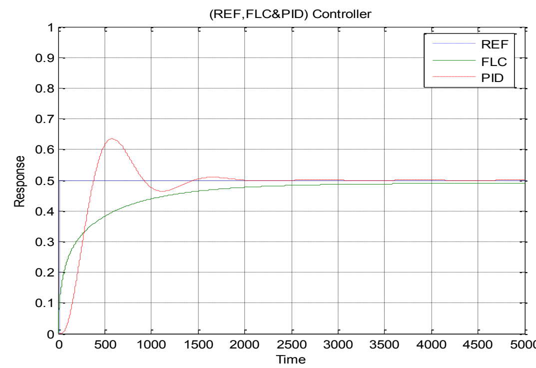


Fig.6 Comparison of the B.S system control, (FLC) fuzzy control, PID control, reference trajectory.

4.2.2 Fuzzy logic controller of the system using ANFIS methodology

We apply the ANFIS methodology to adapt the parameters of the fuzzy controller according to real data about the System as in Table (2). This method is described in [7].

4.2.2.1 ANFIS architecture

The ANFIS neuro fuzzy controller was implemented by Jang (1993) and employs aTakagi – Sugeno-Kang (TSK) fuzzy inference system. The basic ANFIS architecture is shown in Figure 7. Square nodes in the ANFIS structure denote

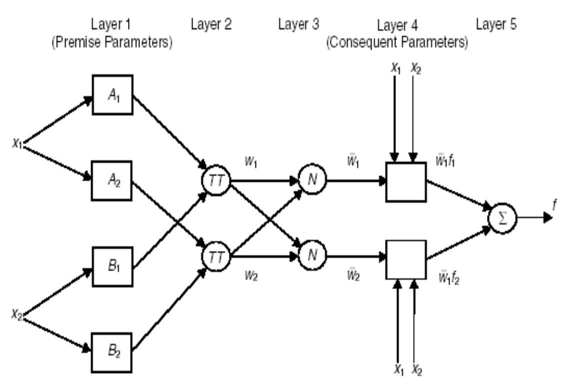


Fig. 7: Adaptation network based fuzzy inference system (ANFIS) architecture (after Graven)

parameter sets of the membership functions of the TSK fuzzy system. Circular nodes are static / non – modifiable and perform operations such as product or max/min calculations. A hybrid learning rule is used to accelerate parameter adaption. This uses sequential least squares in the forward pass to establish the premise parameters.If the fuzzy inference system has inputs x1 and x2 and output F as shown in Fig. 7, then a first – order TSK rule base might be

Rule 1: If $x_1$is A_1 and $x_2$is B_1 then

$$f_1 = p_1 x_1 + q_2 x_2 + r_1$$

Rule2: if $x_1$is $A_2$and $x_2$is B_2 then

$$f_2 = p_2 x_1 + q_2 x_2 + r_2$$

Rule n: If $x_1$is A_n and x_2 is B_n

$$f_n = p_n x_1 + q_n x_2 + r_n \tag{19}$$

Where A_1…….A_n, B_1……B_n are membership functions and P_1…..P_n, q_1……..q_n and r_1…..r_n are constants within the consequent functions.

Layer 1 contains adaptive nodes that require suitable premise membership functions (triangular, trapezoidal, bell etc). Henc

$$y_{1,i} = \mu_{8i}(x_i) \tag{20}$$

Layer2 undertakes a product or T-norm operation.

$$y_{2,i} = w_i = \mu_{Ai}(x_1)\mu_{Bi}(x_2)..\mu_{pi}(x_n) i = 1,2...n \tag{21}$$

Layer 3 calculates the ratio of the firing strength of

$$y_{3,i} = \overline{w_i} = \frac{w_i}{\sum_{i=1}^{n} wi} \tag{22}$$

Layer 4 generates the linear consequent functions as given in equation (19).

Layer 5 sums all incoming signals

$$y_{5,i} = f = \sum_{i=1}^{n} \bar{w_i} fi = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i} \tag{23}$$

Limitation of the ANFIS technique is that it cannot be employed on multivariable systems. The Coactive (CANFIS) developed by Craven (1999) extends the ANFIS architecture to provide a flexible multivariable control environment **The linguistic control rules are established consi**dering the dynamic behavior of the system drive and analyzing the error and its variation. These control rules are expressed as follows:

If Error is LP and Change Error is LP then output drive= p1 × Error + q1 × Change Error + r1
If Error is LP and Change Error is MP then output drive = p2 × Error + q2 × Change Error+ r2, . .

This is a Surgeon fuzzy model for controlling our system. We used the ANFIS methodology to estimate the parameters of the membership functions and the consequent functions. We used a fuzzy model of four rules and two membership functions for each linguistic variable. This was the fuzzy controller that gave the best results. In Fig. 8a we show the non-linear surface of the fuzzy model. In Fig. 8b we show Fuzzy rule viewer for calculating the output of the fuzzy system for specific values. The parameters of the membership functions and the consequent functions are obtained. We show in Fig. 9a the architecture of the fuzzy system with the ANFIS approach. The fuzzy rules generated by the ANFIS method are shown in Fig 9b. These rules are generated automatically with the ANFIS method. We also show in Fig. 9 c the membership functions generated automatically by ANFIS. Fig.9d shows ANFIS architecture showing the inputs (e, Δe) and outputs (u) of the system .Table 5 shows consequent parameters (pi, qi, ri**)**.

Table 5: Consequent parameters

pi	qi	ri
7.83	-8.519	-1.75
-5.222	-3.749	4.096
0.699	9.11	3.981
-0.678	1.932	-3.178

Fig. 10 presents the simulation results of the ANFIS control of the present system .These results are compared with those obtained by fuzzy control (FLC) and PID control of the (B.S.) level. Figure 11shows the error response of the three cases and the comparison with them. The root mean square error (RMSE) comparison between three cases in range of time tabulated as in Table 6.

Table 6: Comparison between (FLC, ANFIS &PID) Controllers

Control method	RMSE	Steady state error	Over shot%
FLC	0.0340	0.09	-18
ANFIS	0.0324	0.0039	-0.78
PID	0.0468	0.1267	25.3

Comparing the statistic data with 4 curves tabulated as in Table **7.**

Table 7: Statistical data of (PID,FLC &ANF) controllers

	ERF.	PID	FLC	ANF
MAX	0.5	0.627	0.49	0.496
MEAN	0.496	0.4918	0.4784	0.4837
MEDIAN	0.5	0.5	0.49	0.496
STD	0.0369	0.0659	0.0421	0.0448
RANGE	0.5	0.6207	0.49	0.961

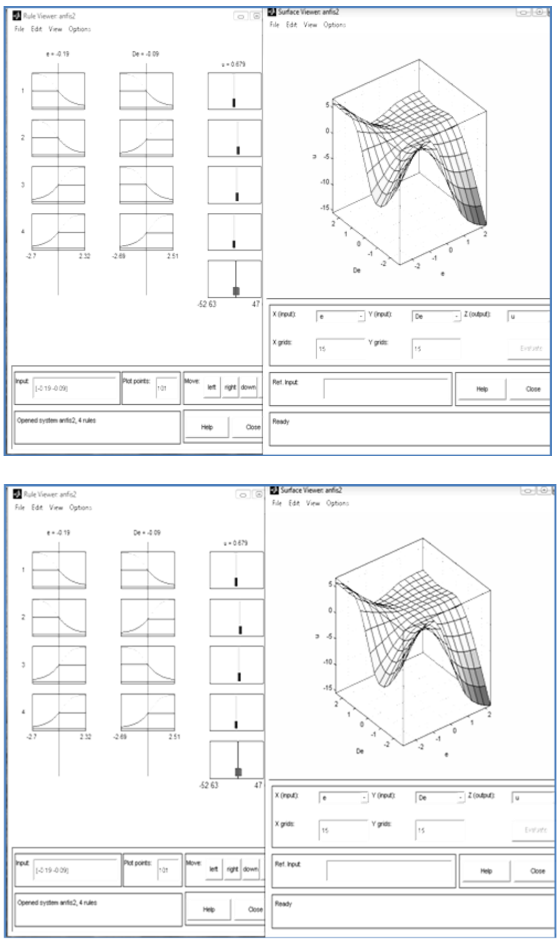


Fig. 8. (a):Non-linear surface of the Sugeno fuzzy model (b): Fuzzy rule viewer for calculating the output of the fuzzy system for specific values.

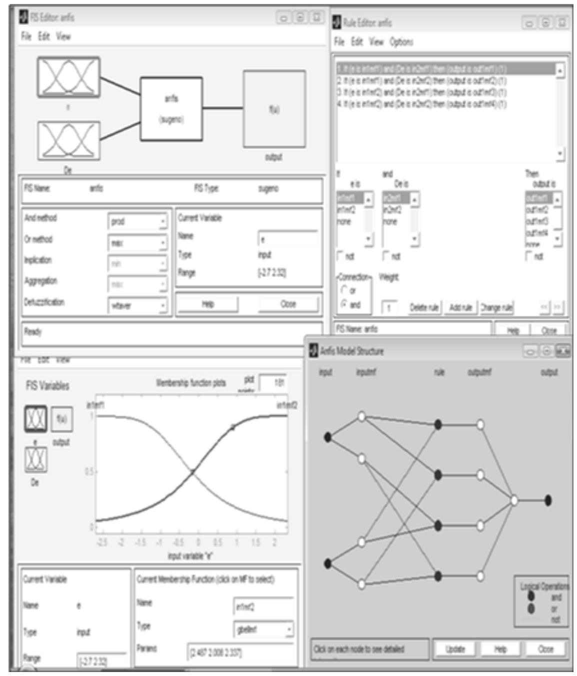


Fig. 9: (a):Architecture of the Sugeno fuzzy system with the ANFIS approach, (b):Fuzzy rules generated by the ANFIS method, (c): Membership functions generated by the ANFIS method, (d): ANFIS architecture showing the inputs (e, ∆e) and outputs (u) of the system

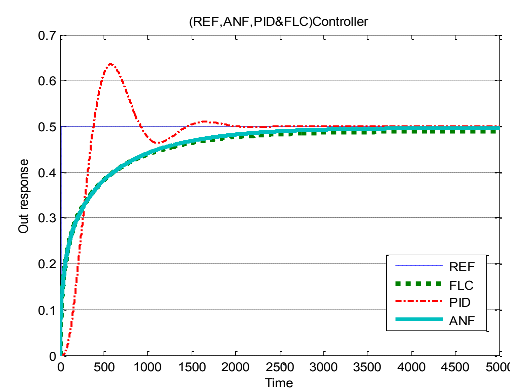


Fig. 10 Comparison of B.S level control

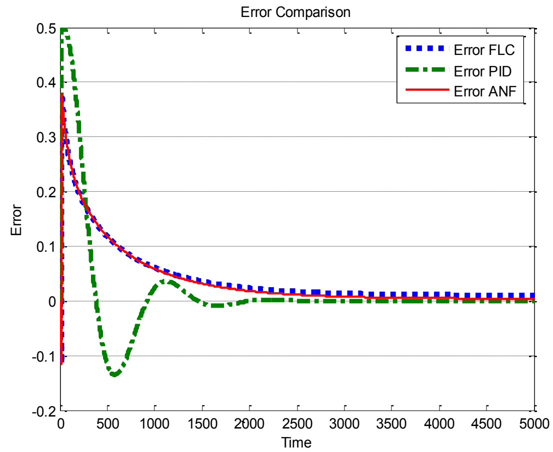


Fig. 11: Error responses of three cases

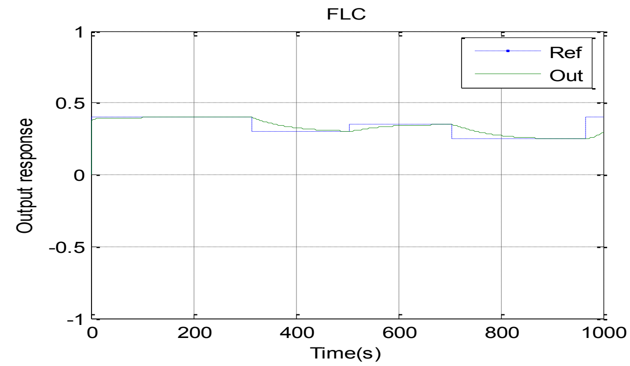


Fig.12 Output response at different point

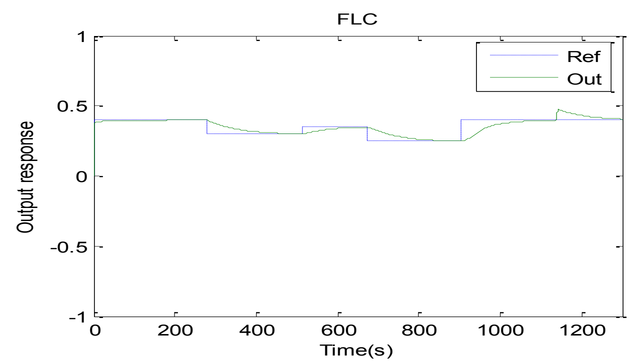


Fig.13 FLC due to reference point load disturbance

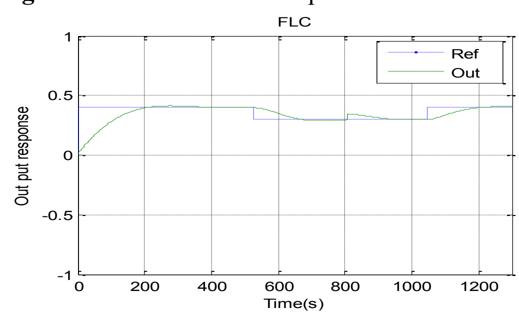


Fig.14 Response due to change in reference point

5. RESULTS

There are three major benefits of the (B.S) control system: the energy saving, disturbances rejection, and robustness. These benefits are mainly achieved by reducing overshoot and recovering time after disturbances. In our (system), the overall control objective was to regulate the Benfield level at 30% at the outlet of the effect with constant flow rates in the absence or presence of disturbances. Particularly, Benfield level is to be controlled by adjusting the steam flow rate incoming the first effect (co2). Based on the simulated models of the B.S and the FLC, obtained in previous sections, a complete fuzzy control system FCS for system was developed. The simulation is conducted using MATLAB7.0.4/Simulink and Fuzzy Logic Toolbox .Figure 2 shows the general structure of a fuzzy feedback control system. The transient process of our system have been obtained and analyzed as follows:

1-Investigating the system (NLM) due to change in set point (step) (.24, 0.2) is obtained .Figure 12 shows the output response at different points (t1=300, t2=500, t3=700 and t4=870 s) and change in reference point (0.3, 0.35, 0.25 and 0.4). Change (in2= 0.24 to 0.29 load disturbance), Figure 13 shows the (FLC) due to reference point (step, change at t, 300, 500, 700and 800). Figure 14 shows the response due to change (in2= 0.01, 0.04) and change in step 0.4, 0.3 and 0.4

2-Change set point (0.3, 0.45 , 0.35) and during change concentration from(0.01, 0.06 i. e. 20% are performed .Figure 15shows the response of the system due to FLC . change [in4, 0.01 , 0.03 ,0.02 (0.2604 at t, 427s)],[in3 , 0.08, 0.1 (0.375 at t, 621s),0.02(0.24,at t, 759s)and change set point (0.35 , 0.25 and 0.4). Figure 16 shows the output response tracking reference point

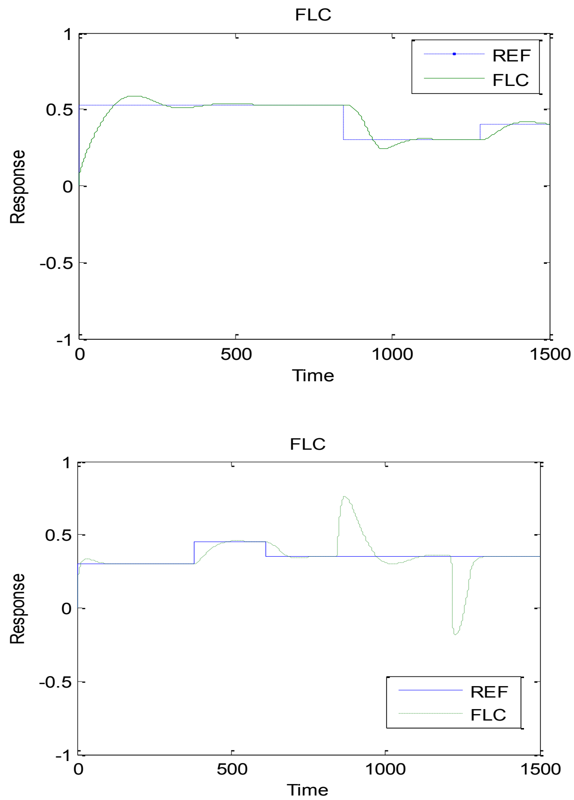


Fig. 15 Response of the system due to FLC

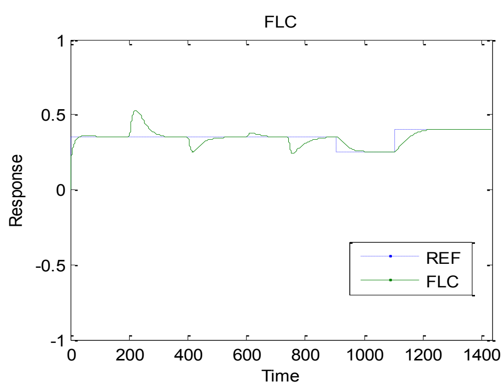


Fig. 16 Output response tracking reference point

3-The simulink immplemention of the linear model system is obtained with PID controller (proporational ,2 and integral,0.6 . Block diagram of the Fuzzy Logic with gains eg=1.8 , Deg=4 and ug =56.Figure 17 shows the comparison with PID controller and FLC (19 rules , step change , 0.3 , 0.38 and 0.34 at different time (t1,200,t2,300and t3,400). Fig. 18 shows the performance of the system (ReF, FLC , PI controllers).

4- Beside above in our (system), the overall control objective was to regulate the Benfield level at 38% at the outlet of the effect with constant flow rates in the absence or presence of disturbances. Particularly, Benfield level is to be controlled by adjusting the steam flow rate incoming the first effect (co2 –T102).

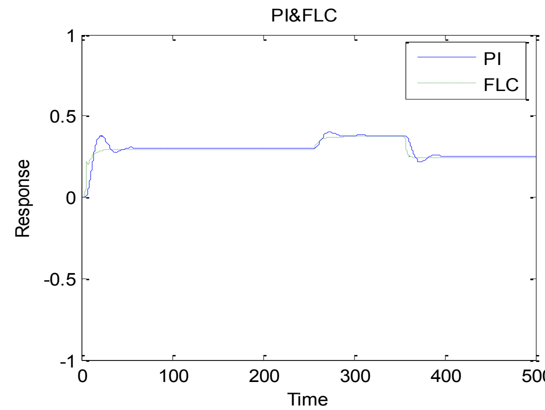


Fig. 17 Comparison with PID controller and FLC

Figure 19 presents the simulation results of the ANFIS control of the present system. These results are compared with those presents the simulation results of the ANFIS control of the present system. These results are compared with those obtained by fuzzy control (FLC) and (PIC) control of the B.S level. Figure 20 shows the error response of the three cases and the comparison with them. The root mean square error (RMSE) comparison between three cases in range of time tabulated as:

TYPE	RMSE
FLC	0.0624
ANFIS	0.0275
PID	0.0648

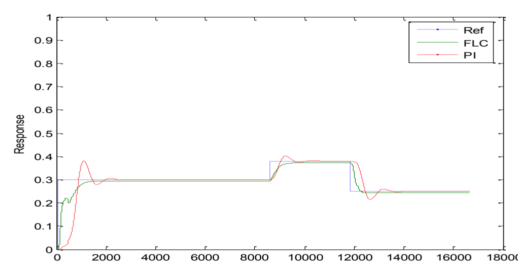


Fig 18 Comparison of the B.S system control, (FLC) fuzzy control, PID control, reference trajectory

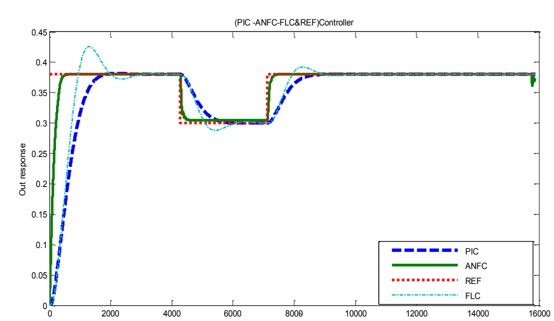
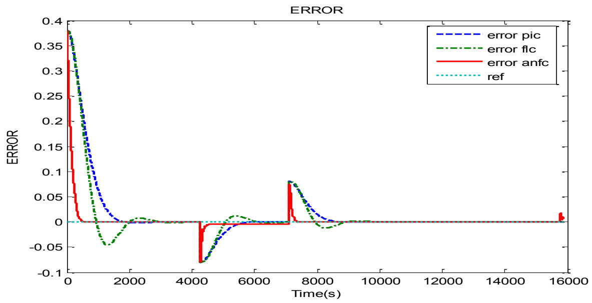


Fig. 1 9 Comparison of the B.S level control: ANFIS control , fuzzy control , PIC control , reference trajectory



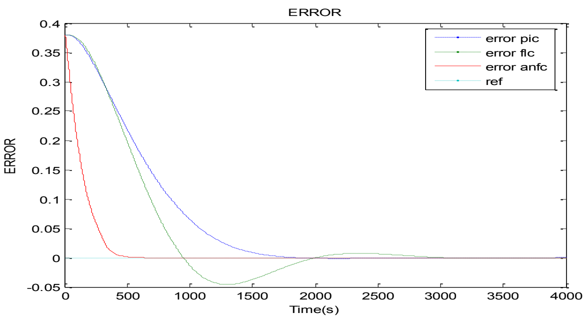


Fig. 20 Error responses of the three cases

6. CONCLUSIONS

In this paper, the powerful aspects of artificial intelligence techniques applications in industry have been investigated. In this paper, where we presented different types of controllers for the concentration of Benfield solution in Urea plant. The results reported here indicate, that from, neuro-fuzzy controller and PID controller, neuro fuzzy control scheme shows the best performance. It also compares results with a classical PID controller and with a fuzzy Mamdani controller, to measure how much the adaptive fuzzy approach could improve the performance. Of course, our fuzzy controller (designed with ANFIS) was better in tracking and adaptability than the other controllers. Another advantage of this method over classical quantitative controllers is that it does not require a fixed sampling time. Therefore, the proposed design confirms the fact that fuzzy control is relevant to the control fast of non-linear processes such as system drives where quantitative methods are not always appropriate.

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