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NON-LINEAR MODEL OF CO_2 REMOVAL THROUGH BENFIELD STAGE IN UREA PLANT SYSTEM*

Gamal M. Samy[1+], Mohamed A-k Soliman[2], and Magdy O. Tantawy[3]

(1) Gas Plant, Fertilizer Co., Semadco Talkha, Mansoura, Egypt
(2) Computers & Systems Eng. Dept., Faculty of Engineering, Zagazig, Egypt
(3) Comm. Dept., Modern Academy for Eng. and Technology, Egypt

ABSTRACT

A nonlinear model for Practical study of fluid system that includes Benfield Solution (B.S.) in urea plant system is presented .The present work measures the practical values of the quantity and level of B.S. inside different containers of the process and study the dynamic behavior of that process by constructing a deterministic, lumped, parametric, continuous time model using transfer function and state space. This model is used to design a suitable control system. The experimental studies beside the theoretical analysis are carried with proper results. Adaptive neural network based fuzzy inference system (ANFIS) as an intelligent neuro -fuzzy technique used for modeling system and a given practical training data set is partitioned into a set of clusters based on subtractive clustering method.

KEY WORDS: Mathematical Model, Nonlinear System (NL). Linear System (LN).Fuzzy model, Neuro-Fuzzy Model, Adaptive Neuro-Fuzzy Inference System (ANFIS), Fuzzy Subtractive Clustering Model, Benfield Solution (B.S.)

NON MODELE LINEAIRE DE L'ELIMINATION DU CO2 PAR L'ETAPE BENFIELD DANS LE SYSTÈME USINE D'UREE

RÉSUMÉ

Un modèle non linéaire pour l'étude pratique du système fluide qui comprend Benfield Solution (BS) dans le système usine d'urée est présenté. Le présent travail mesure la valeur pratique de la quantité et le niveau de BS l'intérieur des conteneurs différents du processus et étudier le comportement dynamique de ce processus, en construisant un déterministe, regroupées, paramétrique, modèle en temps continu en utilisant la fonction de transfert et de l'espace d'état. Ce modèle est utilisé pour concevoir un système de contrôle approprié. Les études expérimentales à côté de l'analyse théorique sont réalisées avec des résultats corrects. Adaptive réseau neuronal système d'inférence floue (ANFIS) comme une intelligente neuro-flous technique utilisée pour le système de modélisation et une formation pratique donnée ensemble des données est partitionné en un ensemble de clusters basés sur la méthode de clustering soustractive.

MOTS-CLES : modèle mathématique, système non linéaire (NL). Système linéaire (LN). Modèle flou, neuro-flous modèle, Adaptive système d'inférence neuro-flous (ANFIS), Fuzzy modèle de clustering soustractive, Benfield Solution (BS)

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+ Contact author (+20 123525351)

1. INTRODUCTION

Building a model of any physical system or process is an essential tool for analysis and design of the appropriate controller. Most modern models use a purely mathematical representation of the behavior of the process to be analyzed. A mathematical model of the system is a description of its structure and its internal and external functional relationships. A mathematical model consists of a combination of algebraic and differential equations that express the physical laws which describe performance characteristics of equipment obtained from experimental data. A mathematical modeling is needed to design a control system. The designed control system will guarantee that the operational objectives of the process are satisfied in presence of every day changing disturbances. The mathematical models can provide the control designer with a complete description of how the process reacts to various inputs. On the other hand, if it is needed to study and improve the already built control system or study a certain functional properties of the dynamics for any chemical process, then simulation methods can be considered.[2, 3, 4,5,6]

Conventional process control systems utilize linear dynamic models. For highly nonlinear systems, control techniques directly based on nonlinear models can be expected to provide significantly improved performance [7, 8].Industrial processes generate a lot of information for operators. The operators have many measurements to observe and control at the same time. This can be helped by combining the knowledge. Clustering (see e.g. [9] and [10]) is one of the methods for combination, because the information is saved in databases and it is available. Industrial processes are usually highly non-linear and it is very difficult or impossible to make accurate models with conventional modeling techniques.

A neuro fuzzy approach for a given set of input-output training data is proposed in two phases. Firstly, the data set is partitioned automatically into a set of clusters. Then a fuzzy if-then rule is extracted from each cluster to form a fuzzy rule base. Secondly, a fuzzy neural network is constructed accordingly and parameters are tuned to increase the precision of the fuzzy rule base. This network is able to learn and optimize the rule base of a Sugeno like Fuzzy inference system using hybrid learning algorithm, which combines gradient descent, and least mean square algorithm. This proposed neuro fuzzy system has the advantage of determining the number of rules automatically and also reduce the number of rules, decrease computational time, learns faster and consumes less memory [11].The fusion of neural networks and fuzzy logic in neuro fuzzy models provide learning as well as readability. Control engineers find this useful, because the models can be interpreted and supplemented by process operator [12]. The present system as shown in (Fig. 1), consists of drum (107), feeding Benfield Solution through valve (18) from tower (102) under the pressure system. The pumps(17&01) take from D(107) to T(101) through Fv(41) &(42) .The flow to T(02) from T(101) through valves (29&62) ,the transmitter (29) measures the level in the tower (101), and transmitter (18) measures the level in D(107) [1] .Some chemical processes ,the stage of creating Benfield solution (Potassium-carbonate solution),a Benfield hot carbonate system is used for carbon dioxide removal and recovery as by - product for use in Urea manufacture

[2NH3+ $CO_2 \longleftarrow$ H2NCONH2 (Urea) +H2O]

2. DESCRIPTION OF THE SYSTEM

In Urea plant where CO_2 removal is given in (Fig. 2). A model of chemical processes is presented for the stage of carbon dioxide removal ,nature gas reforming and the syngas shift conversion where a large amount of carbon dioxide need to be removed to make syngss suitable for Ammonia unit . A Benfield hot carbonate system is used for carbon dioxide removal and recovery as by - product for use in Urea manufacture. The Raw synthesis gas which contains carbon dioxide is reduced in the present system by the Benfield activated (potassium - carbonate solution) carbonate process. In the absorption at elevated pressure, the CO_2 is removed by an aqueous solution of potassium carbonate. The present system under studding as shown in (Fig. 1) is simplified as drum D (107), feeding

Benfield solution through valve (18) from another tower (T102) under the pressure the pumps (101, 117) pumps the fluid to absorption tower, T (101) through valves (41, 42). The transmitter (29) measures the level in the absorption tower, T (101), and the transmitter (18) measures the level in D (107). [3]

D (107)

A1 = Cross - section area, (ft2)
Cv = Valve coefficient,
7.98 = Conversion factor gal to ft3.

T (101)

A2 = Cross - Section area, (ft2)
0.283 = conversion factor ft3 to m3.

T (102)

A3 = Cross - Section area, (ft2)

0.283 = conversion factor ft3 to m3

FV41

Normal Flow. Q = 360 m3 / hr
Cv = 274
Pressure drop Δ p = 7.17 kg/cm2, at normal flow
S. G, Specific gravity
S. G. = 1.246

FV 42

Q = 110 m3/hr
C_V = 504
Δ P = 7.49 (kg/cm2)
S.G. = 1.246

LV 29

Inlet Pressure = 30 kg/cm2
Cv = 480
S.G. = 1.26
Δ P = 25 kg/cm2 at normal flow

HV 62

Q = 250 m3/hr
Inlet pressure = 30 kg/cm2 at normal flow
Δ P = 30 kg/cm2
Cv = 124
S.G. = 1.26

3. MODELS OF THE SYSTEM

3.1 Mathematical Model

Modeling of the industrial processes usually starts with a balance on a conserved quantity: mass or energy. This balance is being written as: [2]

[Rate of mass /energy (into process)] - [Rate of mass /energy (out of process)] = Rate of accumulation of mass / energy in process.(1)

This balance and all other auxiliary equations, is covering – almost- all the domains of the engineering, such as thermodynamics, heat transfer, fluid flow, mass transfer, reaction engineering, etc .This makes the modeling of industrial processes most interesting and challenging. First the balance on a conserved quantity mass using the measurement recording and experience of operation, can be study the change of flow in the system as in Fig. 1.

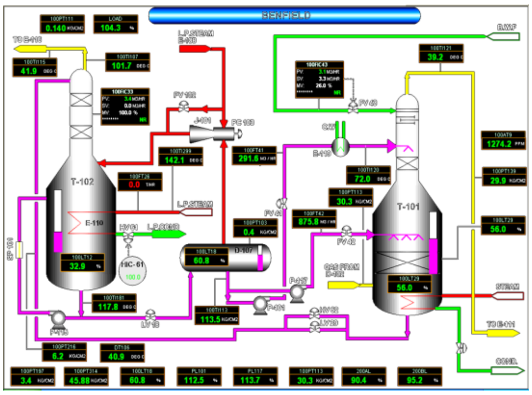


Fig. 1-a: A typical diagram of B.S. stage.

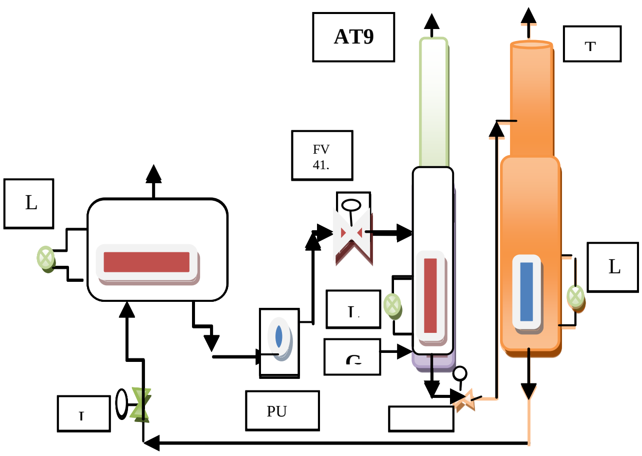


Fig. 1-b: Schematic diagram of present system.

An unsteady state mass balance around the drum, D (107) gives

$$\rho q_i(t) - \rho q_1(t) = \rho A_1 \frac{dh_1(t)}{dt} \qquad \textbf{(2)}$$

where:

ρ, is the density of Benfield solution (ib_m/ft^3)

h_1 (t), is the level of the Benfield solution liquid, (ft), its Laplace transform is $H_1(s)$

q_i (t), is the inlet flow, ft^3/min., its Laplace transform is $Q_i(s)$.

A_1 is a cross section area of D (107), (ft^2).

Providing the equation for the flow of liquid through the valves is given by

$$q_1(t) = C'_{v_1}\sqrt{h_1(t)}$$

$$C'_{v_1} = \frac{C_{v_1}}{7.48}\sqrt{\frac{\Delta p_1}{G}}$$

$$\Delta p_1\{t\} = p + \frac{pgh_1(t)}{144 g_c} + P_2 \quad (3)$$

where:

C_{v_1}, is the valve coefficient, [gal/min./$\sqrt{psi}$, where psi (Libra/inc^2)]

G, is the specific gravity of liquid flowing through valve, dimensionless.

ΔP_1, is the normal pressure drop a cross the valve, (kg/cm^2)

Eq.s. (2, 3) describe the input and output flow through the drum, D (107).

By the same method the unsteady-state balance of the flow through the tower T (101) is given by.

$$\rho q_1(t) - \rho q_2(t) = \rho A_2 \frac{dh_2(t)}{dt} \quad (4)$$

where:

A_2, is the a cross section area of T (101) in (ft^2)

Again the valve expression provides another equation:

$$q_2(t) = C'_{v_2}\sqrt{h_2(t)} \quad (5)$$

$$C'_{v_2} = \frac{C_{v_2}}{7.48}\sqrt{\frac{\Delta p_2}{G}}$$

$h_2(t)$, is the level of Benfield solution in the tower, (ft).

C_{v_2}, is the valve coefficient for valve (29), gal/min./$\sqrt{psi}$

Δp_2 is the normal pressure drop for valve (29), (kg/cm^2**).**

$$q_i(t) - C'_{v_1}\sqrt{h_1(t)} = A_2 \frac{dh_1(t)}{dt} \quad (6)$$

$$C'_{v_1}\sqrt{h_1(t)} - C_{v_2}\sqrt{h_2(t)} = A_2 \frac{dh_2(t)}{dt} \quad (7)$$

Also an unsteady- state balance around third tower (T102) gives

$$\rho q_3(t) - \rho q_i(t) = \rho A_3 \frac{dh3(t)}{dt} \quad (8)$$

$$q_i(t) = C'_{v1}\sqrt{h_3(t)}$$

where

$c'_{v1}(t) = c'_{v3}$, Say

$= 26.53$ m^3/min

$h_3(t)$, is the level of Benfield solution in the tower(T102), (ft). By the same way used for equations(2,4) Equation (8) can be written as:

$$C_{v2}\sqrt{h_2(t)} - C'_{v3}\sqrt{h_3(t)} = A_3 \frac{dh_3(t)}{dt} \quad (9)$$

Equations (2) through (9) describe the system process. These equations must be linearized to determine the transfer function. Substituting Eqs. (3 , 5) into Eqs. (4 , 2) and dividing by density yields.

The parameters of the system to be estimated at the normal values of operation and after calculations can be written as**:**

$A_1 = 37.6$ m^2

$C'_{v_1} = 26.53$ m^3 / min

$$C_1 = \frac{1}{2}C'_{v_1}\left(\bar{h}_1\right)^{-\frac{1}{2}}$$

$$= \frac{1}{2} * 26.53 * 1$$

$$= 13.27 \quad m^2 / min$$

$$\tau_1 = \frac{A_1}{C_1} = \frac{37.6}{13.27} = 2.83 \quad (min)$$

$A_2 = 9.6$ m^2

$C^{`}_{v_2}$ = from specifiction of (HV 62, LV 29)

$C^{*}_{v_2} = 38.48 \qquad m^3/\min$

$C_2 = \frac{1}{2} C^{*}_{v_2} \left(\vec{h}_2\right)^{-\frac{1}{2}}$

$= 10.13 \qquad m^2/\min$

$\tau_2 = \frac{A_2}{C_2} = \frac{9.6}{10.13} = 0.95 \qquad (\min)$

$K_1 = \frac{1}{C_1} = \frac{1}{13.27} = 0.0753 \qquad m.\min/m^3$

$K_2 = \frac{C_1}{C_2} = \frac{13.27}{10.13} = 1.31 \qquad \text{dim}\,ensionless$

$c_3 = \frac{1}{2} C^{*}_{v_1} \left(\bar{h}_3\right)^{-\frac{1}{2}}$

$= \frac{1}{2} * 26.53 * (1.45)^{-1/2}$

$= 11.016 \qquad m^2/\min$

$\tau_3 = \frac{A3}{C3} = \frac{63.59}{11.016} = 5.773 \qquad (\min)$

$A_3 = 63.59 \qquad m^2$

$k_3 = \frac{c_2}{c_3} = 10.13/11.016 = 0.9195$

The analytical solutions of these equations are not possible because of the nonlinear nature of the second term on the left-hand side of the equation. Fig. (2) shows a block diagram of the non-linear model. The only way to solve this equation analytically is to linearize the nonlinear term. The only other way to solve Eqs. (6, 7 and 9) are by numerical methods (computer solution).Equations (6 , 7 and 9) describe nonlinear system (put x_1=h_1, x_2=h_2 and x_3=h_3) and we can be obtained this form:

$$A_1 \frac{dx_1}{dt} = -f_1(x_1)\sqrt{x_1} + q_1(t)$$

$$A_2 \frac{dx_2}{dt} = -f_2(x_2)\sqrt{x_2} + f_1(x_1)\sqrt{x_1}$$

$$A_3 \frac{dx_3}{dt} = -f_2(x_2)\sqrt{x_2} - f_3(x_3)\sqrt{x_3}$$

Where

$f_1(x_1) = c^{/}_{v_1}$, $\qquad f_1(x_2) = c^{/}_{v_2}$ and

$f_1(x_3) = c^{/}_{v_3}$

We can put in this form

$$A_1 \frac{dx_1}{dt} = -f^{\backslash}_1(x_1) + q_1(t)$$

$$A_2 \frac{dx_2}{dt} = -f^{\backslash}_2(x_2) + f^{\backslash}_1(x_1)$$

$$A_3 \frac{dx_3}{dt} = f^{\backslash}_2(x_2) - f^{\backslash}_3(x_3)$$

Where

$$f^{\backslash}_1(x_1) = f_1(x_1)\sqrt{x_1}$$

$$f^{\backslash}_1(x_1) = f_2(x_2)\sqrt{x_2}$$

$$f^{\backslash}_3(x_3) = f_3(x_3)\sqrt{x_3}$$

we can put in this form

$$\dot{x} = Ax + Bu$$

$$y = CX + du$$

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -\frac{1}{A_1} f^{\backslash}_1(x_1) \\ -\frac{1}{A_2} f^{/}_2(x_2) + \frac{1}{A_2} f^{'}_1(x_1) \\ \frac{1}{A_3} f^{\backslash}_2(x_2) - \frac{1}{A_3} f^{\backslash}_3(x_3) \end{bmatrix} + \begin{bmatrix} \frac{1}{A_1} q_1(t) \\ 0 \\ 0 \end{bmatrix} = \qquad (9a)$$

$$\begin{bmatrix} -\frac{1}{A_1} & 0 & 0 \\ \frac{1}{A_2} & -\frac{1}{A_2} & 0 \\ 0 & \frac{1}{A_3} & -\frac{1}{A_3} \end{bmatrix} \begin{bmatrix} f^{\backslash}_1(x_1) \\ f^{\backslash}_2(x_2) \\ f^{\backslash}_3(x_3) \end{bmatrix} + \begin{bmatrix} \frac{1}{A_1} \\ 0 \\ 0 \end{bmatrix} q_1(t)$$

where

y=CX
=

$$\begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix}$$

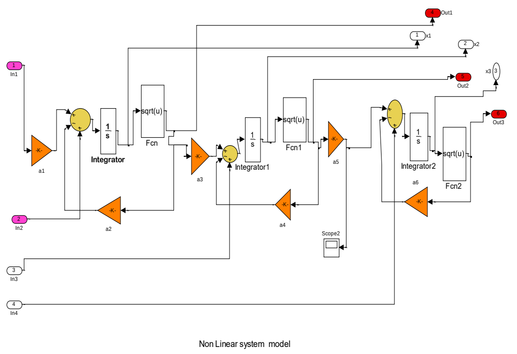


Fig. 2: Block diagram of non linear model.

3.2 Linearization of the model

The linear model can be obtained from the nonlinear model as follows:

Eq. (6) can be rewritten as :

$$Q_i(t) - C_1 H_1(t) = \frac{A_1 \, d\, H_1}{d\, t} \qquad (10)$$

where

$$C_1 = \left.\frac{\partial q_1}{\partial h_1(t)}\right|_{\text{at steady state}} = \frac{1}{2} C_{v_1}^{\cdot} \frac{1}{\sqrt{\vec{h}_1}}$$

and the deviating variables

$$Q_i(t) = q_i(t) - \bar{q}_i$$
$$Q_o(t) = q_o(t) - \bar{q}_o$$

$$H_1(t) = h_1(t) - \vec{h}_1$$

where bar symbol indicates the nominal steady state variables

Also Eq. (7) can be rewritten as :

$$C_1 H_1(t) - C_2 H_2(t) = A_2 \frac{dH_2(t)}{dt} \qquad (11)$$

where

$$C_2 = \left.\frac{\partial q_2(t)}{\partial h_2^{(t)}}\right|_{\text{at steady state}} = \frac{1}{2} C_{v_2}^{\cdot} / \sqrt{\vec{h}_2}$$

and

$$H_2(t) = h_2(t) - \bar{h}_2$$

From Eqs. (10 , 11) we get.

$$\frac{A_1}{C_1}\frac{dH_1(t)}{dt} + H_1(t) = \frac{1}{C_1} Q_i(t) \qquad (12)$$

and

$$\frac{A_2}{C_2}\frac{d\, H_2(t)}{dt} + H_2(t) = \frac{C_1}{C_2} H_1(t) \qquad (13)$$

rearranging Eqs. (12, 13) yields

$$\tau_1 \frac{dH_1(t)}{dt} + H_1(t) = K_1\, Q_i(t) \qquad (14)$$

and

$$\tau_2 \frac{dH_2(t)}{dt} + H_2(t) = K_2 H_1(t) \qquad (15)$$

and also from Eq. (9) we can write

$$\tau_3 \frac{dH_3(t)}{dt} + H_3(t) = K_3 H_2(t) \qquad (16)$$

where

$K_1 = \frac{1}{C_1}$ (m.min/m^3).

$K_2 = \frac{C_1}{C_2}$ (dimensionless)

$\tau_1 = \frac{A_1}{C_1}$ (Minutes)

$\tau_2 = \frac{A_2}{C_2}$ (Minutes)

$\tau_3 = \frac{A_3}{C_3}$ (Minutes)

$K_3 = \frac{C_2}{C_3}$

K_1, K_2, k3 are the process gain

Taking the Laplcae transform of Eqs. (10, 11) and rearranging, therefore,

$$H_1(s) = \frac{k_1}{\tau_1 \; s+1} Q_i(s) \quad (17)$$

$$H_2(s) = \frac{k_2}{\tau_2 \; s+1} H_1(s) \quad (18)$$

From Eqs. (14, 15)and (16) in the same form the desired transfer function can be get

$$H_3(s) = \frac{K_1 K_2 \, k_3}{(\tau_1 \, s+1)(\tau_2 \, s+1)(\tau_3 \, s+1)} Q_i(s) \quad (19)$$

which can be written as:

$$G_p(s) = \frac{H_3(s)}{Q_i(s)} = \frac{K_1 K_2 \, k_3}{(\tau_1 s+1)(\tau_2 s+1)(\tau_3 s+1)} \quad (20)$$

where

$G_p(s)$, is the system transfer function model.The block diagram for this system can be represented as shown in Fig. 3

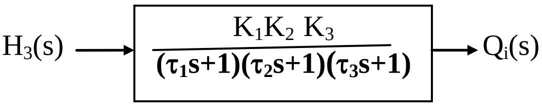


Fig. 3: Block diagram of the system

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

$$G_p(s) = \frac{0.091}{15.543 s^3 + 24.538 s^2 + 9.558 s \; +1} \quad (21)$$

Also Eqs. (14, 15and 16) can be put in the form of state variable representation.

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

As the following

$$\begin{bmatrix} \dot{H}1 \\ \dot{H}2 \\ \dot{H}3 \end{bmatrix} = \begin{bmatrix} -\frac{1}{\tau 1} & 0 & 0 \\ \frac{k2}{\tau 2} & -\frac{1}{\tau 2} & 0 \\ 0 & \frac{k3}{\tau 3} & -\frac{1}{\tau 3} \end{bmatrix} \begin{bmatrix} H1 \\ H2 \\ H3 \end{bmatrix} + \begin{bmatrix} \frac{k_1}{\tau_1} \\ 0 \\ 0 \end{bmatrix} Q_i(t) \quad (22)$$

where the matrix A can be obtained and the matrix B

$$A = \begin{bmatrix} -0.3534 & 0 & 0 \\ 1.3789 & -1.0526 & 0 \\ 0 & 0.15928 & -0.17322 \end{bmatrix} \quad (23)$$

$$B = \begin{bmatrix} 0.02661 \\ 0 \\ 0 \end{bmatrix} \quad (24)$$

$$Y=CX= \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x1 \\ x2 \\ x3 \end{bmatrix} \quad (25)$$

where the matrix C2 is:

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

The state variable of the present system described by equations (22, 23, 24, and 25) can be implemented using MATLAB7.0.4/Simulink as shown Fig. 4. Investigating the system response to known behavior of this system as linear and nonlinear model for different types of forcing function as step function[in1 ,square with amplitude 0.1, in2=0.01, in3=0.38and in4=0.01as in Fig. 2] is given in Fig. 5 (a) and (b) .Fig. 6 shows the output response of linear system and nonlinear system response**.** Fig. 7 shows the output response of linear system (a) (the linear system is stable only for a limited value of K) and nonlinear system response (b). Comparison of these models with RMSE (the root mean square error of the system) is obtained for LN model (RMSE=0.2794) and NL model (RMSE=0.294).The formula of RMSE is given as:

$$RMSE = \sqrt{\frac{\sum_{K=1}^{N}(y_r - y(k))^2}{N}} \qquad (26)$$

where e is the usual error (i.e., yr – y), yr is the reference, y is the actual output and N is the number of the sample,

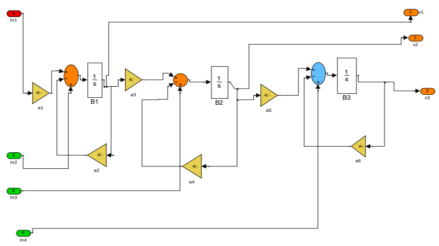
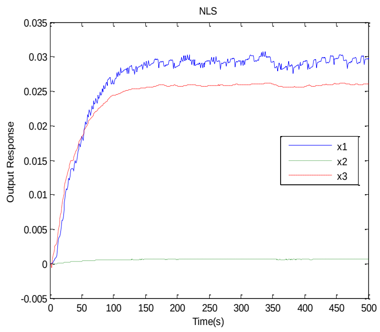
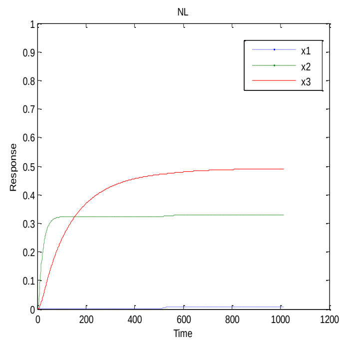


Fig. 4: Block diagram of linear model.



(a)



(b)

Fig. 5: Process outputs to step input

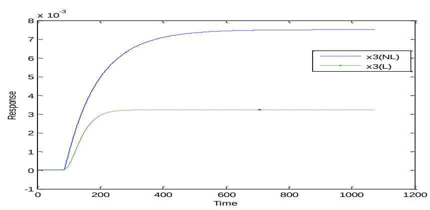
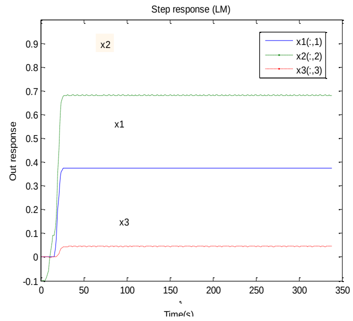
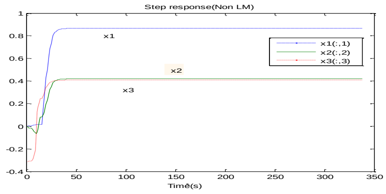


Fig. 6: Output response of linear system and nonlinear system response.



(a)



(b)

Fig. 7: (a) Output response of linear system, (b) nonlinear system response.

3.3 Fuzzy Model

Fuzzy clustering methods can be used in modeling, identification and pattern recognition. Several objective functions used for Takagi-Sugeno model identification, usually minimized by fuzzy clustering methods. The decision of the number of the clusters is perhaps the most critical point in fuzzy clustering. Many methods have been introduced for the selection of the clusters, see e.g. [13] and [14].Subtractive clustering, [Chi94], is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data. The cluster estimates obtained from the subclust function can be used to initialize iterative optimization-based clustering methods (fcm) fuzzy clustering method and model identification methods. The subclust function finds the clusters by using the subtractive clustering method. The genfis2 function in MATLAB builds upon the subclust function to provide a fast, one-pass method to take input-output training data and generate a Sugeno-type fuzzy inference system that models the data behavior. The genfis2 function generates a model from data using clustering, and requires you to specify a cluster radius. The cluster radius indicates the range of influence of a cluster when you consider the data space as a unit hyper cube. Specifying a small cluster radius will usually yield many small clusters in the data, (resulting in many rules). Specifying a large cluster radius will usually yield a few large clusters in the data, (resulting in fewer rules). The genfis2 function using a cluster radius of 0.2 and 0.3. The variable (RMSE) is the root mean square error of the system generated by the training data. To validate the model, we apply test data to the FIS (fuzzy inference system).

3.4 Neuro-Fuzzy Model

In order to design a neuro-fuzzy model the ANFIS (Adaptive Neuro Fuzzy Inference System) is used (Sugeno, 1985). In the first stage fuzzy inference system is generated using fuzzy subtractive clustering and accomplishes by extracting a set of rules that models the data behavior. Second stage then uses linear least squares estimation to determine each rule's consequent equations. Tuning of parameters is performed using hybrid learning algorithm. For the consequent parameters training, the least squares method is used, because the output of the ANFIS is a linear combination of the consequent parameters. The ANFIS structure has first order Sugeno model structure. Gaussian and triangular membership functions with product inference rule are use at the fuzzyfication level. Each of 7 network inputs is defined with 2 membership functions.[15,16,17]

4. PRACTICAL RESULTS

In this work , we mainly present the process of building the soft sensing model of CO_2 absorption from syngas (AT9) or level (LT12) of Benfield solution (B.S) in T(102) (concentration of this fuel),as shown in Fig.1 . The variables of the plant are:
AT9(500 2000) ppm or(.o5 % 0.2%) CO_2 absorption in tower(T101) ,T181 (115c^0 120 c^0) temperature of B.S ,LT12 (15% 45%) B.S level in tower (T1o2), T115 (35 c^0 45 c^0) the temperature in the reactor (TEMP), LT18 (53% 65%) B.S level in drum (D107), LT29 (45% 60%) B.S level in tower (T101) and loads of pumps .According to the analysis of technological mechanisms, the CO_2 (AT9) or B.S (LT12) is related to these 7, (5) variables, which can be measured and recorded.

Y (k) = f (T115 (k), T181 (k), pl01 (k), p117 (k), ------) (27)

Where y (k) represent the quantity of CO_2 ratio in syngas at outlet of tower (T101) and f (-) is the complex multivariable non linear function. The task is to find the relationship between (CO_2), AT9 (absorption from syngas) and the selected (7 or 5) variables so that we can predict the (AT9) estimation value of CO_2 or level of (B.S.) LT12in tower (T102) on line .The source of data acquisition is the process data, which are recorded and collected from the DCS (distributed control system) system and the corresponding daily laboratory analysis. An amount of (125) samples of data each variable has been collected, (100) samples used for training and about (25) samples used for test. Using clustering method and ANFIS method, we built soft sensing models. Fig. 8 shows predicted values of the fuzzy model due to fuzzy model (FM), neuro- fuzzy model (ANFM) compared against the real values of (B.S.) level (show the concentration of this solution). Comparison of these models with RMSE is represented in Table (1). From Table (1) we learn that the ANFM method has the best generation results of these methods and at the same time in both RMSE and rules. The results obtained by neuro-fuzzy network is shown on Fig. 8 with RMSE= 0.3031 which is remarkably improvement .Fig. 9 shows the difference between the real values of (B.S.) level in data test and the estimated signals due to fuzzy model (FM &ANFM) in different variables. Fig. 10 also shows the results of CO_2 (AT9) on ANFIS model, FM model and measured value (actual data). Fig. 11 shows the difference between the estimated values due to fuzzy model (FM) and neuro fuzzy model (ANFM) of CO_2.

Fig. 12 shows the comparison between the real values of (CO_2- ppm-part per million) in data test and the estimated signals due to fuzzy model (FM &ANFM) .Fig. 13 shows the difference between real data test and the estimated values in data test due to fuzzy model (FM) and neuro fuzzy model (ANFM) of CO_2. The results obtained by neuro-fuzzy network is shown on Fig. 10 with RMSE= 0.3031 which is a remarkable improvement.

Table (1): Model comparison for practical application

Model	Radius	RMSE	RULES
FM1-7VARIABLES INPUT	0.2	0.935	5
FM2-7VARIABLES INPUT	0.3	0.3583	12
ANFM-7VARIABLES INPUT	-	0.3031	13

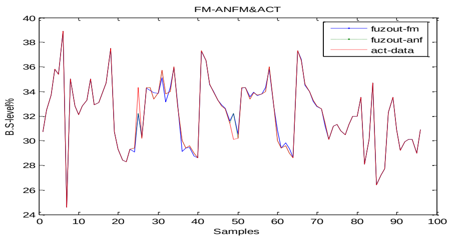


Fig. 8: Predicted values of the fuzzy model compared with the real values.

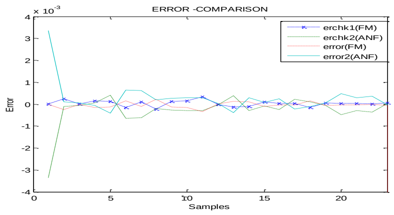


Fig. 9: Differences between real and estimated signal of (B .S.) level.

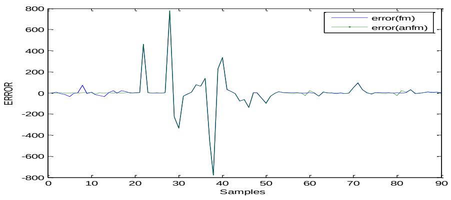


Fig. 11: Differences between real and estimated signal of CO_2.

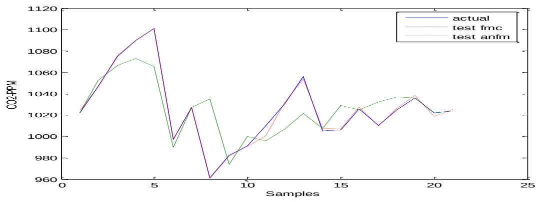


Fig. 12: Comparison between measured and estimated data test(CO_2) for neuro-fuzzy model and (FM)

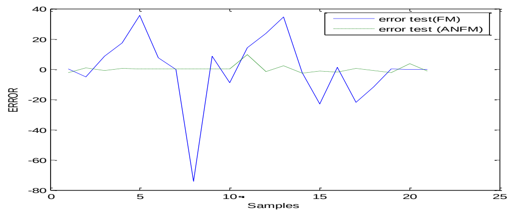


Fig. 13 differences between the real test data (CO_2) and the estimated signal of CO_2.

5. CONCLUSION

In the present work a model for CO_2 removal through Benfield stage in Urea plant system is build. Construction and operation of such a model is not mentioned in references. This work deals with formulation and construction of a suitable mathematical model (Benfield solution) that can be used to design a suitable control system. Moreover, the derived model of B.S. may be serving as a basic simulated model for analysis and design of advanced control strategies for that system. The results obtained illustrates that the product quality estimated based on neuro fuzzy system completely satisfies the requirement of B.S level (concentration) and (CO_2) measurement using the method proposed in this paper, we also built a tool for estimation of CO_2 in the process. Comparison between these two models is represented in Table 2 we learn that the proposed method (ANFIS) has better generation than the other method (FM).

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