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In-Line Mixing on Concentration Control Using Computed Multi-Variable Neural Networks Based Techniques

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Abstract: In-line mixing problems affected by controlled variables, such as conductivity, pH, viscosity which strongly depends on complementary physical variables disturbances, such as temperature and pressure variations are appropriate candidates to be solved using neural network model-based functional approximation techniques. The aim for this type of non-linear control problems is to compute the proportions of input product flow rates yielding a final product, thus satisfying as much physical properties as manipulated input flow rates exists in a considered plant. The core of the contribution is a functional approximation approach implemented on the basis of back propagation neural networks associated to the proposed control design strategies (CVFFC and CVFBC).

Key words: Computed variable control, conjugate gradient algorithm, feedforward control, in-line mixer, feedforward neural networks, fletcher-river algorithm, functional approximation

INTRODUCTION

Background: One interesting extension of conventional control was the idea of controlling the variables that are of real interest by computing its values from auxiliary measurements (Luyben, 1990). Traditionally, some mixing problems were solved successfully by means of conventional computational methods and means. With the help of existing computational methods (Andrasik *et al*., 2004) much more complex types of computed variables can now be calculated. Several variables of a process can be measured and all the other variables can be calculated from a rigorous model of the process or from virtual sensors based on soft-computing techniques. For instance, the nearness of flooding in distillation columns can be calculated from heat input, feed flow rate and temperature and pressure data. Another application is the calculation of product purities in a distillation column from measurements of several tray temperatures and flow rates by the use of mass and energy balances, physical property data and vapour-liquid equilibrium information.

The use of available and sophisticated computational methods made these rigorous estimators feasible (Hagan *et al*., 1996). It opens up a number of interesting possibilities in the control field without limitations in applying such powerful methods, even with the scarcity of engineers who understand both control and chemical engineering processes well enough to apply them effectively.

A typical class of mixing problems involve linear models, such the problem of thermal mixing where the problem is to control the temperature of an output flow from a tank by proportioning the input flow into the tank or the problem of concentration mixing where two fluids of different concentrations are mixed to produce a desired concentration by varying the input flow rate. In both cases, the material and energy-balance equations are the basis of process modelling.

Some other mixing problems are not linear, such those problems involving temperature, pressure, viscosity, conductivity, pH or composition among others. For instance, the liquids used in hydraulic systems generally exhibit large changes in viscosity with relativity small changes in temperature. The relative changes in viscosity per degree is called the temperature coefficient of viscosity C_T being defined as:

$$C_T = \frac{d\mu}{\mu dT} \tag{1}$$

Where:
T = Actual temperature
μ = Absolute viscosity

Pressurized liquids tend to increase viscosity where this phenomenon is particular evident in oils. At low or moderate pressure, this increase is relatively small but at high pressures, the viscosity increases quite rapidly

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(Stern *et al*., 1958). The exponential relationship between viscosity and pressure is given by an expression of the form:

$$\mu = \mu_0 e^{\alpha P} \tag{2}$$

Where:

α = Pressure coefficient of viscosity
μ_0 = Viscosity at atmospheric pressure
μ = Viscosity at pressure P

Equation 2 is actually only a rough approximation, since the pressure coefficient α is not a constant but is dependent on pressure, temperature and type of liquid (liquid components). Because of this rough approximation, precision control problems require another alternative modelling method.

Continuous mixing control problem: Since, agitated vessels are expensive, simple devices, such as in-line mixers are often considered for composition control systems. Properly applied, these devices are effective but careful attention to the following design criteria is required: Reagent delivery hysteresis, loop gain and neutralization stage interaction (Hoyle and McMillan, 1995). An in-line mixer can be a dynamic mixer, such as a centrifugal pump or a baffled section of pipe called a static mixer as shown in Fig. 1. The static mixer provides radial mixing but little backmixing. It can be considered to be a plug flow process dominated by dead time. Disturbances and noise pass through the mixer unattenuated. With such a mixer, the best controller response to fast disturbance and noise is no response at all because any corrective action will arrive too late and will create yet another disturbance. The advantages of in-line mixers are its small dead time, loop period and recovery time. Conventionally, control structures based in the combination of feedback, feedforward, cascade and ratio control are used.

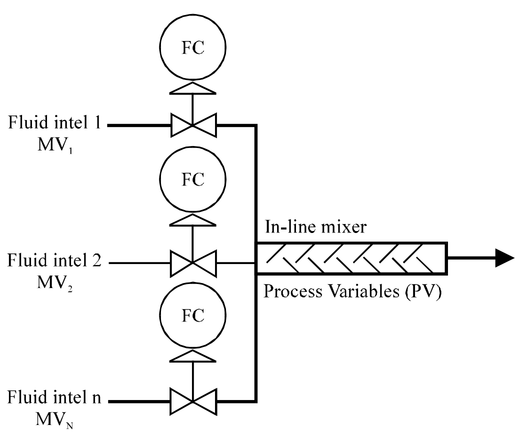

Fig. 1: Continuous mixer structure

The mixer exhibits certain pure time delay due to the inherent transport lag. This time lag D is described as the linear function of fluid flow rate q, the net cross section of the pipe A and the length of pipe L from the control valves to the end of mixer which in time domain yields:

$$D = \frac{L.A}{q} \tag{3}$$

So that the inherent time lag is e^{-DS} expressed in complex variable domain or Laplace transform domain. The research carried out describes the proposed control strategies for a continuous in-line mixer/reactor designed to optimise the fast chemical reactions required in many of today's chemical processes. It allows development and manufacture of nanomaterials in a process controlled to the molecular level of mixing. In most conventional chemical reactors, inadequate mixing and mass-transfer rates limit the value and performance of a fast chemical reaction. As a result, product yields are low and unwanted by-products are produced.

Overcoming the following drawbacks is the aim of this analysis:

- Avoiding the effect of time lags on feedback control which suppose an important disturbance on mixing control loop
- Simplification of the conventional control structures

Computed multivariable control strategies: In order to overcome the drawbacks mentioned in past section, the following model based computing multivariable control strategies are proposed, developed and experimentally validated or tested.

- Computed variable Feedforward-Cascade Control (FFC)
- Computed variable Estimated Feedback Control (EFC)
- Computed variable Feedback Control (FBC)

FFC consists in compute the manipulated variables, as function of the desired controlled variables and input process variables. EFC consists in estimate the process variables to be applied on a feedback control mode. FBC consists in measure the process variables to be applied on a feedback control mode.

In order to show the control strategy based in the computed variable modes, a process consisting in mixing a fluid at different flows and temperatures to achieve a desired temperature and flow as process variable output is described. The basic and necessary physical equipment to implement an in-line mixer (Fig. 2). The following notation is used in the in-line mixer process in Fig. 2:

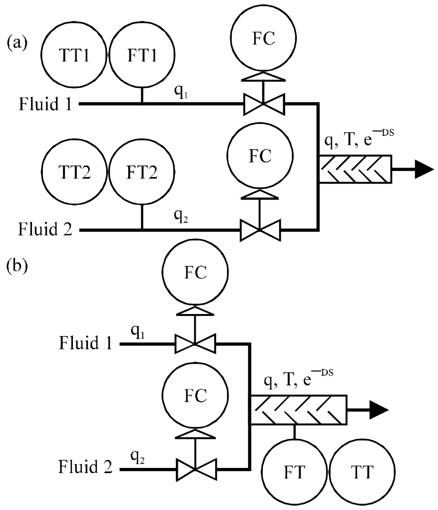

Fig. 2: In-line mixer and control equipment: a) Computed variable FFC and EFC; b) Computed variable FBC

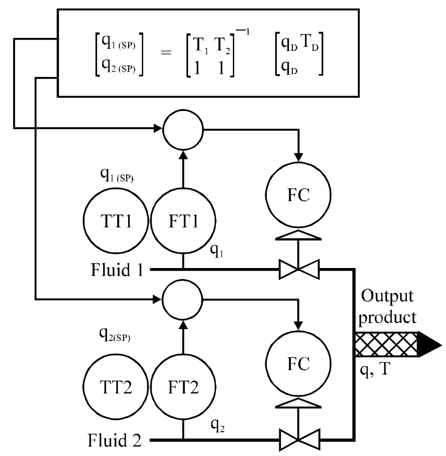

Fig. 3: The control strategy for FFC of a continuous in-line mixer

Φ = Output energy flow rate
q = Output mass flow rate measured by the sensor FT
T = Output temperature measured by TT
Ce = Specific heat of the fluid
T_1 = Input temperature of fluid 1 measured by sensor TT1
T_2 = Input temperature of fluid 2 measured by sensor TT2
q_1 = Mass flow rate of fluid 1 measured by FT1
q_2 = Mass flow rate of fluid 1 measured by FT2

Such an in-line mixing process can be modelled by applying first physical principles, such as mass and energy balances and generally any physical equilibrium condition. Energy balance is:

$$q_1.Ce_1.T_1 + q_2.Ce_2.T_2 = (q_1 + q_2).Ce.T \quad (4)$$

Material balance is:

$$q = q_1 + q_2 \quad (5)$$

Where:

q_1 = Manipulated Variables (MV)
q_2 = Manipulated Variables (MV)
$Ce_1.T_1$ = Plant parameters
$Ce_2.T_2$ = Plant parameters (P)
T = Process Variables (PV)
q = Process Variables (PV)

Strategy FFC: The aim in FFC strategy is to compute the manipulated variables, as function of the desired controlled variables. Assuming both fluids are of same chemical characteristics so that the specific heat of both fluids are equal, the math-model is achieved by applying the model described by Eq. 4 and 5. Hence, a matrix based math-model is achieved as:

$$\begin{vmatrix} q_1 \\ q_2 \end{vmatrix} \begin{bmatrix} T_1 & T_2 \\ 1 & 1 \end{bmatrix} = \begin{vmatrix} qT \\ Q \end{vmatrix} \quad (6)$$

Which generalized implies that:

$$M\vec{V} \times [P] = P\vec{V} \quad (7)$$

Where:

$M\vec{V}$ = Vector of manipulated variables
[P] = Matrix of plant parameters
$P\vec{V}$ = Vector of process outputs or controlled variables

Consequently, the desired manipulated variables specified by its setpoint values from Eq. 6 are modelled as:

$$\begin{bmatrix} q_{1(SP)} \\ q_{2(SP)} \end{bmatrix} = \begin{bmatrix} T_1 & T_2 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} q_D T_D \\ q_D \end{bmatrix} \quad (8)$$

From Eq. 8 follows that the manipulated variables setpoints may be generally specified in matrix form as:

$$M\vec{V} = [P]^{-1} P\vec{V} \quad (9)$$

Where:

$q_{1(SP)}$, $q_{2(SP)}$ = Manipulated variables setpoint or desired values
$q_D.T_D$, q_D = Required output product values satisfying Eq. 8

Such open loop strategy is depicted in Fig. 3.

Strategy FCC: Starting from the mixing process balance model described by Eq. 6, the estimated output flow rate q' and temperature T' can be achieved as:

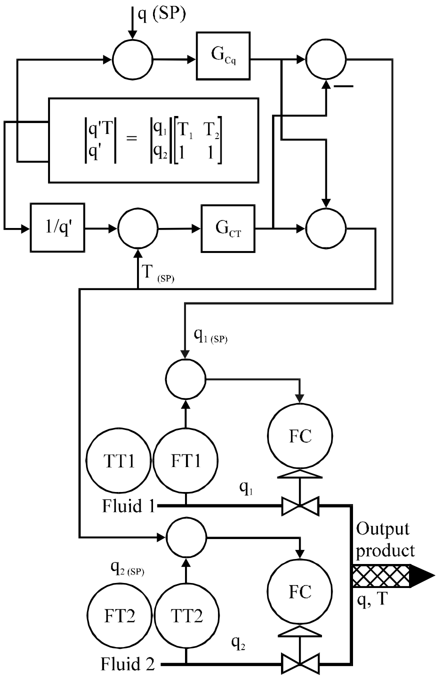

Fig. 4: The control strategy for EFC of a continuous in-line mixer

$$\begin{vmatrix} q'T' \\ q' \end{vmatrix} = \begin{vmatrix} q_1 \\ q_2 \end{vmatrix} \begin{bmatrix} T_1 & T_2 \\ 1 & 1 \end{bmatrix} \quad (10)$$

Where q' T' and q' are the estimated controlled variables. Consequently, the required flow rate setpoints necessary to satisfy Eq. 10 are given as:

$$\begin{vmatrix} q_{1SP} \\ q_{2SP} \end{vmatrix} = \begin{vmatrix} (q_{SP} - q') & (T_{SP} - T') \\ (q_{SP} - q') & -(T_{SP} - T') \end{vmatrix} \begin{vmatrix} G_{Cq} \\ G_{CT} \end{vmatrix} \quad (11)$$

$$\begin{vmatrix} G_{Cq} \\ G_{CT} \end{vmatrix}$$

is the vector of feedback controllers and:

$$\begin{vmatrix} (q_{SP} - q') & (T_{SP} - T') \\ (q_{SP} - q') & -(T_{SP} - T') \end{vmatrix}$$

is a matrix of control errors. The control strategy EFC resulting from Eq. 10 and 11 is depicted in Fig. 4.

Strategy FBC: The aim of computed variable feedback control FBC is to compute the control variables and or manipulated variables as function of both control errors, according the control structure described by Eq. 11.

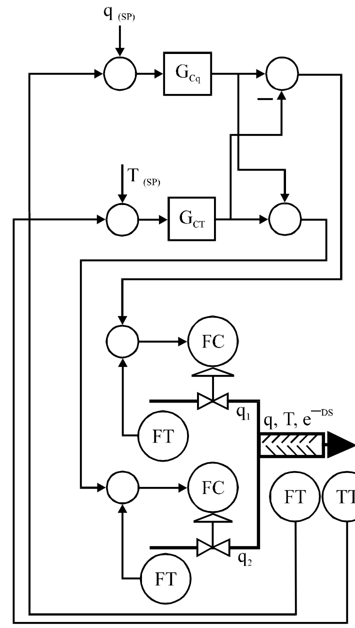

Fig. 5: The control strategy for FBC of a continuous in-line mixer

$$\begin{vmatrix} q_{1SP} \\ q_{2SP} \end{vmatrix} = \begin{vmatrix} (q_{SP} - q) & (T_{SP} - T) \\ (q_{SP} - q) & -(T_{SP} - T) \end{vmatrix} \begin{vmatrix} G_{Cq} \\ G_{CT} \end{vmatrix} \quad (12)$$

Where G_{Cq} and G_{CT} are respectively, the process controllers applied on flow rate control and temperature control loop. Figure 5 shows feedback control strategy.

Some linear mixing process models: In analogous way, other chemical engineering mixing problems can be solved by means of proposed methodology. For instance, the case of mass and energy flow rates mixing control or the case of energy flow rate, mass flow rate and density are useful examples.

Mass and energy flow rate

Energy balance:

$$q_1.Ce1.T_1 + q_2.Ce2.T_2 = \Phi \quad (13)$$

Material balance:

$$q_1 + q_2 = q \quad (14)$$

Where Φ is the thermal energy flow rate. The model in matrix form is:

$$\begin{bmatrix} \Phi \\ q \end{bmatrix} = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix} \begin{bmatrix} Ce1.T_1 & Ce2.T_2 \\ 1 & 1 \end{bmatrix} \quad (15)$$

The computed variable control by FFC yields the expression:

$$\begin{bmatrix} q_{1(SP)} \\ q_{2(SP)} \end{bmatrix} = \begin{bmatrix} Ce1.T_1 & Ce2.T_2 \\ 1 & 1 \end{bmatrix}^{-1} \begin{bmatrix} \Phi_D \\ q_D \end{bmatrix} \quad (16)$$

Where Φ_D and q_D are the required output product values. The computed variable control by EFC demands the following combination of expressions given by Eq. 17 and 18. The estimation of product outputs for the computed variable control by EFC yields the expression:

$$\begin{bmatrix} \Phi' \\ q' \end{bmatrix} = \begin{bmatrix} q_1 \\ q_2 \end{bmatrix} = \begin{bmatrix} Ce1.T_1 & Ce2.T_2 \\ 1 & 1 \end{bmatrix} \quad (17)$$

$$\begin{vmatrix} U_\Phi \\ U_q \end{vmatrix} = \begin{vmatrix} q_{1(SP)} \\ q_{2(SP)} \end{vmatrix} = \begin{vmatrix} (q_{SP} - q') & (\Phi_{SP} - \Phi') \\ (q_{SP} - q') & -((\Phi_{SP} - \Phi')) \end{vmatrix} \begin{vmatrix} G_{C\Phi} \\ G_{Cq} \end{vmatrix} \quad (18)$$

Energy flow rate, mass flow rate and density: The control problem solution requires a number of manipulated variables at least equal to that of the process variables. For the case of density, mass and energy flow rates, follows that:

Process balances:

$$\begin{aligned} & q_1 + q_2 + q_3 = q \\ & q_1.Ce_1.T_1 + q_2.Ce_2.T_2 + q_3.Ce_3.T_3 \\ & = q.Ce.T = q_E \\ & q_1/\delta_1 + q_2/\delta_2 + q_3/\delta_3 = q/\delta \end{aligned} \quad (19)$$

From Eq. 17, the computed variable control by FCC is given as:

$$\begin{bmatrix} q_1 \\ q_2 \\ q_3 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ Ce_1T_1 & Ce_2T_2 & Ce_3T_3 \\ 1/\delta_1 & 1/\delta_2 & I/\delta_3 \end{bmatrix} = \begin{bmatrix} q_{(D)} \\ q_{E(D)} \\ q_{(D)}/\delta_D \end{bmatrix} \quad (20)$$

And the computed variable control by EFC is:

$$\begin{bmatrix} q_{1(SP)} \\ q_{2(SP)} \\ q_{3(SP)} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ Ce_1T_1 & Ce_2T_2 & Ce_3T_3 \\ 1/\delta_1 & 1/\delta_2 & I/\delta_3 \end{bmatrix}^{-1} = \begin{bmatrix} q_{(D)} \\ q_{E(D)} \\ q_{(D)}/\delta_D \end{bmatrix} \quad (21)$$

Model based linear case studies are efficiently solved as shown earliar. A more serious problem arises when the products to be mixed yields an output product for which there is not an acceptable linear model.

Modelling drawbacks regarding mixing processess: Due to the inherent non-linear behaviour of the studied mixing processes, it is not possible to describe analytically most of them based in material and energy balances. For instance, the energy and mass balance between two products of different specific heats is given as:

$$\begin{aligned} & \Phi = q_1.Ce1.T_1 + q_2.Ce2.T_2 = (q_1 + q_2).Ce.T \\ & q_1 + q_2 = q \end{aligned} \quad (22)$$

Balances given by Eq. 22 introduce a new unknown Ce. Another equation to complete the set in Eq. 22 will be necessary to achieve an analytic model based solution. In the same way, the mixture of two fluids of different conductivities where the individual conductivities are function of its respective temperatures must be modelled under a non-linear function. Such drawbacks are the motivation to develop another strategy where neural networks based functional approximation is a relevant tool.

PROPOSED NON-LINEAR COMPUTED MULTIVARIABLE DESIGN TECHNIQUE

To solve the problems for which analytical models based in physical laws or material and energy balances does not provide an acceptable or satisfactory solution, an alternative method based on functional approximation is proposed.

In-line mixing problems affected by controlled variables, such as conductivity, pH, viscosity with strong dependence on complementary physical variables, such as temperature and conductivity or pressure variations are appropriate candidates to be solved using functional approximation. For instance, the conductivity σ of a mixed fluid is typically a measure of the mixed product concentration C. In fact, the mixture of two fluids of different conductivities where the individual conductivities are function of its respective temperatures can be expressed as:

$$\begin{aligned} & (q, C) = f(q_1, q_2, C_1, C_2) \\ & (q, C) = f(q_1, q_2, T_1, T_2, \sigma_1, \sigma_2) \end{aligned} \quad (23)$$

The modes FFC of computed variable control is given as:

$$(q_{1(SP)}, q_{2(SP)}) = f_2(q_D, C_D, T_1, T_2, \sigma_1, \sigma_2) \quad (24)$$

The control problem solved by a computed variable control technique consists in computing the setpoints of a number of manipulated variables (flow rates) to satisfy the required values of a number less or

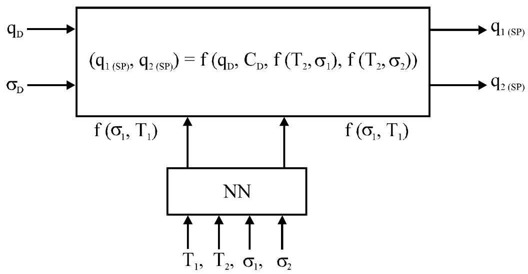

Fig. 6: FFC algorithm based on functional approximation techniques

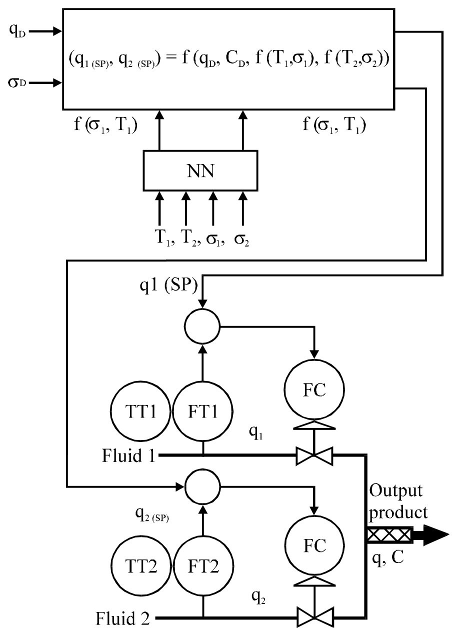

Fig. 7: Computed variable FFC control strategy based on functional approximation applied to an in-line mixer

equal to that of the controlled variables. Such definition implies the computation of $q_{1(SP)}$, $q_{2(SP)}$ such that by means of an in-line mixing process, it will be possible to achieve a final product, thus satisfying desired characteristics, such as flow rate q_D and conductivity C_D as stated by Eq. 23.

Non-linear functional approximation is the required computational technique widely used which will be applied to implement such non-linear continuous in-line mixing problems. Feedforward neural networks (Hagan and Menhaj, 1994) are one of the most appropriate and a popular tool to implement non-linear continuous and differentiable functions and the conjugate gradient training algorithm is widely used in feedforward training tasks (Beale, 1972; Charalambous, 1992). Such a training technique is used in this work to approximate the behaviour of a concentration mixing problem under

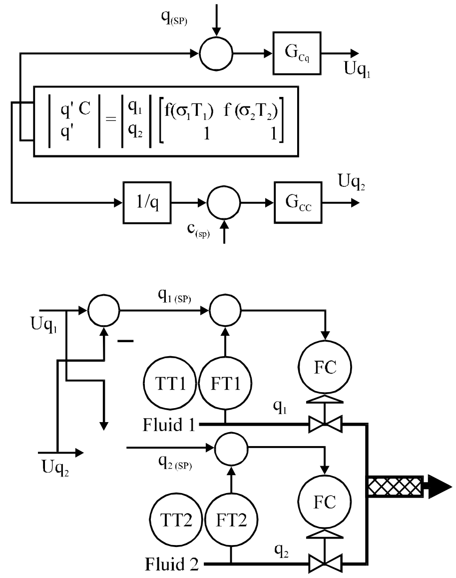

Fig. 8: Computed variable EFC control strategy based on functional approximation applied to an in-line mixer

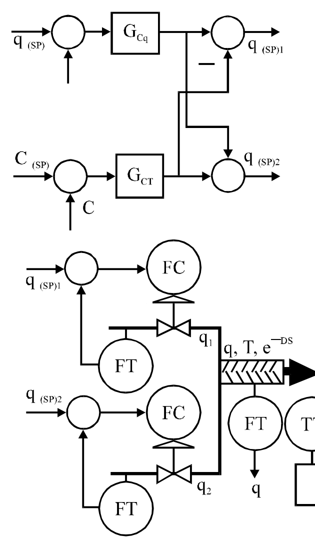

Fig. 9: Computed variable FBC control strategy based on functional approximation applied to an in-line mixer

changes in the temperatures and conductivities of the input fluids. In Fig. 6, it is depicted a general scheme of an input/output neural network structure to implement the concentration control problem using the strategy FFC by applying Eq. 23 and 24.

In Fig. 7, the FFC control strategy is applied to an in-line mixer, using the neural network based approximation technique.

In Fig. 8, the FFC control strategy is applied to an in-line mixer, using the neural network based approximation technique.

In Fig. 9, the FBC control strategy is applied to an in-line mixer, using the neural network based approximation technique.

Case study

Concentration control of a continuous in-line mixer: The definition and application of the appropriate inverse model when applicable (Wachira *et al*., 2005) because direct models are also useful, provides a suitable function to specify the desired final product (q_D, C_D) as:

$$\left(q_{1(SP)}, q_{2(SP)}\right) = f\left(q_D, \sigma_D, C_1, C_2\right) \quad (25)$$

Consequently, the functional approximation models given by Eq. 23 and 24 can be implemented on the basis of backpropagation neural networks as shown in Fig. 6 and 7.

For the case of mixing two input fluid at different temperatures and concentrations, satisfying a desired specified output flow rate and concentration, follows that the balance for the concentration C, according the control scheme depicted in Fig. 7 is:

$$\begin{aligned} q_1.C_1 + q_2.C_2 &= q.C \\ q_1 + q_2 &= q \end{aligned} \quad (26)$$

Taking into account, the non-linear behaviour of the conductivity as function of the temperature and concentration follows that:

$$\begin{aligned} q_1.f\left(T_1,\sigma_1\right) + q_2.f\left(T_2\sigma_2\right) &= q.f\left(T,C\right) \\ q_1 + q_2 &= q \end{aligned} \quad (27)$$

Or in matrix form:

$$\begin{bmatrix} q_1 \\ q_2 \end{bmatrix}\begin{bmatrix} f\left(T_1,\sigma_1\right) & f\left(T_2,\sigma_2\right) \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} f\left(T,\sigma\right) \\ q \end{bmatrix} \quad (28)$$

$$\begin{bmatrix} q_{1(SP)} \\ q_{2(SP)} \end{bmatrix}\begin{bmatrix} f\left(T_1,\sigma_1\right) & f\left(T_2,\sigma_2\right) \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} f\left(T,\sigma\right)_D \\ q_D \end{bmatrix} \quad (29)$$

Control implementation: Control implementation is experimentally carried out on a continuous in-line mixer pilot plant, after a previous preliminary case study by simulation of the in-line mixing problem applying Eq. 29. In order to achieve the data to implement the functional approximation model by feedforward neural networks a database must be constructed. The aim is to control the aqueous solution of NaOH into a range of 0-15% in weight. Sodium hydroxide also known as caustic soda is a caustic metallic base characterized by its ability to form a strong alkaline solution when dissolved in a solvent, such as water. It is used in the industries, mostly as a strong chemical base in the manufacture of pulp and paper, textiles, drinking water, soaps and detergents and as a drain cleaner being considered as the most used base in chemical laboratories. The conductivity of a solution of NaOH in water is a non-linear function of its concentration and temperature. Due to this non-linear characteristic, a typical conductivity measuring system accuracy is only as good as its temperature compensation. Since, common solution temperature coefficients vary on the order of 1-3% per °C, measuring instruments with adjustable temperature compensation should be utilized. Nevertheless, solution temperature coefficients are somewhat non-linear and usually vary with actual conductivity as well. Thus, calibration at the actual measuring temperature will yield the best accuracy. To solve the problem of the in-line mixer concentration measuring system calibration at any operating concentration and temperature, a non-linear function of the conductivity as function of concentration and temperature must be experimentally achieved for every solution for which a database containing the characteristics of the specific solution is to be used. Concentration control precision is an important objective.

The specific database for NaOH: The database relating concentration C of NaOH in pure water with the conductivity σ in micro Siemens/cm and temperature T in degrees Celsius is shown in Table 1.

In order to use the experimental data in the neural networks tool training task, a normalized data base must be achieved by converting the available data into a range of -1, 1. After the data conversion the pattern vector data p is reduced in the order of T/100 and σ/100 while the target vector t is reduced in the order of C/100. Hence, the original data once normalized yields the following values:

p = [0.20 0.20 0.20 0.20 0.20 0.40 0.40 0.40 0.40 0.40 0.60 0.60 0.60 0.60 0.60 0.80 0.80 0.80 0.80 0.80; 0.8 0.6 0.4 0.2 0 0.8 0.6 0.4 0.2 0 0.8 0.6 0.4 0.2 0 0.8 0.6 0.4 0.2 0 0]

t = [0.30 0.25 0.16 0.05 0 0.24 0.18 0.08 0.04 0 0.16 0.010 0.052 0.03 0 0.135 0.08 0.045 0.02 0]

Table 1: Conductivity as function of concentration and temperature for a solution of NaOH and water

σ\T	20	40	60	80
800	30	24	16.0	13.5
600	25	18	10.0	8.0
400	16	8	5.2	4.5
200	5	4	3.0	2.0
0	0	0	0.0	0.0

Training with matlab neural toolbox: Using the information available in Table 1, corresponding to a solution of NaOH and water, several feedforward NN structures have been tested against performance to solve the proposed problem. Acceptable results were achieved using the neural network structure described by Table 2 where neural network toolbox of Matlab has been used (Demuth and Beale, 2000a, b). Table 2 shows also the specified training characteristics. The concentration as function of temperature and conductivity for NaOH is continuous along the range of useful input values. Consequently the feedforward neural network precision achieved is characterized by a mean square error of about 1.76e-8 which is sufficient.

Functional approximation is implemented on the basis of feedforward neural networks trained by means of a Backpropagation training algorithm. The conjugate gradient method called Fletcher and Reeves (1964) algorithm which provides the required precision (Moller, 1993; Powell, 1977) have been used.

The trained neural network is applied after considering the data reduction due to the normalized task. In Fig. 10, it is shown how to use the trained neural network by interfacing the input/output data with conversion scales Fig. 10. Interfacing trained neural networks applied on the concentration controllers applied on the NaOH concentration control.

In-line mixer concentration control simulation: In order to explore how the proposed feedforward-cascade strategy on the in-line mixer is performing, a simulation phase previous to the practical implementation is carried out. Using the control scheme described in Fig. 7 and the trained neural networks under the architecture shown in Table 2, simulation results are achieved. Figure 11 shows the response of the concentration in % weight under a change in concentration demand. Figure 12 shows the input flow rates under an output demanded flow. It is observed that the changes in flow demand and the consequent flow rates, the concentration remain closely to the setpint value or concentration demand.

It can be seen in Fig. 12 that during the first 4 sec, the valve 1 is completely closed. Due to this disadvantage, the concentration obtained does not match the concentration demand. So that it is necessary to take into account hat the final flow and concentration demands must be into the range of realizable values in order to avoid flow valves saturation.

Table 2: Neural network training characteristics

Action	Command
Net initialization	net = init (net)
Feedforward NN structure and training algorithm	net = newff (minmax (p), [15,10,1] {tansig, tansig, purelin}, traincgf)
Results display	net.trainParam.show = 5
Training epochs	net.trainParam.epochs = 300
Training command	(net,tr) = train (net, p, t)
NN simulink structure	gensim (net, -1)
Training results	TRAINCGF-srchcha-calcgrad, Epoch 118/300, MSE 1.76e-8/0, Gradient 0.000194/1e-6

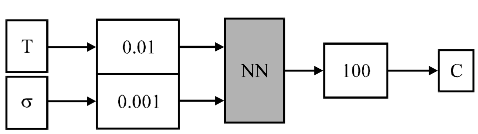

Fig. 10: Interfacing trained neural networks applied on the concentration controller applied on the NaOH concentration control

In-line mixer concentration control experimentation: An in-line mixer based pilot plant is being used to experimentally validate the proposed control technique FFC. The physical structure of the plant is reconfigurable and permits the configuration shown in Fig. 7 and 9 by modifying some equipment connections. To carry out the experimental validation, the structure shown in Fig. 7 is applied. Such structure exhibits some advantages with respect to the optional configurations depicted with Fig. 8 and 9. Such advantages are referred to:

- Avoiding phase lag due to the additional feedback controller mainly due to the integral action
- Avoiding at least a control loop which supposes beneficial savings regarding the instrumentation, operational and maintenance costs

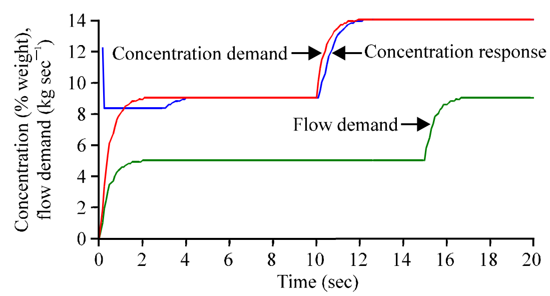

Fig. 11: Concentration response under changes in concentration demand and flow demand

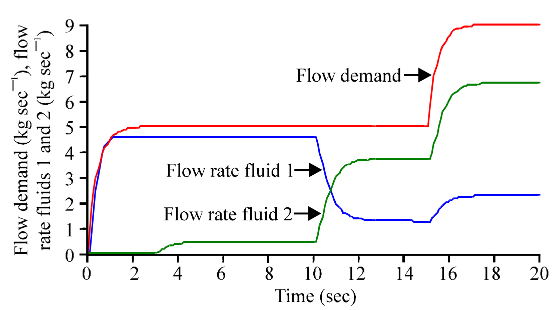

Fig. 12: Input fluid low rate under changes in flow demand

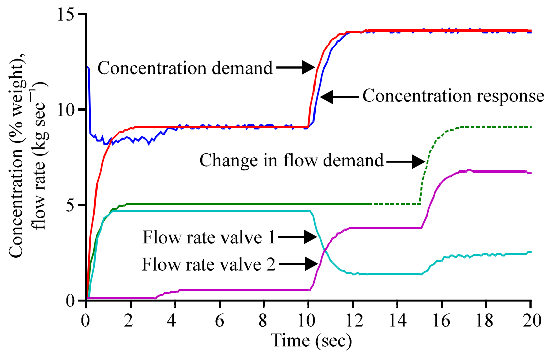

Fig. 13: Experimental result for the continuous in-line mixer implemented under the structure of Fig. 7

The experiments carried out were conducted under the same conditions than for the case study carried out by simulation which are described in Fig. 13. Since, the disturbances and changes in demanded variables were applied at times similar to that of the simulated case study, the comparison of results between the experimental and simulated data provides us an acceptable insight of the control performance. Disturbances due to changes in demanded flow and demanded concentration are conveniently rejected. Nevertheless measured data is responsible for the fluctuation of the output concentration. The total output flow is also under the influence of input data. As consequence, such control technique success is restricted to required precision.

CONCLUSION

In this research, some contributions to improve the procedures to solve linear and non-linear in-line mixing problems have been presented. These contributions are based on a new computed multi-variable control strategy, the FFC algorithm which definitely contributes in:

- Avoiding the effect of time lags on feedback control loops which suppose the avoidance of an important disturbance in mixing control loop
- The inherent simplification of the conventional control structures

Linear and non-linear solutions were studied and a non-linear case, experimentally presented. For the general case, the non-linear MIMO case, a solution based on functional approximation was illustrated. Functional approximation was implemented on the basis of feedforward neural networks trained by means of a backpropagation training algorithm; the conjugate gradient Fletcher and Reeves algorithm which provides the required precision.

Furthermore, the proposed control algorithm applied on the experimental in-line mixer plant, yields satisfactory results very similar to that predicted by simulation.

With regard to performance and rapid response, the precision under changes (disturbances) of input variables, suppose the main added value of the control strategy.

It can be pointed out as an important advantage that for the sake of the lack of a conventional mixing tank and the lack of feedback measuring devices due to proposed strategies, minimum time delay on the mixing process control is achieved.

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