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Experimental application of linear/nonlinear dynamic matrix control to a reactor of limestone slurry titrated with sulfuric acid

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Abstract

In this work, pH control of $CaCO_3$–sulfuric acid neutralization process was realized in a stirred continuous reactor under optimum operating conditions in which the solubility of $CaCO_3$ was maximum. The pH of the solution was controlled by using linear and nonlinear dynamic matrix control algorithm with an on-line computer control system in the reactor. A step response model was used for the dynamic matrix control. For this purpose a unit step effect was given to the manipulated variable and the changes in the pH value were obtained on-line. In the nonlinear dynamic matrix control NARMAX model was developed as an addition to the above model. When the system was in open loop, random loads were given to the manipulated variable and input and output values were obtained on-line. Using these values, NARMAX model parameters were obtained with nonlinear regression. Developed DMC and NLDMC algorithms were applied to the neutralization process and the success of the algorithms was tested according to ISE and IAE values.

Keywords: Linear/nonlinear dynamic matrix control; pH control; Limestone dissolution process

1. Introduction

SO_2 combines with water vapor in the air and then this gas forms droplets of sulfuric acid, which fall to the ground as acid rain, causing harm to everything living and nonliving. Over 200 processes have been reported in literature for the removal of SO_2 from flue gases and among these processes about 20 of them have been used in power plants and in other industries. These processes can generally be classified as wet and dry processes. In the wet limestone flue gas desulphurization process, powdered limestone dissolves and neutralizes acidity produced by SO_2 absorption in the liquid phase. It is well known that the soluble salts have an effect on the dissolution rate of the limestone used as the absorbent. Many studies have been carried out on the reactions of calcium carbonate with acidic solutions [1].

There is a considerable attention of pH control in recent literature. Because pH process has a simple model, these processes are ideal for clarifying new methods concerned with nonlinear control and simple and low-priced experimental equipments can be used in order to conduct reliable experiments. One of the reasons for the popularity of pH control in literature is the fact that pH control problems have not been solved yet. pH control is very important in chemical industries, wastewater treatment, polymerization reactions, fatty acid production, biochemical processes and SO_2 removing processes. However, in highly nonlinear pH neutralization process, a change in the feed composition or in ion concentration causes a high sensitivity in pH. These attitudes have caused problems in traditional PID controllers. A lot of researchers work on modeling and controlling pH processes [1]. But nonlinear control requires numerical analyses and much more experimental research, therefore it is limited. Dynamic matrix control has been proposed by Cutler [2] and it has many applications in industry. Effective linear control strategies in nonlinear systems are realized only if a design parameter (control parameters, sampling time, tuning parameters, etc.) is adjusted well because its original model is linear. There are a lot of studies on extended DMC control algorithm. DMC is extended to handle different operation regions and input disturbances [3]. A multiple model framework of step response models is utilized. Nonlinear model based control of the free radical solution polymerization of styrene in a jacketed batch reactor were applied and its performance was examined to achieve the required monomer conversion and molecular weight [4]. Zhao et al. [5] developed application software using a method of nonlin-

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Nomenclature

a_i	step response coefficient
A	dynamic matrix composed of the step response coefficient
b_i	model coefficients
d	disturbance effect
D	particle size
F	Fisher's F value
I	number of the coefficients in the regression equation
IAE	integral of absolute error
ISE	integral of square error
k	number of sampling time
M	move horizon
N	number of experimentation
NT	the number of step response coefficient needed to sufficiently describe the process dynamics
P	length of the prediction horizon
$r(t)$	set point
S/L	solid/liquid ratio
S_{b_i}	standard error of the coefficient
S_e^2	error mean square
S_r^2	residual mean square
T	temperature (°C)
u	input
$\Delta u(k)$	the change in the input
U_i	real value of the parameters
$U_{i\mathrm{av}}$	average values of the parameters
ΔU_i	incremental value of the parameters
X_i	independent variables matrix
X_1	coded value of the pH
X_2	coded value of the T
X_3	coded value of the S/L
X_4	coded value of the D
$y(t)$	output
y^{past}	the effects of the known past inputs on the future outputs
y^{sp}	set point
Y	observation vector
Y_i	ith experimental value of the conversion
$\hat{Y}_i$	ith estimated value of the conversion
$\bar{Y}_i^0$	average value of the conversion

Greek letters

γ and λ	time varying weights on the output error and on the input change, respectively

ear dynamic matrix control based on multiple operating models. This software is applicable to a pH neutralization process and a styrene polymerization reactor.

Self-tuning PID control was applied to a jacketed batch reactor in which limestone slurry was titrated with sulfuric acid [1]. As a result of incomplete dissociation of limestone in water and the equilibrium reaction with sulfuric acid, the system behaves like a buffer solution between pH 2 and pH 7. Therefore, the process gain varies extremely over the range of pH value which is controlled. The dynamic behavior of the system was observed. The system was initially brought to optimal steady-state condition, then solid $CaCO_3$ with 250–375 mm particle size and 3% S/L ratio was added to the system, and the time variation of pH was observed experimentally [1]. Self-tuning control action was employed because it was regarded as the best control action for this application. Second order auto regressive moving average with external input (ARMAX) system model was utilized for control algorithm. For the model parameter estimation, pseudo random binary sequence (PRBS) was given to the open-loop system and input–output data were measured. Bierman algorithm was used to evaluate the parameters of the ARMAX model. The STPID algorithm was implemented experimentally to control the pH of the continuous reactor and sulfuric acid flow rate was chosen as the manipulated variable [1].

Model predictive control has received attention as an industrially implemented advanced control method. This control method is used in different industries like refinery and petrochemical plant [6]. MPC method is very simple and the simplicity of this method accounts for its popularity. MPC has almost become an "easy to use" engineering tool. The vast majority of MPC applications are based on a linear model. MPC can be described as an open loop optimal control technique where feedback is incorporated via the receding horizon formulation. Open loop control strategy is calculated at every sampling time. The available data is updated for the model identification at the next sampling time. Among the popular applications of model predictive control are DMC, MAC, GMC and IMC [4,6–10]. The main differences between MPC methods lie in their models which define the process. The linear and nonlinear MPC utilize linear and nonlinear models respectively [6]. The MPC considers a future control horizon and constraints are directly included in the algorithm. The basis of MPC system is to compose a mathematical model of the process to be controlled. It is important to choose parameters and structure of the model. The DMC which is an MPC algorithm is a computer control algorithm used to solve complex control problems by maintaining a prediction of the system's future outputs based on the history and knowledge of the system's dynamics. Most of the control techniques, which include DMC, are based on linear models, therefore they are not convenient to control nonlinear systems. Thus there are a lot of studies to extend the MPC techniques to the control of nonlinear processes.

The aim of this work is to apply the system identification techniques to limestone–sulfuric acid neutralization process under optimum conditions and control of pH with linear and nonlinear dynamic matrix control. The contribution of the present work is the application of this method to an experimental system. The pH control of $CaCO_3$–sulfuric acid neutralization process under optimum operating conditions (pH, particle size and solid/liquid rate) by DMC and NLDMC algorithms is investigated. Polynomial type NARMAX model is determined for NLDMC algorithm with system identification methods. When the system is in open loop, random load changes are given to the manipulated variable and input and output values are obtained on-line. Using these values, NARMAX model parameters are obtained with nonlinear regression. Developed DMC and NLDMC algorithms are applied to the process and success of the algorithms is tested.

2. Dynamic matrix control

DMC is a control algorithm used to control complex problems arising from operating a process. When an objective function for the predictive control is defined, DMC becomes an algorithm which optimizes the objective function. The DMC is based on parametric system model which allows the multi-input–multi-output algorithm to control the multivariable system with set of linear equation [2]. The performance of DMC depends on a number of design parameters like length of the control time interval, the number of future moves for the manipulated variable and the number of time intervals in the output prediction [2].

Linear/nonlinear DMC algorithm is described as follows [11].

2.1. Linear DMC

DMC mainly consists of four parts:

a. Model

If we consider the single input/single output case the model becomes

$$y(k)=\sum_{i=1}^{\mathrm{NT}} a_i \Delta u(k-i)+a_{\mathrm{N}} u(k-\mathrm{NT}-1)+d(k) \tag{1}$$

b. Estimation of disturbance effect

The disturbance effects can be determined by subtracting the effects of past inputs on output from the measurement of the output

$$d(k)=y^{\text{measurement}}(k)-\left[\sum_{i=1}^{\mathrm{NT}} a_i \Delta u(k-i) - a_{\mathrm{NT}} u(k-\mathrm{NT}-1)\right] \tag{2}$$

c. Prediction into the future

The future prediction is defined as follows:

$$y^{\text{lin}}=y^{\text{past}}+A\Delta u+d \tag{3}$$

d. Calculation of the control inputs

The control inputs are calculated as below:

$$\min_{\Delta u}\sum_{i=1}^{P}\gamma^2(i)[y^{\text{setpoint}}(k+i)-y^{\text{Li}}(k+i)]^2 + \sum_{j=1}^{M}\lambda^2(j)[\Delta u(k+M-j)]^2 \tag{4}$$

If we solve the Eq. (3) with least squares solution, we get the following equation:

$$\Delta u=(A^{\mathrm{T}}\Gamma^{\mathrm{T}}\Gamma A+\Lambda^{\mathrm{T}}\Lambda)^{-1}A^{\mathrm{T}}\Gamma^{\mathrm{T}}\Gamma(y^{\text{setpoint}}y^{\text{past}}-d) \tag{5}$$

2.2. Nonlinear DMC

Nonlinear DMC algorithm is used for predictive control purposes.

For nonlinear model based control, NARMAX model is given as

$$y(t)=a_1 y(t-1)+a_2 y(t-2)-b_0 u(t-k)^3 \tag{6}$$

where y is the pH value and u presents the acid flow rate.

In nonlinear model based control algorithm, an extended linear and nonlinear disturbance based model is defined. There is a new disturbance vector d which contains contributions from the nonlinearities of the system as d^{nl} and external disturbances as d^{ex}. So the estimates of the future outputs over the prediction horizon can be written as

$$y^{\text{nl}}=y^{\text{past}}+A\Delta u+\mathrm{d}^{\text{ext}}+\mathrm{d}^{\text{nl}} \tag{7}$$

The aim of using nonlinear dynamic matrix control algorithm is to clarify the disturbance vector which is used in prediction. If DMC control law is applied to a nonlinear plant, the vector d will contain contribution from nonlinearities defined as d^{nl}

$$\begin{bmatrix} d(k+1)\\ \vdots \\ d(k+P)\end{bmatrix}=\begin{bmatrix} d^{\text{ext}}(k+1)\\ \vdots \\ d^{\text{ext}}(k+P)\end{bmatrix}+\begin{bmatrix} d^{\text{nl}}(k+1)\\ \vdots \\ d^{\text{nl}}(k+P)\end{bmatrix} \tag{8}$$

If we combine the Eqs. (3) and (8) we get the following equation:

$$y^{\text{el}}=y^{\text{past}}+A\Delta u+d^{\text{ext}}+d^{\text{nl}} \tag{9}$$

where d^{nl} varies from one sampling time to another and d^{ext} is assumed to be constant.

The optimal DMC inputs for the developed linear model are

$$\Delta u=(A^{\mathrm{T}}\Gamma^{\mathrm{T}}\Gamma A+\Lambda^{\mathrm{T}}\Lambda)^{-1}A^{\mathrm{T}}\Gamma^{\mathrm{T}}\Gamma(y^{\text{setpoint}}y^{\text{past}}-d^{\text{ext}}-d^{\text{nl}}) \tag{10}$$

The output from nonlinear model (y^{nl}) is given at all the future sampling times in the following equation:

$$\begin{bmatrix} y^{\text{nl}}(k+1)\\ \vdots \\ y^{\text{nl}}(k+P)\end{bmatrix}=\begin{bmatrix} y^{\text{el}}(k+1)\\ \vdots \\ y^{\text{el}}(k+P)\end{bmatrix}=y^{\text{past}}+A\Delta u+d^{\text{ext}}+\begin{bmatrix} d^{\text{nl}}(k+1)\\ \vdots \\ d^{\text{nl}}(k+P)\end{bmatrix} \tag{11}$$

where d^{ext} is assumed to be constant and d^{nl} varies from one operating point to another over the prediction horizon. The purpose here is to obtain the vector $d^{\rm nl}$. One method of solving nonlinear equations of $d^{\rm nl}$ is the fixed-point algorithm [11] as

$$d_{l+1}^{\rm nl} = d_l^{\rm nl} + \beta(y_{l+1}^{\rm nl} - y_{l+1}^{\rm el}) \tag{12}$$

Here, l is the iteration number and β is a factor used to expand the region of convergence. The control action $\Delta u(k)$ at the increment time is implemented on the plant and calculations are repeated at the next increment time. Then iterations on nonlinear model based control calculations are repeated at the next increment time.

3. Application to a reactor

3.1. Reaction mechanism

In our experimental system, calcium hydroxide ($Ca(OH)_2$) is fed to the system at a constant flow rate and it reacts with sulfuric acid (H_2SO_4) which flow is the manipulated variable and product is calcium sulfate ($CaSO_4$). The sulfuric acid is allowed to react with calcium carbonate($CaCO_3$), which is given as a load effect. The reactions are given below

(a)$Ca(OH)_2 + H_2SO_4 \rightarrow CaSO_4 + 2H_2O$

(b)$CaCO_3 + H_2SO_4 \rightarrow CaSO_4 + CO_2 + H_2O$

4. Experimental system

In the experiments a continuous stirred tank with a capacity of 2 l is used (Fig. 1). Reactor jacket is heated by a water bath, so the reactor medium is kept at 60 °C. Base solution which is calcium hydroxide in the present study is fed to the reactor at a constant flow rate. The manipulated variable in the system is sulfuric acid (H_2SO_4) flow rate. The values of manipulated variable are determined with on line signal which come from computer and thus the amount of acid solution to be fed to the reactor is adjusted [12].

4.1. Experimental method

The aim of the work is to keep the pH value at 3.5. Solid $CaCO_3$ is added instantly as random load changes when pH value reaches 3.5 The measurement of pH is performed by a pH sensor. Control variable in the experimental systems is pH. During the experiment $Ca(OH)_2$ is fed to the system continuously. Desired operating conditions of the system are given in Table 3.

5. Determination of optimal operating condition

Optimal operating condition is related to the control of the jacketed batch reactor in which limestone neutralization occurs by using sulfuric acid. Operating parameters for limestone slurry titrated with sulfuric acid were investigated by statistical model identification. It was clearly observed that four independent variables had an effect on the conversion. These were temperature, pH, particle size and solid/liquid ratio. The dependent variable was the conversion. To determine the maximum conversion, optimal values of the independent variables were evaluated by utilizing the Box Wilson optimization method and the response surface methodology (RSM) [13]. In these methods, the form of the relationship between the response and the independent variables is unknown. Therefore a suitable functional relationship between the dependent and independent variables is looked for by approximation through sequential steps of applying polynomials of increasing degrees until an optimum operating conditions for the system is reached. The relationship between the dependent and independent variables is given below by using a statistical model.

$$\begin{aligned} Y = {} & b_0 + b_1X_1 + b_2X_2 + b_3X_3 + b_4X_4 + b_{12}X_1X_2 \\ & + b_{13}X_1X_3 + b_{14}X_1X_4 + b_{23}X_2X_3 + b_{24}X_2X_4 \\ & + b_{34}X_3X_4 + b_{123}X_1X_2X_3 + b_{234}X_2X_3X_4 \\ & + b_{134}X_1X_3X_4 + b_{124}X_1X_2X_4 + b_{1234}X_1X_2X_3X_4 \end{aligned} \tag{13}$$

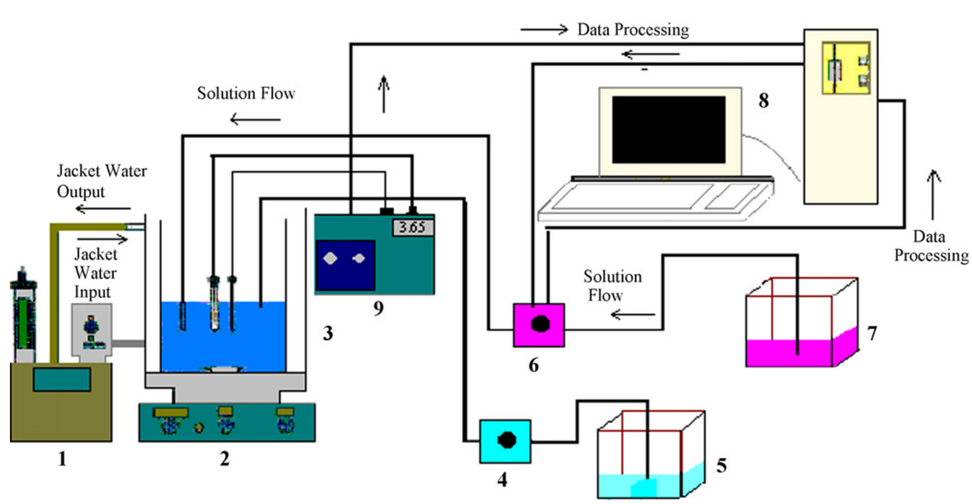

Fig. 1. Experimental system. 1: thermo bath, 2: stirrer, 3: reactor, 4: base pump, 5: base tank, 6: acid pump, 7: acid tank, 8: computer, 9: pH meter.

Table 1
Optimal design matrix

Exp. no.	X_1	X_2	X_3	X_4	Y
1	+1	+1	+1	−1	5.76
2	+1	+1	+1	+1	9.44
3	+1	+1	−1	−1	2
4	+1	+1	−1	+1	5.44
5	+1	−1	+1	−1	9.04
6	+1	−1	+1	+1	16.64
7	+1	−1	−1	−1	6.4
8	+1	−1	−1	+1	8.48
9	−1	+1	+1	−1	29.6
10	−1	+1	+1	+1	56
11	−1	+1	−1	−1	23.52
12	−1	+1	−1	+1	46.4
13	−1	−1	+1	−1	51.2
14	−1	−1	+1	+1	64
15	−1	−1	−1	−1	15.44
16	−1	−1	−1	+1	50

where X_i presents codified values The related equations were given as

$$X_i = \frac{U_i - U_{iav}}{\Delta U_i}, \quad i = 1, 2, \ldots, n \tag{14}$$

$$U_{iav} = \frac{U_i^{max} + U_i^{min}}{2}, \quad i = 1, 2, \ldots, n \tag{15}$$

$$\Delta U_i = \frac{U_i^{max} - U_i^{min}}{2}, \quad i = 1, 2, \ldots, n \tag{16}$$

The model coefficients were calculated by the following equation using the MATLAB package program (The Math Works Inc., Natick, MA, USA):

$$b_i = \frac{\sum_{j=1}^{i^n} X_{ij} X_i}{N} \tag{17}$$

According to the two-level factorial experimental design technique, 2^n experiments are required to identify the statistical model, where '2' indicates the lowest and the highest values of the selected operating variables and 'n' is the number of the parameters. The conversion values obtained by applying the design matrix given in Table 1 were used to were used to determine the values of the constants in the linear-regression model. The parameters of identified statistical model are given in Table 2. The error mean square was found as ($n_0 = 3$)

$$S_e^2 = \frac{\sum_{i=1}^{n_0} (Y_i^0 - \bar{Y}_i^0)}{n_0 - 1} \tag{18}$$

In order to determine the significance of each coefficient, Student's t-test was applied. The static model constants were found as

$$t_i = \frac{|b_i|}{S_{b_i}}, \quad i = 0, 1, \ldots 1234 \tag{19}$$

$$S_{b_i} = \frac{S_e}{\sqrt{N}}, \quad i = 0, 1, \ldots 1234 \tag{20}$$

Fisher's F test was applied to see the fitness of the new estimated regression equation which was obtained by the removal of the insignificant coefficients. According to this test the F value was determined by using the following equation:

$$F = \frac{S_r^2}{S_e^2} \tag{21}$$

In this equation S_r^2 is the residual mean square, and it was determined as given below

$$S_r^2 = \frac{\sum_{i=1}^{N} \left(Y_i - \hat{Y}_i \right)^2}{N - l} \tag{22}$$

The optimal conditions were determined as given in Table 3. The identified statistical model defining the conversion in a jacketed batch reactor is given below:

$$\begin{aligned} Y = {} & 24.97 - 17X_1 - 2.63X_2 + 5.19X_3 - 7.08X_4 \\ & -2.94X_1X_3 + 5.05X_1X_4 - 2.33X_2X_3 + 1.88X_1X_2X_3 \\ & -1.26X_2X_3X_4 - 1.51X_1X_3X_4 + 1.85X_1X_2X_3X_4 \end{aligned} \tag{23}$$

In the present work, 2^n factorial design was used for three main reasons. It provides information on the effect of several variables almost as soon as a comparable amount of information can be generated on the effect of one variable alone. In addition, it can later be developed into a composite design in order to identify the second-order polynomial by adding only star point (which is the distance of the axial points from the center and center points to the 2^n factorial experiments). It also provides a measure of interactions between independent variables.

For the reasons mentioned above, incomplete factorial designs such as fractional factorial design and the multi factorial design could be used in order to determine the effect of the independent variables on the dependent variable.

Table 2
The parameters of identified statistical model

$b_0 = 24.97$	$b_4 = -7.08$	$b_{23} = -2.33$	$b_{234} = -1.26$
$b_1 = -17$	$b_{12} = 0.46$	$b_{24} = 0.1$	$b_{134} = -1.51$
$b_2 = -2.63$	$b_{13} = -2.94$	$b_{34} = 0.7$	$b_{124} = -0.29$
$b_3 = 5.19$	$b_{14} = 5.05$	$b_{123} = 1.88$	$b_{1234} = 1.85$

Table 3
Optimal operating conditions

Parameters	Optimum values
PH	3.5
T (°C)	60
S/L	0.03
D (mm)	0.375/0.250

6. Results

The output change was obtained for DMC algorithm with unit step response before the control experiment was realized as seen in Fig. 2.

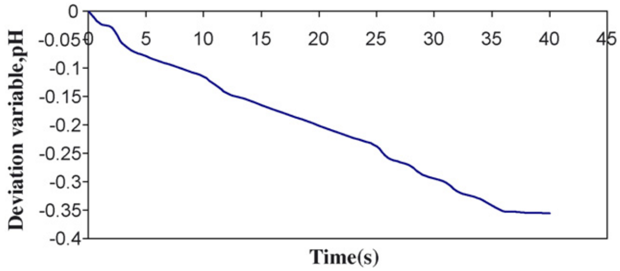

Fig. 2. The change in pH with deviation variable by giving the unit step response. NC (control horizon): 1, NP (prediction horizon): 3, λ (weight factor): 0, NT: 36.

For the prediction horizon the low values (NP = 3) were chosen as the inherent process nonlinearities which did not serve for adequate long term projections of the controller outputs. Accordingly, for the control horizon value (NC = 1) was selected. These low values of NP and NC were kept relatively small with the composite pseudo-inverse matrix, which is a key factor for the quick calculation of the controller action. NT is chosen as 36, which is 60% of the step response.

K_{mat} was calculated from Eq. (24) as below

$$A = \begin{bmatrix} 0 \\ -0.079 \\ -0.115 \end{bmatrix}$$

$$K_{mat} = [A^T A + \lambda I]^{-1} A^T = [0, -4.03, -5.87] \tag{24}$$

K_{mat} values in Eq. (24) and DMC algorithm were written in Visual Basic. pH control of the process was realized with DMC control algorithm. For this purpose process was brought to a steady state under optimum operating conditions and afterwards acid solution was given to the reactor at a constant flow rate by the pump which was adjusted by a computer program. At the same time $Ca(OH)_2$ solution was also given to the reactor at a constant flow rate. When the system was in steady state condition, solid $CaCO_3$ was introduced into the system to apply load effect. As a result pH value increased. In this state a computer program which was loaded with DMC algorithm sent a signal to the pump and this adjusted the pump's flow rate. The performance of this method was determined with ISE and IAE values

$$\mathrm{ISE} = \sum_{t=0}^{t} [y(t) - r(t)]^2 \tag{25}$$

$$\mathrm{IAE} = \sum_{t=0}^{t} |y(t) - r(t)| \tag{26}$$

Calculated ISE and IAE values are given in Figs. 3 and 4. Acid flow rate in Figs. 3 and 4 are calculated from the values of the pump. The calibration is achieved by using the equation given below

$$u = 15.196x - 48.011 \quad \text{where} \quad x \geq 3 \text{ and } u = 0 \quad \text{where} \quad x < 3$$

u is the acid flow rate as ml/min and x presents the values of the pump. The load disturbance is a step change, which is 30 g

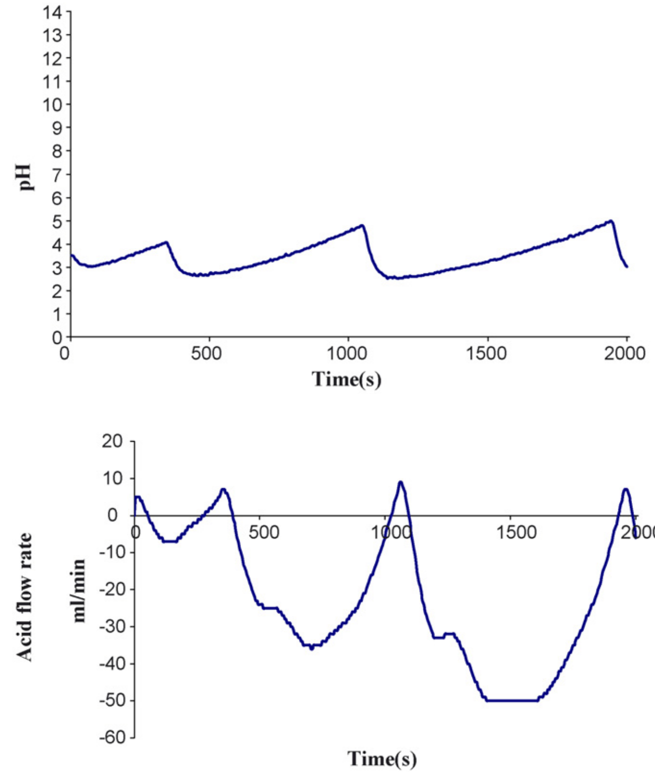

Fig. 3. The change in pH and acid flow rate with time by DMC control algorithm (set point 3.5 and acid concentration 0.05 M).

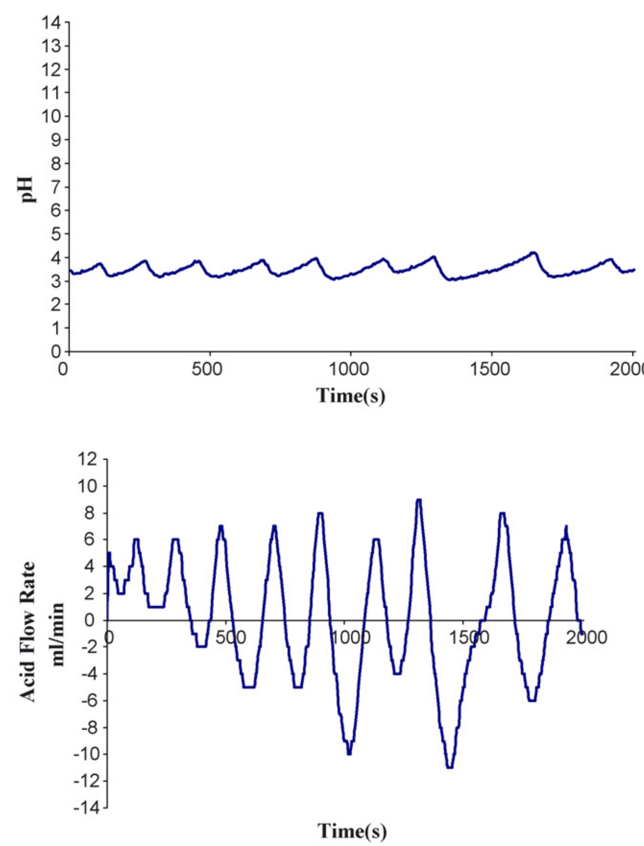

Fig. 4. The change in pH and acid flow rate with time by DMC control algorithm (set point 3.5 and acid concentration 0.004 M).

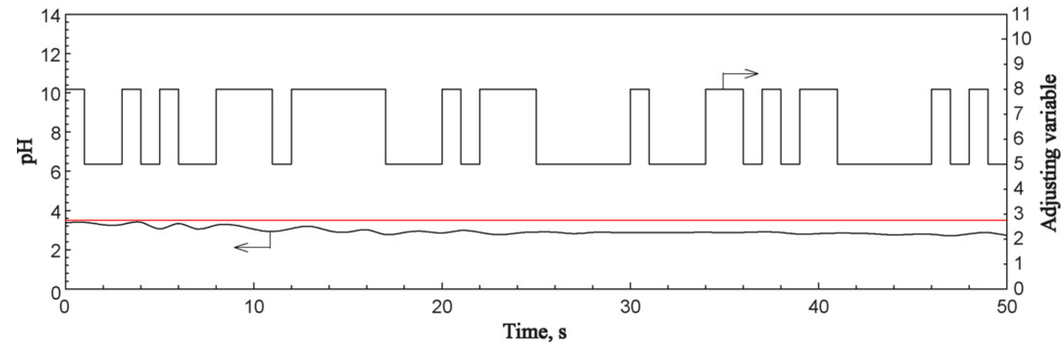

Fig. 5. Changes in pH and pump flow rate under the PRBS load effect.

Table 4
Model parameter values

Model parameters	Parameter values
a_1	0.9498
a_2	−0.0186
b_0	0.001

of $CaCO_3$. This solid $CaCO_3$ dissolution is a slow process. The system behavior is nonlinear, that is why pH profile shows oscillatory behavior in Figs. 3 and 4.The pH value of the reaction mixture which is controlled by using DMC algorithm follows the pH set point 3.5 with the maximum absolute error of 0.4.

For better performance of DMC control algorithm first NARMAX type of the process was determined. While P.R.B.S. signal was given to the acid flow rate, 30 g of $CaCO_3$ was added as a step type load effect, and then the change of pH with time was observed on-line. Model parameters were calculated from the changes of pH with time as seen in Fig. 5. Model parameters were calculated with Gauss Newton method by using Matlab program. The model was determined as $[y(t) = a_1 y(t-1) + a_2 y(t-2) - b_0 u(k)^3]$. These three parameter values are given in Table 4.

NARMAX model was combined with linear DMC control algorithm and experiments were repeated. As seen in Figs. 6 and 7, ISE and IAE values obtained during NDMC control of pH were smaller than those obtained during linear ones.

Addition of 30 g of solid $CaCO_3$ is a step load effect. $CaCO_3$ dissolution continues during the control. Dissolution of $CaCO_3$ shows a random disturbance which is very effective on the manipulated variable during the control. Constant base flow rate also has an effect on the manipulated variable. In Eq. (10) the manipulated variable evaluated by using iteration is not unstable, but process is very nonlinear. Nonlinear model based control calculations take considerable CPU time which causes time delay

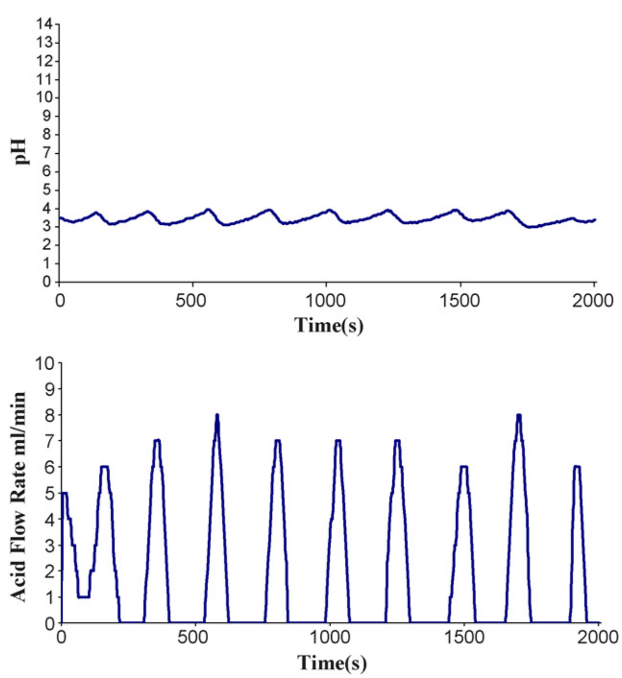

Fig. 6. Changes in pH and acid flow rate with time by NLDMC control algorithm (set point 3.5 and acid concentration 0.05 M).

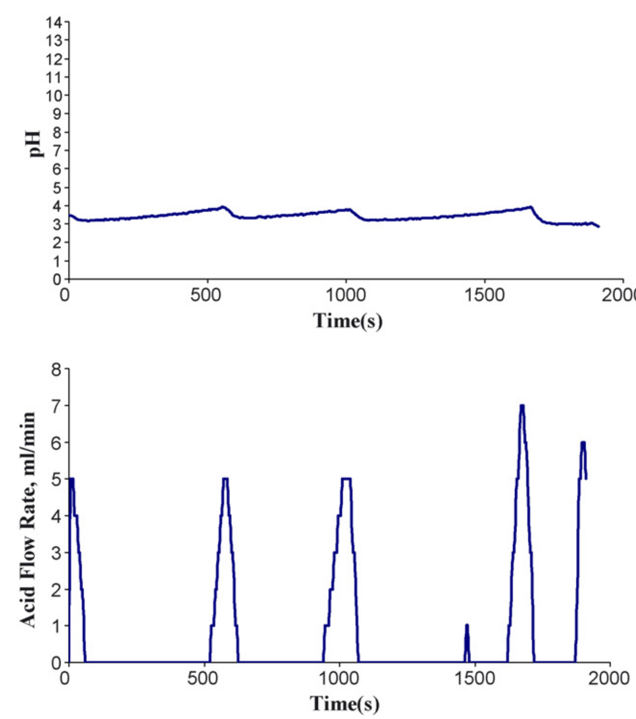

Fig. 7. Change in pH and acid flow rate with time by NLDMC control algorithm (set point 3.5 and acid concentration 0.004 M).

Table 5
ISE and IAE values for linear DMC

Figure no.	Set point for pH	ISE	IAE
4.2	3.5	167.82	219.49
4.3	3.5	24.44	82.65

Table 6
ISE and IAE values for nonlinear DMC

Figure no.	Set point for pH	ISE	IAE
4.5	3.5	22.28	81.62
4.6	3.5	23.31	78.05

in evaluating the value of the manipulated variable and this results in the oscillatory behavior of pH values and acid flow rates.

7. Conclusion

In this work, control of $CaCO_3$–H_2SO_4 neutralization process with linear and nonlinear dynamic matrix control method was examined.

At the start of the control work, the reactor reaction mixture was brought to a steady state at constant pH value. During the experiments all the other parameters except for the manipulated variable (pH), were kept at constant values. (Temperature: 60 °C and base solution flow rate 2 ml/s.) In steady state condition, control program was run and the system performance was observed. From here a graph of pH–time and acid flow rate–time was drawn. Calculated ISE and IAE values are given in Tables 5 and 6.

It is concluded from the ISE and IAE values that nonlinear DMC gives better results than those obtained by linear DMC. Using a polynomial type empirical model with this algorithm gave a good result. In approximation of linear model for the nonlinear process, iteration was a disadvantage. In our work, sampling time was very important in linear DMC control. When nonlinear equation was determined correctly, nonlinear DMC showed all the characteristics of DMC.

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