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On Fractional Order Predictive PI Controller Design for a MIMO Reactive Distillation Process

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Abstract: In this paper, fractional-order predictive PID control scheme is applied in composition control of boiling fractions of a reactive distillation plant set up for the esterification reaction between acetic acid and ethanol. The controller shares similar structural features with Model-based Predictive Controller (MPC) as many attractive benefits of Dynamic Matrix Control (DMC) are retained such as constraint handling capability. However, it optimizes a different objective function formulated to achieve a more robust control action. These robust properties make it attractive to multivariable process control applications. Process's state space model is assumed to be available and the model is augmented for prediction of future outputs. Thereafter, a structured cost function is defined which retains the design objective of fractional-order predictive PI controller. Optimisation of this cost function results in realising a near-optimal MIMO controller with reduced input control efforts. Simulation studies using Giwa's reactive distillation column demonstrates better control performance over dynamic matrix control of the same system. It also rejects disturbances, both measured and unknown disturbances, better than Dynamic Matrix Control system under similar conditions. A major contribution of this paper is the development of a MIMO fractional order predictive PI controller for multivariable process control applications such as composition control of a reactive distillation column.

Keywords: Model-based predictive control, Fractional order PID control, Linear multivariable control, Process control, Dynamic matrix control

1. INTRODUCTION

The presence of interactions (coupling effects) and directionality in Multi-Input-Multi-Output (MIMO) systems complicates the design and tuning of multivariable control systems for optimal performance. This limits the scope of application of most parametric model-based design algorithms to Single Input Single Output (SISO) applications. Efforts have been made over the past decades to extend conventional PID controller design methods to MIMO process control applications but with varying degree of success.

Majority of these methods rely on defining a special detuning factor to counteract effects of multivariable interaction (Vu & Lee, 2008). For instance, Niederlinski modified Ziegler-Nichol's tuning rule for MIMO processes by using a detuning factor to meet a sensitivity bound. Also, Biggest Log-modulus Tuning (BLT) method, which is a frequency domain PID controller design method, was proposed by Luyben to extend classical SISO PID tuning rule to MIMO systems. All these design methods are only defined for conventional PID controller design and do not address fractional-order controllers.

Al-Arfaj and Luyben (2000) presented a one-point control configuration for dual composition control of a reactive distillation column. A major outcome of their experimental study was that a single-end temperature could keep both distillate and bottoms product at satisfactory purity levels provided that reactive-zone hold up was sufficiently large (Al-Arfaj & Luyben, 2000). Giwa (2012) developed a realistic state space model of a three - by - three reactive distillation column experimentally set up for the esterification reaction between acetic acid and ethanol. Many predictive control algorithms were reviewed by the authors for their column control application including an implementation of Dynamic Matrix Control (DMC) (Giwa & Karacan, 2012). Giwa's reactive distillation column model is the focus of this paper and the DMC controller is chosen for comparison due to the inherent optimal property. It should be noted that frequency domain-based methods of designing FOPID controller have also been recently developed for multivariable distillation application (Edet & Katebi, 2018). The design scheme uses internal model control principle with promising results although without the predictive feature of MPC.

In this paper, the SISO Fractional Order Predictive PI control narrative (FOPPI) proposed in (Edet & Katebi, 2017) is generalised for MIMO systems and applied to improve composition purity of a three -by- three reactive distillation column. The rationale for considering FOPPI for distillation column control includes inherent benefits such as effectiveness in dealing with the coupling effects of variables, robust performance of FOPID structure as well as the anticipatory action that comes with the predictive feature.

This paper is organised as follows: A review of some multivariable control system design narratives is given here followed by a short overview of the reactive distillation process in section 1.1. In section 2, multivariable system analysis is given. The MIMO FOPPI controller is derived in section 3 while section 4 presents the simulation studies and reactive distillation column control results. Discussion of results follows in section 5 while major conclusions of the paper are summarised in section 6.

1.1 An Overview of the Reactive Distillation Process

An experimental column, set up for esterification reaction between acetic acid and ethanol to produce an ester (ethyl acetate), was used to identify a useful state space model for the process (Giwa & Karacan, 2012). The equilibrium-type esterification reaction is given below in (1):

$$CH_3COOH + C_2H_5OH \overset{K_{eq}}{\rightleftharpoons} CH_3COOC_2H_5 + H_2O \qquad (1)$$

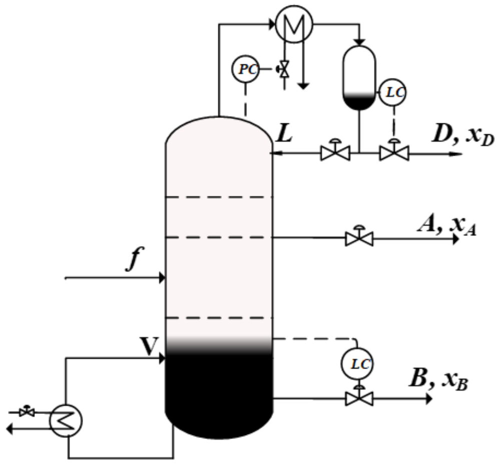

Fig. 1. Diagram of a trayed distillation column showing 3 input flow rates (boil up ***V***; feed ***f***; reflux flow rate ***L***) and 3 outputs (Distillate is ***D*** with molar concentration x_D; intermediate product is ***A*** with concentration x_A and Bottoms is ***B*** with concentration x_B).

Summary of steady state data of the column, main streams measurements and experimental description are available in the paper. It should be noted that concentration of boiling fractions is directly related to the temperature on each tray. Hence, temperature measurement is taken on each tray and molar composition is directly inferred. The inputs are the relevant flow rates and boil up while the outputs are the product concentrations (x_A, x_B and x_D) which are directly inferred from temperature on *A*, *B* and *D* trays respectively.

The level of interaction in a multivariable distillation system can be estimated using relative gain array (RGA). This information is a useful guide in variable pairing for some form of multi-loop decoupled control. In MIMO system, the relative gain of *ij*th loop (λ_{ij}) is defined as the ratio of the gain of *ij*th loop when all other loops in the system are open to the gain of the same loop when all the other loops are closed. RGA is generally computed as a function of frequency. It is the corresponding matrix of relative gains (G_{ij}) as given in: $\lambda_{ij} = \left[G\right]_{ij}\left[G^{-1}\right]_{ji}$.

A high condition number and relative gain array of the system indicates high level of variable interaction. Multivariable interaction increases the difficulty in diagonalising the system for all frequencies by any choice of controller. Similarly, a small RGA signifies lower level of interaction between the associated variables. Physical relationship of variables is also given primary consideration during variable pairing before designing the multivariable controller. It is assumed in this work that parameters are effectively paired using similar techniques and each sub-transfer function of the model is open loop stable. Many processes in practice are found to be open loop stable.

2. MULTIVARIABLE PROCESS ANALYSIS

2.1 Controllability and Observability

FOPPI controller is derived based on an augmented process state space model. Consequently, it is important to investigate the poles (eigenvalues), controllability (state reachability) and observability of the augmented system before designing a control system. Let the characteristic equation of the augmented state space system be $C(\lambda)$:

$$C(\lambda) = \begin{vmatrix} \lambda I - A_p & 0_{n1}^T \\ -C_p A_p & (\lambda-1)I_{mxm} \end{vmatrix} \Rightarrow (\lambda-1)^m \left|\lambda I - A_p\right| = 0 \quad (2)$$

where λ represents eigenvalues of the state space model with coefficient matrices: A_p, B_p, C_p and size *m*; *I* = identity matrix.

Lower triangular matrix property is used to solve (2) for eigenvalues of the system. The determinant of a block lower triangular matrix equals the product of determinant of diagonal matrices. Therefore, eigenvalues of augmented state space model equal the union of eigenvalues of original plant and the *m* number of eigenvalues, $\lambda = 1$. This embeds integral action in the resultant predictive control system as *m* number of integrators are embedded in the augmented state space model.

In addition, controllability of the augmented state space model is presented. Since the augmented model introduces integral modes, it is desirable to analyse all sufficient conditions required for stability of these integral modes.

Bay's sufficient condition for stability of these integral modes is in the minimal realisation condition of plant model. He proved that a minimal realisation is both controllable and observable (Wang, 2009). Many practical multivariable processes have model information available as step response data or identified Laplace transfer function models. When converting these models to state space for discrete predictive control design, a minimal realisation is required.

If (A_p, B_p C_p) system is both controllable and observable having minimal realisable transfer function $G_p(z) = C_p\,(zI-A_p)^{-1}B_p$, then the augmented system with transfer function:

$$G(z) = \frac{z}{z-1} G_p(z)$$

is both controllable and observable if and only if the plant model $G_p(z)$ has no zero at $z = 1$ where z = discrete variable.

3. FOPPI CONTROLLER DESIGN FOR MIMO SYSTEMS

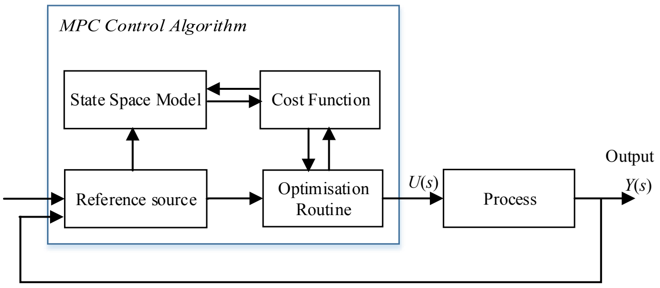

Fig. 2. Basic diagram of MPC control implementation.

Most common MPC algorithms produce optimal control action by minimising a cost function J of the form:

$$J = \sum_{i=1}^{p} \left\| r(k+i) - y(k+i) \right\|_2 Q + \sum_{j=1}^{N} \left\| \Delta U(k+j-1) \right\|_2 R \quad (3)$$

where U is the control input; $y(k)$ is the predicted output at kth time instant; r is the desired reference, Q and R are appropriate weights. However, FOPID controller's objective (Δu_{pi}) can be expressed using G-L definition of fractional-order derivative as:

$$\Delta u_{pi}(k) = k_p \Delta e(k) + K_I \left(e(k) - \sum_{j=1}^{k} B_j e(k-j) \right) \quad (4)$$

where: $B_j = \dfrac{1+\mu}{j} b_{j-1}; K_I = k_i T_s^{\mu}$; μ = fractional order;

b_j is binomial coefficient;$b_0 = 1;\ b_1 = \mu b_0; b_2 = \left(1 - \dfrac{1+\mu}{2}\right) b_1;$

$b_j = \left(1 - \dfrac{1+\mu}{j}\right) b_{j-1}; k_i$ = integral gain; k_p = proportional gain;

T_s = sampling period; e(k) = error at kth time. Derivation of (4) is available elsewhere (Edet & Katebi, 2017). It follows from (4) that proportional term and a fractional-order integral term can be used for minimisation of effects of disturbances as well as achieve set-point tracking. Derivative component is unnecessary because anticipatory action is inherently ensured by the MPC framework. These two terms are sufficient to formulate another quadratic cost function which is minimised to obtain the proposed MIMO FOPPI controller. The FOPID controller (4) given as $\Delta u_{pi}(k)$ is not implemented directly. Direct implementation of $\Delta u_{pi}(k)$ must be band-limited. In contrast, MPC framework is used for implementation of the fractional order predictive PI controller to achieve a better disturbance rejection and performance indices as shown in a non-minimum phase simulation diagram of Fig. 3. Control signal limits can also be defined inherently as constraints during the optimisation routine. In deriving the new MIMO FOPPI controller, a MIMO state space model is formulated and augmented as follows:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{bmatrix} A_p & 0_m^T \\ C_p A_p & I_{m\times m} \end{bmatrix} \begin{pmatrix} \Delta x(k) \\ y(k) \end{pmatrix} + \begin{bmatrix} B_p \\ C_p B_p \end{bmatrix} \Delta u(k)$$

$$y(k) = [0_m \quad I_{m\times m}] \begin{pmatrix} \Delta x(k) \\ y(k) \end{pmatrix};\ \text{where:}$$

m_1 = number of inputs; m_2 = number of outputs and n_1 = number of states in the system.

$x_1 = \Delta x(k+1);\ \ x_2 = \Delta y(k+1); 0_m$ is $m \times n_1$ zero matrix;

$A_p \in \Re^{n_1 x n_1}$ is n_1 x n_1 system matrix; $B_p \in \Re^{n_1 x m}$ is n_1 x m input matrix; $C_p \in \Re^{m x n_1}$ is m x n_1 output matrix; and I_{mxm} is identity matrix with dimension m by m.

It is assumed that the number of inputs (m_1) is equal to the number of outputs (m_2) as only square systems are considered. Also, if this m-square system has n_1 states, each of the measurable output can be independently controlled without any steady state error using a similar approach to Dynamic Matrix Control (DMC). In addition, it is also assumed that noise sequence in the system is negligible. Therefore, the augmented state space system given in (5) is suitable for control design for any MIMO control system.

$$\begin{pmatrix} \Delta x(k+1) \\ y(k+1) \end{pmatrix} = A \begin{pmatrix} \Delta x(k) \\ y(k) \end{pmatrix} + B \Delta u(k) \quad (5)$$

$$y(k) = C \begin{pmatrix} \Delta x(k) \\ y(k) \end{pmatrix} \ \text{where:}$$

$$A = \begin{bmatrix} A_p & 0_m^T \\ C_p A_p & I_{m\times m} \end{bmatrix};\ B = \begin{bmatrix} B_p \\ C_p B_p \end{bmatrix};\ C = [0_m \quad I_{m\times m}];$$

p = prediction horizon; N = control horizon and $p \ge N$; future predicted states can be obtained recursively.

The augmented state space model is used to predict future output. Therefore, prediction matrices H, H_p and H_j are obtained recursively from process model. Thereafter, the proposed control law is derived. At a sampling instant k, within a prediction horizon p, the aim of the control system is to bring the future predicted output $\hat{Y}(k+1)$ as close as possible to the desired set-point signal $Y_d(k+1)$ assuming the set-point signal remains constant in the optimisation window. The task is therefore reduced to finding the best control parameter vector ΔU such that an error function between the set-point and the predicted output is minimised. Control effort is also penalised. The structured quadratic cost function to be minimised is formed directly from (4) as shown in (6). Integral (fractional) component of error has been introduced for robustness. That is: substituting (4) in (3) yields the objective function defined below in (6):

$$J = \sum_{k=1}^{p} \begin{bmatrix} k_p \left(\Delta E(k+1)\right)^2 + K_I \left(E(k+1)\right)^2 + \\ K_I \sum_{j=1}^{k} B_{j-1} \left(E(k+1-j)\right)^2 \end{bmatrix} + \gamma \sum_{k=1}^{N} \Delta u(k)^2 \tag{6}$$

where: $\gamma =$ control signal weight. The future output is the sum of free output response and forced output as shown:

$$\hat{Y}(k+1) = \hat{Y}_p(k+1) + Y_f(k+1)$$

where $Y_f(k+1) =$ forced output signal due to the control input. The error signal is the difference between the desired set-point and the predicted output:

$E(k+1) = Y_d(k+1) - \hat{Y}(k+1) = Y_d(k+1) - \hat{Y}_p(k+1) - H\Delta u(k).$

This is because the forced output is expressed as follows: $Y_f(k+1) = H\Delta u(k)$ where:

$$H = \begin{bmatrix} CB & 0 & 0 & ... & 0 \\ CAB & CB & 0 & ... & 0 \\ CA^2B & CAB & B & ... & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ CA^{p-1}B & CA^{p-2}B & CA^{p-3}B & ... & CA^{p-m}B \end{bmatrix}_{p\times mN}.$$

This is a generic case where m inputs increase the dimension of the prediction matrix. J can be re-written in vector form as:

$J = k_p \Delta e^T \Delta e + K_I e^T e + K_I \sum_{j=1}^{k} B_j e_j^T e_j + \gamma \Delta u^T \Delta u$; where:

$$e = \left[e(k+1), e(k+2), e(k+3), ..., e(k+p)\right]^T$$

$$\Delta e = \begin{bmatrix} \Delta e(k+1), \Delta e(k+2), \Delta e(k+3) \\ ,..., \Delta e(k+p) \end{bmatrix}^T$$

$$e_j = \begin{bmatrix} e(k+1-j), e(k+2-j), e(k+3-j) \\ ,..., e(k+p-j) \end{bmatrix}^T$$

Also, the size of desired output and predicted output vectors depends on prediction horizon as follows:

$$Y_d = \left[y_d(k+1), y_d(k+2), y_d(k+3), ..., y_d(k+p)\right]^T$$

$$\Delta Y_d = \begin{bmatrix} \Delta y_d(k+1), \Delta y_d(k+2), \Delta y_d(k+3) \\ ,..., \Delta y_d(k+p) \end{bmatrix}^T$$

$$Y_{dj} = \begin{bmatrix} y_d(k+1-j), y_d(k+2-j), y_d(k+3-j) \\ ,..., y_d(k+p-j) \end{bmatrix}^T$$

$$\hat{Y}_p = \left[\hat{y}_p(k+1), \hat{y}_p(k+2), \hat{y}_p(k+3), ..., \hat{y}_p(k+p)\right]^T$$

$$\Delta \hat{Y}_p = \begin{bmatrix} \Delta \hat{y}_p(k+1), \Delta \hat{y}_p(k+2), \Delta \hat{y}_p(k+3) \\ ,..., \Delta \hat{y}_p(k+p) \end{bmatrix}^T$$

$$\hat{Y}_{pj} = \begin{bmatrix} \hat{y}_p(k+1-j), \hat{y}_p(k+2-j), \hat{y}_p(k+3-j) \\ ,..., \hat{y}_p(k+p-j) \end{bmatrix}^T$$

Prediction matrices H, H_p and H_j derived recursively from process model are as shown below:

$$H = \begin{bmatrix} h_1 & 0 & 0 & 0 & 0 \\ h_2 & h_1 & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ h_N & h_{N-1} & h_{N-2} & \cdots & h_1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_p & h_{p-1} & h_{p-2} & \cdots & h_{p-N+1} \end{bmatrix}_{p\times mN}$$

where each element of matrix H is directly computed from coefficients of the process state space model. The other prediction matrices (H_p and H_j) are obtained from matrix-H as shown below:

$$H_p = \begin{bmatrix} h_1 & 0 & \cdots & 0 \\ h_2 - h_1 & h_1 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ h_p - h_{p-1} & h_{p-1} - h_{p-2} & \cdots & h_{p-N+1} - h_{p-N} \end{bmatrix}_{p\times mN}$$

$$H_j = H_1, H_2, H_3, ..., H_k.$$

$$H_1 = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ h_1 & 0 & 0 & \cdots & 0 \\ h_2 & h_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{p-1} & h_{p-2} & h_{p-3} & \cdots & h_{p-N} \end{bmatrix}_{p\times mN}$$

$$H_2 = \begin{bmatrix} 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ h_1 & 0 & 0 & \cdots & 0 \\ h_2 & h_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_{p-2} & h_{p-3} & h_{p-4} & \cdots & h_{p-N-1} \end{bmatrix}_{p\times mN} ; \ldots H_k = 0.$$

Substituting for error signals in J and solving for the best control vector yields:

$$J = k_p[\Delta Y_d - \Delta\hat{Y}_p - H_p\Delta u]^T[\Delta Y_d - \Delta\hat{Y}_p - H_p\Delta u]$$
$$+K_I[Y_d - \hat{Y}_p - H\Delta u]^T[Y_d - \hat{Y}_p - H\Delta u]$$
$$+\sum_{j=1}^{k}\left(k_j[Y_{dj} - \hat{Y}_{pj} - H_j\Delta u]^T[Y_{dj} - \hat{Y}_{pj} - H_j\Delta u]\right) + \gamma\Delta u^T\Delta u.$$

To find the minimum point, solve for the gradient of J with respect to Δu :

$$\frac{\partial J}{\partial \Delta u} = 0;$$
$$\Rightarrow\left[k_p H_p^T\Delta Y_d + k_p H_p\right]\left(\Delta Y_d - \Delta\hat{Y}_p\right) +$$
$$\left[K_I H^T + K_I H\right]\left(Y_d - \hat{Y}_p\right) + \sum_{j=1}^{k}\left[k_j H^T + k_j H\right]\left(Y_{dj} - \hat{Y}_{pj}\right)$$

$$= 2\gamma\Delta u + \Delta u\left[2k_p H_p^T H_p\right] + \Delta u\left[2K_I H^T H\right] +$$
$$2\Delta u\sum_{j=1}^{k} k_j\left[H_j^T H_j\right]; \text{where } k_j = K_I\frac{1+\mu}{j}b_{j-1}.$$

Solving for optimum control increment yields the control law given in (7):

$$\Delta u(k) = k_p H_p^T L\phi(\Delta Y_d - \Delta\hat{Y}_p) + K_I H^T L\phi(\Delta Y_d - \Delta\hat{Y}_p) + \sum_{j=1}^{k} k_j H_j^T L\phi(\Delta Y_d - \Delta\hat{Y}_p) \tag{7}$$

where I_m and 0_m are m by m identity and zero matrices;

$$L = [I_m, 0_m, 0_m, \ldots, 0_m]^T;$$

$$\phi = \left(k_p H_p^T H_p + K_I H^T H + \sum_{j=1}^{k}(k_j H_j^T H_j) + \gamma I\right)^{-1}.$$

Equation (7) describes the MIMO FOPPI controller. Two small parameters (k_p and k_I) are provided for tuning.

4. SIMULATION, IMPLEMENTATION AND RESULTS

Giwa's distillation state space model is given in (8):

$$\begin{pmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \end{pmatrix} = \begin{bmatrix} 0.9981 & 0.0024 & -0.0009 \\ -0.0034 & 0.9957 & -0.0008 \\ -0.0009 & -0.0052 & 0.9945 \end{bmatrix}\begin{pmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{pmatrix} + \begin{bmatrix} 0.0003 & 0.0013 & -0.0565 \\ -0.0005 & 0.0019 & -0.0818 \\ -0.0025 & 0.0067 & -0.2808 \end{bmatrix}\begin{pmatrix} \Delta u_1 \\ \Delta u_2 \\ \Delta u_3 \end{pmatrix} \tag{8}$$

$$\begin{pmatrix} y_1(k) \\ y_2(k) \\ y_3(k) \end{pmatrix} = \begin{bmatrix} -12.8258 & 4.0787 & 0.1685 \\ -3.7520 & -0.8266 & -1.9955 \\ -6.2674 & -17.6857 & -0.7129 \end{bmatrix}\begin{pmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \end{pmatrix}$$

Composition of top distillate, segment draw-off and bottom plate product is inferred from temperature measurements at each tray in this experimental column. The output temperature of interest is a 70.75 ^{o} C for distillate tray. This was found to be very important because, in the production of ethyl acetate from this esterification reaction, 70.75 ^{o} C is the optimal temperature for desired product quality of over 98% purity. Steady state values of nominal plant outcome without control system was found to be 69.89 ^{o}C for distillate product, 70.81 ^{o} C for reaction segment and 87.99 ^{o} C for bottom product which is not good enough for optimum product's purity (Giwa & Karacan, 2012).

Therefore, a composition controller is required to drive the output temperature at the top of the column to 70.75 ^{o} C. The MIMO FOPPI controller along with DMC controller are compared with these common tuning parameters:

$N_p = 200$; $N_c = 50$; λ=0.0009.

5. DISCUSSION

The design of product's composition control system for the 3-by-3 Giwa reactive distillation column using FOPPI control algorithm is found to deal adequately with multivariable interactions. The composition of top distillate, segment draw off and bottom plate product is inferred from temperature measurements at each tray in this experimental column and are highly inter-coupled. The output temperature of interest is 70.75 ^{o} C for the distillate tray. This was found to be very important because, in the production of ethyl acetate from this esterification reaction, 70.75 ^{o} C is the optimal temperature for desired product quality of over 98% purity. In the absence of composition control system, steady state values of nominal plant outcome were reported to be 69.89 ^{o} C for distillate product, 70.81 ^{o} C for reaction segment and 87.99 ^{o} C for bottom product. However, composition controller is found to drive the output temperature at the top of the column to 70.75 ^{o} C. Simulation was carried out using step changes in inputs in order to assess both the transient response and steady state response of the control system. When compared with DMC controller, the rise time for the FOPPI control system is less than 10 seconds when properly tuned with small parameters: $0 < [k_P, k_I] < 1$. The distillate

(Fig. 4) and bottoms (Fig. 6) responses show improved benefit of FOPPI compared to DMC. Fig. 5 shows that FOPPI compares favourably with DMC with respect to bottoms although with a slightly higher overshoot. FOPPI generally produces better responses at the expense of these extra tuning parameters.

6. CONCLUSIONS

A MIMO FOPPI controller which combines predictive features of discrete time MPC as well as robust features of fractional order PI controller has been applied in composition control of a reactive distillation column. Simulation studies have been presented to demonstrate improved benefits such as better disturbance rejection when compared with dynamic matrix control system without incurring additional (significant) computational overhead. This is the comparative benefit of using the proposed MIMO FOPPI controller. The control structure enables it to inherently deal adequately with multivariable interaction.

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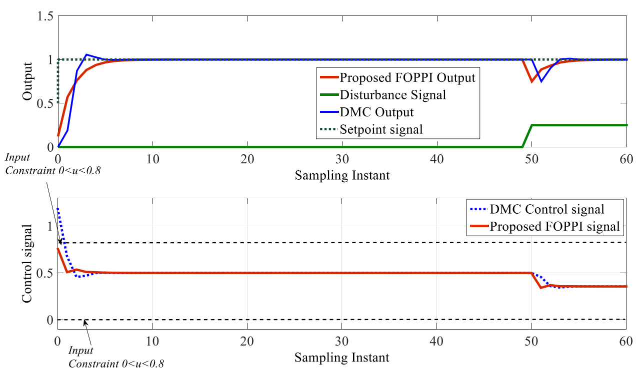

Fig. 3 Disturbance rejection - unit step simulation of both DMC and FOPPI controllers in a non-minimum phase system

shows that the FOPPI controller responds faster in rejecting disturbances and uses smaller control effort.

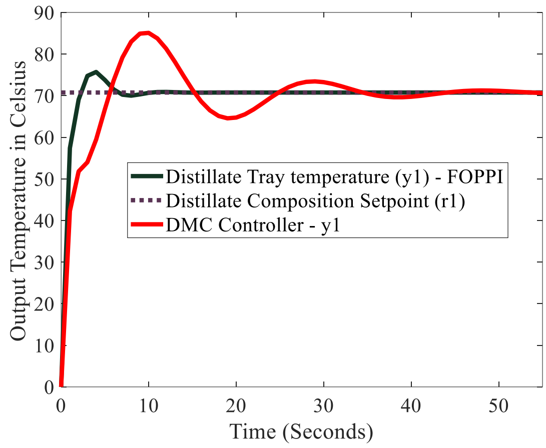

Fig. 4 Top composition – step response. FOPPI controller regulates the tray temperature to expected value

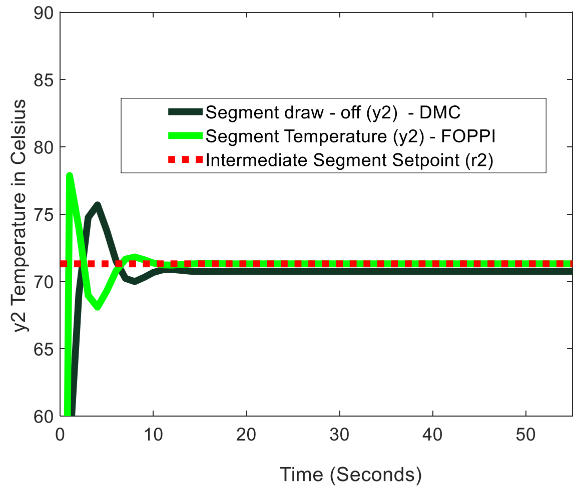

Fig. 5 Side-stream draw off – The FOPPI controller (in green) regulates the tray temperature to the expected value.

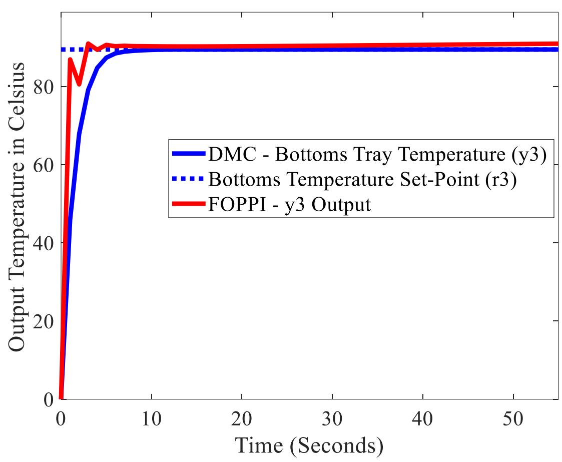

Fig. 6 Bottoms Product – Step response shows regulation of bottoms product as expected.