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Constrained Model Predictive Control for Fluorocarbon Refrigerant Distillation Column

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ABSTRACT: This is the simulation study of controlling industrial distillation with model predictive control scheme. The development of empirical model for binary distillation process has been carried out in this work. Mixture including three components, namely monochloro difluoro methane (R22) Trifluoromethane (R23) Dichlorofluoromethane (R21), was obtained from anhydrous hydrogen fluoride (AHF) and chloroform used as a feed mixture.Crude product mixture of Dichlorofluoromethane(R21) and monochloro difluoro methane (R22) is distilled to get pure R22 in Binary distillation column. Stable control of binary distillation column is of great importance for improvements of operation efficiency and higher product concentration. Decoupled multi-loop Unconstrained Model Predictive Controllers (MPC) are not carried out to manage to eliminate the effects of interactions among the control loops, but they generally become sluggish due to imperfect process models and a close control of the process is usually impossible in real practice. Based on its inherent unconstrained scheme, Constrained Model Predictive Control (CMPC) is employed to handle such highly interacting system. For high quality requirements, a two-input two-output model of the binary distillation column is constructed. Constrained model predictive control is applied in binary distillation column plant and operation of the process close to their optimum operating conditions is achieved.

KEYWORDS: Model predictive control (MPC), process control, FOPDT, binary distillation column,Constrained Model predictive control (CMPC)

I.INTRODUCTION

Distillation columns are unit operations that are very common in chemical, Petrochemical and even sometimes in metallurgical industries. Moreover, they consume a large part of a plant's total energy. The optimization of their design and operation is thus an essential objective. The more and more severe operation constraints which are imposed make their mastering more delicate and implies impressive control strategies. The purpose of a distillation column is to separate a multi component feed into products of different compositions or to purify intermediate or final products. The possibility of distillation relies on the volatility difference existing between different chemical species. When the separation by a simple flash is insufficient, the separation is operated in a distillation column which will allow better separation due to the series of trays. The technology of distillation columns can be complex and this review is limited to the classical case of a column having only one feed, producing the bottom product at the reboiler and the distillate or overhead product at the condenser Fig.1, without any side withdrawal. The distillate can be seen as the production of "light" and the bottom product as the production of "heavy". The role of the reboiler situated at the bottom of the column is to bring to the whole column the energy Q_B necessary for the separation operation, corresponding to the vaporization enthalpy. The condenser can be total or partial, depending on whether it condenses the total or a part of the vapour arriving at the top of the column into a liquid that is separated between the distillate and the reflux. In the simplest case constituted by the total condenser, the absorbed heat Qc (supply of cold) allows us to exactly perform the condensation of the head vapour. The reboiler and the condenser are, in fact, heat exchangers. The feed F mixture monochloro difluoro methane (R22),Dichlorofluoromethane (R21) used to manufacture refrigerant gases can be introduced into the column at different enthalpy levels (subcooled liquid, saturated liquid, liquid-vapour mixture, saturated vapour, overheated vapour). Frequently, the feed is a saturated liquid (at the boiling point), which will be our hypothesis. We consider the column as a binary column, separating a heavy component and a light component.

II.RELATED WORK

The LV-configuration is the best choice of manipulated inputs most commonly used in industrial practice. L/D,V/B configuration may be preferable for the optimal control and energy consumption of distillation columns[2,3].To get a

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realistic evaluation of the controllers the uncertainty and constraints should included [4].Dynamic matrix control is arguably the most popular MPC algorithm currently used in the chemical process industry[7].Tuning of unconstrained and constrained DMC for SISO and multivariable system has been addressed by array of researchers. Systematic trial and error tuning procedure have been proposed in [15, 16].Detailed sensitivity analysis of adjustable parameters and their effects on DMC performance in [17, 18] the method to compute an appropriate prediction horizon and a move suppression coefficient [11].To simplify DMC tuning, [19] also proposed the M=1 controller configuration of DMC.

III. GENERALITIES FOR DISTILLATION COLUMN CONTROL

The most common objective in a distillation process is to maintain the top and bottom compositions at a desired specification. A typical distillation column Fig.1 can be represented as a block diagram Fig.2 which possesses five control inputs u corresponding to five valves (flow rates of distillate D, bottom product B, reflux L, reboiler vapour V1 (indirectly manipulated by the heat power at the reboiler QB), top condensed vapour Vn (indirectly manipulated by the power withdrawn from the condenser)n and five controlled outputs y.

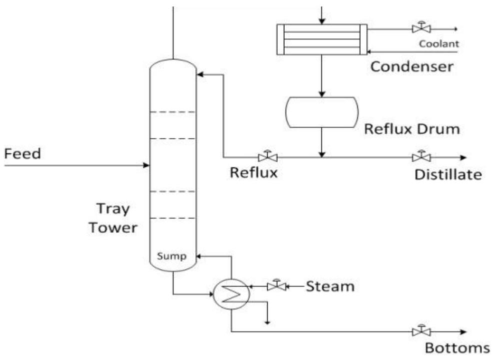

Fig. 1 Binary Distillation Column

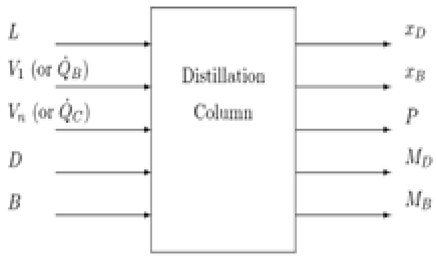

Fig. 2 Multi variable control of distillation column

Three of the controlled variables (holdup at the reboiler M_B and at the condenser M_D , and pressure P or vapour holdup M_V) must be carefully controlled to maintain the stability of the operation. In fact, [1]show that even binary columns whose pressure and levels are controlled can present multiple stationary states. There remain two degrees of freedom for the top and bottom compositions X_D and X_B. The other inputs are those which are not affected inside the system: the disturbances d and the set points Y_R. The disturbances in the column, in general, are related to the feed (flow rate F, feed enthalpy expressed with respect to the liquid fraction kF and the feed composition ZF). In a general manner, disturbances are classified as measured disturbances and unmeasured. The set points can change, for example, when an on-line economic optimization is performed. The outputs can be measured (pressure P, holdup $M_B$and M_D , top and bottom compositions with time delay); besides, the temperature is generally measured at several locations. For the distillation column, we can consider that the state variables are the liquid and vapour mole fractions at the level of each plate; unfortunately, in general, they are not measured inside the column. The temperature measurement on sensitive plates allows us, by means of the thermodynamic equilibria and knowing the pressure, to estimate the profile of mole fractions.

IV. DIFFERENT TYPES OF DISTILLATION COLUMN CONTROL

SINGLE-INPUT SINGLE-OUTPUT CONTROL

The simplest used approach consists of controlling only one composition, generally top Y_D. This is a single-input single-output control and, in this case, a flow rate is manually controlled by the operator. Taking into account strict specification, dual control, which is aiming to control both the top X_D and bottom X_B mole fractions, is desirable and will be presented in the following. According to [2], dual control allows us to spare 10 to 30% energy by avoiding over-purification and out of norms product loss.

DUAL DECOUPLING CONTROL

Most distillation columns may b treated as 5*5 control problem the manipulated inputs u and controlled outputs y are

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$$u = \begin{pmatrix} L \\ V \\ D \\ B \\ VT \end{pmatrix} ; y = \begin{pmatrix} XD \\ XB \\ P \\ MD \\ MB \end{pmatrix}$$

The standard configurations, as used by [3], include the follows L, D, V, B and their ratios. Use of these manipulated variables has the advantage of being relatively easy to implement and simple to understand for the operators. [4] show that the use of ratios does not have any linearizing effect, but introduces multivariable controllers which may be tuned as single-loop controllers. Usually combinations of L and D are used for the top, and combinations of V and B are used. for the bottom. One of the main difficulties in multivariable feedback control lies in the interaction of the control loops Different solutions were proposed, e.g. using a ratio between the reflux and the condenser vapour to reduce interaction. [5] studied the decoupling from a linear model of the column.

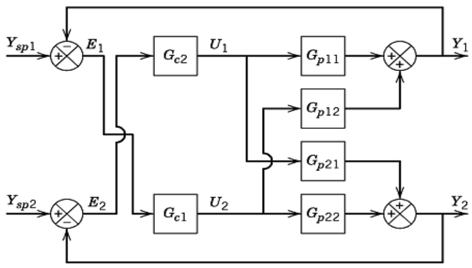

Fig 3: Decoupling Diagram of multi variable process

According to [6], who studied four configurations: (L, V), (D, V), (D, B), (LID, VIB) by the frequency RGA method, the best structure for most columns would be the two-ratio configuration (L/D, V/B) in the case of dual control.

V. MODEL PREDICTIVE CONTROL

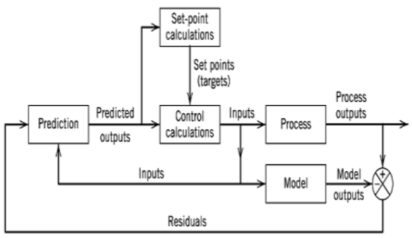

Fig.4: Block Diagram of MPC

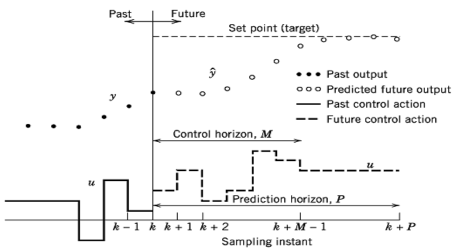

Fig. 5: Moving horizon Concept of MPC

The overall objectives of an MPC controller have been summarized by [7]:

1. Prevent violations of input and output constraints.
2. Drive some output variables to their optimal set points, while maintaining other outputs within specified ranges
3. Prevent excessive movement of the input variables.
4. Control as many process variables as possible when a sensor or actuator is not available.

A block diagram of a model predictive control system is shown in Fig.4 a process model is used to predict the current and future values of the output variables. The residuals, the differences between the actual and predicted outputs, serve as the feedback signal to a Prediction block. The predictions are used in two types of MPC calculations that are performed at each sampling instant: set-point calculations and control calculations. Inequality constraints on the input and output variables, such as upper and lower limits, can be included in either type of calculation. Note that the MPC configuration is similar to both the internal model control configuration and the Smith predictor configuration because

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the model acts in parallel with the process and the residual serves as a feedback signal. However, the coordination of the control and set-point calculations is a unique feature of MPC. Furthermore, MPC has had a much greater impact on industrial practice than IMC or Smith predictor, because it is more suitable for constrained MIMO control problems.
The set points for the control calculations, also called targets, are calculated from an economic optimization based on a steady-state model of the process, traditionally, a linear model. Typical optimization objectives include maximizing a profit function, minimizing a cost function, or maximizing a production rate. The optimum values of set points change frequently due to varying process conditions, especially changes in the inequality constraints. The constraint changes are due to variations in process conditions, equipment, and instrumentation, as well as economic data such as prices and costs. In MPC the set points are typically calculated each time the control calculations are performed. The MPC calculations are based on current measurements and predictions of the future values of the outputs. The objective of the MPC control calculations is to determine a sequence of control moves (that is, manipulated input changes) so that the predicted response moves to the set point in an optimal manner. The actual output y, predicted output ŷ, and manipulated input u for SISO control are shown in Fig. 4. At the current sampling instant, denoted by k, the MPC strategy calculates a set of M values of the input {u(k + i - 1), i = 1, 2, .. , M}. The set consists of the current input u(k) and M- 1 future inputs. The input is held constant after the M control moves. The inputs are calculated so that a set of P predicted outputs y (k + i), i = 1, 2, ..., P} reaches the set point in an optimal manner. The control calculations are based on optimizing an objective function .The number of predictions P is referred to as the prediction horizon while the number of control moves M is called the control horizon. A distinguishing feature of MPC is its receding horizon approach. Although a sequence of M control moves is calculated at each sampling instant, only the first move is actually implemented. Then a new sequence is calculated at the next sampling instant, after new measurements become available; again only the first input move is implemented.

PREDICTIONS FOR SISO MODELS

The MPC predictions are made using a dynamic model, typically a linear empirical model such as a multivariable version of the step response or difference equation models .Alternatively, transfer function or state-space models can be employed. For very nonlinear processes, it can be advantageous to predict future output values using a nonlinear dynamic model. Step-response models offer the advantage that they can represent stable processes with unusual dynamic behaviour that cannot be accurately described by simple transfer function models. Their main disadvantage is the large number of model parameters. Although step-response models are not suitable for unstable processes, they can be modified to represent integrating processes. Next, we demonstrate how step-response models can be used to predict future outputs. Similar predictions can be made using other types of linear models such as transfer function or state-space models. The step-response model of a stable, single-input, single-output process can be written as

$$y(k+1) = y_0 + \sum_{i=1}^{N-1} S_i\, \Delta u(k-i+1) + S_N u(k-N+1) \quad (1)$$

where y(k + 1) is the output variable at the (k + 1)sampling instant, and u(k- i + 1) denotes the change in the manipulated input from one sampling instant to the next, u(k- i + 1) = u(k- i + 1) - u(k- i). Both y and u are deviation variables. The model parameters are the N step-response coefficients, S_1 to S_N $\hat{y}(k+1)$ denote the prediction of $y(k+1)$ that is made at time k. If $y_0 = 0$, this one-step ahead prediction can be obtained from (1) by replacing $y(k+1)$ with $\hat{y}(k+1)$:

$$\hat{y}(k+1) \quad = \sum_{i=1}^{N-1} S_i\, \Delta u(k-i+1) + S_N u(k-N+1) \quad (2)$$

Equation (1) can be expanded as

$$\hat{y}(k+1) = S_1 \Delta u(k) + \sum_{i=2}^{N-1} S_i\, \Delta u(k-i+1) + S_N u(k-N+1) \quad (3)$$

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The first term on the right-hand side indicates the effect of the current input $u(k) = u(k) - u(k-1)$.The second term represents the effects of past inputs, $\{u(i), i < k\}$. An analogous expression for a two-step-ahead prediction can be derived in a similar manner. Substitute $k = k' + 1$ into (1)

$$\hat{y}(k'+2) \;=\; \sum_{i=3}^{N-1} S_i\, \Delta u(k'-i+2) + S_N u(k'-N+2) \quad (4)$$

Because Eq. (3) is valid for all positive values of k', without loss of generality, we can replace k' with k and then expand the right-hand side to identify the contributions relative to the current sampling instant k,

$$\hat{y}(k+2) = S_1 \Delta u(k+1) + S_2 \Delta u(k) + \sum_{i=3}^{N-1} S_i\, \Delta u(k-i+2) + S_N u(k-N+2) \quad (5)$$

An analogous derivation provides an expression for a j-step ahead prediction where j is an arbitrary positive integer:

$$\hat{y}(k+j) = \sum_{i=1}^{j} S_i\, \Delta u(k+j-i) + \sum_{i=j+1}^{N-1} S_i\, \Delta u(k+j-i) + S_N u(k+j-N) \quad (6)$$

The second and third terms on the right-hand side of Eq. (4) represents the predicted response when there are no current of future control actions. Because this term accounts for past control actions, it is referred to as the predicted unforced response and denoted by the symbol, $\hat{y}^0(k+j)$. thus, we define

$$\hat{y}^0(k+j) \text{ as}(k+j) \triangleq \textstyle\sum_{i=j+1}^{N-1} S_i\, \Delta u(k+j-i) + S_N u(k+j-N) \quad (7)$$

and write (6) as:

$$\hat{y}(k+j) = \sum_{i=1}^{j} S_i\, \Delta u(k+j-i) + \hat{y}^0(k+j) \quad (8)$$

The above equation can be used to derive a simple predictive control law based on single prediction. Now, we consider the more typical situation in which the MPC calculations are based on multiple predictions rather than on a single prediction. The equation is simplified and vector matrix notation is employed.

A vector of predicted unforced response, equivalent to equation (7) defined as

$$\hat{y}^0(k+1) \triangleq \text{col}[\; \hat{y}^0(k+1),\, \hat{y}^0(k+2) \ldots.\, \hat{y}^0(k+p)] \quad (9)$$

Vector of control actions for the next sampling instants,

$$\Delta u(k) \;\triangleq \text{col}[\Delta u(k), \Delta u(k+1) \ldots. \Delta u(k+M-1) \quad (10)$$

The MPC control calculations are based on calculations $\Delta u(k)$ so that the predicted outputs more optimally to the new set points. Now the (8) conveniently written in vector matrix notation as

$$\hat{y}(k+1) = S\Delta u(k) + \hat{y}^0(k+1) \quad (11)$$

PREDICTIONS FOR MIMO MODELS

$$\hat{Y}_1(k+1) = \textstyle\sum_{i=1}^{N-1} S_{11,i}\, \Delta u_1(k-i+1) + S_{11N} u_1(k-N+1) + \sum_{i=1}^{N-1} S_{12,i}\, \Delta u_2(k-i+1) + S_{12N} u_2(k-N+1) \quad (12)$$

$$\hat{Y}_2(k+1) = \textstyle\sum_{i=1}^{N-1} S_{21,i}\, \Delta u_1(k-i+1) + S_{21N} u_1(k-N+1) + \sum_{i=1}^{N-1} S_{22,i}\, \Delta u_2(k-i+1) + S_{22N} u_2(k-N+1) \quad (13)$$

The previous analysis for SISO systems can be generalized to MIMO systems by using the Principle of Superposition. For simplicity, we first consider a process control problem with two outputs, Y1 and y2, and two inputs, u1 and u2. The predictive model consists of two equations and four individual step-response models, one for each input-output pair.

MODEL PREDICTIVE CONTROL LAW

The control calculations are based on minimizing the predicted deviations from the reference trajectory. Let k denote the current sampling instant. The predicted error vector, E(k + 1), is defined as

$$\hat{E}(k+1) \;\triangleq Y_r\; (k+1) - \tilde{Y}(k+1) \qquad (14)$$

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The general objective of the MPC control calculations is to determine, $\Delta U(k)$, the control moves for the next M time intervals,

$$\Delta U\ (k) = col[\Delta u(k), \Delta u(k+1), \dots, \Delta u(k+M-1) \quad (15)$$

The M-dimensional vector $\Delta U(k)$, is calculated so that an objective function (also called a performance index) is minimized. Typically, either a linear or a quadratic objective function is employed. For unconstrained MPC the objective function is based on minimizing some of three types of deviations or errors [7]:
1. The predicted errors over the predicted horizon, E(k + 1)
2. The next M control moves, $\Delta U(k)$,
3. The deviations of u(k + i) from its desired steadystate value Usp over the control horizon

For MPC based on linear process models, both linear and quadratic objective functions can be used [7], [8].To demonstrate the MPC control calculations, consider a quadratic objective function J based on the first two types of deviations:

$$\min_{\Delta U(k)} J = \hat{E}\ (k+1)^T Q\ \hat{E}(k+1) + \Delta U(k)^T R \Delta U(k) \qquad (16)$$

where Q is a positive-definite weighting matrix used to refer error weight and control weight R is a positive semi-definite matrix. Both are usually diagonal matrices with positive diagonal elements. The weighting matrices are used to weight the most important elements of $\hat{E}(K+1)$ or $\Delta U(K)$. If diagonal weighting matrices are specified, these elements are weighted individually. The MPC control law that minimizes the objective function in Eq. (20-54) can be calculated analytically.

$$\Delta U(k)\ = (S^T QS + R)^{-1} S^T Q\hat{E}^0 \qquad (17)$$

This control law can be written in a more compact form,

$$\Delta U(k)\ = (S^T QS + R)^{-1} S^T Q\hat{E}^0\ \ (k+1) \qquad (18)$$

where the controller gain matrix Kc is defined to be

$$K_c \triangleq\ (S^T QS + R)^{-1} S^T Q \quad (19)$$

CONSTRAINTS IN MPC

During the initial stage of development of the MPC algorithms it was usually optimization without additional explicit constraints, but also an additional mechanism of influencing the shape of a solution trajectory was used, by applying a reference trajectory For a linear process model the optimization without constraints leads to an analytical solution, to a formula possible for implementation and calculation in real time using the control equipment of even fairly small computing power. Development of the microprocessor technology and the following increase of calculation possibilities enabled real time numerical solutions of linear-quadratic optimization problems with additional inequality constraints. This became one of the main reasons for a development and a significant increase of the number of industrial applications of the predictive control algorithms. The following constraints are important in applications and are possible to be considered directly in the MPC algorithms [9]

1. Constraints on values (amplitudes) of process control inputs:
   $$u_{min} \le u(k+p|k) \le u_{max},\ p = 0, 1, \dots, Nu - 1$$
2. Constraints on increments of process control inputs:
   $$-u_{max} \le u(k+p|k) \le u_{max},\ p = 0, 1, \dots, Nu - 1$$
3. Constraints on values of controlled outputs, which in a concise form can be written as
   $$y_{min} \le y(k+p|k) \le y_{max},\ p = N1, N1 + 1, \dots, N$$

The constraints are classified into three major types Hard constraints Soft constraints Terminal constraints [10] Hard constraints are constraints which must be satisfied. For instance, they may be limits on actuators or on valves (which must lie between 0% and 100%) open. Soft constraints are those which should be satisfied if possible. For instance, there may be temperature or pressure limitations to prevent fatigue damage to equipment or to ensure quality. It is assumed that if necessary, soft constraints can be ignored. Usually soft constraints are on outputs/states although they could also be applied to inputs. Such violations may have no effect on nominal stability results. Terminal constraints are these are somewhat artificial in that they arise from the control algorithm.

In many control applications the desired performance cannot be expressed solely as a trajectory following problem. Many practical requirements are more naturally expressed as constraints on process variables. There are three types of

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process constraints Manipulated Variable Constraints: these are hard limits on inputs u(k) to take care of, for example, valve saturation constraints. Manipulated Variable Rate Constraints: these are hard limits on the size of the manipulated variable moves u(k) to directly influence the rate of change of the manipulated variables. Output Variable Constraints: hard or soft limits on the outputs of the system are imposed to, for example, avoid overshoots and undershoot [11]

VI.SIMULATION RESULTS

The simulation results of simplified 2*2 distillation control scheme interprets the relationship between product compositions X_D and X_B against reboiler heat and reflux flow rate from this analysis we get perfect tracking of the specified set point change (y1 = 2, y2 = 2), but the manipulated variables are ringing. Fig.6 we could have anticipated this by calculating the poles of the controller. One way to minimize ringing is to make the prediction horizon significantly larger than the control horizon. Fig 7.

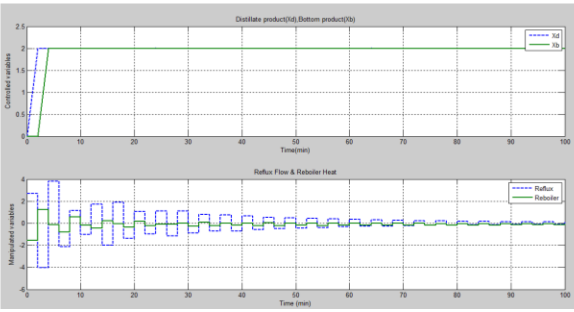

Fig.6: Unconstrained MPC response

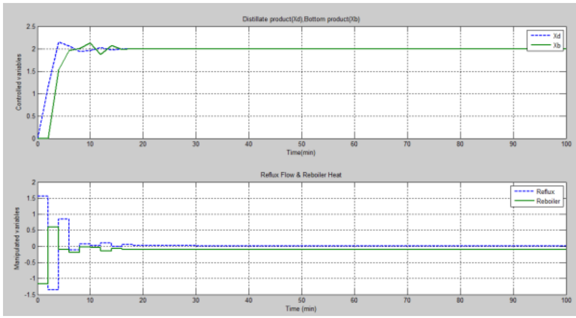

Fig.7: Minimized ringing effect

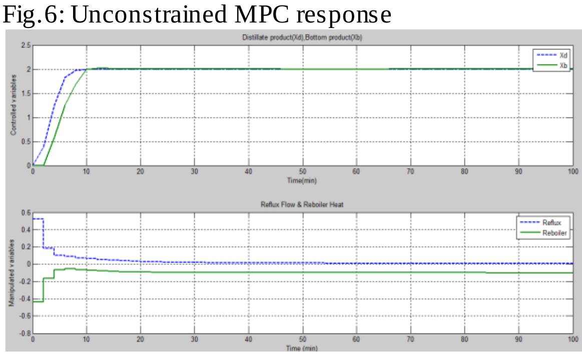

Fig.8: Minimized ringing effect

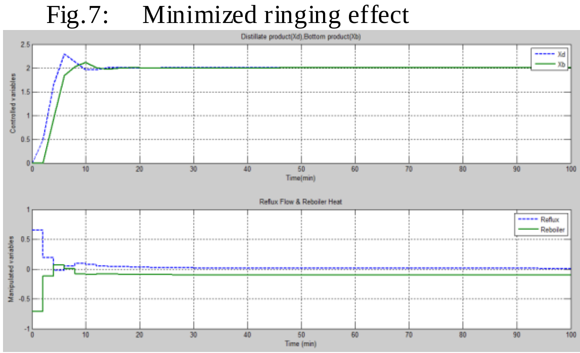

Fig.9:Minimization of ringing effect by increasing weight

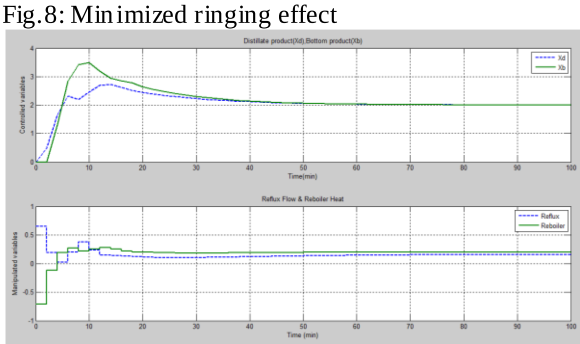

Fig.10: Response due to unmeasured disturbance

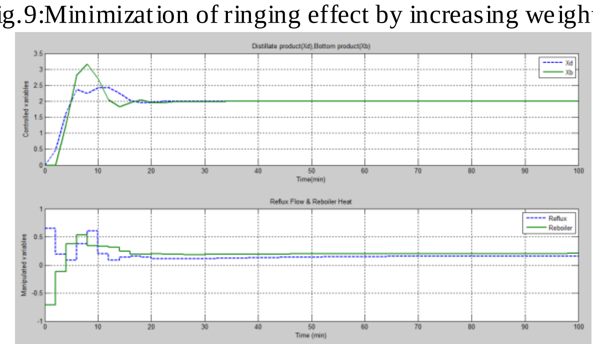

Fig.11: Disturbance compensation by unconstrained MPC

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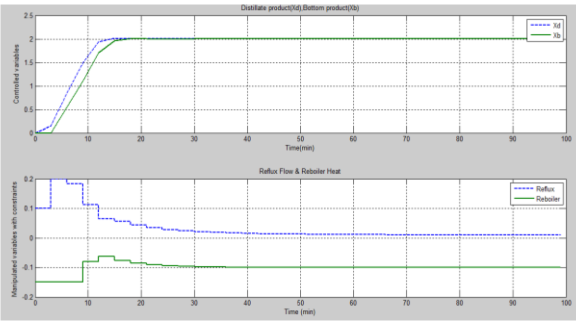

Fig.12: Response of CMPC

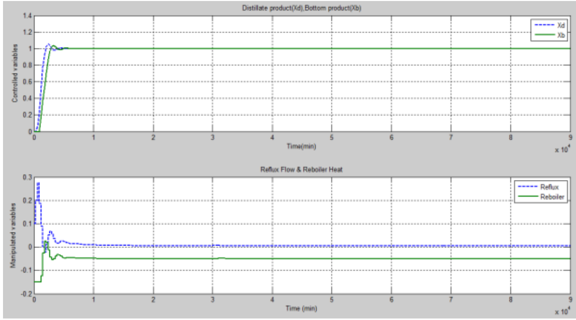

Fig.13: Response of CMPC

Another one effective way is to use blocking. In the case of blocking, each element of the vector M indicates the number of steps over which $\Delta u = 0$ during the optimization. This completely eliminates the ringing, at the expense of a more sluggish servo response and a larger disturbance in y2.Fig 8 Another one approach is to increase the weights on the manipulated variables Fig 9. The servo-response looks good Even though the Fig 10 exhibits response to a unit-step in the unmeasured disturbance, w (k). The resulting response has a rather long transient. The results of the constrained model predictive controller compensate the disturbance much more rapidly which showed in Fig 11.
As shown in figures both the unconstrained DMC and constrained DMC exhibit similar performance. In this case unconstrained DMC exhibits a somewhat better performance than constrained DMC which is what would be expected. Hence the addition of constraints does not have an unconstructive impact on the performance. The output of the DMC controller exhibits a good set point tracking capability with no peak overshoot and a fast rise time. This tuning strategy successfully rejected disturbances that impacted the process. Process constraints were included Fig.12 & 13 to illustrate that the tuning parameters are valid even though they were derived for the unconstrained control law.

VII.CONCLUSION

In this work we studied very proficient alternative modelling methods exclusively designed for process control, termed empirical identification. The model developed using this method provides the dynamic relationship between selected input and output variables. The empirical models for the binary distillation column could relate the reflux ratio and reboiler heat duty to the top and bottom product temperatures. Model predictive control is employed to handle the highly interacting multivariable system of binary distillation column. A two input two-output model of binary distillation column is constructed for the high quality requirements of the process studied. The analysis of simple empirical model, provides information on how top product composition depends on reflux ratio. The State space models obtained from empirical method were used to MPC and CMPC algorithms. The sampling interval is determined by the time constant of the plant and by computer hardware, although it should be determined by the high frequency behaviour of the plant or by constraints in the measurement devices. Compared with MPC, the run results of CMPC scheme demonstrate its better performance to control reflux ratio and reboiler heat. CMPC schemes can handle manipulated variable constraints explicitly and operation of the product temperatures close to their optimum operating conditions is achieved. The simulation results show that the proposed CMPC scheme is an effective way to control binary distillation column. In the future research the design can be further improved to increase the percentage of algorithm implemented by hardware.

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