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Decoupling Constrained Model Predictive Control of Multi-component Packed Distillation Column

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Abstract: In this work, separation of multi-component mixture was conducted in a continuously fed laboratory scaled distillation column. Mixture including five components, namely methanol-ethanol-n buthanol-isoamine alcohol-anisol, was obtained from ethyl alcohol production plant and was used as a feed mixture. Stable control of packed 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 packed distillation column is constructed. Constrained model predictive control is applied in packed distillation column plant and operation of the process close to their optimum operating conditions is achieved.

Key words: Packed distillation column · Decoupling · Constrained model predictive control

INTRODUCTION

The multi-component distillation operation is multivariable and highly non-linear process, that presents a very complex dynamics. It constitutes therefore a very serious control problem, been at the same time very widely used in process plant [1]. Distillation column are substantial energy consumers. Their energy requirements can be considerably reduced when applying heat integration. Synthesis of multi-component separation sequences is an important process design problem in chemical industry. It is concerned with the selection of a separation method and the selection of the best sequence of separators to split a multi-component mixture into several products, relatively pure species . Distillation columns are important process units in petroleum refining and need to be maintained close to be optimum operating conditions on account of economic incentives. Therefore, these units have been considered for application of advanced control and optimization. The optimal operating point usually lies at some constraints and the operation of the distillation columns close to the optimum is an important objective. Based on the market conditions, the real time optimizer updates the optimum periodically. At these updates, the objective of the control system is to move the process to the new optimal operating point. At o ther times, the objective of the control system is to cancel the effect of disturbances on the controlled variables by making minimal changes in the manipulated variables from their optimal values. In addition, the constraints on the manipulated and other process variables need to be satisfied [2]. Agrawal [3] suggested single distillation column structures with partitions and multiple reboilers and condensers for separation of a multi-component feed and the total number of reboilers and condensers required for such structures was generally equal to the number of components in the feed. Pelkonen *et al*. [4] was investigated an extensive set of experimental data on multi-component distillation with non-ideal systems in structured packed column An example how to use date was shown by comparing the experimental data with simulation results when applying different mathematical models.

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Over the last twenty years, many papers and applications of model-predictive control (MPC) have appeared in the open literature [5-8], MPC has been successfully applied in chemical process industries. The MPC algorithm has many attractive features such as dead time compensation, multivariable control and handling of system constraints. The MPC algorithm optimizes the process outputs over some finite future time interval known as the prediction horizon P. At the current time step, the future outputs are predicted using a dynamic model of the process. This model is used to compute the present and future M (M £ P) control actions (the control horizon), which minimize a user-specified performance index.

After the Mth time step, it is assumed that the control action is constant. Only the first of the resulting optimal inputs is implemented on the process. This entire process is repeated at each time step. The choice of model representation is an important issue in MPC. A linear MPC system utilises a simple transfer function model to represent the process. In practice, most of the systems encountered in chemical engineering have severe nonlinear dynamics. However, controllers based on a linear approximation of the process are only effective in a limited range around the nominal operating conditions. In a nonlinear MPC, a nonlinear dynamic model is used. Such models are accurate over a broad range of operating conditions. Therefore, a nonlinear MPC allows processes to be run over a larger operating range without controller. retuning. The formulation of the constrained optimization problem has been proposed using linear programming (LP) [9-14]. Gupta [15] was studied to utilize the solution of a constrained optimization problem involved in model predictive control.

MPC has become an industry standard to solve complex constrained multivariable control problems in the process industry with its wide usage in refinery and petrochemical processes [16]. Currently, constraint MPC is being successfully used in the control of various dynamic systems and its use is becoming more widespread [17-19]. However, chemical plants in modern industries have become increasingly complex, which leads to excessive targets and constraints. The study of constraint MPC is also a major problem [20-21]. In Olaru and Dumur [21], the methods to avoid constraints redundancy in MPC are discussed. As an important part of a two-stage constraint MPC algorithm, steady-state target calculation faces many problems and challenges. There are many manipulated variables and controlled variables in the process of MPC dynamic optimization. The steady-state target must satisfy the requirements of system safety, energy and technical conditions. Zhao and Zongli [22] were studied the problem of infinite horizon constrained linear quadratic regulation (LQR) for discrete-time systems. It is known that there exists a finite horizon such that the infinite horizon constrained LQR problem can be solved as a finite horizon constrained LQR problem. They first proposed several algorithms to estimate the upper bound on the length of this finite horizon. Conservativeness and computational complexity of these algorithms are compared through numerical examples.

In this work, Constrained Model predictive control is employed to handle the highly interacting multivariable system of packed distillation column. A two input two-output model of packed distillation column is constructed for the high quality requirements of the process studied. Compared with unconstrained MPC, the run results of constrained MPC scheme demonstrate its better performances in process control. CMPC schemes can handle manipulated variable constraints explicitly and operation of product temperatures close to their optimum operating conditions is achieved. The run results show that the proposed CMPC scheme is an effective way to control packed distillation column.

Process Description: Distillation columns, which are widely used for separation and refining operations, require a phenomenal amount of energy for their operation. Nevertheless, minimization of energy usage is possible if the compositions of both the top and bottom product streams are controlled to their design values, i.e. deal temperature control. A common scheme is to use reflux flow to control top product temperature whilst heat input is used to control bottom product temperature. However, changes in reflux also affects bottom product temperature and component fractions in the top product stream are also affected by changes in heat input. Several loop interactions can therefore occur in the dual temperature control of distillation columns.

The loop interactions in the examples given above occur naturally, i.e. as a result of their physical and chemical make-up. Loop interactions may also arise as a consequence of process design: typically the use of recycle streams for heat recovery purposes. An example is where the hot bottom product stream of distillation column is used as the heating medium to heat the reboiler as shown in Figure 1. Suppose heat input to the reboiler is used to control the temperature of bottom product stream. If for some reason, the composition of this stream

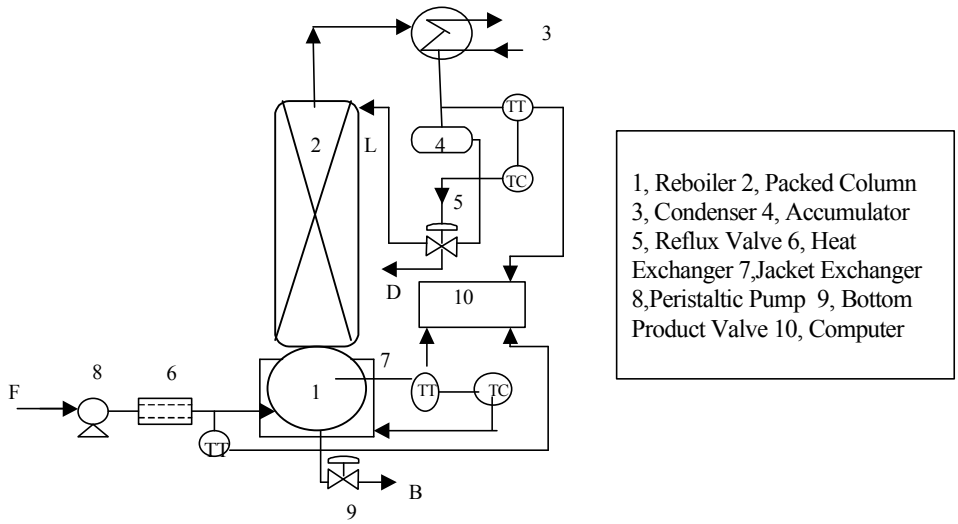

Fig. 1: Experimental Equipment

changes, then the heat input will change in an attempt to maintain the composition at its desired level. However, changes in heat input will alter the temperature of the bottom product stream, which will then affect the temperature of the feed stream. Changes in feed temperature will in turn influence bottom product temperature. It is therefore clear that interaction exists between the composition and pre-heat control loops. Unless proper precautions are taken in terms of control system design, loop interactions can cause system instability. The purpose of this article is to show analytically why control loop interactions are undesirable. Two simple approaches to dealing with loop interactions are then introduced: a method for establishing the most appropriate manipulated inputs-controlled outputs pairs and the design of multivariable control strategies that aim to eliminate interactions between control loops.

Another popular approach to dealing with control interactions is to design non-interacting or decoupling control schemes. Here, the objective is to eliminate completely the effects of loop interactions. This is achieved via the specification of compensation networks known as decouplers. Essentially, the role of decouplers is to decompose a multivariable process into a series of independent single-loop sub-systems. If such a situation can be achieved, then complete or ideal decoupling occurs and the multivariable process can be controlled using independent loop controllers. Figure 2 shows a widely used multi-SISO (two-input two-output) system with two decouplers, namely $D_{12}(s)$ and $D_{21}(s)$.

$$D_{12} = \frac{-G_{12}(s)(s=0)}{G_{11}(s)(s=0)} \quad (1)$$

$$D_{21} = \frac{-G_{21}(s)(s=0)}{G_{22}(s)(s=0)} \quad (2)$$

Where $G_{ij}(s)$(i=1,2; j=1,2) are process models.

One difficulty of this kind of control lies in the choice of the proper input-output pairing. When manipulated variables are not properly selected, interactions between controlled and

Manipulated variables can result in undesirable control loop interactions, leading to poor control performances. Another difficulty is that static decoupling (based on steady-state gains) is used much more often than dynamic decoupling in practice because the dynamic version may not be physically realizable [23-24]. Therefore, a close control of the process based on conventional multi-SÝSO PID controllers is usually impossible in real practice for a long time and the controllers generally become sluggish especially when model mismatch occurs due to great disturbances, such as the changes in feed composition ore and feed flow rate, etc.

Process Models: For many processes it is a time consuming work to develop fundamental process models, while developing a transfer function based model is quiet desirable by performing a plant test. The most common plant test is to make a step change in the manipulated input and observe the measured process output response. Then a model is developed to provide the best match between the model output and the observed plant output [23-24]. By far the most commonly used model, for control

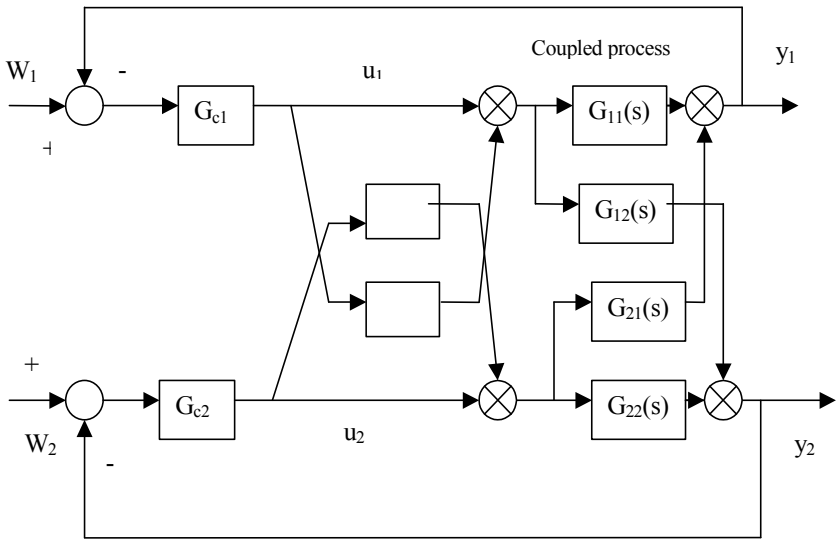

Fig. 2: Multi-SISO system with decouplers.

system design purpose, is the first-order plus time-delay model or second-order plus time-delay model, while the former can be represented by the transfer function relationship

$$y(s) = \frac{K_P e^{\tau s}}{\tau_P s + 1} u(s) \tag{3}$$

Where Kp is process gain, τ is dead time, τ_p is process time constant. To obtain relevant model, the same parameters must be determined. To determine these parameters, one of the most utilized methods is the step test application. From the reaction curve obtained at the end of this test, the parameters are easily evaluated. In the step test, a step change is given to manipulated variable μ(R or Q_R) and then the reaction curve is obtained by observing output variables y (T_D and T_B) change with time.

Let R and Q_R denote manipulated variables, reflux ratio and reboiler heat duty respectively and T_D and T_B controlled variables, namely top product temperature and bottom product temperature. Packed distillation process model can be written as:

$$Y = GU \tag{4}$$

Where;

$$Y = \begin{bmatrix} y_1(s) \\ y_2(s) \end{bmatrix} = \begin{bmatrix} T_D(s) \\ T_B(s) \end{bmatrix} \tag{5}$$

$$u = \begin{bmatrix} u_1(s) \\ u_2(s) \end{bmatrix} = \begin{bmatrix} R(s) \\ Q_R(s) \end{bmatrix} \tag{6}$$

$$G(s) = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix} \tag{7}$$

It's obvious that strong interactions exist between the manipulated and controlled variables. As for conventional multi-loop PID controllers as shown in Figure 2, a two-input two-output system needs 2 decouplers to solve the problems of loop interactions. Moreover, static decoupling is often used which will degrade the control performance in real practice, while MPC scheme is much suitable for this case.

Constrained Model Predictive Control Algorithm: The underlying philosophy of DMC scheme [25] consists of predictive model, reference trajectory, feedback correction and rolling optimization as shown in Figure 3. DMC can be stated as follows: at any sampling instant, given a reasonably accurate predictive model and the desired future closed loop behavior (or a reference trajectory), plan the set of future control moves in such a way that the predictive output is as close to the reference trajectory as possible without any violations in the operating constraints. DMC scheme is based on finite step response models which are obtained by making a unit step input change to a process operating at steady state as mentioned above. The step response model is the vector of step response coefficients,

$$A = [a_{11}\ a_{12}\ a_{13}.....a_{1N}]^T \tag{8}$$

Where a_{1i} represents the step response coefficient for the ith sample time. N is the model length which

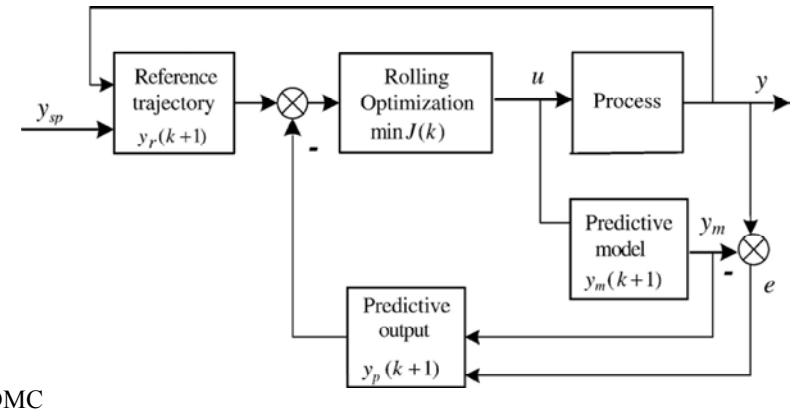

Fig. 3: Diagram of DMC

tableshould be long enough so that the coefficient values are relatively constant, i.e. the process is close to a new steady state.

Mathematically, the control problem is posed as a minimization of a quadratic objective function of the future prediction errors subject to constraints on future manipulated variables and controlled variables. Let the process dynamics of the MIMO system be represented by the following convolution model:

$$y_m(k+1) = y_0(k = 1) + A\Delta\mu(k) \tag{9}$$

Where ym(k+1) is the model output vector, $y_m(k+1)=[y_m(k+1)\ y_m(k+1) \ldots y_m(k+P)]^T$; Δu(k) is the control action, $\Delta u(k)= [\Delta u(k)\ \Delta u(k+1) \ldots \Delta u(k+M-1)]^T$; $y_0(k+1)$ is the initial output vector without control action, $y_0(k+1) = [y_0(k+1)\ y_0(k+2) \ldots y_0(k+ P)]^T$ and A(k) is the unit step response coefficient matrix, (P×M). P is the prediction horizon and M is the control horizon. The values of the unit step response coefficients are obtained by normalizing the transient responses of the circuit for step changes in inputs by dividing the step response values by the respective steady-state gains.

Due to the measurement noise and the unmodelled load disturbance effects as well as the plant-model mismatch, the predictive output should be corrected by the real output y(k) to realize close-loop control.

$$y_p(k+1) = y_m(k+1) + g_0[y(k)-y_m(k)] = y_m(k+1) + g_0 e(k) \tag{10}$$

Where $y_p(k+1)$ is the predictive output after correction, g_0 is the coefficient matrix usually defined as $g_0 = [1\ \ 1....,1]$ and e(k) is the error by feedback correction,

$$e(k) = y(k) - y_m(k) \tag{11}$$

Note that Δu(k) represents the future manipulated input moves to be decided by the optimization procedure. Thus, the DMC problem can be stated as

$$J(k) = [y_r(k+1) = -y_p(k+1)]^T Q \tag{12}$$
$$[y_r(k+1) - y_p(k+1)] + \Delta u(k)^T R \Delta u(k)$$

Where $y_r(k+1)$ is the expected vector, $y_r(k+1) = [y_r(k+1)\ y_r\ (k+2) \ldots y_r(k + P)]^T$; Q is the error weighting factor vector, $Q=\mathrm{diag}[q_1\ q_2 \ldots q_p]^T$ and R is the input weighting factor vector, $R=\mathrm{diag}[r_1\ r_2 \ldots r_M]^T$.

Magnitude and rate constraints on the manipulated variables and the controlled variables are expressed as followed:

Manipulated variable constraints:

$$u_{\min} \le u(k) \le u_{\max},\ \ k = 0,1,....M-1 \tag{13}$$

Manipulated variable rate constraints:

$$\Delta u_{\min} \le u(k) - u(k-1) \le \Delta u_{\max},\ \ k = 0,1,....M-1 \tag{14}$$

Controlled variables constraints:

$$y_{\min} \le y(k) \le y_{\max},\ \ k = 0,1,.....P-1 \tag{15}$$

MPC scheme is implemented in a receding horizon framework. At any sampling instant, the optimization problem is formulated over the prediction horizon and a future manipulated variable trajectory is calculated that minimizes the objective function satisfying all the constraints. Only the first move is applied to them plant and this step is repeated for next sampling instant.

The desired closed loop behavior and MPC tuning parameters have a straight forward relationship. If tighter control of some specific controlled variables is desired, it can be achieved by choosing a corresponding higher weight in the factor Q. Also excess variations in manipulated variables moves can be suppressed by an appropriate choice of R.

Experimental System: Experiments were carried out in a laboratory scale packed column to distil the multi-component mixture. All experimental equipment's were shown in Figure1. In the experiments, overhead product composition and temperature changes with time were observed at steady-state and dynamic conditions. Mixture including five components, namely methanol-ethanol-n buthanol-isoamine alcohol-anisol, was used as a feed mixture. The column utilized has 1 m packing height. Packing type is raschng ring 20-15 mm sizes. The reboiler was made from 2 L glass container. A peristaltic pump was utilized to feed the relevant liquid into the column. Reflux ratio was adjusted by on-line computer. The system temperatures were measured with three thermocouples. Each thermocouple was connected to a controller module and was transferred to the computer with a Digital/ Digital (D/D) converter. Temperature data measured at each second was recorded. Temperature profiles observed on the computer were recorded and samples were taken regularly from the top and bottom of the column. The samples were analyzed by GC/MS. When the concentrations and temperatures of top and bottom product are constant, the system is said to have reached the steady-state condition.. In control studies, the top and bottom product temperatures were controlled by giving positive and negative step effects to set points of the top and bottom product temperatures and the concentration of feed mixture.

RESULTS

For the purpose of control study and industrial application many experiments have been conducted in the process around the normal operating point to show whether the increase in a particular manipulated variable increases, decreases or has a complex relationship with the controlled variables and whether the action is slow or fast.

Step Response Models: When the multi-component distillation column works under the steady-state condition at total reflux, reflux ratio and feed flow rate are adjusted to 1.5 and 0.22 mol/min, respectively and then 36.79 % mol ethanol in mixture is fed to column for continuous operating condition. The system works under this condition and occurrence of the steady-state condition is waited. This steady-state condition is given in Table 1.

The manipulated variables are reflux ratio R and reboiler heat duty Q_R and controlled variables are top and bottom product temperatures (T_D and T_B). One experiment was performed for each input variable and the responses of all output variables were recorded. When the multi-component packed distillation column works at continuous steady-state condition, a negative step change from 1.5 to 0.25 is given to the reflux ratio and then the system stars to show dynamic behavior. Top and bottom product temperatures shown in Figures (4 and 5) are obtained. Another step change is given to the reboiler heat duty from 700 cal/min to 880 cal/min. Dynamic responses of product temperatures are drawn in Figure (6 and 7). Statistical method is used to fit parameters in transfer functions and transfer function matrixes are obtained as follows:

$$\begin{bmatrix} T_D(s) \\ T_B(s) \end{bmatrix} = \begin{bmatrix} \dfrac{1.84e^{-11.7s}}{56.1s+1} & \dfrac{1.04e^{-4.64s}}{16.55s+1} \\ \dfrac{2.88e^{-8.15s}}{74.6s+1} & \dfrac{2.39e^{-1.24s}}{9.94s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ Q_R(s) \end{bmatrix} \quad (16)$$

Constrained Model Predictive Control Results: The system based on this control strategy was put into operation. The schematic diagram of DMC applied in

Table 1: Operating parameters and steady state results

Distillation Column Parameters	X_F (%mol)	X_D (%mol)	R	Q_R	M_B	T_F	T_B	T_D	F	B	D
Experimental Data	20.20 (a)	24.74 (a)	1.5	700	59.6	51	77	70.5	0.22	0.027	0.253
	36.79 (b)	75.26 (b)									
	7.93 ©										
	17.62(d)										
	17.46 (e)										

Components : (a): Methanol, (b): Ethanol, (c): n-butanol, (d): İsoamil alkol, (e): Anisol; MB: Reboiler holdup

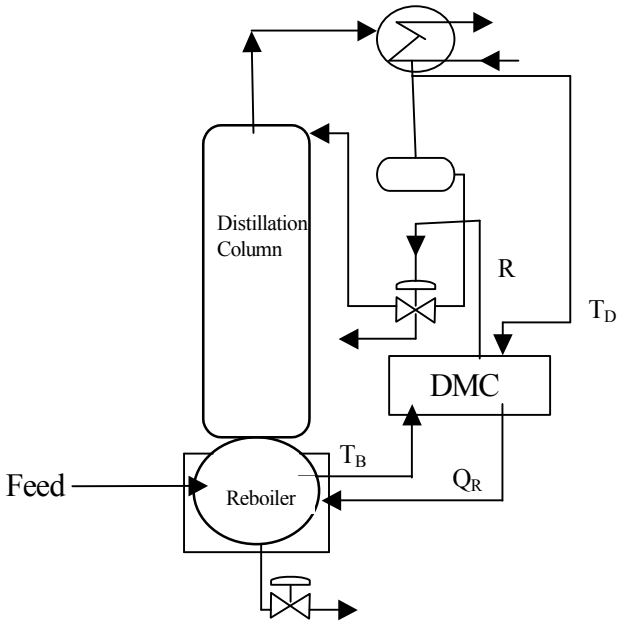

Fig. 4: The schematic diagram of DMC applied in the packed distillation column process.

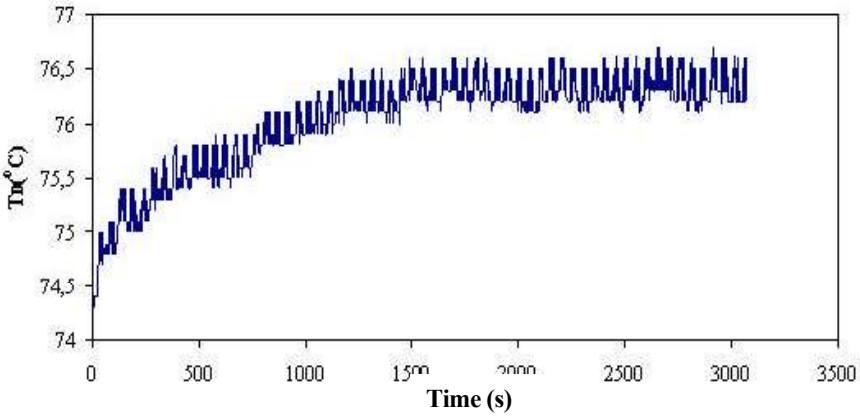

Fig. 5: Dynamic response of the top product temperature to a negative step change in reflux ratio from 1.5 to 0.25.

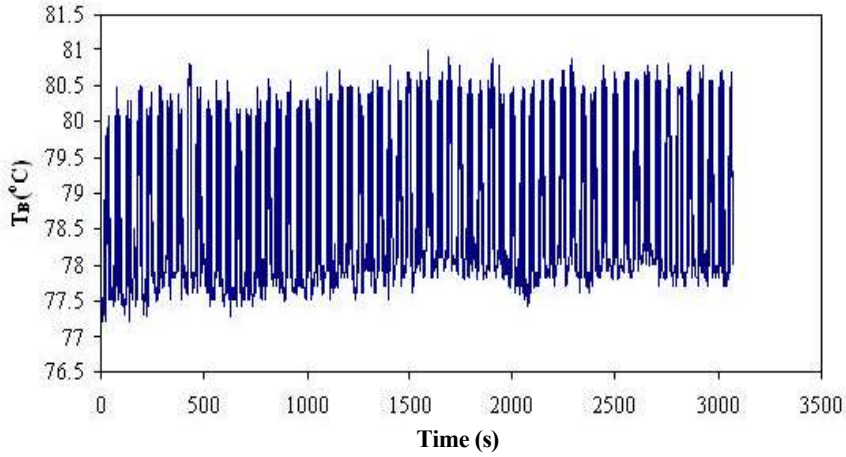

Fig. 6: Dynamic response of the bottom product temperature to a negative step change in reflux ratio from 1.5 to 0.25.

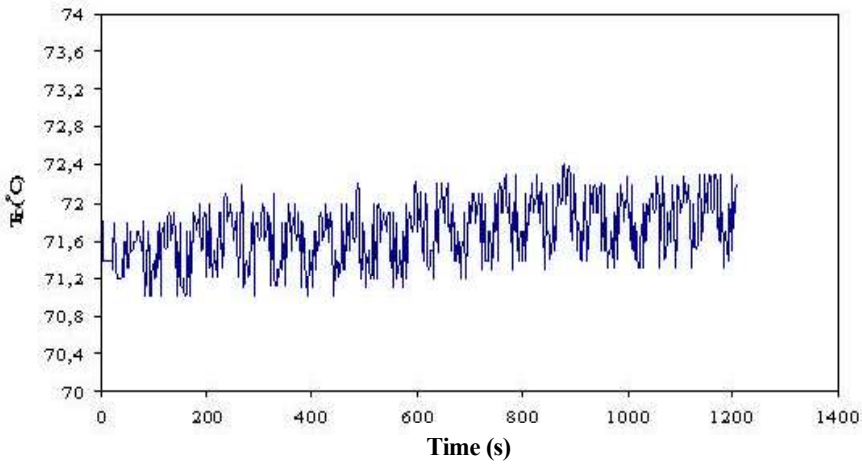

Fig. 7: Dynamic response of the top product temperature to a positive step change in reboiler heat duty from 700 cal/min to 880 cal/min.

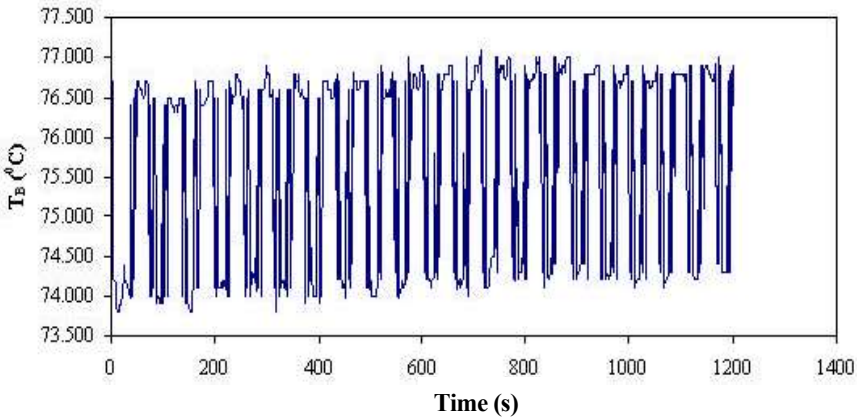

Fig. 8: Dynamic response of the bottom product temperature to a positive step change in reboiler heat duty from 700 cal/min to 880 cal/min.

Table 2: Constraints on the manipulated variables in the packed distillation process

	u_1 (reflux ratio)	u_2 (reboiler heat duty)
Minimum value	-0.4	-0.5
Maximum value	0.4	0.5

the packed distillation column process is shown in Figure 8. The following tuning and weighting factors are used while applying the MPC and CMPC scheme to control the packed distillation process: Prediction horizon P=20, control horizon, M=5, weights on errors Q=diag[1 0.4 0.6]^T and weights on the manipulated variables R=diag[1 0.5 0.4]^T. It is important to make certain that the model length is long enough to capture the steady state change and it is also crucial to tune the prediction horizon to be long enough. Generally, control horizon is much shorter than prediction horizon, yielding more robust performance.

Input constraints are considered. The manipulated variables are limited to acceptable values established by the normal operation of the plant for safety or economic reasons. The constraints introduced on the manipulated variables in packed distillation process are shown in Table 2.

Figure 9 and Figure 10 show the closed loop response for a unit step feed composition as a load change. Figure 9 is given for top product temperature (y_1) as a controlled variable and reflux ratio (u_1) as a manipulated variable. The function MPC and CMPC are used to generate the controller and to simulate the closed-loop response. Their results are compared each other. As shown in Figure 9, CMPC result is better than MPC. Figure 10 shows the closed loop response to control bottom product temperature. In this figure, y_2 is bottom product temperature as a controlled variable and u_2 is reboiler heat duty as a manipulated variable. MPC is produced larger overshoot than CMPC.

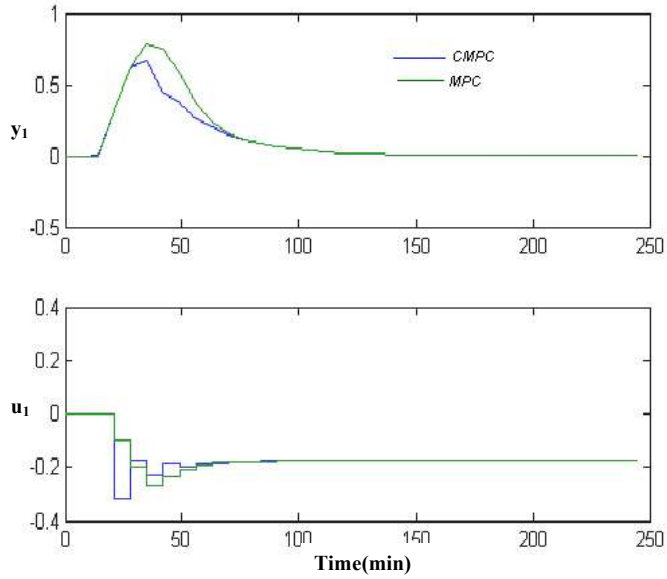

Fig. 9: Response of the top product temperature using CMPC and MPC in the face of a pozitive unit load change in feed mole fraction of ethanol

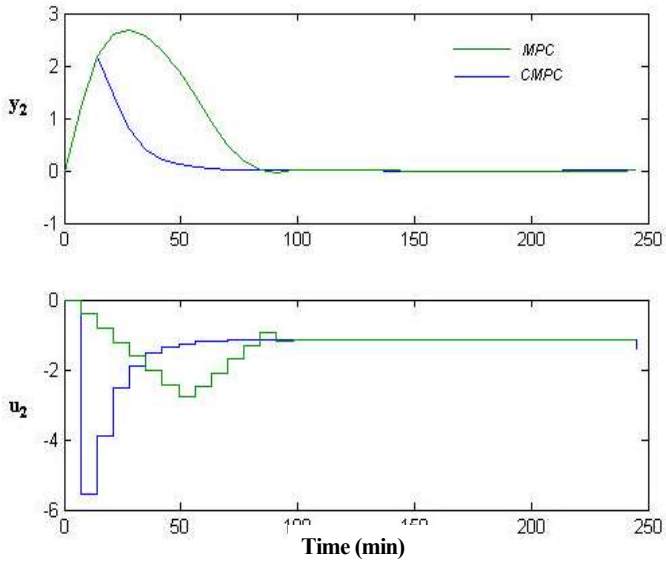

Fig. 10: Response of the bottom product temperature using CMPC and MPC in the face of a pozitive unit load change in feed mole fraction of ethanol

Figures 11 and 12 are given for a negative step change. These figures employed here are particularly for the illustration of the changing procedure from one stable point to another operating point when great disturbances occur to the process, such as a decrease of the feed composition. At the 10 min, there is bigger overshoot with MPC for y_1 and y_2 than that of CMPC and. CMPC performance is also better than that of MPC.

The set point changes of the controlled variables with CMPC and MPC simulations are also studied. The control objective in this study is set point tracking across the range of nonlinear operation. The design goal in this study is a faster rise time and quick settling time.

The transient response to a positive unit set point change in the top product temperature, with the bottom product temperature set point unchanged, is given in Figure 13. At time 10 min, MPC produce high overshoot and CMPC response is the best which can be expected. Figure 14 shows the transient response to a positive unit set point change in the bottom product temperature.

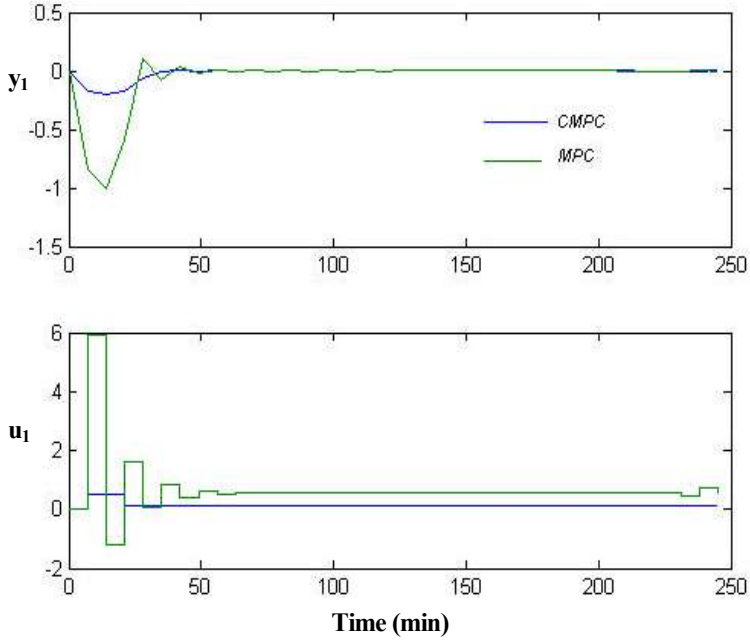

Fig. 11: Response of the top product temperature using CMPC and MPC in the face of a negative unit load change in feed mole fraction of ethanol

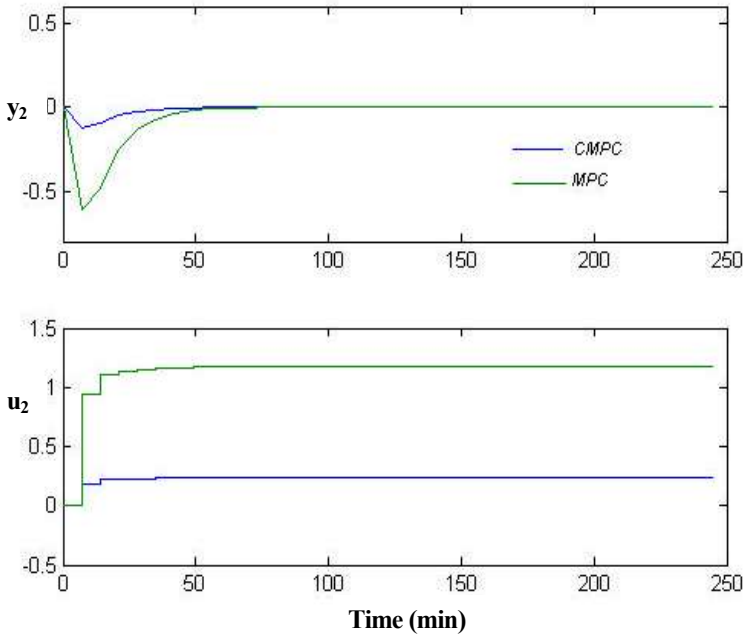

Fig. 12: Response of the bottom product temperature using CMPC and MPC in the face of a negative unit load change in feed mole fraction of ethanol

CMPC and MPC results are stable but CMP response is faster than MPC and there is not any offset for both controllers. Another simulation is a negative unit step changes for outputs. Figure 15 and Figure 16 compare the responses for top product temperature and bottom product temperature using CMPC and MPC. As we can see CMPC simulations are significantly faster than those obtained with MPC.

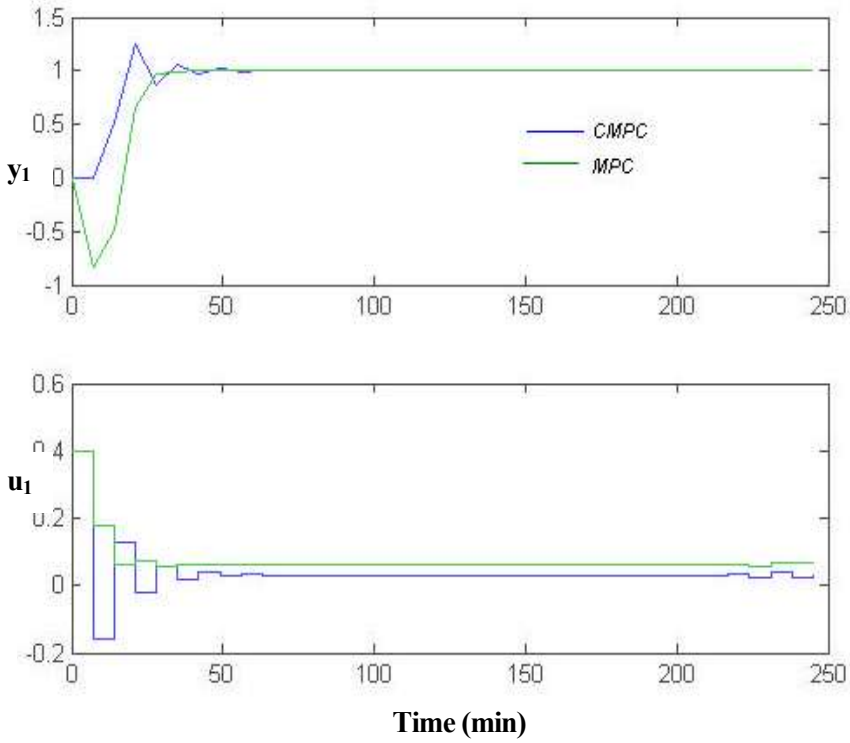

Fig. 13: Response of the top product temperature using MMPC controller in the faceof a positive unit set point change in the top product temperature.

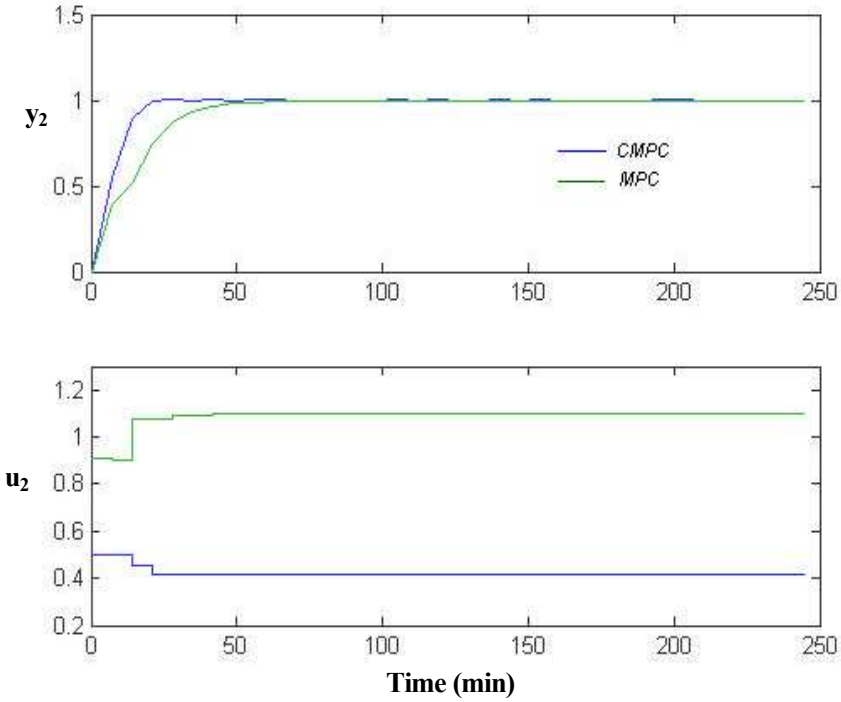

Fig. 14: Response of the bottom product temperature using MMPC controller in the face of a positive unit set point change in the bottom product temperature.

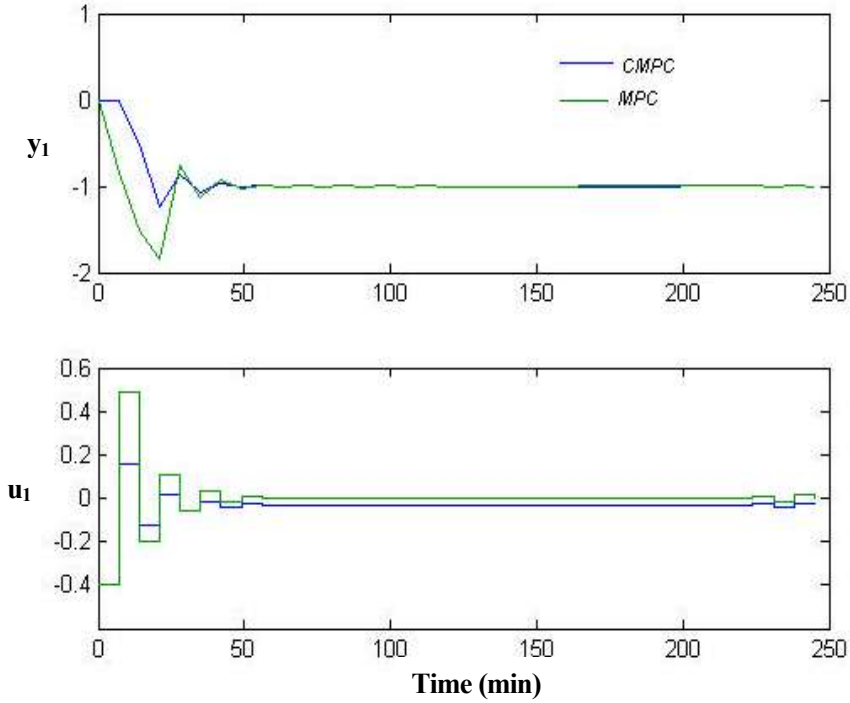

Fig. 15: Response of the top product temperature using MMPC controller in the face of a negative unit set point change in the top product temperature.

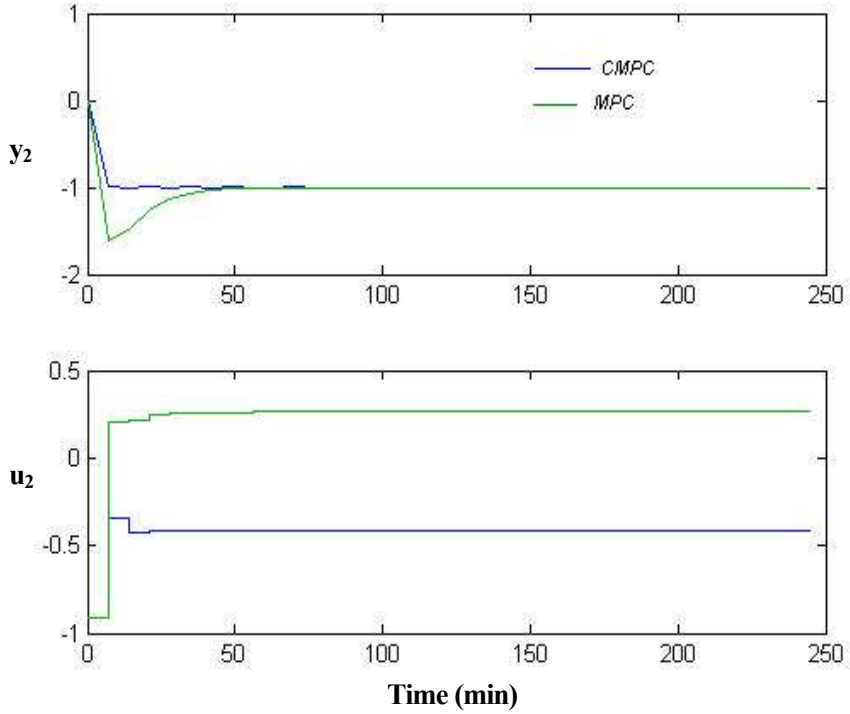

Fig. 16: Response of the bottom product temperature using MMPC controller in the face of a negative unit set point change in the bottom product temperature.

CONCLUSION

In this work presents a very efficient alternative modeling methods specifically designed for process control, termed empirical identification. The models developed using this method provides the dynamic relationship between selected input and output variables. The empirical models for the multivariable laboratory packed distillation column could relate the reflux ratio and reboiler heat duty to the top and bottom product temperatures. In comparison to this simple empirical model, the fundamental model provides information on how all of the top product composition depends on variables such as reflux ratio.

The empirical methods involve designed experiments, during which the process is perturbed to generate dynamic data. The success of the methods requires close adherence to principles of experimental design and model fitting. Statistical model identification was used for determining the parameters of the system transfer function. Transfer functions obtained from empirical method were used to MPC and CMPC algorithms.

Model predictive control is employed to handle the highly interacting multivariable system of packed distillation column. A two input two-output model of packed distillation column is constructed for the high quality requirements of the process studied. Compared with MPC, the run results of CMPC scheme demonstrate its better performances in process control. CMPC schemes can handle manipulated variable constraints explicitly and operation of the product temperatures close to their optimum operating conditions is achieved. The run results show that the proposed CMPC scheme is an effective way to control packed distillation column.

Symbol Used

a : [-] Step response coefficient
A : [-] Dynamic matrix
D_{ij} : [-] Decouplers
e : [-] Error
G_{ij} : [-] Transfer function
K_p : [-] Process gain
M : [-] Control horizon
P : [-] Prediction horizon
Q_R : [cal/min] Reboiler heat duty
R : [-] Reflux ratio
T_B : [°C] Bottom product temperature
T_D : [°C] Top product temperature
u : [-] Input variable
y : [-] Output variable

Greek Symbols

τ : [min] Dead time
τ_P : [min] Process time constant

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