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Identification, Analysis and Implementation of Model Predictive Controller (MPC) for Binary Distillation Column

***Abstract**. Distillation column is one of the important equipment in petroleum refining; it is used to separate two or more components from a homogenous fluid mixture. The aim of the present work is to identify the model of real binary distillation column installed in SKIKDA Refinery, to design a suitable controller using model predictive control (MPC) concepts. The distillation column has 36 trays with feed entering on the 27th tray it is used to separate Naphta B from Naphta C. The distillation column model was developed through an experimental identification using MATLAB Toolbox. A suitable model predictive controller was designed to enhance productivity throughout the distillation process by the use of MATLAB software simulation.*

***Streszczenie.** Kolumna destylacyjna jest jednym z ważnych urządzeń w rafinacji ropy naftowej; służy do oddzielania dwóch lub więcej składników z jednorodnej mieszaniny płynów. Celem niniejszej pracy jest zidentyfikowanie modelu rzeczywistej binarnej kolumny destylacyjnej zainstalowanej w rafinerii SKIKDA, aby zaprojektować odpowiedni sterownik przy użyciu koncepcji sterowania predykcyjnego modelu (MPC). Kolumna destylacyjna ma 36 półek z wsadem wprowadzanym na 27 półkę, która służy do oddzielania nafty B od nafty C. Model kolumny destylacyjnej został opracowany poprzez eksperymentalną identyfikację przy użyciu MATLAB Toolbox. Odpowiedni sterownik predykcyjny modelu został zaprojektowany w celu zwiększenia wydajności w całym procesie destylacji przy użyciu symulacji oprogramowania MATLAB. 9 (**Identyfikacja, analiza i implementacja modelu regulatora predykcyjnego (MPC) dla kolumny destylacyjnej binarnej**)*

Keywords: MPC; DMC; Receding Horizon; Step Response; Distillation Column; System Identification Toolbox.
Słowa kluczowe: DMC; Ustępujący horyzont; Odpowiedź skokowa; Kolumna destylacyjna; Skrzynka narzędziowa identyfikacji systemu

Introduction

Distillation control has been the subject of many books and papers over the past half century [1-4]. Distillation is a method for separating binary and multicomponent liquid mixtures into pure components. Even today, it belongs to the most commonly applied separation technologies and is used at large scale. The separation process requires three things. Firstly, a second phase must be formed so that both liquid and vapor phases are present and can contact each other on each stage within a separation column. Secondly, the components have different volatilities so that they will partition between the two phases to a different extent. Lastly, the two phases can be separated by gravity or other mechanical means.

Distillation columns come in many flavors, and no one control structure fits all columns. Differences in feed compositions, relative volatilities, product purities, and energy costs impact the selection of the "best" control structure for a given column in a given plant. Researchers have tried to control distillation column using different conventional as well as intelligent control techniques. Nonlinear control [5], nonlinear model predictive control [6], robust control [7], and model predictive control [8-9].

In this paper we will simulate an MPC control of a distillation column. Predictive control is a field which has attracted much research interest and attention over recent decades, judging by the number of publications available, addressing theoretical and application issues.

The paper is organized in five sections. After this introduction, section 2 talks about the distillation column principle. Section 3 gives more detail about the distillation set-up subject of study and its corresponding system identification procedure used in this work. The section 4 gives a review to MPC method and theory. In section 5, a chemical process is introduced and simulation results are shown. Final section gives some concluding remarks.

Distillation Column

Distillation columns are made up of several components, each of which is used either to transfer heat energy or to enhance mass transfer. A typical distillation column contains a vertical column where trays or plates are used to enhance the component separations, a reboiler to provide heat for the necessary vaporization from the bottom of the column, a condenser to cool and condense the vapor from the top of the column, and a reflux drum to hold the condensed vapor so that liquid reflux can be recycled back from the top of the column. Most of distillation control systems, either conventional or advanced, assume that the column operates at a constant pressure. Pressure fluctuations make the control more difficult and reduce the performance. The liquid flow rate L and the vapor flow rate V are the control inputs. The objective of the controller is to maintain the product outputs concentrations of the Top product and the bottom product despite the disturbance in the feed flow F and the feed concentration.

The first step in any distillation calculation is to establish the material and energy balances over the unit. A total material balance over the whole column unit at steady state can be described as [10], [11]:

$$F = B + D \tag{1}$$

Where F is the molar flow rate of the feed, D is the molar flow rate of the distillate and B is the molar flow rate of the bottom. The corresponding component balance for a binary mixture as (the mole fractions are with reference to the most volatile component):

$$Fz_F = Bx_B + Dx_D \tag{2}$$

Separate balances can also be set up over subsections of the column, e.g. over the top of the column:

$$V_{n+1} = L_n + D \tag{3}$$

$$V_{n+1}y_D = L_n x_D + D \tag{4}$$

Where V_{n+1} is the molar flow rate of the vapor into the top section and L_n is the molar flow rate of liquid leaving the top section. Equivalently, balances over the bottom of the column are:

(5) $$V_m = L_{m-1} + B$$

(6) $$V_m y_m = L_{m-1} x_{m-1} - B x_B$$

Where L_{m-1} is the molar flow rate of the liquid into the bottom section and V_m is the molar flow rate of vapor leaving the bottom section.

Balances can also be established over each stage. For stage n, four streams are involved as shown in Fig.1: the vapor stream entering stage n from the stage below (n+1), the liquid stream entering stage n from the stage above (n-1), and the vapor and liquid streams leaving stage n, respectively. The total and component material balances over stage n at steady state are thus given by:

(7) $$V_{n+1} + L_{n-1} = L_n + V_n$$

(8) $$V_{n+1} y_{n-1} + L_{n-1} x_{n-1} = L_n x_n + V_n y_n$$

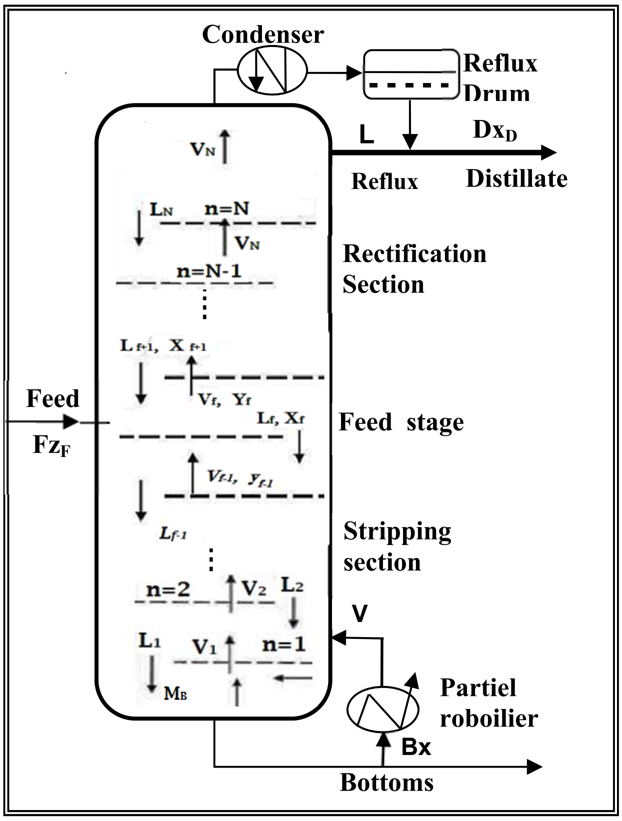

Fig.1: Distillation Column

Note that we choose to number the stages starting from the bottom of the column. We denote Ln and Vn as the total liquid- and vapour molar flow rates leaving stage n (and entering stages n-1 and n, respectively).

Based on the equilibrium stage concept [12], a distillation column section is modelled as:

The global mass balance for the volatile component on stage i:

(9) $$\frac{dM_i}{dt} = L_{i+1} - L_i + V_{i-1} - V_i$$

Component balance:

(10) $$\frac{d(M_i x_i)}{dt} = L_{i+1} x_{i+1} - L_i x_i + V_{i-1} y_{i-1} - V_i y_i$$

By differentiating (10) and substituting for (9), the following expression is obtained:

(11) $$\frac{dx_i}{dt} = \frac{L_{i+1}x_{i+1} + V_{i-1}y_{i-1} - (L_{i+1} + V_{i-1})x_i - V_i(y_i - x_i)}{M_i}$$

Energy balance:

(12) $$\frac{d(M_i h_i)}{dt} = h_{i+1}L_{i+1} - h_i L_i + H_{i-1}V_{i-1} - H_i V_i$$

Or

(13) $$M_i \frac{dh_i}{dt} + h_i \frac{dM_i}{dt} = h_{i+1}L_{i+1} - h_i L_i + H_{i-1}V_{i-1} - H_i V_i$$

Because the term $\frac{dh_i}{dt}$ is approximately zero, substituting for the change of hold up $\frac{dM_i}{dt}$ in (13), and rearranging the terms, the following expression is obtained:

(14)
$$V_i = \frac{h_{i+1}L_{i+1} + H_{i-1}V_{i-1} - (H_i V_i + h_i L_i)}{H_i - h_i}$$

Equations for the feed tray: (Stage n=f)

Total mass balance:

(15) $$\frac{d(M_f)}{dt} = F + L_{f+1} + V_{f-1} - L_f - V_f$$

Component balance:

(16) $$\frac{d(M_i x_i)}{dt} = F_{ZF} + L_{f+1}x_{f+1} + V_{f-1}y_{f-1} - L_f x_f - V_f y_f$$
$$\Rightarrow \frac{dx_i}{dt} = \frac{L_{i+1}x_{i+1} + V_{i-1}y_{i-1} - (L_{i+1} + V_{i-1})x_i - V_i(y_i - x_i)}{M_i}$$

Energy balance:

(17) $$\frac{d(M_f h_f)}{dt} = h_f F + h_{i+1}L_{i+1} + H_{i-1}V_{i-1} - h_i L_i - H_i V_i$$
$$\Rightarrow V_i = \frac{h_F F + h_{i+1}L_{i+1} + H_{i-1}V_{i-1} - (L_{i+1} + V_{i-1})h_i - V_i(y_i - x_i)}{H_i - h_i}$$

Equations for the top tray (stage n=N+1)

Total mass balance:

(18) $$\frac{d(M_N)}{dt} = L + V_{N-1} - (L_N + V_N)$$

Component balance:

(19) $$\frac{d(M_N x_N)}{dt} = Lx_D + V_{N-1}y_{N-1} - L_N x_N - V_N y_N$$

Energy balance:

(20) $$\frac{d(M_N h_N)}{dt} = h_D L + H_{N-1}V_{N-1} - (h_N L_N + H_N V_N)$$
$$\Rightarrow V_N = \frac{h_D L + H_{N-1}V_{N-1} - (L + V_N)h_N}{H_N - h_N}$$

Bottom Tray (stage n=2)

Total mass balance:

(21) $$\frac{d(M_2)}{dt} = L_3 - L_2 + V_B - V_2$$

Component balance:

(22) $$\frac{d(M_2 x_2)}{dt} = L_3 x_3 - L_2 x_2 + V_B y_B - V_2 y_2$$

Energy balance:

(23) $$\frac{d(M_B h_B)}{dt} = h_3 L_3 + H_B V_B - h_2 L_2 - H_2 V_2$$
$$\Rightarrow V_2 = \frac{h_3 L_3 + H_B V_B - (L_3 + V_B)h_2}{H_2 - h_2}$$

Re-boiler and Column Bottoms (stage n=1)

Total mass balance:

(24) $$\frac{dM_1}{dt} = L_2 - V_1 - B$$

(25) $$\frac{d\{M_1x_1\}}{dt} = L_2x_2 - V_1y_1 - Bx_1$$

Energy balance:

(26) $$\frac{d(M_1h_1)}{dt} = h_2L_2 + Q_B - (h_1B + H_1V_1)$$
$$\Rightarrow V_1 = \frac{h_2L_2+Q_B-h_1B-M_B\frac{dh_1}{dt}-h_1\frac{dM_1}{dt}}{H_1}$$

Process Description

Crude from storage tanks located in offsite area flows under gravity to the CDU plant battery limit and further pumps to pre-flash drum inlet through Crude charge pumps. The crude is preheated in existing preheat train. Preheated crude then enters to Desalter for removal of salts crude. The crude from Desalter is further heated and flashed in pre-flash drum where water and light ends in the crude oil are flashed-off. Preheated crude is furtherer heated and partially vaporized in to two parallel operating existing Charge Heaters. The Heater is designed with fuel gas firing burners.

Atmospheric column has three side draws: Kerosene (kero), Light Gas Oil (LGO) and Heavy Gas Oil (HGO) all of which are drawn through side strippers. Unstabilized naphtha after is fed to Stabilizer-A & Stabilizer B Bottom product, Stabilized Naphtha product is directly routed under its own pressure to splitter-I. Splitter-I bottom product (Naphtha B+C) is pumped to Splitter-II and C6 Cut Splitter. C6 cut Splitter bottom product is pumped and joined with the Splitter-II bottoms to make Naphtha product stream. Splitter-II column has 36 trays with feed entering on the 27th tray. Column is operated at temperature & pressure 140 °C & 1.0 kg/cm2g. The overhead products go to Reflux Drum after totally being condensed in condenser. Condensed overhead liquid is collected in Splitter-II Reflux Drum. Accumulated liquid in reflux drum is sucked by pumps and sent as reflux to the column overhead (on the 36th tray). Liquid distillate Naphtha B (Overhead condensate) is sent to storage However before going to storage the product is further cooled via the Cooler to achieve the temperature of 38°C.

Column bottom product is heated in shell side exchanger Reboiler through Hot Oil. Reboiler outlet temperature is controlled by regulating the hot oil flow through reboiler via temperature controller which acts by sensing the 3rd tray temperature of the column.

Reboiling liquid goes back to column under tray 1. Bottom product of splitter II (Naphtha C), sucked by bottom pumps is sent to storage via passing through various exchangers for cooling, Column bottom is operated at temperature 204.2°C. Bottom product joined by Naphtha C from C6 Cut Splitter coming at 140°C, is sent to Stabilizer Feed / Splitter-II Bottom Exchanger first for reducing the average temperature from 154°C to 132°C. This stream is further cooled by passing through Splitter-Bottom Cooler and Naphtha C Water Cooler to reduce the temperature to 38°C.

Process Variables

In general, the control of any system is based on its dynamics; for distillation column, many control configurations are used [13-14]. In our case we choose an LV configuration. The L-V control structure, which is called energy balance structure, can be viewed as the standard control structure for dual composition control of distillation column. In this control structure, the reflux flow rate L and the boil-up flow rate V are used to control the “primary” outputs associated with the product specifications.

To generate an informative input/output data set of a process, it is necessary to vary the inputs of the process in some fashion so that there are deviations in the process outputs. The frequency at which an input is changed must be related to the dominant time constant of the process. If the switching frequency is too high, very little effect is seen in the process outputs. If the switching frequency is too low, stead y-state gain information is present in the data but very little information on the transient or dynamic characteristics of the process. To obtain useful process data, the input sequences must have a reasonable magnitude of variation. That is, the change in input signal must be such that the output signal variation is noticeable above process noise and disturbances [15].

The distillation column case of study is considered as a 2x2 system [16] where the inputs are the Reflux (L) and the boil up (V) and as outputs we have the top and bottom temperatures (concentrations).

Distillation Column Set Up
Description

The control of SKIKDA refinery is managed by the YOKOGAWADCS (CS3000), an OPC server (EXAOPC server) is installed to allow communication between the DCS and other subsystems, and we used it for data collection, a PC in which we installed the MATLAB with the following toolboxes: OPC Toolbox and System Identification Toolbox according to the following System Architecture **(Fig.2)**:

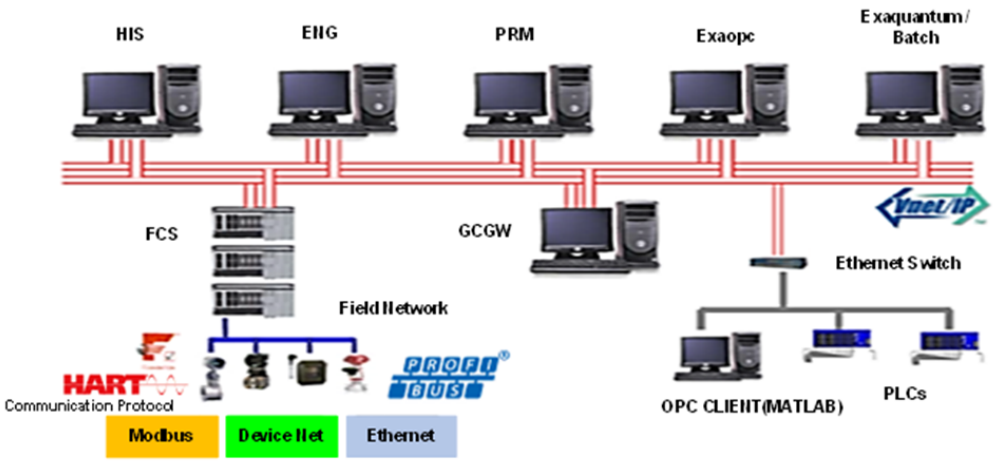

Fig.2: System Architecture

Where: **FCS:** Field Control Station; **HIS:** Historian Information System; **ENG:** Engineering Function
PRM: Plant Resource Manager; **Exacopc:** software component developed by Yokogawa Electric Corporation; **GCGW:** Generic Subsystem Gateway Package, **PLCs:** Programmable Logic Controllers

Exaquantum / Batch: is an intelligent and scalable ISA-88 based Batch PIMS (Plant Information Management System).
Exaopc: is an OPC server running on a Microsoft Windows platform which can be connected to a variety of PCSs (Process Control Systems) providing OPC clients with process data and alarm events

To ensure the communication between the OPC Server (EXAOPC) and the OPC Client (MATLAB PC) we should set the IP address of the OPC client to be in the same domain of the OPC Server. Once the communication is established, we begin to access to DCS controller (FCS) that contained the requested Tags.

Model Identification

Using MATLAB Toolbox, we have estimated the mathematical model of the distillation column by choosing the process model estimation method. Before starting the identification of our system, a pre-processing of the data is required in order to eliminate the measurement noise and for this purpose we have to use a filter. In our work we considered that our system is linear [17] and therefore it is subjected to the principle of superposition because we will determine the relation between the first input and the two outputs and the same will be done for the second input so each output will be a function of the two inputs.

In order to have a good and reliable model, we have to select useful portions of the original data which describe the dynamics of the distillation column. It is good and common practice in identification to evaluate an estimated model's properties using a fresh data set, that is, one that was not used for the estimation. It is thus good advice to let the Validation Data be different from the Working Data, but they should of course be compatible with these. All estimation routines are accessed from the pop-up menu Estimate in the Ident window. The models are always estimated using the data set that is currently in the Working Data box [18]. The aim of this study is to construct a linear MIMO black-box model for the distillation column. This model will be created from a set of MISO submodels. The resulting models are ranked based on their Fit value. The results of the transient response based on open loop system are shown in Figures (Fig.3(a)-6(a)) for different step changes of *Reflux Flow Rate* (R) and *SetTempReboiler* heat duty (H) on the controlled variables the distillate composition (X_D) and bottom composition (X_B) (See Fig.3(b)-6(b)).

The identification process was performed by applying random magnitude input step changes of random duration. The steps were made in both positive and negative directions (Reflux flow rate of 77-83 m^3/h and a SetTempReboiler of 197-199 m^3/h) to ensure that the model accounts for the ill-conditioning. The results of the identification are shown in Figures (Fig.3(c)-6(c)). Figures, Fig.3(c) and Fig.4(c), depict the estimation plot for the top Temperature with the *Reflux flow rate* and *SetTempReboiler* inputs respectively, therefore, the Figures, Fig.5(c) and Fig.6(c), illustrate the estimation plot for the Bottom Temperature with the *Reflux flow rate* and *SetTempReboiler* inputs respectively. As model validation, the prediction of the dataset is compared with the measured data based on a Fit measure according the (**Eq. 26**) as follow:

$$Fit = 100\%\left(1 - \frac{|\hat{y}(t) - y(t)|}{|y(t) - \bar{y}(t)|}\right) \quad (27)$$

The obtained fit function results are presented in the Table 1.

Table 1- Illustrates the results of the Fit measure:

	Input	Fit (%)
Top Temperature	Flow Reflux	**52.65**
	Set Temp Reboiler	**66.33**
Bottom Temperature	Flow Reflux	**55.25**
	Set Temp Reboiler	**29.67**

The following models for the top and bottom temperature are combined into one MIMO transfer function model given in Eq. **(28)** with time constants and delays in seconds.

$$\begin{bmatrix} X_D \\ X_B \end{bmatrix} = \begin{bmatrix} \frac{193.4s+1.613}{7529s^2+79.77\,s+1}\,e^{-1.97s} & \frac{15.87\,s+2.465}{1758s^2+214.1s+1} \\ \frac{134.3\,s+0.6928}{1012\,s^2+210.9\,s+1}\,e^{-0.038s} & \frac{-0.7079\,s+1.026}{27.56s^2+11.99\,s+1} \end{bmatrix} \begin{bmatrix} L \\ V \end{bmatrix} \quad (28)$$

The plant is having two controlled variables y1, y2 and two manipulated variables u1, u2. The two controlled variables are composition of the distillate product ($\boldsymbol{X_D}$) and bottom product ($\boldsymbol{X_B}$). The manipulated variables are reflux (**L**) and reboiler flow rate (**V**).

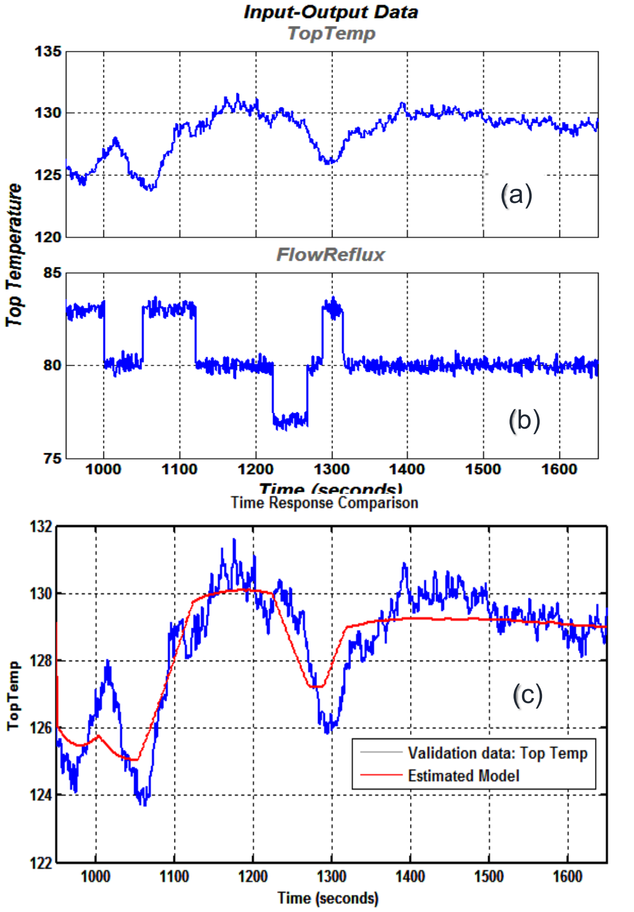

Fig.3: Column distillation Responses, (a) Top Temperature measure from Flow Reflux input, (b) Flow Reflux input, (c) Validation of the Top temperature from Flow Reflux input (Fit function=52.65%)

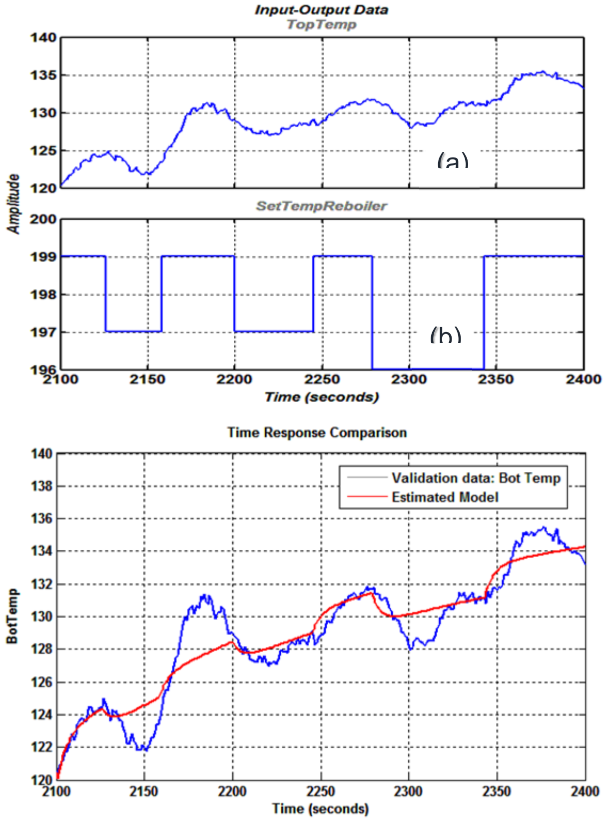

Fig.4: Column distillation Responses, (a) Temperature measure from Set Temp Reboiler input, (b) S (c) emp Reboiler input, (c) Validation of the Top temperature from emp Reboiler input (Fit function=66.33%)

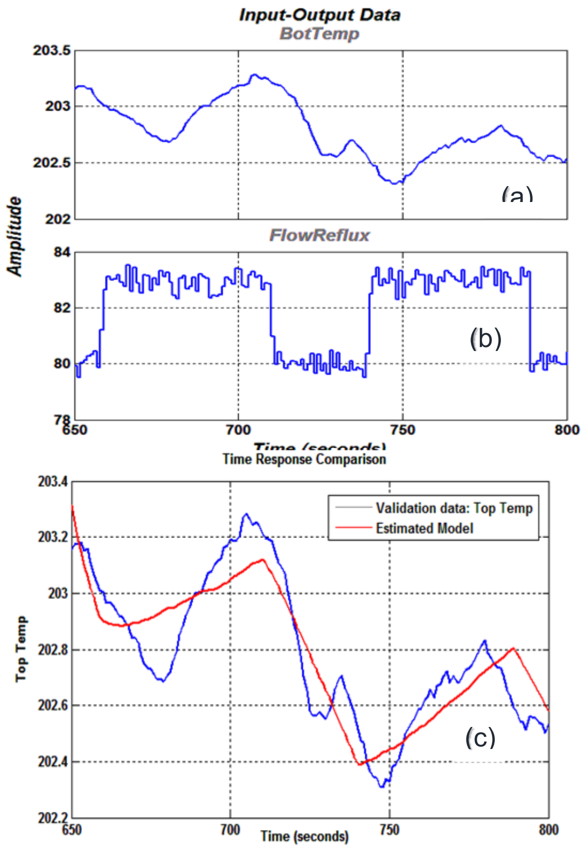

Fig.5: Column distillation Responses, (a) Bottom Temperature measure from Flow Reflux input, (b) Flow Reflux input, (c) Validation of the Bottom temperature from Flow Reflux input (Fit function=55.25%)

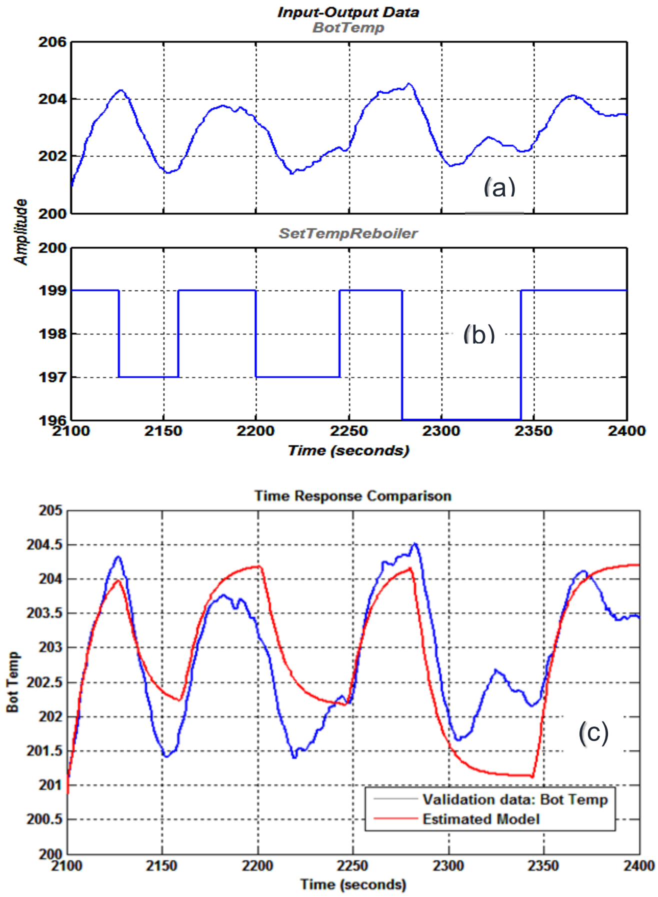

Fig. 6: Column distillation Responses, (a) Bottom Temperature measure from Set Temp Reboiler input, (b) Set Temp Reboiler input, (c) Validation of the Bottom Temperature from Set Temp Reboiler input (Fit function=29.67%)

Model Analysis

Residual (estimation errors) analysis is a very well developed field of model diagnosis and validation [19] and is very much a strong component of cross-validation. An enormous amount has been written about this field and many text books have been published providing its different applications and adaptations [20 & 21]. Studying the difference between the model output and the output of the true systems, residual analysis, allows for the study of the existence and nature of model inadequacies, thus its place in model validation. The analysis of correlations amongst estimation residuals (estimation errors) and between the estimation residuals and the system inputs are commonly used linear validation approaches. This analysis may be considered as a direct quantification of the concept behind residual plotting and consists of the following two tests [22]:

- ✓ ***The Whiteness Test:*** This test is based on the condition that the residuals or the prediction errors between the model and the system, of a good model should be independent of each other and of past data. Therefore, a good model has residuals that are uncorrelated.

- ✓ ***The Independence Test:*** Is a measure of the correlation between the residuals and the corresponding inputs. A good model has residuals uncorrelated to past inputs. The identified model was the subject of the two tests as shown in the figures below (Fig.7-10).

The results of the analysis test are shown in Figures (Fig. 7- 10). Figures (Fig.7(a) – 10(a)) depict the correlation function of output residuals between the estimation model and measured data. This measure is close to one indicating the good estimation of the column distillation MIMO model. However, Figures (Fig.7(b) – 10(b)) show the correlation function between inputs and residuals from outputs. This measure is used to investigate the coupling between the input and output model. The results give an element close to zero to indicate a less influence for the corresponding output. A good model has residuals uncorrelated to past inputs.

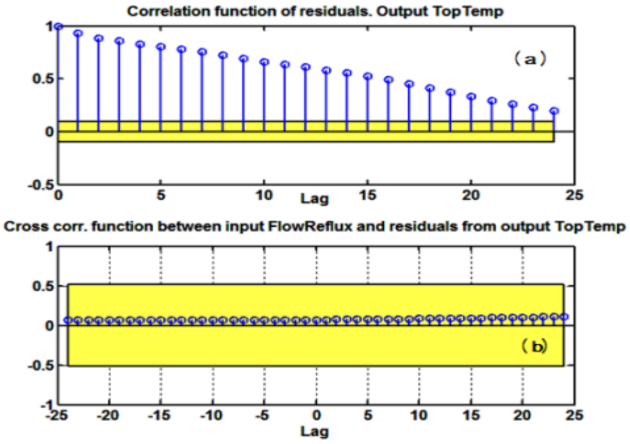

Fig.7: Performance test of the Column distillation model, (a) Correlation function of Output Top Temp residuals, (b) Cross-correlation function between input Flow Reflux and Output Top Temp residuals.

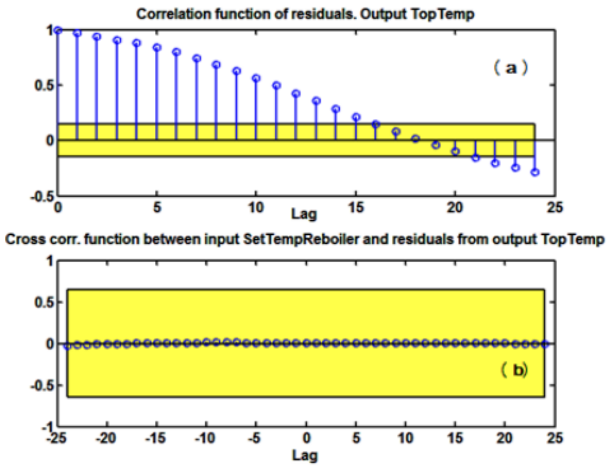

Fig.8: Performance test of the Column distillation model, (a) Correlation function of Output Top Temp residuals, (b) Cross-correlation function between input Set Temp Reboiler and Output Top Temp residuals.

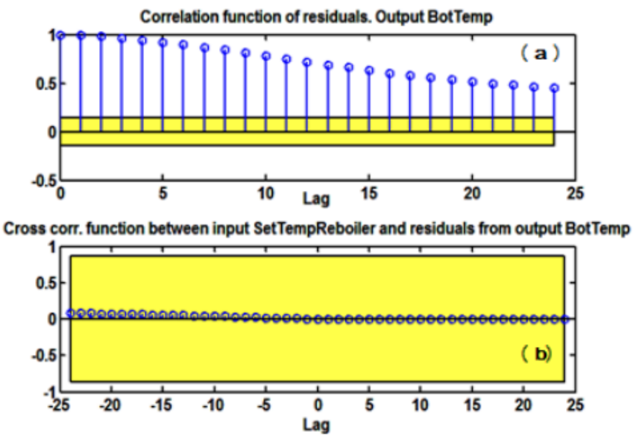

Fig.9: Performance test of the Column distillation model, (a) Correlation function of Output Bot Temp residuals, (b) Cross-correlation function between input Flow Reflux and Output Bot Temp residuals.

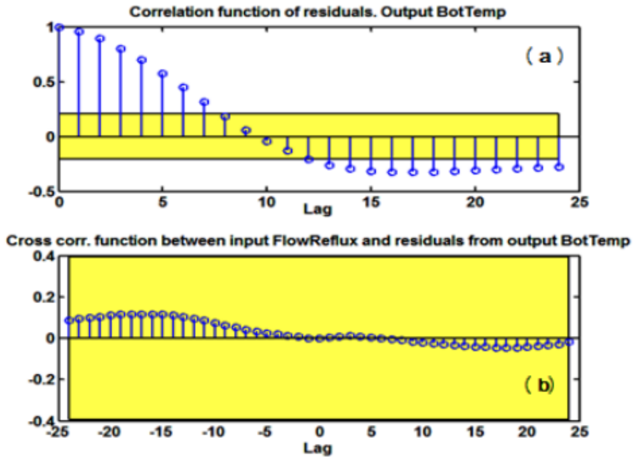

Fig.10: Performance test of the Column distillation model, (a) Correlation function of Output Bot Temp residuals, (b) Cross-correlation function between input Set Temp Reboiler and Output Bot Temp residuals.

Model Predictive Controller

Model predictive control refers to the class of control algorithms that compute a manipulated input profile by utilizing a process model to optimize an open loop performance objective subject to constraints over a future time horizon. It is based on three concepts which are [23]:

✓ *Explicit use of a model to predict the process output at future time instants.*
✓ *Calculation of a control sequence minimizing an objective function.*
✓ *Receding strategy, so that at each instant the horizon is displaced towards the future, which involves the application of the first control signal of the sequence calculated at each step.*

MPC includes several algorithms (DMC, MAC, GPC, PFC, EPSAC, EHAC…..etc) we will shed light on the state-space model algorithm. The fundamental framework of MPC algorithms is common for any kind of MPC schemes [24].

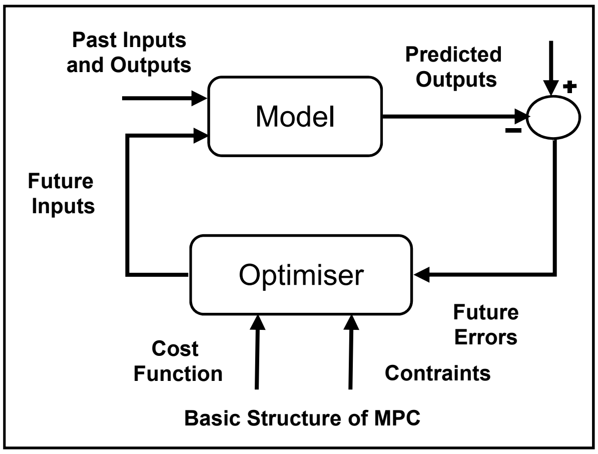

Fig.11: MPC Scheme

Suppose that we have a state-space representation of a MIMO system (m inputs and q outputs):

$$\begin{cases} x_m(k+1) = A_m x_m(k) + B_m u(k) \\ y(k) = C_m x_m(k) \end{cases} \quad (29)$$

The augmented system is obtained by choosing a new state variable vector

(30) $$x(k) = [\Delta x_m(k)^T\ y(k)]$$

The new augmented system:

(31) $$\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_m & o_m^T \\ C_m A_m I_{q\times q} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_m \\ C_m\, B_m \end{bmatrix} \Delta u(k)$$

(32) $$y(k) = \begin{bmatrix} o_m\ I_{q\times q} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix}$$

The outputs are:

(33) $$Y = Fx(k_i) + \emptyset \Delta U$$

Where:

(34) $$F = \begin{bmatrix} CA \\ CA^2 \\ CA^3 \\ . \\ . \\ CA^{N_p} \end{bmatrix}$$

And ∅ is:

(35) $$\emptyset = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ CA^2B & CAB & CB & \dots & 0 \\ . & . & . & \dots & . \\ . & . & . & \dots & . \\ CA^{N_p-1}B & CA^{N_p-2}B & CA^{N_p-3}B & \dots & CA^{N_p-N_c}B \end{bmatrix}$$

The optimal solution for the control is:

(36) $$\Delta U = (\emptyset^T \emptyset + R')^{-1}\left(\emptyset^T R'_s r(k_i) - \emptyset^T F x(k_i)\right)$$

Simulation Results:

The real time data are taken from the Real Pilot distillation column. After black-box linear system identification, the model parameters are obtained from the experimental responses curves for the step change in the above binary distillation column. The controller objective is to minimize the difference between the controlled temperature and its reference trajectory, together with minimal change of the inputs between two successive **MPC** steps. The weight matrix Q_u for the inputs is adapted to encourage the use of the flow rates of the column. The weight matrix Q_y for the outputs punished the deviation for the top temperature slightly more than that of the reboiler temperature. The **MPC** controller for the Pilot distillation column validated using **MATLAB** environment and the result are obtained through the simulation study.

In MIMO system, the model horizon M is determined according to the slowest response output. The slowest step response curve is observed for the Top Temperature to step change in Fig.12. The simulation has been done with respect to the following considerations: The prediction horizon (P=25) and the control horizon (C=25). The chosen tuning parameters for MPC algorithm are as Follows:

$$T_s = 5s, N = 2000, Q_y = 10 \text{ and } Q_u = 0.3$$

During the simulation both constrained and unconstrained MPC control are implemented considering two manipulated variables (***Reflux Flow Rate*** (**R**) and ***SetTempReboiler*** heat duty (**H**)) and controlled variables the distillate composition (X_D) and bottom composition (X_B) of binary distillation column. The response reaches the steady state, even in the presence of disturbance.

In order to assess the proposed control scheme, the simulation was executed according to these scenarios:

Case Study I: Healthy System

In this case study, step response model without disturbance is used for MPC design. In order to get coefficients of step response model, it is necessary to obtain the open loop responses of controlled variables by giving unit step changes to the manipulated variables. The responses of controlled variables, the distillate composition (X_D) and bottom composition (X_B) of binary distillation column, are shown in Figure (Fig.12).

Results discussion of case_01

The simulation scenario considers temperature-tracking problem with step change in reference. The step change of temperature on top of the column was performed, from steady state $y_s = 130°C$ to desired $y = 128°C$ and bottom of the column $y_s = 200°C$ to desired $y = 205°C$. Figures (Fig. 12a,b) show the MPC response of column distillation for a step change.

The result shows that MPC control the temperature in the presence of set point changes and maintains the controlled variable around the set point with a smaller rise time during the transient response. Above figures (Fig.12a & Fig.12b) are responses without disturbances of distillation column model, figure (Fig.12a) depict the controlled Top Temperature and (Fig.13b) illustrates the controlled Bottom Temperature. Therefore, the figures (Fig.12c & Fig.12d) give the manipulate variables (u_1, u_2) respectively.

If there are no disturbance in operating condition, the control system is to achieve the steady state of product quality that the purity of the distillate product x_D and the impurity of the bottoms product x_B at the sired values.

MPC control action indicates that when the temperature at the outlet of the distillation column goes above the reference temperature, the control input is decreased to take output temperature to the reference temperature level. Also, when the output temperature goes below the reference temperature, the control input rises again to take the output temperature to the reference temperature level. In addition, it is observed that the controller starts to take action before any changes in the reference signal, which is an important feature of MPC controller.

Case_02: System affected by a measurement disturbance at level= 1%.

In this case study, step response model with a disturbance at level 1% of the magnitude. The responses of controlled variables, the distillate composition (X_D) and bottom composition (X_B) of binary distillation column, are shown in Figure (Fig.13).

Case_03: System affected by a measurement disturbance at level= 5%.

In this scenario, we apply a disturbance input at level of 5% on the measurement (error tolerated for sensors in industrial instrumentation), the response of the system is illustrated in figure (Fig.14).

Disturbance Analysis

It is well known that distillation processes are in general very sensitive to disturbance effects, thus a successful controller should provide good disturbances rejection capabilities. But even the performance of well-tuned controller can be deteriorated in presence of significant disturbances. To examine the controller performance different disturbance tests were performed. The Fig.13 shows the controlled temperatures when the set points is affected by measurement noise at 1%. The MPC controller eliminate this disturbance and manages to maintain the outputs inside their respective control zones.

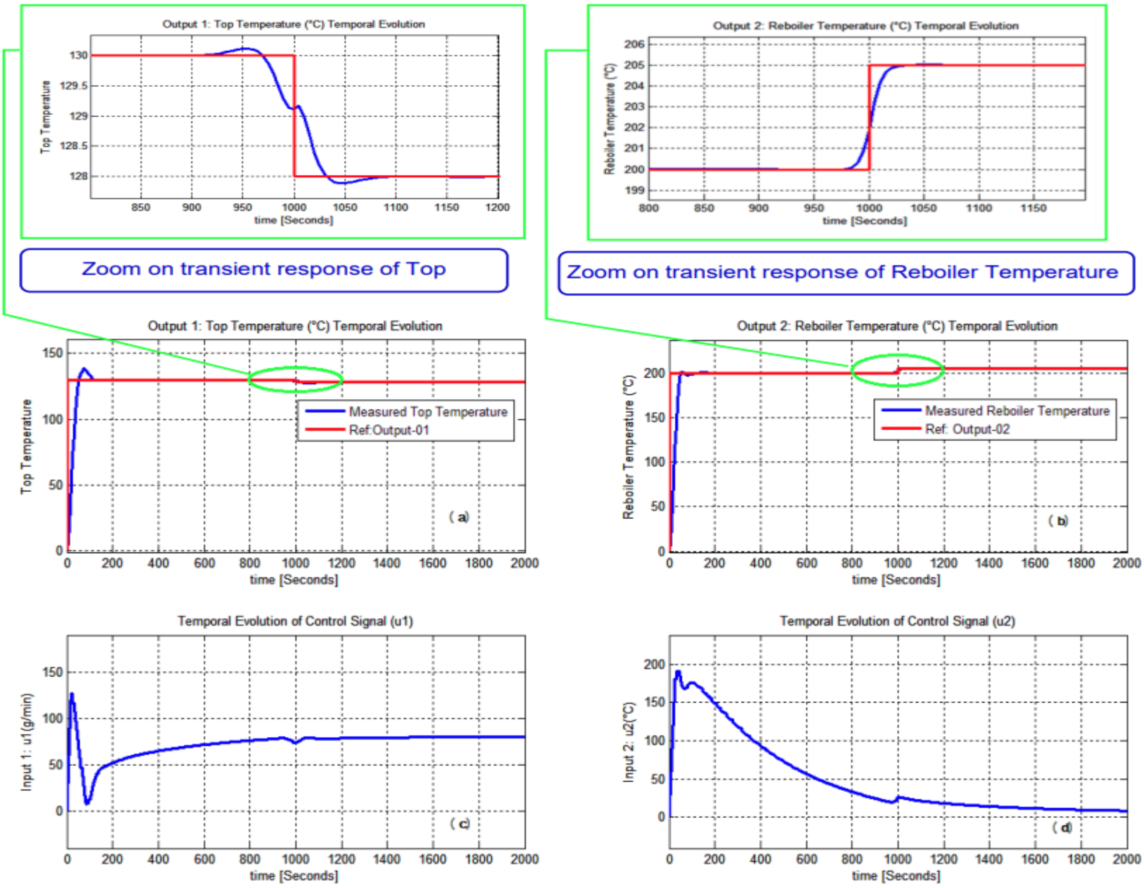

Fig.12: System response for varying reference values of Flow Reflux and Set Temp Reboiler under Model Predictive Controller, (a) Top Temperature response, (b) Bot Temperature response, (c) Control signal input for Top Temperature, (d) Control signal input for Bot Temperature.

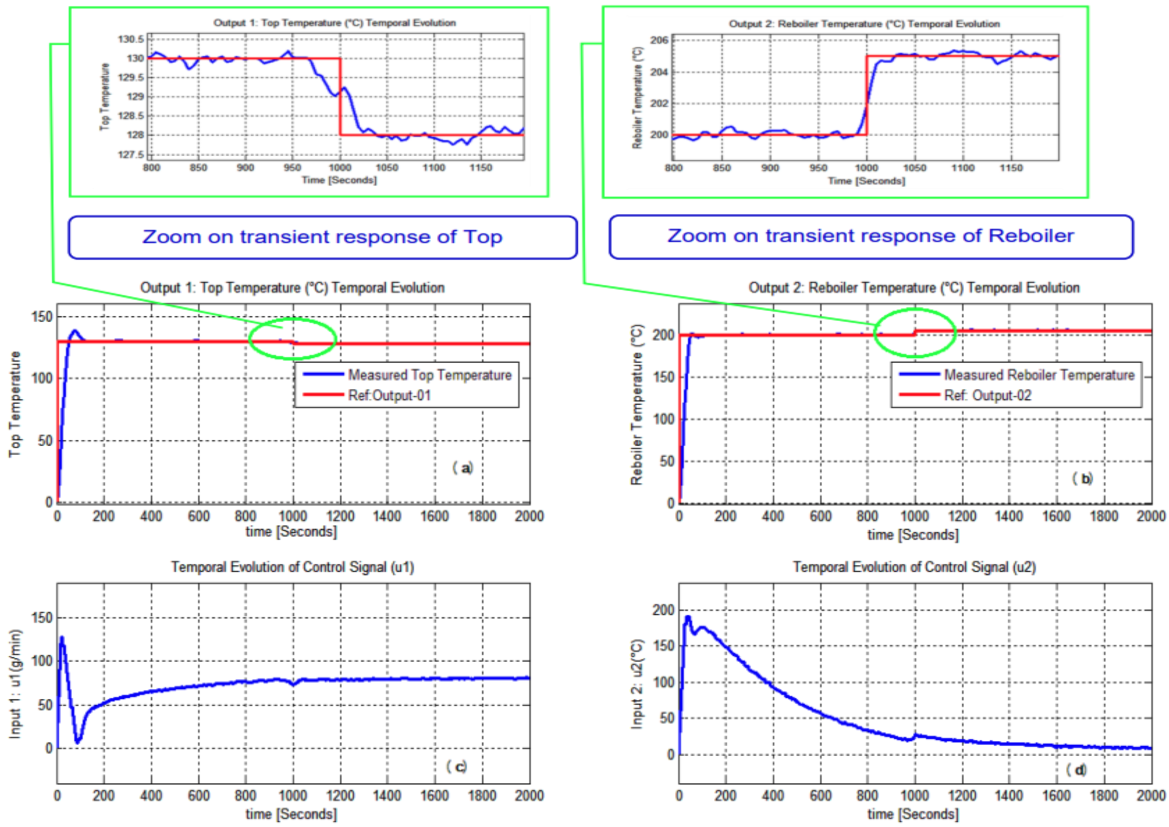

Fig.13: System response for varying reference values of Flow Reflux and Set Temp Reboiler under Model Predictive Controller with addition of 1% of noise, (a) Top Temperature response, (b) Bot Temperature response, (c) Control signal input for Top Temperature, (d) Control signal input for Bot Temperature.

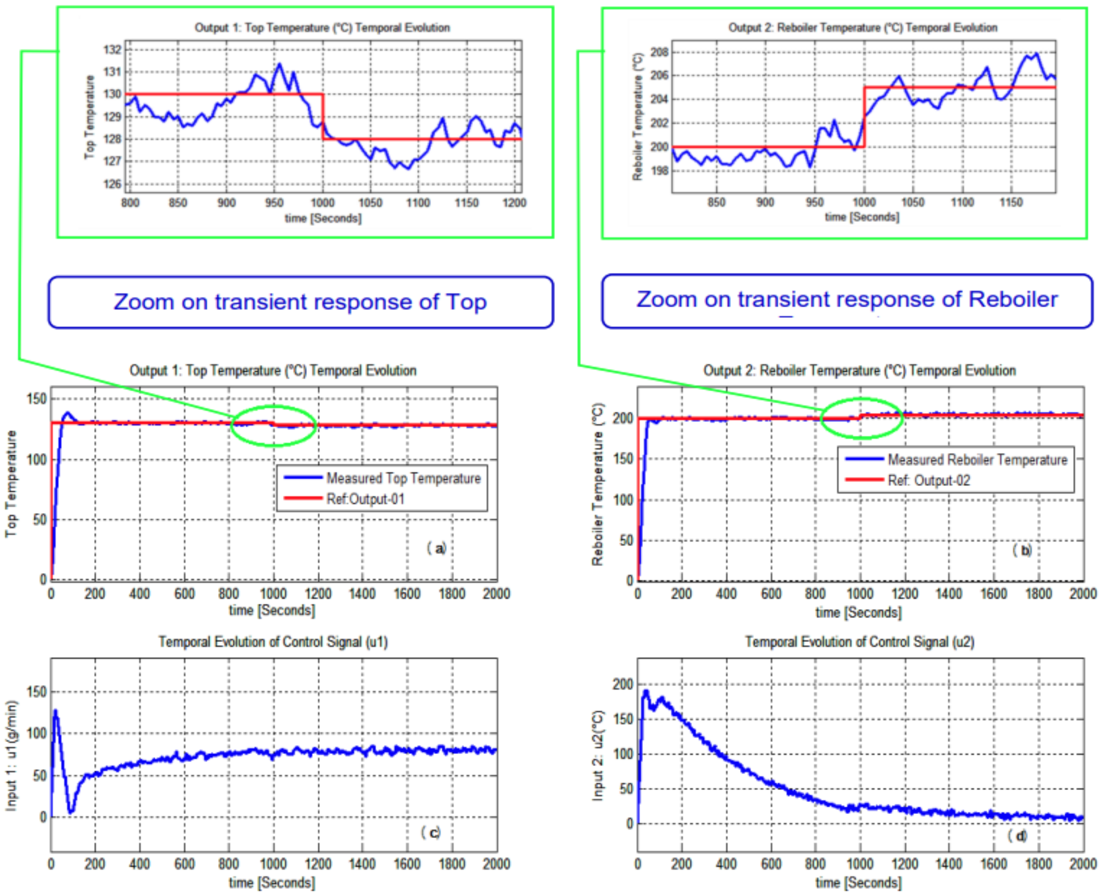

Fig.14: System response for varying reference values of Flow Reflux and Set Temp Reboiler under Model Predictive Controller with addition of 5% of noise, (a) Top Temperature response, (b) Bot Temperature response, (c) Control signal input for Top Temperature, (d) Control signal input for Bot Temperature.

Assuming that the measurement disturbance is at 5%, the case of the Fig.14, we can see easily that the MPC controller is able to respond to this disturbance and control the temperature of the column without a large oscillation and offset while simultaneously neglecting the effects of unmeasured disturbances. A large number of simulations were performed in this work to check the robustness of the MPC controller against different scenarios. Simulation results demonstrate that the MPC controller achieves a suitable control performance for disturbance rejection.

Conclusion

In this work a binary distillation column model was identified from data using Matlab Identification system Toolbox, and it was validated by residual cross correlation test, the model was the subject of MPC control simulation study using MATLAB software. The distillation column model was estimated using Identification Toolbox System based on Black Box Modeling Philosophy, data was collected from real binary distillation column installed in the crude distillation unit of SKIKDA refinery. The MPC controller implemented to the binary distillation column model considering two manipulated variables namely Reflux and Boil up flow used to maintain two temperatures at their set points under the operation constraints and in the presence of disturbances. The simulation result shows good tracking capacity, best constraints support and good disturbance rejection ability. MPC controller has been found to be very satisfactory for the binary distillation column control.

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