A Study on Models experimental validation and comparison and Linearization of the Distillation Process

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Abstract- In this paper we are presenting a Study on Models experimental validation and comparison and Linearization of the Distillation Process. For the feed section, operating pressure on the feed section is given at 5.6 atm. The feed temperature for the preheater is the temperature at which the required phase equilibrium is established. Mathematical modeling simulations are completed in three stages: the basic nonlinear model, the full-order linear model and the low-order linear model. Results from simulation and analysis are helpful for the initial stages of a petroleum project feasibility study and design. Low-order linear models are used as reference models for the MRAC controller. The controller of MRAC and MPC theoretically allows plant outputs to track reference setpoints to achieve the desired product quality between disturbances and model-plant mismatch as an effect of feed-stock disturbances. In this paper, mathematical model building calculations and low-order linear adaptive controllers are based only on physical rules from the process. Identification of the actual system, including experimental production factors, specific design structures, estimation of parameters and system validation, is not mentioned here. Furthermore, the MRAC controller is not suitable for on-line handling of process bottlenecks.

Index terms- Experimental, Validation, Process, Study, Model etc

I.INTRODUCTION

The feed can be considered as a pseudo-mixture of ligas iso-butane, n-butane and propane and naphthas iso-pentane, n-pentane and higher components. The column is designed with N = 14 trays. The model is simplified by omitting some components simultaneously, as the column dynamics and the modeling of the dynamics are based on these pseudosources [3]. For the feed section, operating pressure on the feed section is given at 5.6 atm. The

feed temperature for the preheater is the temperature at which the required phase equilibrium is established. Consulting the equilibrium flash evaporation EFV curve at 5.6 atm, the required feed temperature is chosen at 120 theC corresponding to a point of 45% of the vapor phase feed rate VF.[15] For the correction section, the typical pressure drop per tray is 7.75 kPa. Thus, the pressure at the top section is 4 atm. The top section temperature is set at 46 .C, consulting the Cox chart. Then, we can calculate the reflux flow rate L through energy balance the equation. [15] For the stripping section, the column base pressure is about 5.6 atm feed pressure because the pressure drop in this section is neglected. In this section the equilibrium temperature at 4.6 nm is set at 145 .C, consulting the EFV Curve and Cox charts. Then, we can calculate the reboiler duty or heat input QB to increase the temperature of the stripping section from 120°C to 144 theC. Table 5.1 summarizes the initial calculated data for the main streams of the input feed flow rate, output distillate overhead product: LPG and output bottom product raw gasoline. [15]

The rate of accumulation of material in a system is equal to the amount entered and generated, less the amount leaving and consumed within the system. The model is simplified under assumptions in [1,9].

1. Constant relative volatility throughout the column and the vapor-liquid equilibrium relation can be expressed by

$$y_n = \frac{\alpha x_n}{1 + (\alpha - 1)x_n}'$$

Where xn is the liquid concentration on nth stage; yn is the vapor concentration on nth stage; α is the relative volatility.

2. The overhead vapor is totally condensed.

- 3. The liquid holdups on each tray, the condenser, and the reboiler are constant and perfectly mixed.
- 4. The holdup of vapor is negligible throughout the system
- 5. The molar flow rates of the vapor and liquid through the stripping and rectifying sections are constant.

Under these assumptions, the dynamic model can be expressed by the following equations: (i) condenser (n = N + 2):

 $M_D \dot{x}_n = (V + V_F)y_{n-1} - Lx_n - Dx_n,$

(ii) tray n(n = f + 2 to N + 1):

$$M\dot{x}_n = (V + V_F)(y_{n-1} - y_n) + L(x_{n+1} - x_n),$$

(iii) tray above the feed flow (n = f + 1):

$$M\dot{x}_n = V(y_{n-1} - y_n) + L(x_{n+1} - x_n) + V_F(y_F - y_n),$$

Table 1.1: The steady state values of concentrations xn and yn on each tray [15].

Stage	Bottom	Tray 1	Tray 2	Tray 3	Tray 4	Tray 5	Tray 6	Tray 7
Xa	0.0375	0.0920	0.1559	0.2120	0.2461	0.2628	0.2701	0.2731
V _n	0.1812	0.3653	0.5120	0.6044	0.6496	0.6694	0.6776	0.6809
Stage	Tray 8	Tray 9	Tray 10	Tray 11	Tray 12	Tray 13	Tray 14	Distillate
Xa	0.2811	0.3177	0.3963	0.5336	0.7041	0.8449	0.9369	0.9654
V.	0.6895	0.7256	0.7885	0.8666	0.9311	0.9687	0.9883	0.9937

Table 1.2: Product quality depending on the change of the feed rates [15].

	Purity of the	Impurity of
	distillate	the bottoms
	product x_D %	product x _B %
Normal feed rate	98.57	4.78
Reduced feed rate	92.35	0.88
10%		
Increased feed rate	98.40	12.88
10%		

(iv) tray below the feed flow (n = f):

$$M\dot{x}_n = V(y_{n-1} - y_n) + L(x_{n+1} - x_n) + L_F(x_F - x_n),$$

(v) tray n(n = 2 to f − 1):

$$M\dot{x}_n = V(y_{n-1} - y_n) + (L + L_F)(x_{n+1} - x_n)$$

(vi) reboiler (n = 1):

$$M_B \dot{x}_1 = (L + L_F) x_2 - V y_1 - B x_1.$$



Figure 1.1: Model simulation with Matlab Simulink[15]

Hence we will use an adaptive controller MRAC to take the system from these steadystate outputs of xD = 0.9863 and xB = 0.0456 to the desired output targets.

II. MRAC BUILDING AND SIMULATION

An adaptive control system is the ability of a controller to adjust its parameters in such a way as to compensate for variations in process characteristics. Adaptive control is widely applied in petroleum industries for two main reasons: Firstly, most processes are wired and a linearized model is used to design the controllers, so that the controller has model-plant mismatch. Have to change and adapt; the second thing is that most processes are obsolete or their characteristics change over time, and this again adapts to changing control parameters.



Figure 1.2: MRAC block diagram [15].

The general form of an MRAC is based on an innerloop Linear Model Reference Controller LMRC and an outer adaptive loop shown in Figure 1.2. In order to eliminate errors between the model and the plant and the controller is asymptotically stable, MRAC will calculate online the adjustment parameters in gains L and M by $\theta L(t)$ and $\theta M(t)$ as detected state error e(t)when changing A, B in the process plant. Simulation program is constructed using Maltab Simulink with the following data [15].

 $\dot{z} = Az + Bu + \text{noise},$

y = Cz,

where $A = \begin{bmatrix} a_1 & 0 \\ 0 & a_2 \end{bmatrix}$, $B = \begin{bmatrix} \beta_1 & 0 \\ 0 & \beta_2 \end{bmatrix}$, $C = \begin{bmatrix} 0.004 & -0.007 \\ -0.001 & 0.007 \end{bmatrix}$, and $a_1, a_2, \beta_1, \beta_2$ are changing and dependent on the process dynamics.

III. SIMULATION RESULTS AND ANALYSIS

We assume that the reduced-order linear model in can also maintain the similar steadystate outputs as the basic nonlinear model. Now we use this model as an MRAC to take the process plant from these steady-state outputs $x_D = 0.9863$ and xB = 0.0456 to the desired targets $0.99 \leq x_D \leq 1$ and $0 \leq x_B \leq 0.03$ amid the disturbances and the plant-model mismatches as the influence of the feed stock disturbances. The design of a new adaptive controller is shown in Figure 5 where we install an MRAC and a closed-loop PID Proportional, Integral, Derivative controller to eliminate the errors between the reference setpoints and the outputs. We run this different controller system with plant-model mismatches, for instance, a plant with

$$A = \begin{bmatrix} -0.50 & 0 \\ 0 & -0.75 \end{bmatrix}, B = \begin{bmatrix} 1.5 & 0 \\ 0 & 2.5 \end{bmatrix}$$

and an adaptive gain $\gamma = 27$. The operating setpoints for the real outputs are $x_DR = 0.99$ and $x_BR = 0.02$. Then, the reference setpoints for the PID controller are $r_D = 0.0261$ and $r_B = -0.0275$ since the real steady-state outputs are $x_D = 0.9654$ and $x_B = 0.0375$. Simulation in Figure 6 shows that the controlled outputs x_D and x_B are always stable and tracking to the model outputs and the reference setpoints the dotted lines, r_D and r_B amid the disturbances and the plant-model mismatches.



Figure 5.4: Values of product specifications as a function of the reflux L1 in constraint region VI.



Figure 5.5: The highest and lowest possible values of L1 before a constraint is breached at different feed rates.

IV. MODELS EXPERIMENTAL VALIDATION AND COMPARISON AND LINEARIZATION OF THE DISTILLATION PROCESS

The Takagi - Sugano fuzzy model has been validated in Matlab by using an ethanol – water mixture from a 12-tray batch distillation column with a veral reflex and considering the characteristics presented in Table 5.3. The initial molar composition of ethanol in the boiler is 0.2317, given that the feed volume corresponds to 97% volume ethanol. The study case, characteristics of process input for heating power (QB) and reflux valve opening (R) are shown in Table 1.4. Fig. 1.5 presents the temperature predicted by the Takagi - Sugano model for the tray in the column body. The rise and fall in temperature due to the reflux (R) action can be seen in all trays. Figure 5.6 presents the temperature graphics corresponding to the non-linear and sharpness-Sugino models of condenser (A) and boiler (B). The change in temperature existing during thermal power (QB) and reflux change (R) is shown. It can be seen that due to the reflux action there is a difference between the results obtained by both models, this difference is provoked by the operating points determined for the flow of liquid and vapor in the Takagi - Sugeno model; However, this difference is small (less than 1.7%).

Tabl	e 1.3:	Mixture	initial	parameters
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1 aoic 1.5.1	virxuie initiai pe	ameters	
Parameter		Value	Units
EtOH volu	me in boiler	3000	mL
H20 volun	ne in boiler	3000	mL
Process tot	al pressure	653.52	mmHg
Table 1.4:	Input parameters		
Input	Signal		Ti
Qs	Step 0-800 J		01
R	Total		0 r



Figure 1.6: Plate temperatures in the distillation column

In Figure 1.6, approximate composition graphics for the distillation column tray are presented by the Takagi-Sugano fuzzy model, these composition values vary according to the position of the tray. In Figure 1.6, simulation results obtained by the nonlinear and Takugi Sugeno models for the light component composition in condenser (A) and boiler (B) are presented. It can be seen that the composition behavior in both trays varies according to the heating power (QB) and reflux (R), as shown in Table 1.4.

An ideal test problem would be one in which simulator results can be compared with plant operating data but unfortunately, it is difficult to obtain transient operating data over simple distillation or fraction columns. Some data are published, but it is not with enough information to simulate columns on a computer. The same is true for the simulated transient response data. In this section, two simulated transient response examples are considered and the results obtained from the simulator developed in this work are compared with published data.

The first test problem considered by this simulator to verify the predicted transient response is the solved example 4.2 of Holland and Leipis (12). The column consists of 5 trays with a total condenser and a partial reboiler. The column operates at 2068 kPa (300 psi) and has a bubble point feed stream on the tray. The disturbance introduced on the column is a feed structure and temperature change. The temperature in the column pressure of the feed with the new composition is the bubble point temperature. The specifications are reproduced in Table 5.4. Holland and Leipis (12) used the Gears algorithm as an integrated technique to simulate the final results. As the initial steady state was not fully defined, it was generated using the simulator developed in this work. The initial steady state results obtained from the simulations are compared with the Holland and Leipis (12) data in Table 1.3. Two sets of data show good agreement.

The results obtained for the simulation are presented in Figures 1.4, 1.5 and 1.6. As can be seen, the transient behavior predicted by this study reflects a trend similar to that predicted by Wong (36). This system is supposed to demonstrate the inverse reaction behavior ie the change in direction of change of propane composition in the distill. This simulation clearly demonstrates this behavior. With the similarities, there are clear differences in the actual values of the composition of propane in the distillate at a given time and also in the estimated time for the system to reach a steady state. Due to the incomplete description of the simulation by Wong (36), it is difficult to ascertain the exact cause of the differences. Differences in behavior prediction can usually be due to differences in thermodynamic packages and differences in integration techniques.

The feed can be considered as a pseudo-mixture of ligas iso-butane, n-butane and propane and naphthas iso-pentane, n-pentane and higher components. The column is designed with N = 16 trays.

$$y_n = \frac{\alpha x_n}{1 + (\alpha - 1)x_n},$$

The model is simplified by combining some components with pseudo components and modeling the dynamics of the column is based only on these pseudo components (3). (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)

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Where xn is the liquid concentration at nth stage; yn nth is the vapor concentration at the stage; α is relative volatility.

Table 1.5: The main streams (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)

Stream	Condensate	LPG	Raw
			gasoline
Temperature (⁰ C)	120	48	154
Pressure (atm)	5.8	5	5.8
Density (kg/m ³)	680	590	730
Volume flow rate (m^3/h)	24.68	9.67	22.90
Mass flow rate (kg/h)	16580	5162	11406
Plant capacity	140000	44000	88000
(ton/year)			

Table 1.6: The steady state values of concentration s x_n and y_n on each tray. (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)

St	Bot	Tra	Tra	Tra	Tra	Tra	Tra	Tray
ag	tom	y 1	y 2	y 3	y 4	у 5	у б	7
e								
x_n	0.0	0.0	0.1	0.2	0.2	0.2	0.2	0.27
	375	92	56	12	47	63	71	42
		4	1	1	5	0	2	
y_n	0.1	0.3	0.5	0.6	0.6	0.6	0.6	0.68
	824	66	14	14	45	68	77	21
		6	2	2	8	5	7	
St	Tra	Disti						
ag	y 8	у 9	у	у	у	у	у	llate
e	-	-	10	11	12	13	14	
x_n	0.2	0.3	0.3	0.5	0.7	0.8	0.9	0.97

	842	16	94	33	14	45	37	64
		6	4	8	1	3	2	
y_n	0.6	0.7	0.7	0.8	0.9	0.9	0.9	0.99
	895	28	87	67	34	68	89	85
		5	6	0	1	9	1	

Table 1.7: Product quality based on changes in feed rates (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)

		Purity of the	Impurity of the
		distillate product	bottoms
		$x_D(\%)$	product $x_B(\%)$
Normal feed r	ate	97.56	4.85
Reduced fe	eed	91.25	0.88
rate 10%			
Increased fe	eed	98.35	12.88
rate 10%			

To derive a linear control model for this nonlinear algebraic system, we assume that the variables diverge only slightly from certain operating conditions (10). The non-linear algebraic equation can then be extended into Taylor's series. (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)





We assume that the low-order linear model can also maintain stable output, similar to the basic stationary model.



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Figure 1.8: Correlation of plant outputs, model outputs, and reference setpoints. (Source: Vu Trieu Minh and Ahmad Majdi Abdul Rani, 2009)



Figure 1.9: Depropanizer Tray Temperature Profile Comparison (Source: Jaspal Singh Sabharwal, 1991)



Figure 1.10: Temperature Profile Comparison (Source: Jaspal Singh Sabharwal, 1991)



Figure 1.11: Response of Distillate Propane Composition to a 10 Percent Increase in Reboiler Duty(Source: Jaspal Singh Sabharwal, 1991)

V. CONCLUSION

Mathematical modeling simulations are completed in three stages: the basic nonlinear model, the full-order

linear model and the low-order linear model. Results from simulation and analysis are helpful for the initial stages of a petroleum project feasibility study and design. Low-order linear models are used as reference models for the MRAC controller. The controller of MRAC and MPC theoretically allows plant outputs to track reference setpoints to achieve the desired product quality between disturbances and model-plant mismatch as an effect of feed-stock disturbances. In this dissertation, mathematical model building calculations and low-order linear adaptive controllers are based only on physical rules from the process. Identification of the actual system, including experimental production factors, specific design structures, estimation of parameters and system validation, is not mentioned here. Furthermore, the MRAC controller is not suitable for on-line handling of process bottlenecks.

Both, state-space non-linear and linear fuzzy models are simulated in Matlab using the ethanol-water mixture from a 12-tray batch distillation pilot plant, considering the actual input parameters (heating power and reflux). The light component compositions and temperatures in each tray of the column are calculated by both models. In addition, the obtained results are compared considering the same operating parameters, the purpose of this comparison is to verify the non-linear state-space and adequate functioning of the Takugi Sugano model so that existing differences can be analyzed. The Takagi -Sugano fuzzy model presents small differences in composition component and tray temperature estimates when a reflux disturbance is presented, because reflux directly affects the operating points established in this model; However, these differences are small enough to be neglected and both models change at any operating state. The Takagi - Sugano fuzzy model for the distillation column represents an alternative tool that leverages fuzzy control theory, allowing the design to be facilitated and applying non-traditional control strategies to non-linear systems, However, if a high resolution response is required, it is needed. Be convenient to consider nonlinear models.

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