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Parameter Estimation and Predictive Control Design for a Nonlinear Reactive Distillation Column

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Abstract: Reactive distillation column is one of the key elements in the process of Petroleum and chemical industries, which is having nonlinear, multivariable and non-stationary characteristics. The conventional controller like PID provides fruitless control action for nonlinear process. This paper deals the design of the various Model predictive controller algorithms to control composition and Temperature of the Reactive distillation column in biodiesel production. Here the Recursive Least square technique is used to estimate the parameters and build the exact model of the Process. The MATLAB policy is used and accomplished of the GPC, SMPC and PID.

Keywords: RLS, GPC, PID, SMPC

I. INTRODUCTION

Recently usage of renewable energy has attracted more attention. Biodiesel, one of the renewable energy sources, has been recognized as an interesting fuel that substituted diesel oil produced from petroleum. The use of biodiesel has two advantages: it reduces the dependency of petroleum oil and as well as reduces environmental pollutants. Biodiesel is produced mostly from edible vegetable oil such as palm oil, sunflower oil, and soybean oil [1]. However, the commercialized production of biodiesel from those vegetable oils still has drawbacks due to purification of biodiesel product. Therefore, it is necessary to develop a process in order to produce biodiesel more efficiently and economically.

To overcome the above said problems, a Reactive Distillation (RD) column, an advanced technology for bio-diesel production has been developed. RD employed for biodiesel production reduces the investment and energy costs. Reactive distillation combines both separation and reaction in one unit and has been applied industrially for number of years. Reactive distillation can offer significant economic advantages for certain cases, particularly for systems that involve reversible reactions.

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Generally innovative process control tools increase the litheness and recital of the chemical plants. The conventional controller (PID) employed to control the distillation column does not pledge tight control action because it is highly nonlinear [2].To solve critical control issues and to achieve better performance in industrial application, PID controllers are used [3,4,5] but they face difficulties in controlling non-linear process and cannot predict immediate change in an input. To overcome these difficulties MPC controller is used and it is mainly used for industries side. Actually the distillation column mathematical model needs to be implemented the predictive controller so that here the real time data will be taken from the distillation column and the model will be developed from the help of system identification technique. Fuzzy logic based model and control approach applied [6] and neural network employed to both the model and identification for distillation column [7]and it has been used to fuzzy-neural based inferential control [8] but all the scenarios did not provided any scope of optimization technique. S. Joe Qin has discussed about industries use of MPC [9]. Some of the tutorial papers [10] by James B. Rawlings help to gain insights in MPC. Some review articles consider MPC on academic perspective. Some paper deal with (SMPC) simplified model predictive control algorithm [11]. The custom of step response model Dynamic matrix control (DMC) increases the computational load [12] .Generalized predictive controller (GPC) is the most popular controller and it's generally used it can be accept the state space representation models and reduce the computational time [13-14].

III. EXPERIMENTAL SETUP:

Linear model can be obtained by two ways one is system identification and another one is linearization of a nonlinear model. System identification techniques used through experimental study is possible, but the nonlinear model of the process having different open loop and closed loop studies as possible [15]. Actually linear block box model can be developed by correlating sequence relationship between input and output data. After obtaining the data model has been developed by using a Recursive least square algorithm (RLS) [16].

The many practical causes it is necessary that parameter estimation takes place concurrently system operation it is parameter estimation problem is called online identification and it is methodology usually leads to recursive procedure for every new measurement for this region is also called as recursive identification. Figure.1. represents the formation of reactive distillation column.

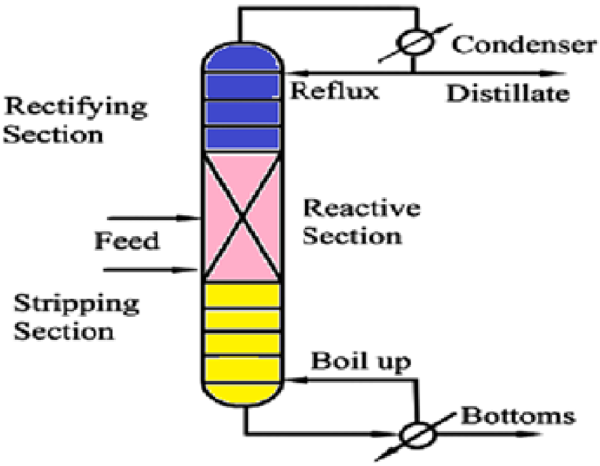

Figure.1 Structure of Reactive Distillation column

III. MODEL PREDICTIVE CONTROLLER

The MPC provides various algorithms like SMPC, DMC and best algorithm is Generalized Predictive Algorithm (GPC). MPC is one of the superior control strategies, which can anticipate the future response of the plant and optimize the control input with the help of a model of the plant. The prediction model will be improved by the model of state space matrices.

The augmented state-space model is given as

$$\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \overbrace{\begin{bmatrix} \beta_m \\ \gamma_m \beta_m \end{bmatrix}}^{\beta} \Delta u(k) \qquad \text{---------} \quad (1)$$

$$y(k) = \overbrace{\begin{bmatrix} 0_m & 1 \end{bmatrix}}^{\gamma} \begin{bmatrix} x_m(k) \\ y(k) \end{bmatrix} \qquad \text{--------} \quad (2)$$

Where $0_m = \underbrace{\begin{bmatrix} 0_m & 1 \end{bmatrix}}_{n_1}$

$\alpha_m, \beta_m \text{ and } \gamma_m$ are represented by the plant parameters. $\Delta u(k1) + \cdots + \Delta u(k_i + N_c - 1)$ are represented by the future control signals .Here the NC represents the control horizon and NP represents the prediction horizon. The future state variables are estimated as

$$x(k_i + 1|k_i) = \alpha x(k_i) + \beta \Delta u(k_i)$$

$$x(k_i + 2|k_i) = \alpha^2 x(k_i) + \alpha\beta \Delta u(k_i) + \beta \Delta u(k_i + 1)$$

$$\vdots$$

$$x(k_i + N_p|k_i) = \alpha^{N_p} x(k_i) + \alpha^{N_p - 1} \beta \Delta u(k_i) + \ldots\ldots$$
$$+ \alpha^{N_p - N_c} \beta \Delta u(k_i + N_c - 1) \qquad \text{----------} \ (3)$$

The future output is,

$$y(k_i + 1|k_i) = \gamma\alpha x(k_i) + \gamma\beta \Delta u(k_i)$$

$$y(k_i + 2|k_i) = \gamma\alpha^2 x(k_i) + \gamma\alpha\beta \Delta u(k_i) + \gamma\beta \Delta u(k_i + 1)$$

$$\vdots$$

$$y(k_i + N_p|k_i) = \gamma\alpha^{N_p} x(k_i) + \gamma\alpha^{N_p - 1} \beta \Delta u(k_i) + \ldots$$
$$+ \gamma\alpha^{N_p - N_c} \beta \Delta u(k_i + N_c - 1) \qquad \text{---------} \ (4)$$

From the eqn (4), output generalized use

$$Y = Fx(k_i) + \emptyset u \qquad \text{----------} \ (5)$$

$$\text{Where } F = \begin{bmatrix} \gamma\alpha \\ \gamma\alpha^2 \\ \vdots \\ \gamma\alpha^{N_p} \end{bmatrix}_{(N_p X 1)} \qquad \text{----------} \ (6)$$

and

$$\emptyset = \begin{bmatrix} \gamma\beta & 0 & 0 & \ldots & 0 \\ \gamma\alpha\beta & \gamma\beta & 0 & \ldots & 0 \\ \vdots & \vdots & \vdots & \ldots & \vdots \\ \gamma\alpha^{N_p - 1}\beta & \gamma\alpha^{N_p - 2}\beta & \gamma\alpha^{N_p - 3}\beta & \ldots & \gamma\alpha^{N_p - N_c}\beta \end{bmatrix}_{(N_p X N_c)} \text{---} \ (7)$$

Eqn (6) and Eqn (7) further used to minimize the cost function. The main objective is predicted output is close as possible to the set point. ΔU is mainly used to change the control signal and it should find the error between predicted output and the set point is minimized

$$R_s^T = \overbrace{\begin{bmatrix} 1 & 1 & \ldots & 1 \end{bmatrix}}^{N_p} r(kk) \qquad \text{----------} \ (8)$$

Here we assume the set point is constant and the cost function J is defined by

$$J = (R_s - Y)^T (R_s - Y) + U^T \bar{R} \mathrm{U} \qquad \text{----------} \ (9)$$

$R = r_{W_{N_c X N_c}}$ Where the r_w is tuning parameter,

Here our objective cost function is minimized and we get J is respect to ΔU

$$\Delta U = (\Phi^T \Phi + R)^{-1} \Phi^T (R_s r(k_i) - Fx(k_i)) \qquad \text{--------} \ (10)$$

IV. RESULT AND DISCUSSION

The real time data are taken from the experimental Reactive distillation column fig (2) and fig (3) shows that response of input and output of the process fig (4) shows that response of model validation curve. Here the GPC values are tuned by Sridhar and cooper tuning method [17]. Then the GPC, PID and SMPC for the Reactive distillation column validated using MATLAB environment and the result is obtained. The MPC controller tuning strategies are shown in Table (1) and then the performance indices in tabulated in Table (2).The composition control response graph shown in fig (5) and the different disturbance rejection response shown in the fig (6).From the responses we prove that GPC gives fast response and quick setting time of the PID and SMPC.

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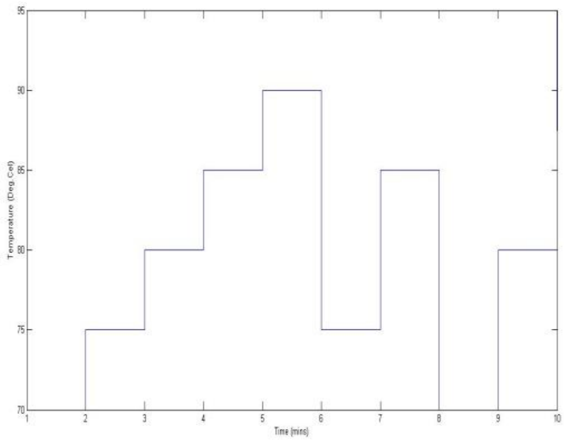

Fig.2.Sudden step change of rebolier temperature

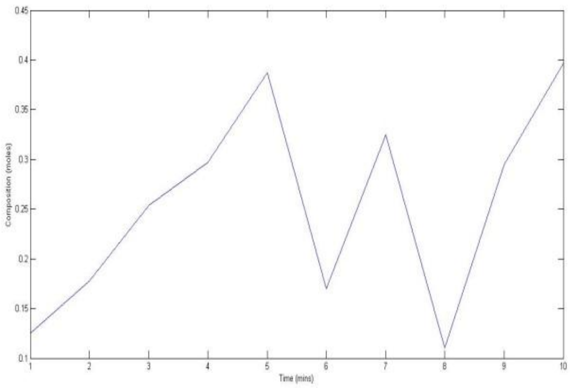

Fig.3.Process reaction curve for composition

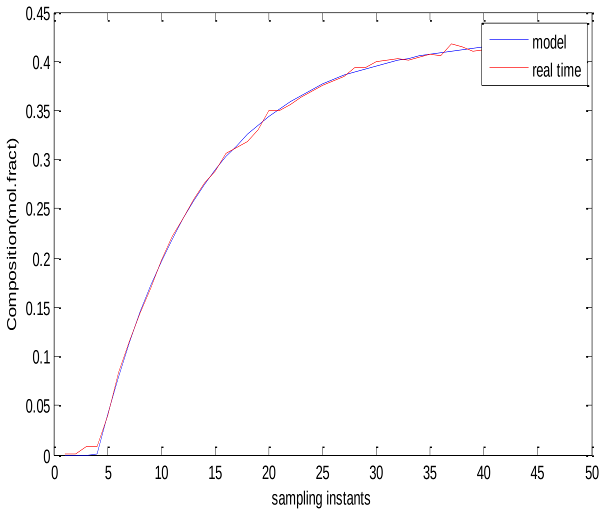

Fig.4.Model validation Curve

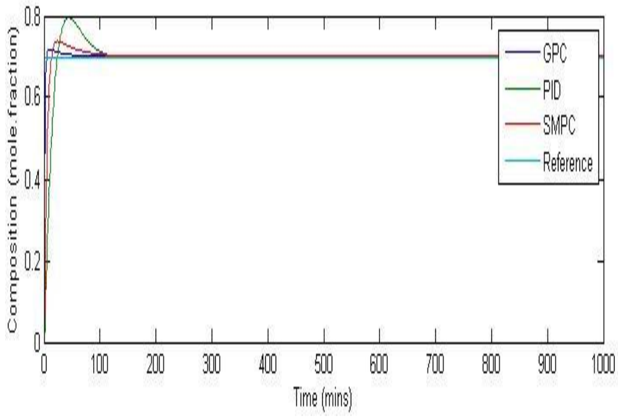

Fig.5. Comparison response of GPC,PID and SMPC it shows that GPC provide better control action compare then PID & SMPC

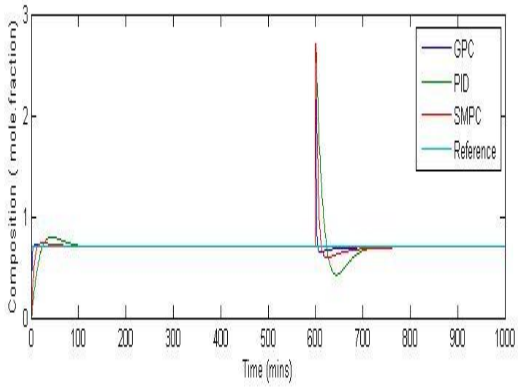

Fig.6. Comparison of Positive disturbance rejection response of GPC, PID and SMPC it shows that GPC provide better control action compare then PID & SMPC

TABLE I: TUNING THE PARAMETERS OF MPC

PARAMETERS	TUNING PARAMETER VALUES	
	GPC	SMPC
NP	6	8
NC	4	6
T	2	3

TABLE II: PERFORMANCE MEASURES

CONTROLLER	ISE	IAE	ITAE
GPC	171.12	292.42	1.450
DMC	221.43	312.43	5.650
SMPC	310.20	800.2	7.301

V.CONCLUSION

In this paper benefit of a Recursive least square model based estimation and design of the model predictive controller (MPC) were discussed. Also the control of composition in a Reactive distillation column for biodiesel application was done. The response of GPC compared with a PID and SMPC controllers.

The comparison has been done between GPC, PID and SMPC, it shows that GPC provided better performance than PID and SMPC by observing the ISE (Integral square error), IAE (Integral absolute error) and ITAE (Integral time-weighted absolute error).

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