Design of Predictive controller for a Nonlinear Backed Reactive distillation column

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Abstract

Reactive distillation syndicates reaction and separation in one unit to simplify the process operation 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 model predictive controller to control composition of the Reactive distillation column.. 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, Fuzzy and Conventional IMC based PID controller.

Keywords: System identification, MPC, IMC , Fuzzy, Reactive distillation column

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. Modelling and controlling reactive distillation column is a difficult task as it is highly nonlinear, multivariable and non stationary process.

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 [3].To solve critical control issues and to achieve better performance in industrial application, PID controllers are used [4,5,6] 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 with the help of system identification technic. Fuzzy logic based model and control approach applied[7] and neural network employed to both the model and identification for distillation column [8]and it has been used to fuzzy-neural based inferential control [9] but all the scenarios did not provided any scope of optimization technic. Has discussed about industries use of MPC[9,10]. The custom of step response model Dynamic matrix control (DMC) increases the computational load .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 .

II.RECURSIVE LEAST SQUARE:

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. 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) . 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.

III. MODEL PREDICTIVE CONTROLLER

The MPC provides various algorithms 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 augmented by the model of state space matrices

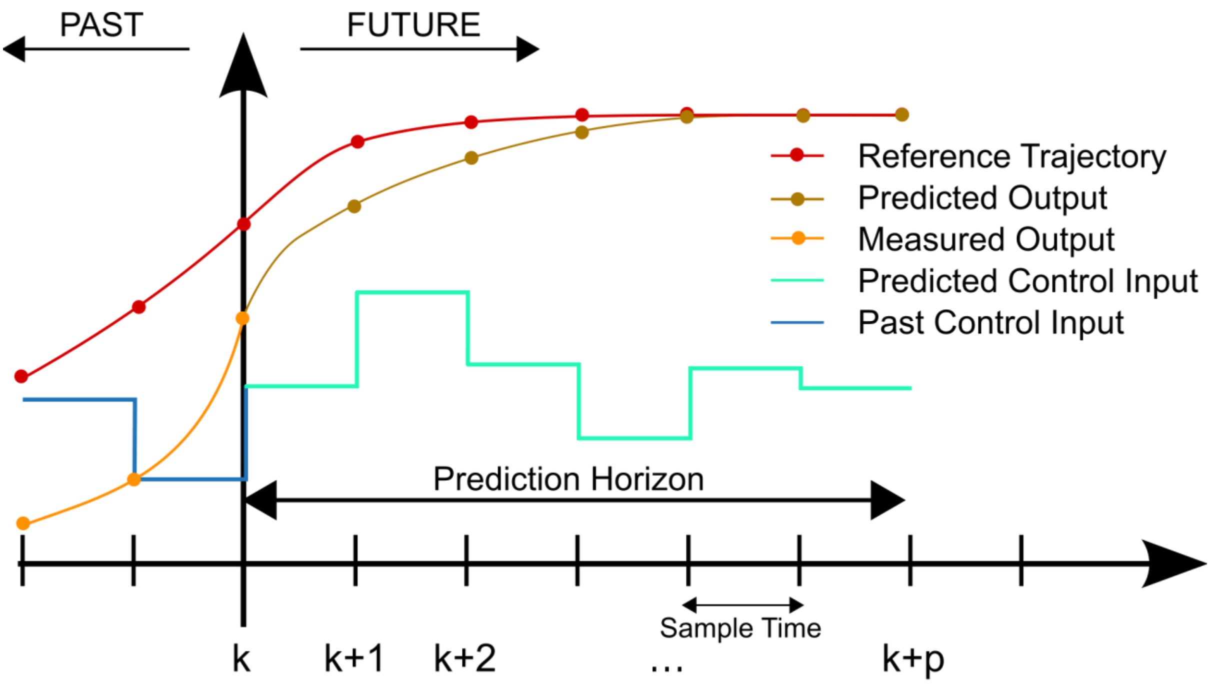

Fig.1. Structure of MPC

The augmented matrix given as

$[\Delta x_m(k+1) y(k+1)] = [\Delta x_m(k) y(k)] + [\beta_m \gamma_m \beta_m]^{\frown\beta} \Delta u(k)$
(1)

$y(k) = [0_m 1]^{\frown\gamma} [x_m(k) y(k)]$ (2)

Where $0_m = [0_m 1]_{\smile n_1}$

$\alpha_m, \beta_m and \gamma_m$ 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 N_C represents the control horizon and N_P represents the prediction horizon. The future state variables are estimated as

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

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

$$\vdots$$

$x(k_i) = \alpha^{N_p} x(k_i) + \alpha^{N_p - 1} \beta \Delta u(k_i) + \ \ldots \ + \alpha^{N_p - N_c} \beta \Delta u(k_i + N_c - 1)(10$

The future output is,

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

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

$$\vdots$$

$$y(k_i) = \gamma\alpha^{N_p}x(k_i) + \gamma\alpha^{N_p-1}\beta\Delta u(k_i) + \ \ldots + \gamma\alpha^{N_p-N_c}\beta\Delta u(k_i + N_c - 1) \quad (3)$$

From the eqn (3), output generalized use

$Y = Fx(k_i) + \emptyset u$(4)

Where$F = [\gamma\alpha\gamma\alpha^2 \ \vdots \ \gamma\alpha^{N_p}]_{(N_p X1)}$

And$\emptyset = [\gamma\beta 00 \ \ldots \ 0\gamma\alpha\beta\gamma\beta 0 \ \ldots \ 0 \ \vdots\vdots\vdots \ \ldots \ \vdots \ \gamma\alpha^{N_p-1}\beta\gamma\alpha^{N_p-2}\beta\gamma\alpha^{N_p-3}\beta \ \ldots \ \gamma\alpha^{N_p-N_c}\beta]_{(N_p X N_c)}$

From the Eqn (4) further used to minimize the cost function. The main objective is predicted output isnear as possible to the set point. $\Delta U$is mainly used to change the control signal and it should find the error among predicted output and the set point is minimized

$$R_s^T = [11 \ \ldots \ 1]^{\frown N_p} r(kk) \quad (5)$$

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

$$J = (R_s - Y)^T(R_s - Y) + U^T \underline{R}\mathrm{U} \quad (6)$$

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

Substituting the output (Y) equation and we get

$$J = (R_s - Fx(k_i))^T(R_s - Fx(k_i)) - 2\Delta U^T\Phi^T(R_s - Fx(k_i)) + \Delta U^T(\Phi^T\Phi + R)\Delta U \quad (7)$$

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

$\Delta U = (\Phi^T\Phi + R)^{-1}\Phi^T(R_s r(k_i) - Fx(k_i)$(8)

IV. RESULTS AND DISCUSSION

The real time data are taken from the experimental distillation column fig (3) and fig (4) shows that response of input and output of the process. Here the GPC values are tuned by Sridhar and cooper tuning method [22]. The PID is adjusted by the internal model controller (IMC) method. Then the IMC based PID controller and Fuzzy and GPC for the Reactive distillation column validated using MATLAB environment and the result is obtained. The GPC controller tunning strategies are shown in Table (1) and the IMC based PID control tuning parameters are shown in Table (2) and then the performance indices in tabulated in Table (3).The response graph shown in fig (5) and the different step changes response shown in the fig (6), fig (7) from the responses we prove that GPC gives fast response and quick setting time of the IMC based PID and Fuzzy.

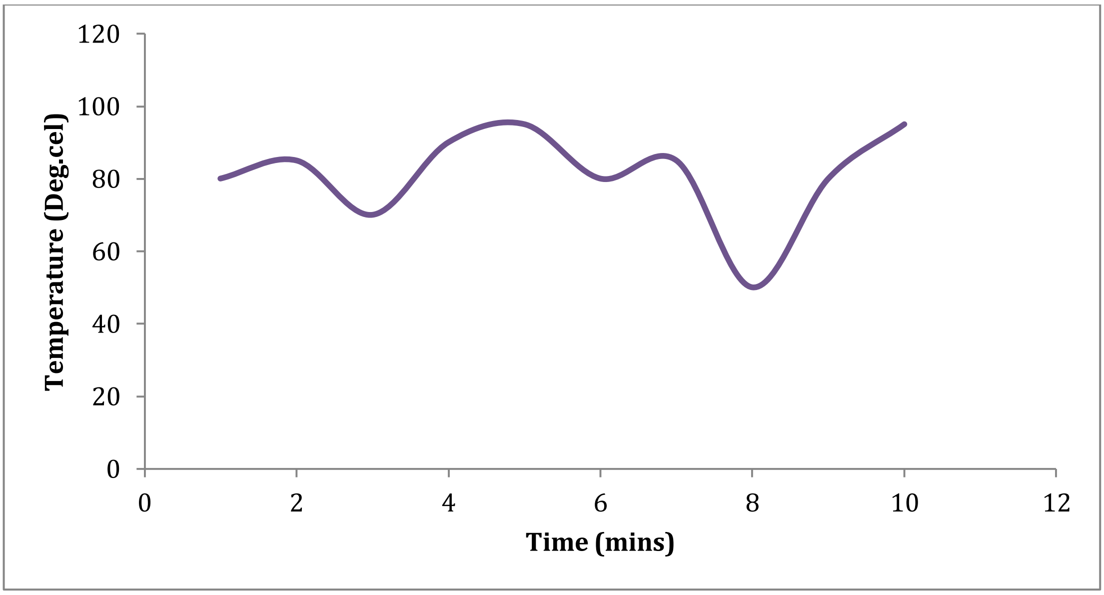

Fig.2.Process reaction curve of rebolier temperature

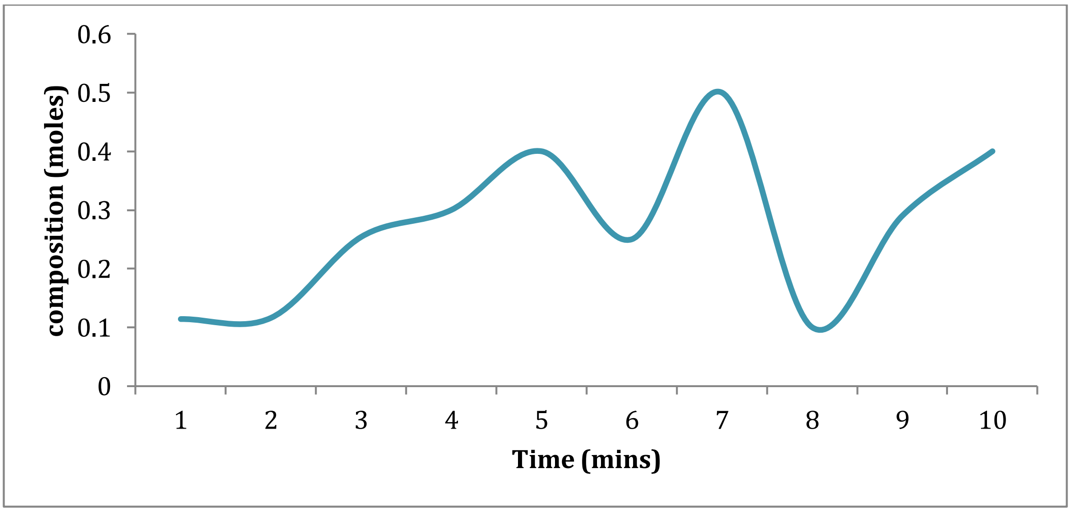

Fig.3.Process reaction curve for composition

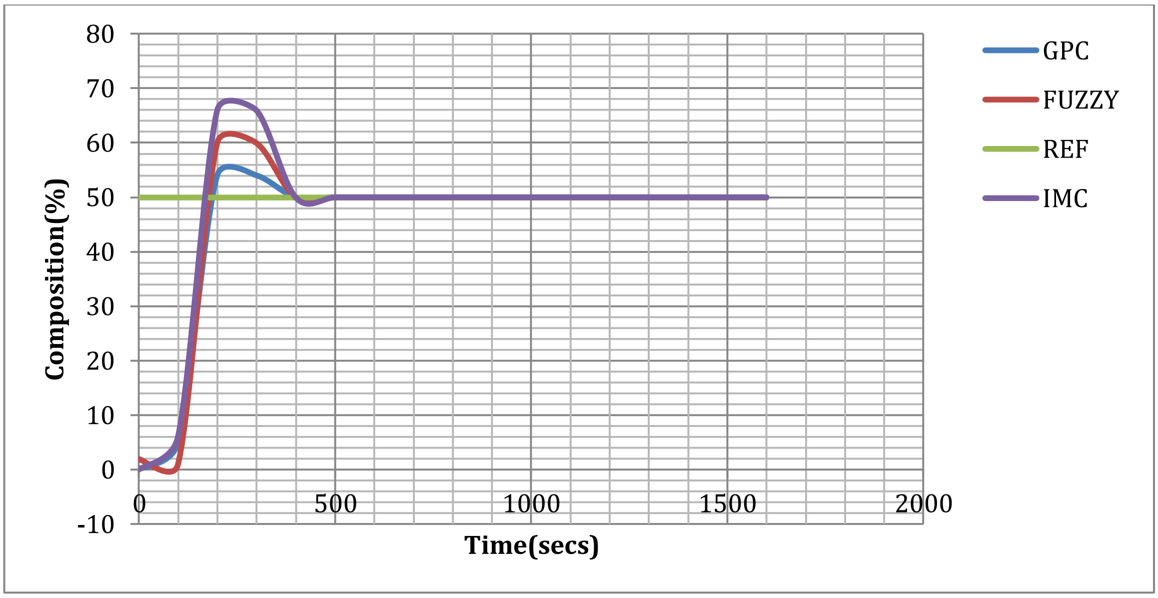

Fig.4.GPC,Fuzzy and IMC response

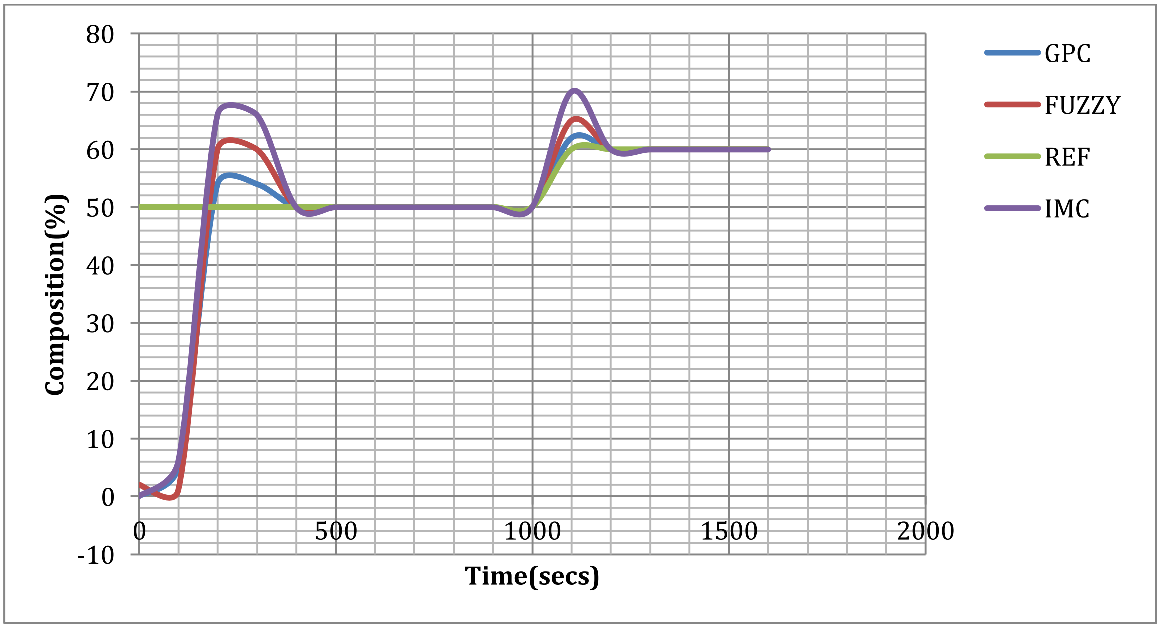

Fig.5. GPC,Fuzzy and IMC Positive step change response

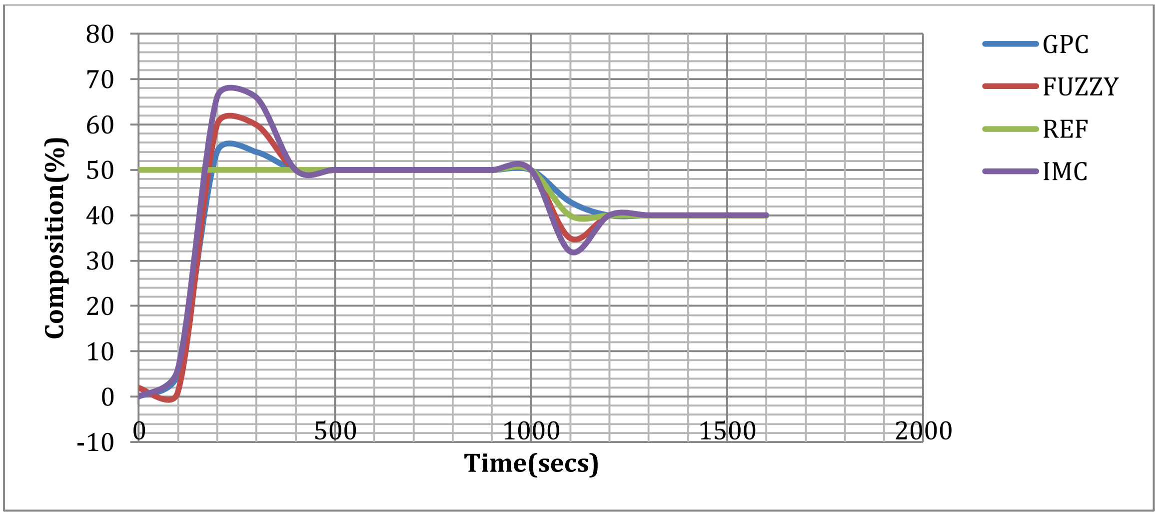

Fig.6. GPC,Fuzzy and IMC Positive step change response

TABLE :1 TUNING THE PARAMETERS OF GPC

PARAMETER	VALUE
N_P	9
N_C	8
T	4

TABLE :2 TUNING THE PARAMETERS OF IMC BASED PID

PARAMETER	VALUE
P	1.6
I	1
D	0.03

TABLE :3 PERFORMANCE MEASURE CHARACTERISTICS

CONTROLLER	ISE	IAE	ITAE
GPC	198.30	382.32	1.752
FUZZY	202.45	405.23	4.653
IMC	300.2	700.2	7.285

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

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