Model Predictive Control For Interactive Thermal Process

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***Abstract*— In industries now a day the control of chemical process is important craft. Mostly all the chemical process are highly nonlinear in nature this cause instability of the process. This paper deals with basic simulation studies on of the interactive thermal process. The Combination processes Continuous stirred tank reactor (CSTR) and heat exchanger were controlled and the mathematical model was developed. This paper deals with the performance evaluation on the comparison of Model predictive control and conventional control in interactive thermal process. In the design of adaptive control, Model predictive control (MPC) scheme is used, in which the prediction method have been applied.A simulation is carried out using matlab. The control was performed to the combined process system using both the predictive control algorithm and conventional controller method and its results were analyzed. Thus it shows that the predictive controller will be suitable for this process then the conventional controller even without parameters change in the process. In a real world situation, these parameters could be estimated by using simulations or real execution of the system. Thus by controlling this process we recycle the waste heat and achieve less power consumption in the industries.**

Keywords- Process control - CSTR & Heat Exchanger, PID controller, MPC(Model Predictive control),Matlab.

I. INTRODUCTION

Chemical Engineering is a vibrant field that has undergone significant changes over the recent years. The extensive progress made in traditional areas such as transport phenomena, reaction engineering and unit operations has provided enough experience for chemical engineers to confidently venture into new areas such as life sciences, rational product design, and nano systems etc. Computational methods and associated tools are expected to play a very significant role in this revolutionary phase of chemical engineering.

In common sense, predictive means to change a behavior to conform to new circumstances. Intuitively, an predictive controller is thus a controller that can modify its behavior in response to the changing dynamics of the process and the character of the disturbances. The core element of all the approaches is that they have the ability to adapt the controller to accommodate changes in the process. This permits the controller to maintain a required level of performance in spite of any noise or fluctuation in the process. An MPC system has maximum application when the plant undergoes transitions or exhibits non-linear behaviour and when the structure of the plant is not known. MPC is called a control system, which can adjust its parameter automatically in such a way as to compensate for variations in the characteristics of the process it control.

III PROCESS DESCRIPTION AND MODELING

The temperature control of a stirred-tank heater system was reported as a classical problem in chemical engineering. These problems are intended to utilize the basic numerical methods in problems which are appropriate to a variety of chemical engineering concepts. The complexity of the problem has been enhanced in the current study by changing simple tank to a reactor carrying out known reaction and also complete controller (both MRAC and PID) mechanism has been adopted. The analysis is extended further to stability of the system and optimization of the controller parameters along with a study on effect of reaction mechanism and other system parameters. The graphical diagram of the interactive thermal process is shown in Figure 1.

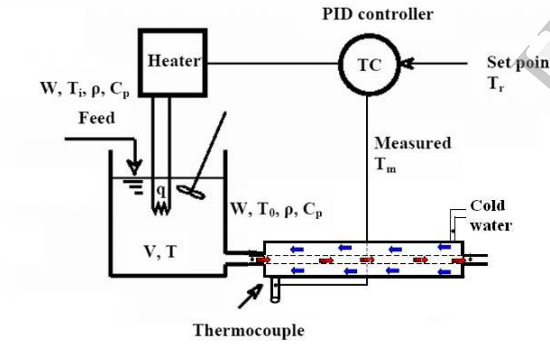

Figure 1 : Interactive thermal process

A continuous stirred tank reactor with a non isothermal reaction A+B Products and with first order rate equation ((-rA) = kCA) is considered. The tank has external heating coil with heat input Q (kJ/min) and the temperature is controlled by a controller in the closed loop feedback circuit as depicted in figure 2. The tank output is given as input to the heat exchanger. The counter-current tubular heat exchanger is used in this process. The inner pipe is a copper tube and the outer one is a stainless steel tube. The reactor hot fluid crosses the circular duct and the cold fluid (water)circulates in the annular duct. The thermocouple probes are placed at the outlet of cold fluid of the tubular heat exchanger. The flow rates of the fluids are constant.

In this paper paper the controlled variable is the fluid outlet temperature and the manipulated variable is the heating coil rate Q.

The geometrical and physical parameters of the Interactive thermal process are reported in Table's

TABLE. a.
Reactor parameter's value

Reactor parameters	Values
F/V,hr-1	4
Ko,hr-1	15e12
(-ΔH),BTU/lbmol	40000
E, BTU/lbmol	33500
ρCp, BTU/ft$_3$	54.65
Tf, 'c	70
Caf, lbmol/ft$_3$	0.132
UA/V	122.1

III MODEL PREDICITVE CONTROL

MPC is a form of control in which the current control action is obtained by solving on-line, at each sampling instant, a finite horizon open-loop optimal control problem, using the current state of the plant as the initial state; the optimization yields an optimal control sequence and the first control in this sequence is applied to the plant.

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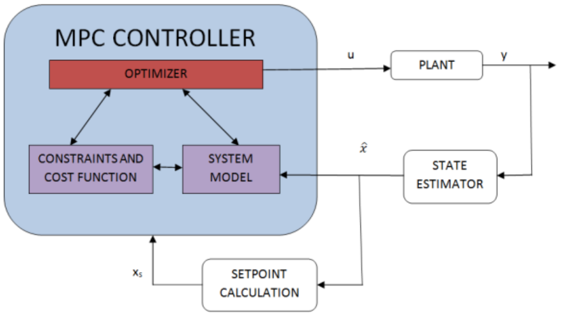


Figure 2 : Model predictive control

Model can be developed by means of past inputs and outputs, and then the predicted output from the model is Compared with the reference trajectory. Future errors can be calculated by optimizer using its cost function and constraint then future inputs are given to the predefined model from the optimizer shown in fig.2.

Linear MPC:

$$x = Ax + Bu \qquad (1)$$

$$F = x_{T}Qx + u_{T}Ru \qquad (2)$$

$$Hx + Gu < 0 \qquad (3)$$

1st equation denotes linear model, 2nd equation denotes quadratic cost function and 3rd equation denotes linear constraints these are all the mathematical equation for linear MPC .Nonlinear MPC:

$$x = (x, u) \qquad (4)$$

$$(X, u) \qquad (5)$$

$$h\,X, u < 0 \qquad (6)$$

4th equation denotes nonlinear model, 5th equation denotes non-quadratic cost function and 6th equation denotes nonlinear constraints these are all the mathematical equation for nonlinear MPC Model plant in state space.

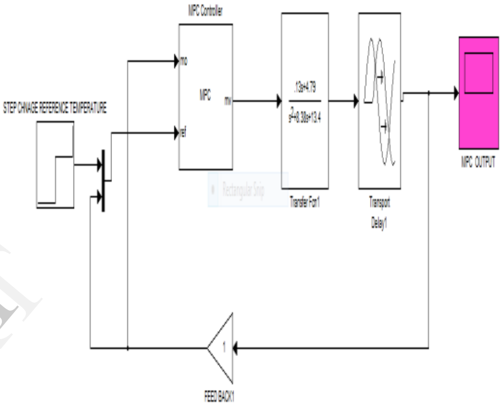
$$x\,k + 1 = Ax\,k + (k) \qquad (7)$$

$$y\,k = C_y\,(k) \qquad (8)$$

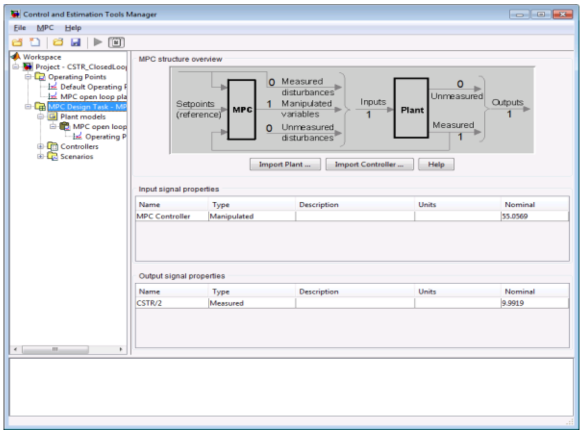
$$z\,k = C_z\,(k) \qquad (9)$$

Equation 7,8and 9 denotes that the state space representation of the system.

IV. SIMULATION OF PROPOSED WORK



. Figure 3 : simulation of MPC controller



Input signal properties

Name	Type	Description	Units	Nominal
MPC Controller	Manipulated			55.0569

Output signal properties

Name	Type	Description	Units	Nominal
CSTR/2	Measured			9.9919

Figure 4 : MPC design for CSTR

V RESULTS AND ANALYSIS

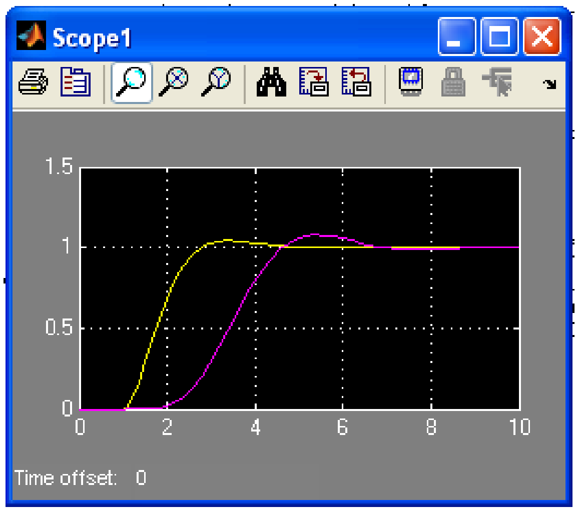


Figure 5. Comparison of Reference model output and Plant output with MPC

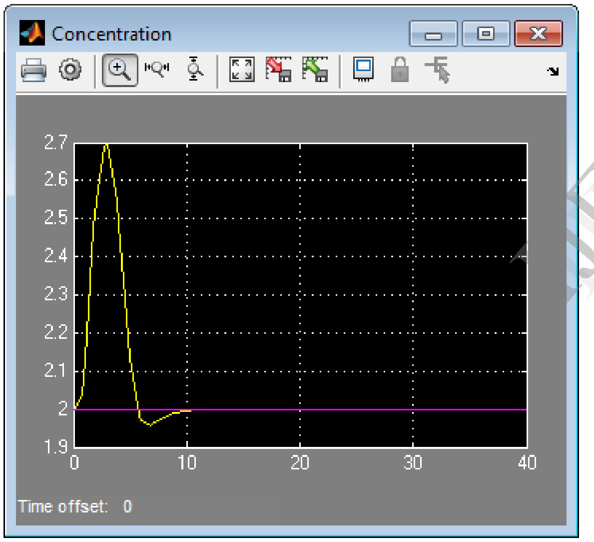


Figure 6 : concentration ouput

The decrease in feed concentration reduces heat generation. If the controller were absent, the reactor temperature would drop significantly, reducing the reduction rate, and the CSTR concentration would increase to roughly 3 kmol/m3. To counteract this, the controller raises the coolant temperature, returning the CSTR temperature to a value slightly below the nominal condition.

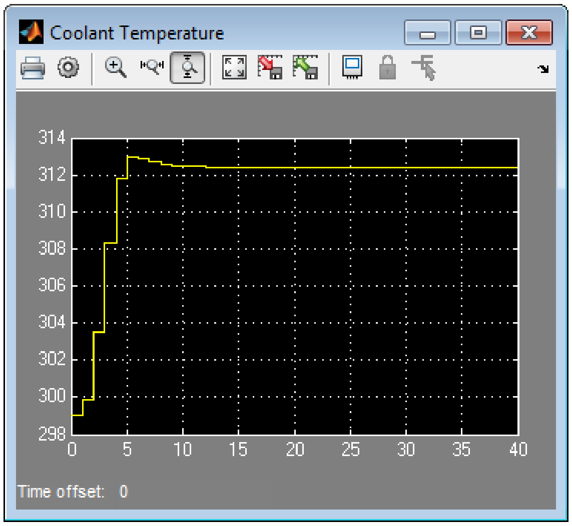


Figure 7 : collant temperature output

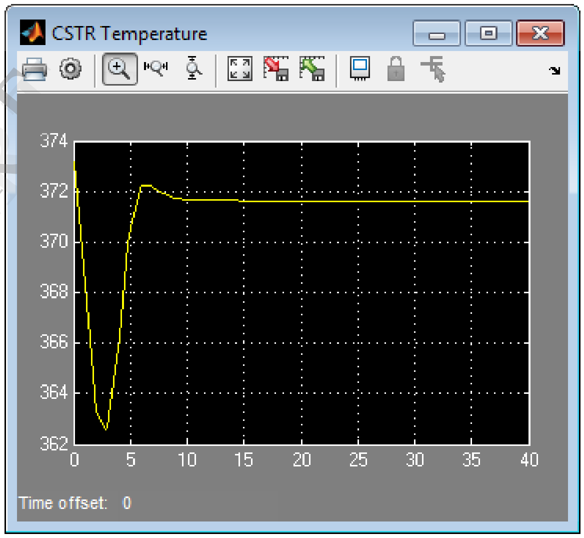


Figure 8 : cstr temperature output

VI CONCLUSION

The proposed predictive control algorithm is tested by using Matlab Simulink program and its performance is compared to a conventional controller. The paper demonstrated that while the conventional controller exhibits the process convergence time is typically large and there is a large overshoot. To resolve these problems of adaptive controller, the proposed controller is redesigned by modifying the mpc And the results show a significant improvement in the performance of predictive control.

The simulations show that very good conversion can be achieved and at the same time the temperatures inside the reactor do not violate the safety constraints, even when there are large disturbances in the feed concentrations. The proposed process control system increases the safety of operations by reducing the impact from external disturbances. This will decrease the risk of unnecessary shutdowns of the process operation and also reduce thepower consumption in industrial interactive thermal process by effective recycling of heat. In future this interactive thermal process is tested with other intelligent controller.

VII.REFRENCES

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