4. Pressure Control With PID

In recent years the performance requirements for process plants have become increasingly difficult to satisfy. Stronger competition, tougher environmental and safety regulation and rapidly changing economic condition have been key factors in tightening product quality specifications. Process control has become increasingly important in the process industries as a consequence of global competition, rapidly changing economic conditions and more stringent environmental role in process control. Here, the first order plus dead time model has tested with PID controller. And the simulation block diagram and simulation results are shown in Figure.3.

A Proportional-Integral-Derivative (PID Controller) control logic is widely used in the process control industry. PID controllers have traditionally been chosen by control system engineers due to their exibility and reliability. The controller attempts to minimize the error by adjusting the process control inputs. A PID controller has proportional , integral and derivative terms that can be represented as:

$$Gc(s) = Kp + \frac{Ki}{s} + Kd\,S \tag{6}$$

where Kp represents the proportional gain ,Ki represents the integral gain, and Kd represents the derivative gain respectively. Using Ziegler-Nichols tuning algorithm for calculating the corresponding Kp , Ki and Td values. The corresponding Kp, Ki, Td values are 4.5,80,20. Using MATLAB/Simulink for simulate these values and get the output response of the PID controller. Simulation result is shown in Figure.3.

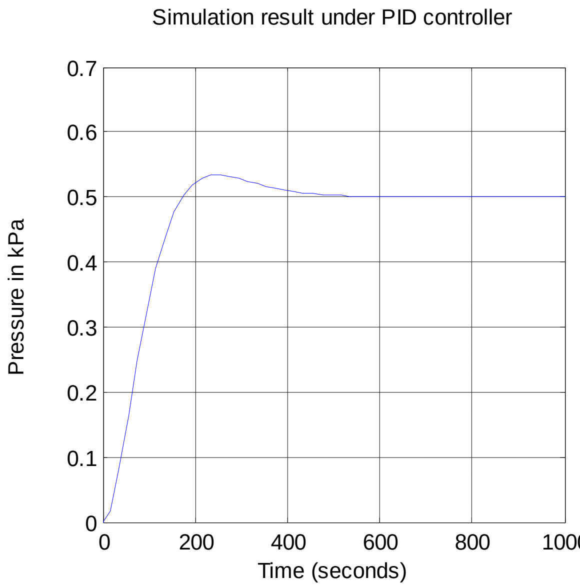

Figure 3: Chamber pressure under PID controller

5. Smith Predictor with PID Controller

The design of controllers for processes with long time delays has been of interest to academics and practitioners for several decades. In a seminal contribution, Smith [1] proposed a technique that facilitates the removal of the time delay term in the closed loop characteristic equation. This method, labelled the Smith predictor, has been the subject of numerous experimental and theoretical studies. A block diagram of the Smith predictor structure is provided in Fig.4.

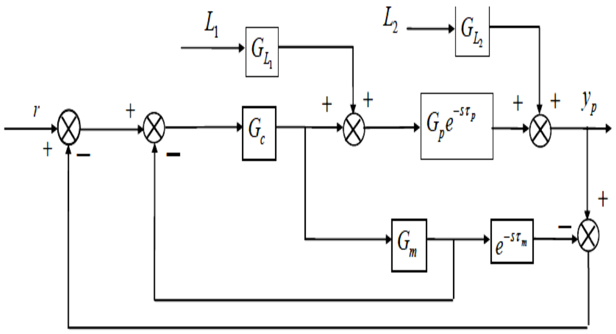

Figure.4: Block diagram of the Smith predictor structure

Smith predictor controller design as given below;

$$G(s) = G_o'(s)e^{-\tau s} \tag{7}$$

G(s) is the transfer function of the given process model.

$$\frac{Y*(s)}{Y(s)} = \frac{C(s)}{1+C(s)G_o'(s)(1-e^{-\tau s})} \tag{8}$$

$$= \frac{C(s)G_o(s)e^{-\tau s}}{1+C(s)G_o(s)(1-e^{-\tau s})+C(s)G_o{'}(s)e^{-\tau s}} \tag{9}$$

$$M(s) = \frac{Y*(s)}{Y(s)} = \frac{C(s)G_o'(s)e^{-\tau s}}{1+C(s)G_o'(s)(1+e^{\tau s}-e^{-\tau o s})} \tag{10}$$

When $\tau = \tau_o$,

$$M(s) = M_o(s) = \frac{C(s)G_o'(s)e^{-\tau s}}{1+C(s)G_o'(s)} = M_o'(s)e^{-\tau s} \tag{11}$$

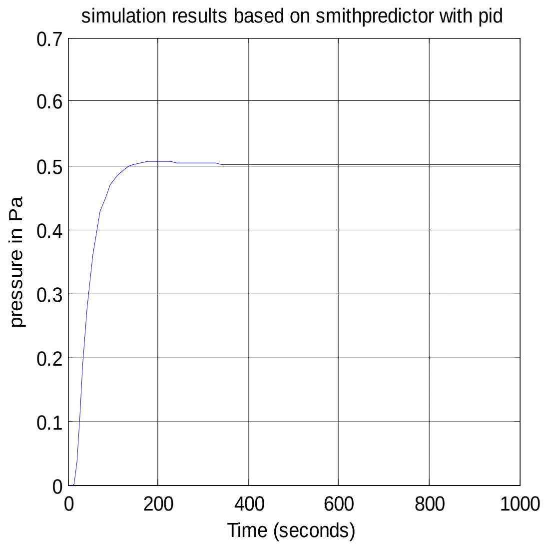

Figure.5: chamber pressure under smith predictor with PID

The Figure.5.shows the output response of the smith predictor with PID controller.

6. Model Predictive Controller (MPC) Design

Model Predictive Control (MPC) is a is an optimal control strategy based on numerical optimization. Future control inputs and future plant responses are predicted using a system model and optimized at regular intervals with respect to a performance index. From its origins as a computational technique for improving control performance in applications within the process and petrochemical industries, predictive control has become arguably the most widespread advanced control methodology currently in use in industry. MPC has a sound theoretical basis and its stability, optimality, and robustness properties are well understood.

Despite being very simple to design and implement, MPC algorithms can control large scale systems with many control variables, and, most importantly, MPC provides a systematic method of dealing with constraints on inputs and states. Such constraints are present in all control engineering applications and represent limitations on actuators and plant states arising from physical, economic, or safety constraints. In MPC these constraints are accounted for explicitly by solving a constrained optimization problem in real-time to determine the optimal predicted inputs. Nonlinear plant dynamics can be similarly incorporated in the prediction model.

The future response of the controlled plant is predicted using a dynamic model. This course is concerned mainly with the case of discrete-time linear systems with state-space representation;

$$x(k + 1) = Ax(k) + Bu(k) \qquad (12)$$

where x(k) and u(k) are the model state and input vectors at the kth sampling instant. Given a predicted input sequence, the corresponding sequence of state predictions is generated by simulating the model forward over the prediction horizon, of say N sampling intervals. For notational convenience, these predicted sequences are often stacked into vectors u, x defined by

$$u(k) = \begin{pmatrix} u(k|k) \\ u(k + 1|k) \\ \vdots \\ u(k + N - 1|k) \end{pmatrix}$$

$$x(k) = \begin{pmatrix} x(k + 1|k) \\ x(k + 2|k) \\ \vdots \\ x(k + N|k) \end{pmatrix} \qquad (12.1)$$

Here u(k + i|k) and x(k + i|k) denote input and state vectors at time k + i that are predicted at time k, and x(k +i|k) therefore evolves according to the prediction model:

$$x(k + i + 1|k) = Ax(k + i|k) + Bu(k + i|k),\ i = 0, 1 \qquad (12.2)$$

with initial condition (at the beginning of the prediction horizon) defined

$$x(k|k) = x(k).$$

The MPC cost function is denoted as follows:

$$J=\sum_{j=1}^{Ny} Z^T(k+j)Q_j z(k+j) + \sum_{j=1}^{Nu} \Delta u^T(k+j-1)L_j \Delta u(k+j-1) \qquad (12.3)$$

where N_y is the prediction horizon, *Nu* is the control horizon, $z(k + j)$ is the state prediction for time $k + j$, $Lj \geq 0$ is the weighting factor on control input, and $Qj(1 \leq j \leq Ny)$ is the symmetrical weighted matrix with appropriate dimension.

$$Q_j = \mathrm{diag}\{q_{jy1}\ldots\ldots\ldots q_{jyna}, q_{ju1}\ldots\ldots\ldots, q_{ju(nb-1)}, q_{js}\}. \qquad (12.4)$$

Using MPC algorithm that is synchronized with the block diagram and the corresponding simulation results are shown in Figure.4 & 5

6.1 The Process Model

The chamber pressure is built as a FOPDT model derived by step response test. And the corresponding model can be derived as,

$$G(s) = \frac{-0.02}{150s+1} e^{-40s} \qquad (13)$$

6.2 MPC algorithm

```
%% Control of a Single-Input-Single-Output Plant
% This example shows how to control a double integrator plant under input
% saturation in Simulink(R).

%% MPC Controller Setup
% Create MPC controller in the workspace.
    Ts = 0.1;                      % Sampling time
    p = 200;                       % Prediction horizon
    m = 100;                       % Control horizon
    mpc_controller=mpc(tf(-0.02,[150 1],'IOdelay',40.0),Ts,p,m); % MPC object
    mpc_controller.MV=struct('Min',1,'Max',1);

    % Input saturation constraints

    %% MPC Simulation Using Simulink(R)
    % The example uses Simulink(R).
    if ~mpccheck toolboxinstalled('simulink')
      disp('Simulink(R) is required to run this example.')
    return
    end

    %%
    % Setup simulation parameters.
    Tstop=1000;                    % Simulation time

    %%
    % Run simulation.
    open_system('mpc_pressure1');% Open Simulink(R) Model
    sim ('mpc_pressure1',Tstop);   % Start Simulation
```

These algorithm is synchronized with the block diagram based on the FOPDT model and obtain the set point tracking and output disturbance of the system.

7. Simulation Results

Consider a first order plus dead time model of the process and the corresponding model is estimated as,

$$G(s) = \frac{Ke^{-\tau s}}{Ts+1} \quad (8)$$

Where K is the process gain, Tis the residence time, τ is the time delay and their nominal values are K=-0.02, T=150 ,and $\tau = 40$. The chamber pressure of the coke furnace range set point is 0.5 and the simulation results are shown below. MATLAB software package is used to determine the response of the system.

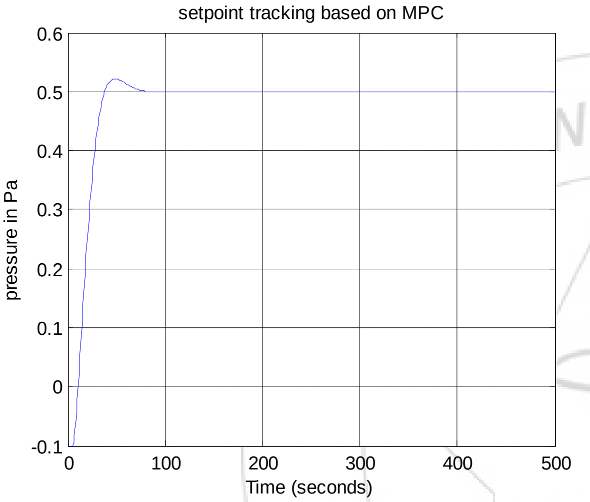

Figure 6: Simulation results based on MPC

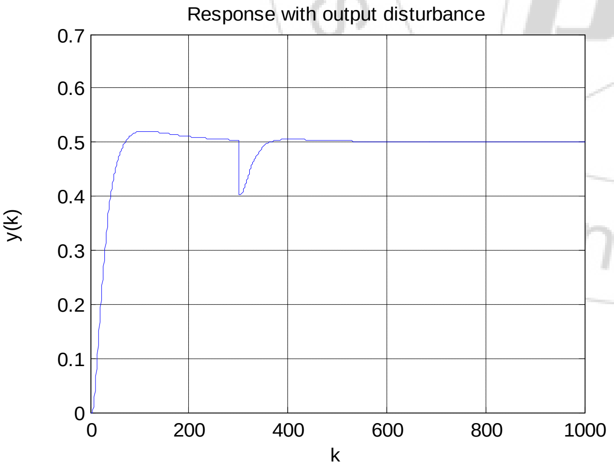

Figure 7: Response under output disturbance

The Figure.6. shows that the set point tracking of the chamber pressure of a coke furnace and the corresponding values obtained from the FOPDT model. Response of the process is very fast to settle and the overshoot is minimized. So, the process model which gives to keep the suitable range of pressure in a coke furnace.

The Figure.7. shows that the process model which is under output disturbance. From this response it is clear that the undershoot is there but the output response settled under disturbance condition.

Compared with the output response of smith predictor with PID controller and the output response of the MPC controller which gives the better response of the chamber pressure in a coke furnace. Smith predictor which gives the smooth response but the settling time is higher. And also the overshoot is minimized. In the case of MPC controller the settling time is reduced and which is acceptable for the industrial applications.

8. Conclusion

In this paper, comparison between the smith predictor with PID and MPC has been proposed and keep the chamber pressure of coke furnace within a suitable range. The output response of the MPC which is compared with the response of the smith predictor with PID controller. The simulation results shows the good control performance using the MPC controller. In this paper, comparison between the smith predictor with PID and MPC has been proposed and keep the chamber pressure of coke furnace within a suitable range. The output response of the MPC which is compared with the response of the smith predictor with PID controller. The simulation results shows the good control performance using the MPC controller

9. Future Scope

From the foregoing analysis, MPC controller based on DMC algorithm will introduce into the process model.

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