Model Predictive Control Approach for Chamber Pressure in a Coke Furnace

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***Abstract* --- In a coke furnace the dynamic relationship between the input and output device is complicated. Since the performance is closely related to the control used and also improved control alternatives are necessary. The control target is to maintain the chamber pressure of coke furnace with in a set range while rejecting the effect of disturbances. This paper proposes a Model predictive controller design using MPC algorithm. The details of the proposed MPC are first described and tested on the process model of the SISO system with FOPDT model Simulation results shows the effectiveness of the proposed method.**

Keywords---Chamber pressure, coke furnace, Model predictive control, FOPDT

I. INTRODUCTION

Coking has played an important role in industry for its high performance of enhanced economic benefits. Coking is important because of its potential of supplying various petrochemical products[1].However control performance using traditional methods may deteriorate because of the uncertainties of coking kinetics and interaction of the subsystems[2].The dynamics in such a processes are complex and even non-linear, which poses difficulty for control performance enhancement. In such a processes, lack of detailed physiochemical process knowledge poses great difficulty to derive accurate the first order plus dead time models. Even if it is a complex model can be constructed, the subsequent controller optimization will remain a tiring job [3].

To ensure safe and proper operation, a coking equipment is divided into number of subsystems such as:

(1) The radiation output temperature control system
(2) The chamber pressure control system
(3) The level control system in a fractionating tower
(4) The air supply system

Among the aforementioned subsystems, this paper will focus on the chamber pressure control system, which keep the chamber pressure within a suitable range. In this system there are many disturbances and the relationship between the input and output devices is complex. These factors cause great difficulty for maintain the suitable range of chamber pressure in a coke furnace.

Input/output process data based models are another choice. However, a tough issue with non-linear input/output data based models is that serious problems may arise if the process dynamics incorporate many patterns, which lead to control performance deterioration since some parameters may change and require identification again [4]. What is more, controller design using such models with large number of process parameters is also difficult [9]. Simple linear input/output data based models can also be used, however, these models may cause limitations of control performance in terms of stability and robustness.

It is shown that proportional integral derivative control (PID) may lack adequate robustness for such processes [5]. As a result model predictive control (MPC) has studied and tested on the first order plus dead time models (FOPDT). Literature work have presented several approaches such as internal model control (IMC) based PID [14] shows good robustness and set point tracking, but poor response under disturbance for processes with dominant lags. P and PI controllers are also reported in [10][12]. Recent advanced strategies can be seen in PFC based PID design using genetic algorithm [13] and a simplified linear iterative predictive functional [15] and so on ,which shows good control performance.

This paper develops a MPC approach using first order plus dead time models in a single input single output systems(SISO) for chamber pressure control system. The resulting performance is also compared with the PID controller. The MPC which gives a good performance under FOPDT models. MPC the control strategy which is easy to handle time delays, inverse response, as well as other difficult process dynamics and also only few tuning parameters are needed. The proposed method is tested on the FOPDT models and shows the improved control performance.

II. THE COKE FURNACE

A. System Description

The overall process flow can be seen in Fig.1.The flow of residual oil is separated into two branches(FRC8103 and FRC8104) and sent into the convection room of the furnace (F101/3) to be heated to about 330 ^{0}C , then the two branches join together and go to the fractionatingtower (T102) for heat exchange with gas oil from the coke towers (T101/5,6). After heat exchange, the heavy part of both residual oil and the gas oil join together (now called circulating oil). The circulating oil is then divided into two branches (FRC8107 and FRC8108) by pumps (102/1, 2, 3) and sent back to the radiation room of the furnace (F101/3) to be heated to about 495^0C. Finally, the two branches join together and go to the coke towers (T101/5, 6) to remove coke, this process is called the coking of residues. The main process flows of the other two furnaces are not same.T101/1, 2 are for furnace 101/1 and T101/3, and 4 are for furnace 101/2. And each time only one of each pair of coke towers works for its corresponding furnace, when it is full, the other one of the pair replaces it, the replacement is called the switch of coke towers and this process recycles.

The switch times of the three furnaces are not the same. The heat exchange with oil gas from the coke towers poses a continuous disturbance on the chamber pressure because it results in the volume and temperature change of the circulating oil and thus has an impact on the fuel volume and the chamber. The coking of residues in the coke towers also put an indirect impact on the chamber pressure, because this process influences the volume of oil gas in the coke towers, thus imposes a disturbance on the chamber pressure during heat exchanging with the residual oils from furnace. During the switch of coke towers, the liquid level of the fractionating tower often drops a lot because some of the oil will changes into oil gas in it and part of inlet oil gasflowing into the fractionating will be used for the heating of coke towers. These cause frequent disturbances to the chamber pressure control of furnaces and it is one of the reasons for aPID controller does not guarantee a good performance of the system.

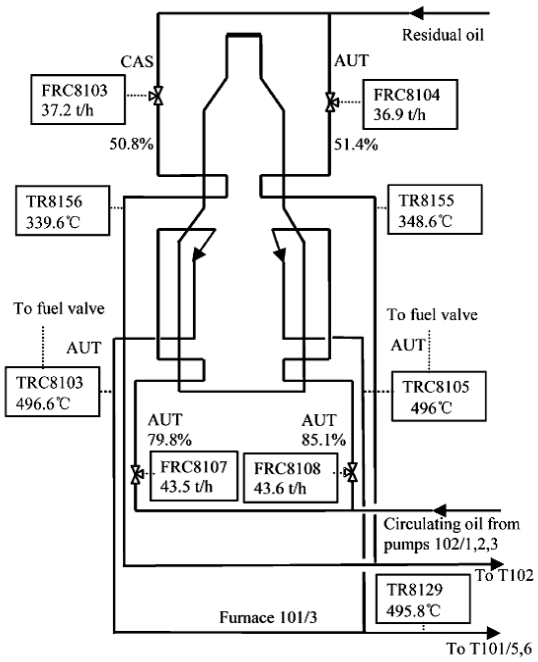

Fig.1. Overall flow of coke unit.

B. The control problem

One of the main control objective is to keep the chamber pressure within a suitable range. This reference is set by the operator during operation. The plant which is exposed to disturbances such as inlet oil flow changes, variation in temperature of oil gas from coke towers, the coke removing in the coke towers, and the switch of each pair of the coke towers, causing variations in the coke towers. Here the manipulated variables are flue dampers and the controlled variables are the chamber pressures.

C. Control Objectives

The proposed model predictive controller (MPC) is to predict the future value of chamber pressure within a suitable range. Compare with the responses of PID and MPC.

III MODELOFTHE FURNACE DYNAMICS

To develop the mathematical model so as to simulate the dynamic behavior of the furnace, we take into account the working chart in Fig 2.The input quantity, which varies in time,is the fuel mass flow rate, mf and the output value is the pressure inside the furnace ,pf. The model includes the mass, energy, and momentum balances, the heat transfer from hot flue gases to water and steam model and the flue gas flow through the model:

- Combustion heat balance:

$$I_f \frac{d(\rho g.ig)}{d\tau} = ma.I_{A} + m_{fb}.Q_i - m_g.i_g - Q_F - Q_1 \quad [kW](1)$$

- Combustion mass balance:

$$V_f . \frac{d(\rho g)}{d\tau} = m_{fb} + m_a - m_g \quad [kg/s] \qquad (2)$$

- Flue gas flow through the furnace:

$$m_g = k_f . p_f \qquad [kg/s] \qquad (3)$$

- Furnace gas pressure:

$$p_g = R_g . \rho_g . T_g \qquad [N/m^2] \qquad (4)$$

- Combustion dynamics:

$$m_{fb} = m_f \left(1 - e^{-\tau/Tf} \right) \qquad (5)$$

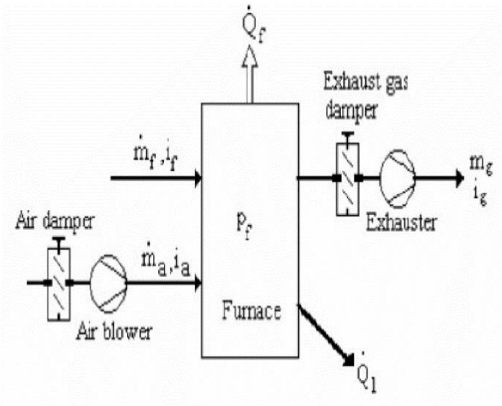

Fig.2. Physical model of the furnace.

According to these equations furnace model can be created in a MATLAB/SIMULINK.

IV 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 industriesas 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 Fig.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:

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

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 Fig.3.

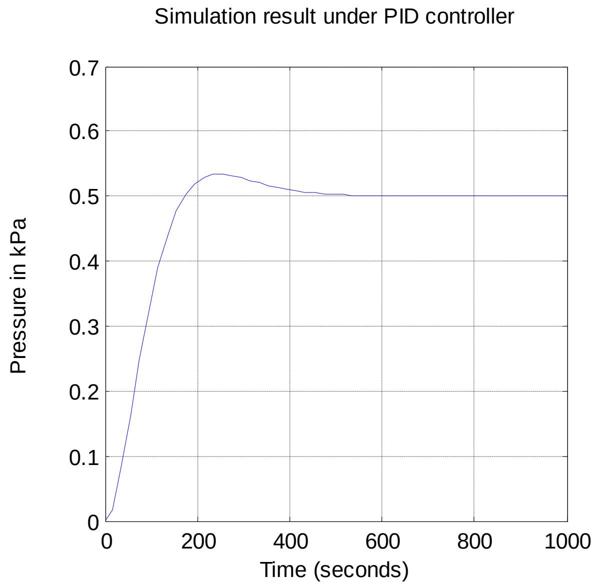

Fig.3.Chamber pressure under PID controller

V 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;

$$x(k + 1) = Ax(k) + Bu(k) \qquad (6)$$

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

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

$$x(k)=\begin{pmatrix} x(k+1|k) \\ x(k+2|k) \\ . \\ . \\ . \\ x(k+N|k) \end{pmatrix} \quad (6.1)$$

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:

$$x(k+i+1|k) = Ax(k+i|k) + Bu(k+i|k),\ i= 0, 1 \quad (6.2)$$

with initial condition (at the beginning of the prediction horizon) defined
x(k|k) = x(k).

The MPC cost function is denoted as follows:

$$J=\sum_{j=1}^{Ny} Z^T(k+j)Q_j z(k+j)$$
$$+\sum_{j=1}^{Nu} \Delta u^T(k+j-1)L_j\, \Delta u(k+j-1) \quad (6.3)$$

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.

$$Q_j=\text{diag}\{q_{jy\,1}\ldots\ldots\ldots\ldots q_{jyna}, q_{ju\,1}\ldots\ldots\ldots, q_{ju\,(nb-1)}, q_{je}\}. \quad (6.4)$$

Using MPC algorithm that is synchronized with the block diagramand the corresponding simulation results are shown in Fig.4&5.

- 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,

$$G(s)=\frac{-0.02}{150s+1}e^{-40s} \quad (7)$$

- 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 ~mpcchecktoolboxinstalled('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.

VI 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.

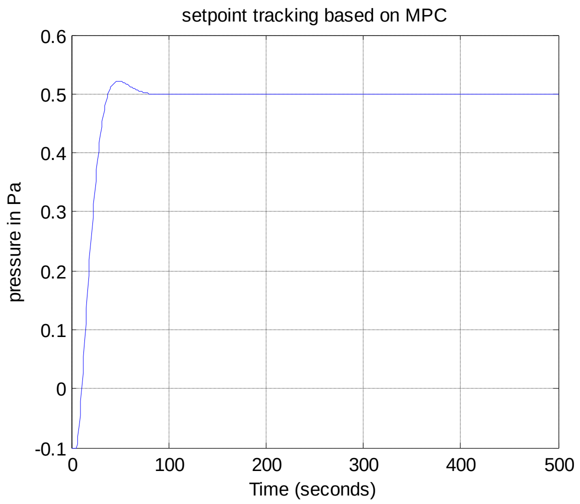

Fig.4. Simulation results based on MPC

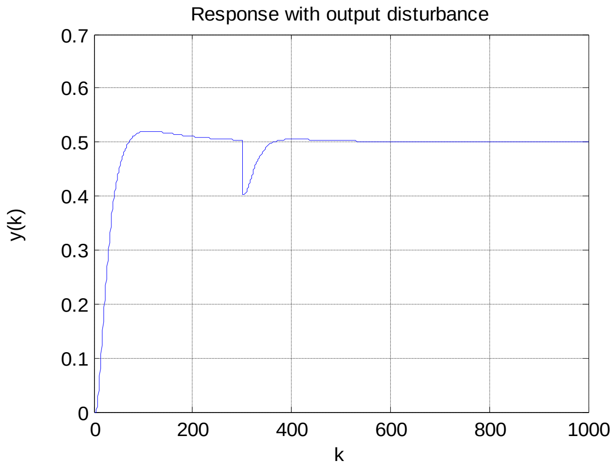

Fig.5.Response under output disturbance

The Fig.4. 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 Fig.5. 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 PID controller the output response of the chamber pressure in a coke furnace using MPC which gives the better response of the process. And also the overshoot is minimized. The proposed controller, the responses are smoother and cannot see the oscillations. So it is acceptable for the industrial applications.

VII CONCLUSIONS

In this paper, an 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 PID controller. The simulation results shows the good control performance under proposed controller.

VIII FUTURE SCOPE

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

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