Model-Based Control for Moisture in Paper Making Process

C. Karthik, K. Suresh, K. Valarmathi and R. Jacob Rajesh

Abstract This project deals with the performance evaluation on the comparison of model-based control for drying process of paper industry. The dryer section is the last part of the paper machine and consists of a large number of rotating steam-heated cast iron cylinders by adjusting the set point of the stream pressure controller to the cylinders. In the design of model reference adaptive control, schema is used, in which the adaptive law has been developed by MIT rule. Similarly, design of PID and MRAC controller is used. This paper presents a nonlinear dynamic control, based on heat and mass balance for steam, cylinder, and paper. The control was performed to the combined drying process system using both the adaptive control algorithm and MPC controller method and its results were analyzed. A simulation is carried out using MATLAB. Simulation results reveal clear benefits of the model reference adaptive control over traditional controller and MPC controller methods. Thus, by controlling, this process proves real incentives for industrial implementation.

Keywords Drying section · System identification · PID · MPC · MRAC

1 Introduction

The function of a paper machine is to form the paper sheet and remove the water from the sheet. A paper machine is divided into three main parts as wire section, press section, and drying section. Nonlinear modeling of moisture control of drying

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process in paper machine has been proposed an approach to define that the paper machine is modeled for designing moisture content control loop using DCS which is available in the paper plant. A transfer function to validate the moisture control process is obtained with the real-time data [1]. MPC as control strategy for pasta drying processes has been proposed an approach to MPC that produces high performance and accuracy, with relatively small computational rate and gives better results than PID [2, 3]. Model predictive control of an industrial dryer has been proposed an approach to its high performance due to the use of the direct control of the product moisture content based on a state observer, to updating the model of the process on which MPC relies [4, 5]. Direct model reference adaptive control of linear systems with input/output delays has been proposed an approach to Direct Model Reference Adaptive Tracking Controller for linear systems with unknown time varying input delays [8]. MRAC using observers with unknown inputs has been proposed a new solution for MRAC, based on the design of a state observer with unknown inputs has been proposed [8].

A multivariable MRAC scheme with sensor uncertainty compensation has been proposed a crucial step, the derivation of a properly parameterized error model in terms of the system and sensor parameter errors and the output tracking errors. Based on the developed error model, stable adaptive laws have been derived for updating the parameter of the compensator and feedback controller [10].

2 System Identification

System identification is a procedure to build a mathematical model of dynamics of a system from measured data. System identification is a process of obtaining models based on a data set collected from experimental setup as well as the real-time models.

2.1 Identification

The design of a control system requires a mathematical model of the dynamics of the process. Different types of identification model structure based on early principles model parameters are estimated from measured data. If the physical laws governing the behavior of the system are known, we can use these to construct so-called *white-box* models of the system. In a white-box model, all parameters and variables can be interpreted in terms of physical entities and all constants are known a priori. At the other end of the modeling scale, we have so-called *black-box* model or identification.

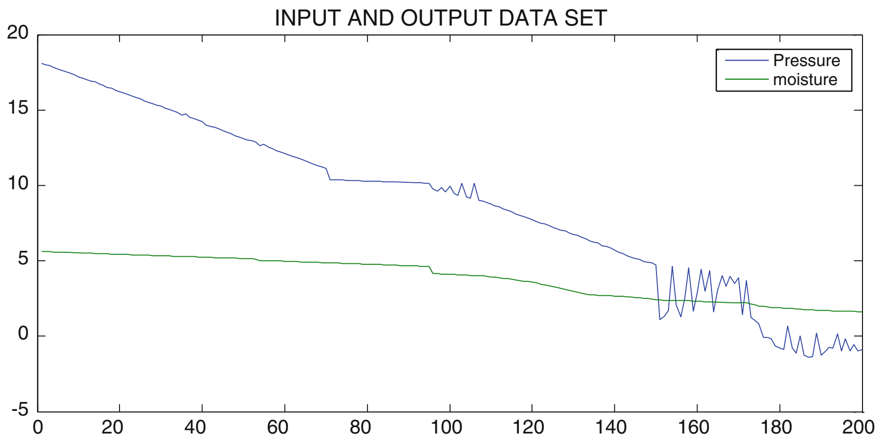

Fig. 1 Data set of input and output

2.1.1 Experiment Design

Collecting data is a very essential step. The data set Z^N should be as informative as possible to fully identify the model. Their pressure and moisture data were collected by using ABB DCS in TNPL. A total of 2,000 data were collected that are shown in Fig. 1.

Model sets or model structures are families of models with adjustable parameters. Parameter estimation amounts to conclude the "best" values of these parameters. The system identification complication amounts to find both the good models. Model Validation is the process of gaining confidence in a model. Crucial this is achieved by "twisting and turning" the model to scrutinize all attitude of it. Of particular importance is the model's ability to reproduce the behavior of the validation data sets. Thus, it is important to review the properties of the residuals from the model when applied to the validation data.

3 PID Controller

A PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller experiments to minimize the error by adjusting the process control inputs. Be able to use common methods of analysis for a system with a PID controller in order to predict the behavior of the system and controller, and to be able to choose PID parameters. Defining $u(t)$ as the controller output, the final model of the PID algorithm is

$$u(t) = Kpe(t) + Ki\int_{0}^{t} e(\tau)\mathrm{d}\tau + kd\frac{\mathrm{d}}{\mathrm{d}t}e(t) \tag{1}$$

3.1 Ziegler–Nichols Tuning

This procedure is only valid for open loop stable plants, and it is carried out through the following steps. Set the true plant under proportional control, with a very small gain, and increase the gain until the loop starts oscillating. Note that linear oscillation is needed and it should be detected at the controller output. Record the controller critical gain $K_p = K_c$ and the oscillation period of the controller output P_c.

4 Model Predictive Control

Future values of output variables are predicted using a dynamic model of the process. The control calculations are based on both future predictions and current measurement. Inequality, equality constraints, and measured disturbances obtain including the control calculations. The calculated manipulated variables obtain implemented set point for lower level control loops. A discrete-time implementation of model-based control algorithm is called as model predictive control.

4.1 MPC Design

The first step in the design is to load a plant model. Its dimensions and signal specifically set the context for the remaining steps. The model can be loaded directly or indirectly by importing a controller or a saved design. To import from MATLAB workspace, radio button should be selected by default. The dialog section labeled in the workspace lists the LTI models. They select the state space model for the process. The dialog section labeled the properties and then displays the number of input and output—their names, signal types, etc (Fig. 2).

5 Model Reference Adaptive Control

The MRAC is one of the main adaptive control approaches. When the system specifications are in terms of a reference model, it tells how the process output should ideally respond to command signals. It is then possible to use MRAC. Model reference adaptive system is to create a closed loop controller with parameters that can be updated to change the response of the system. The output of

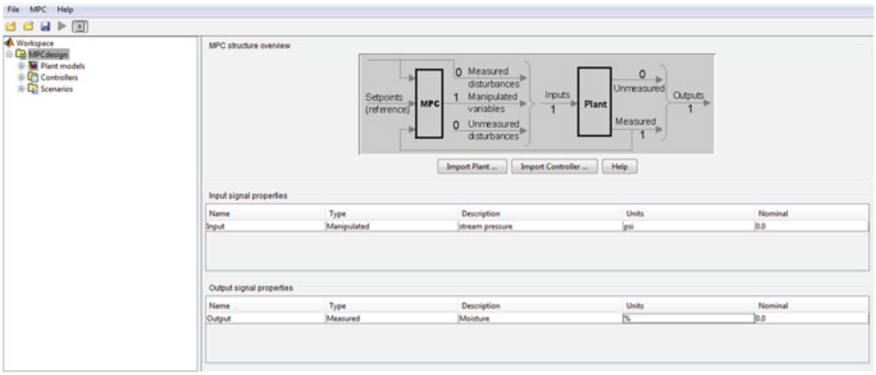

Fig. 2 MPC control and estimation tools manager

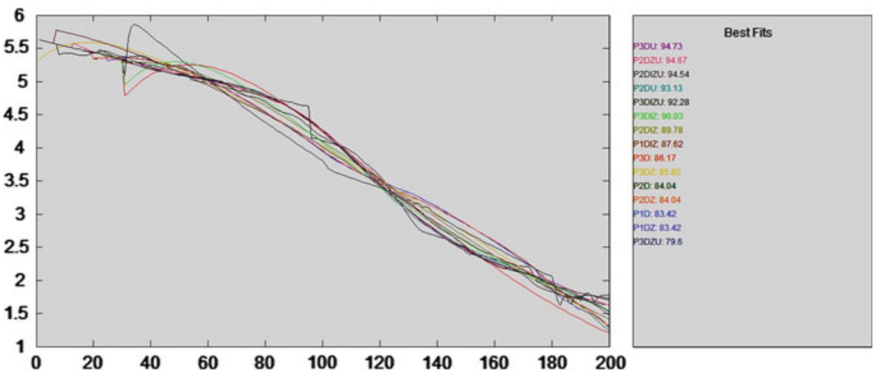

Fig. 3 Process model validation fitness output

the system is compared toward a desired response from a reference model. The control parameters will update based on this error. By adjusting, the mechanism parameters in a model reference adaptive system can be obtained using gradient method (Figs. 3, 4, 5 and 6) (Tables 1 and 2).

5.1 Gradient Method—MIT Rule

$$\text{Capture error}: e = y_{\text{plant ouput}} - y_{\text{modeloutput}} \tag{2}$$

$$\text{Regardingcost function}: J(\theta) = \frac{1}{2} e^2(\theta) \tag{3}$$

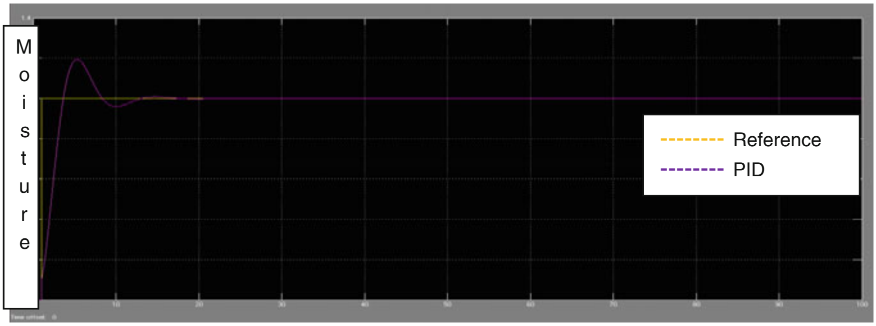

Fig. 4 PID simulation scenario

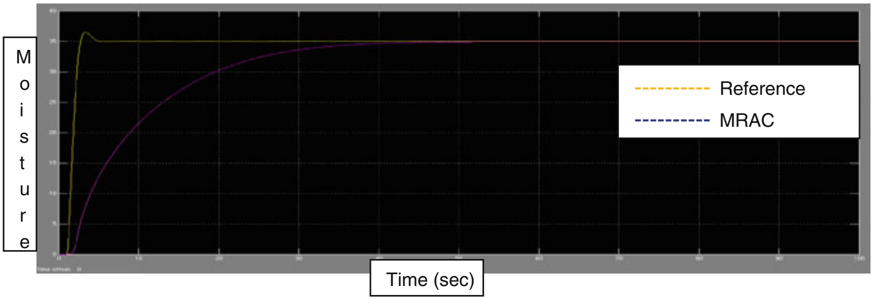

Fig. 5 MRAC simulation scenario

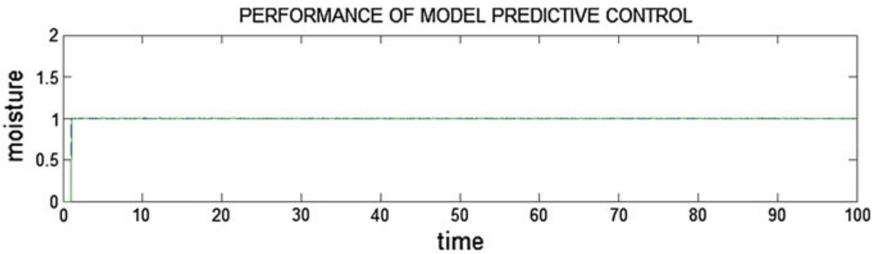

Fig. 6 MPC simulation scenario

$$\text{MIT standard}: \frac{\mathrm{d}\theta}{\mathrm{d}x} = -\gamma\frac{\delta J}{\delta\theta} = -\gamma e\frac{\delta e}{\delta\theta} \tag{4}$$

$$\frac{\mathrm{d}\theta 1}{\mathrm{d}t} = -\gamma(a_{mu_c}|s^3 + a_m)e \tag{5}$$

Table 1 Comparison of process model

Models	MSE for real-time data	Fitness (%)
PID	0.0508	83.42
P2D	0.0471	84.04
P3D	0.0353	86.17
P2DU	0.00872	93.13
P3DU	0.00512	94.74
P1DZ	0.0508	83.42
P2DZ	0.0471	84.04
P3DZ	0.0371	85.82
P2DZU	0.0471	86.48
P3DZU	0.0371	87.45
P1DIZ	0.0285	87.62
P2DIZ	0.0194	89.76
P3DIZ	0.0184	90.03
P2D1ZU	0.00551	94.54
P3DIZU	0.011	92.28

Table 2 Comparision between PID, MPC, and MRAC controller response

Controller performance	PID	MPC	MRAC
Rise time	3 s	2.2 s	13 s
Settling time	22 s	4.6 s	44 s
Peak overshoot	1.118	0	35

$$\frac{\mathrm{d}\theta 2}{\mathrm{d}t} = -\gamma(a_{my_{plant}}|s^3 + a_m)e \tag{6}$$

From $\frac{\mathrm{d}\theta 1}{\mathrm{d}t}$ and $\frac{\mathrm{d}\theta 2}{\mathrm{d}t}$ we get updating controller parameter $\theta 1$ and $\theta 2$ are

$$\theta 1 = \frac{-0.0001}{s}(9s^2 + 7s + 1|s^3 + 9s^2 + 7s + 1) \tag{7}$$

$$\theta 2 = \frac{0.0001}{s}\left(9s^2 + 7s + 1|s^3 + 9s^2 + 7s + 1\right) \tag{8}$$

6 Result and Discussion

From system process model identification, we get third-order transfer function for the model P3DU which is given by,

$$Tf = 1/(s^3 + 9s^2 + 7s + 1) \tag{9}$$

7 Conclusion

The proposed controllers are tested by using MATLAB simulinkprogram. The simulation shows that MPC provides better performance then MRAC and PID controller. The proposed model-based control system increases its efficiency and quality of the product. This will reduce the production cost by controlling the moisture.

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