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Identification and Model Predictive Control Design of a Polymer Extrusion Process

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Abstract

This paper deals with the challenging problem of closed-loop identification and Model Predictive Control (MPC) design in multivariable chemical processes and particularly in a co-rotating twin screw extruder processing powder coatings. To this aim, identification tests based on step response excitation signals were designed to estimate a low order process model in order to assist the model based control design of the process. Then, a discrete time predictive controller was developed to regulate the extruder and improve its control performance and disturbance rejection properties. The predictive control strategy exploits sets of Laguerre orthogonal functions to express the projected control trajectory. The process under MPC control was tested using different simulation scenarios and the results have shown very good performance with fast settling times and good disturbance rejection properties.

Keywords: Model based control; Closed-loop identification; Predictive control design.

1. Introduction

This paper examines the experimental identification towards the design of a model based predictive controller applied to a semi-industrial scale Twin-Screw Extruder (TSE) producing powder coatings. Extrusion process is a complex nonlinear industrial process with inverse response characteristics and strong interactions between the input-output channels. For the majority of the industrial processes open-loop experiments are prohibited due to safety, economic considerations, and efficiency of operation or stability issues and therefore closed-loop identification methods should be performed. Such methods are divided to three main groups, namely the direct, the indirect and the joint input-output approaches. Due to the feedback control configuration of the particular powder coatings extrusion process, the indirect approach (Pouliquen et al., 2010) was exploited in this work with step response excitation signals in different operating conditions. The overall identification strategy and the comparison of the various estimated models can be found in (Meintanis et al., 2017a). The estimated and validated (open-loop) model was then used to develop a predictive control strategy to improve the control performance and disturbance rejection properties of the TSE. In general, a Model Predictive Control (MPC) algorithm solves an on-line optimal control problem, over a fixed horizon, subject to system dynamics and variable constraints. In the conventional MPC methodologies, the control objectives are multiplied by appropriate weights and formulate an objective function that is minimized. The weight selection is in essence the tuning strategy for the controller, since it affects to a great extent the closed loop performance. A number of MPC books (Maciejowski, 2002), (Wang, 2009). and various applications (Aggelogiannaki et al., 2004),(Bemporad, 2006) can be found in the relevant literature. Here, we use an alternative approach where the (incremental) control signal is expressed in terms of a set of Laguerre functions with a pair of parameters that act as design parameters, as we will see later. The feedback control system under MPC control was tested using different simulation scenarios, in both tracking and regulator modes, and the results have shown very good tracking performance with fast settling times and good disturbance rejection properties.

2. Extrusion Process Background

2.1. Powder Coatings Manufacturing: Process Background

Powder coatings manufacturing is a semi-continuous multi-stage process involving the following steps: a) Weighing of the raw materials; b) Premixing (dry blending of the raw materials); c) Extrusion, where the premix is fed into an extruder where it is compacted and heated until it melts; d) Solidification process, which involves the cooling of the processed material via an industrial cooling belt; e) Milling and sieving of the chips to produce a fine powder with a specified particle size range. The most critical part in the powder coatings production line is the extrusion process, which must be carefully controlled to ensure a high quality end product.

2.2. The semi-industrial scale Twin Screw Extruder

Extrusion is a continuous process in which a pair of co-rotating screws is used to force the raw materials through the barrel of the machine and exit through a narrow exit point (die). In such process, the raw materials are simultaneously transported, mixed, stretched and sheared under elevated temperatures to form a homogeneous dispersion. The Twin Screw Extruder (TSE) in the study (EBVP20-SBS) is manufactured and supplied by Steel Belt Systems s.r.l. (Italy). The screw diameter is 21 mm and its length to diameter (L/D) ratio is 28:1. In a normal operation the capacity (throughput) can reach up to 50 kg/h. Furthermore, the extruder barrel is divided into six zones, were each of them has a set-point value for the temperature. The temperature zones are under PID control.

A real time data logging system is interfaced with the programmable logic controller (Siemens PLC) in the extruder. This system continuously monitors and logs the process variables, i.e. temperatures, screw speed, motor torque, feed rate etc. which are sampled in one second intervals. Among the on-line Measured Output (MO) variables, previous studies and experimental trials have shown that the motor torque, Specific Mechanical Energy (SME), and product (or, melt) temperature, have a strong impact on the final product quality attributes. The primary Manipulated Variables (MV) to control these process variables are screw speed, material feed rate and barrel temperature of zones 4-6, respectively. In this work, we have used as MVs (u_1, u_2): the Screw Speed (SS) and the Barrel Temperature (BT) of zones 4-6; and as MOs (y_1, y_2): the Motor Torque (MT) and the final Product Temperature (PT) at the die.

3. Process Modelling: Experimental Identification of the Extrusion Process

A task on the system identification of the TSE process was performed in parallel to the model predictive control design, with the objective to produce a low order efficient model in order to assist the model-based predictive control design and the scaling up to the industrial level. A good identification test plays a key role in a successful identification. The data-set has been generated by applying single variable step tests (current practice in process industry) from various operating conditions to capture the dynamics of the TSE process. The gathered process data were scaled (normalized) to prevent unnecessary domination of certain process variables and prevent data with larger magnitude overriding the smaller. Next, was split into two parts, i.e. the modelling data-set used for process identification and the validation data-set in order to verify the accuracy of the estimated models. Continuous-time models were estimated using Prediction Error (PE) and Subspace Identification Method (SIM) algorithms with various model structures. All the estimated process models were validated by a series of specially designed model validation tests where both sum of squares of step response errors and prediction errors were used. The overall identification strategy and the results are given in (Meintanis et al., 2017a). The estimated continuous time model for the TSE process is

$$\underline{y}(s) = G(s)\cdot\underline{u}(s),\; G(s) = \frac{1}{\Delta(s)}\begin{bmatrix} n_{11}(s) & n_{12}(s) \\ n_{21}(s) & n_{22}(s) \end{bmatrix} \tag{1}$$

where, $\Delta(s) = s^4 + 12.02s^3 + 20.21s^2 + 0.3423s - 0.0003$, and

$$n_{11}(s) = 0.0014s^3 + 0.00277s^2 - 3.386\cdot 10^{-3}s + 0.00162$$
$$n_{12}(s) = -0.002663s^3 - 0.02661s^2 + 8.581\cdot 10^{-3}s - 0.00021$$
$$n_{21}(s) = -0.00095s^3 - 0.00018s^2 - 1.44\cdot 10^{-4}s - 0.000198$$
$$n_{22}(s) = 0.002657s^3 + 0.02662s^2 + 0.00047s + 0.00028$$

Then, the transfer function model (1) was converted to a minimal state space realization using MATLAB, in order to ensure controllability, observability, followed by converting it to the equivalent discrete-time process model, as in (2), which was then used as the basis for the design of the predictive control strategy.

4. Model Predictive Control Design of the Polymer Extrusion Process

The overall design objective of Model Predictive Control (MPC) is to compute a trajectory of future manipulated variables to optimize the future behavior of the plant outputs. In general, a predictive control algorithm solves an on-line optimal control problem subject to system dynamics and variable constraints. The core MPC algorithm is based on a model of the system to be controlled, a performance index driving the selection of the decision variables, a set of constraints to be fulfilled, and a state estimator to reconstruct the internal states of the plant model.

4.1. MPC Problem Formulation

The control design algorithm is based on the linear $p-$input, $q-$output discrete-time prediction model

$$x_n(k+1) = A_n x_n(k) + B_n u(k) + \xi(k),\; y(k) = C_n x_n(k) \tag{2}$$

where $x_n(k) \in \mathbb{R}^n$ is the state vector at time instant k, $u(k) \in \mathbb{R}^p$ is the vector of manipulated variables to be determined by the controller, $y(k) \in \mathbb{R}^q$ is the process outputs and $\xi(k)$ the disturbances. The state-space matrices A_n, B_n, C_n of the open-loop process model can be found in (Meintanis et al., 2017b).
The predictive control law requires to obtain the incremental control signal $\Delta u(k) = u(k) - u(k-1)$ as the manipulated variable for the future plant output. Hence, we need to augment the original state-space model (2) by defining a new state-variable vector $x(k) = \begin{bmatrix} \Delta x_n(k) & y(k) \end{bmatrix}^T$, $\Delta x_n(k) = x_n(k) - x_n(k-1)$, as follows:

$$x(k+1) = Ax(k) + B\Delta u(k) + \Delta\xi(k),\ y(k) = Cx(k) \tag{3}$$

where, $A = \begin{bmatrix} A_n & 0_{n\times q} \\ C_nA_n & I_{q\times q} \end{bmatrix}$; $B = \begin{bmatrix} B_n \\ C_nB_n \end{bmatrix}$; $C = \begin{bmatrix} 0_{q\times n} & I_{q\times q} \end{bmatrix}$. We assume that the plant is controllable and observable and that the state vector $x(k_i)$, at sampling instant $k_i > 0$, is available through measurement (or via estimator). Then, the future control trajectory, ΔU, is captured by $\Delta u(k_i), \Delta u(k_i+1), \ldots, \Delta u(k_i+N_c)$ and the prediction of the future state variables vector $x(k_i+1|k_i), x(k_i+2|k_i), \ldots, x(k_i+N_p|k_i)$ ($N_c < N_p$) in a compact matrix form is given by

$$\mathbf{X} = \Phi_A x(k_i) + \Phi_B \Delta U \tag{4}$$

where,

$$\Phi_A = \begin{bmatrix} A & A^2 & \cdots & A^{N_p} \end{bmatrix}^T;\ \Phi_B = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \cdots & & & \\ A^{N_p-1}B & A^{N_p-2}B & \cdots & A^{N_p-N_c-1}B \end{bmatrix}$$

and N_c, N_p are the control and prediction horizons respectively. For set-point tracking the future plant output is predicted by:

$$\mathbf{Y} = C\mathbf{X} = C\Phi_A x(k_i) + C\Phi_B \Delta U \tag{5}$$

The cost function for set-point tracking is written as follows

$$J = [x(k_i+N_p) - x_{ss}]^T W_0 [x(k_i+N_p) - x_{ss}] + [R_s - Y]^T Q [R_s - Y] + \Delta U^T R \Delta U$$

where, $Q \geqslant 0, R > 0$ are the weight matrices and x_{ss} the steady-state values of the state variables at the prediction horizon. Note that, for the simplicity of the design, the state terminal weight W_0 is neglected, i.e. $W_0 = 0$. Furthermore, in the MPC formulation there are three types of constraints, i.e. (i) constraints on the amplitude of the Manipulated Variables (MV); (ii) constraints on the rate of change of the MVs; and (iii) constraints on the Measured Outputs (MO). All of them are expressed in terms of the vector ΔU and in a compact matrix form as $M\Delta U \leqslant \mu$, where M is an $n \times p(N_c - 1)$ matrix formed by the inequality constraints.

4.2. Design of a Model Predictive Controller using Laguerre Orthogonal Functions

The proposed design algorithm adopted from (Wang, 2004), differs from the traditional MPC design by describing each $i-$th control signal with a Laguerre network $L_i(\cdot)$ with a pair of parameters a: decay factor, N: model order. For instance, in order to express the $i-$th control signal Δu_i at instant time k, we have, $L_i(k)^T \eta_i$. Similarly, the total control trajectory ΔU is given by

$$\Delta U = \begin{bmatrix} bl.diag\{L_1(0)', \ldots, L_p(0)'\} \\ bl.diag\{L_1(1)', \ldots, L_p(1)'\} \\ \vdots \\ bl.diag\{L_1(N_c)', \ldots, L_p(N_c)'\} \end{bmatrix} \cdot \begin{bmatrix} \eta_1 \\ \eta_2 \\ \vdots \\ \eta_p \end{bmatrix} = \tilde{L} \cdot \eta \qquad (6)$$

Accordingly, the cost function and the original constraints are also expressed in terms of the Laguerre parameters vector η. Based on the Receding Horizon Control principle, the applied control signal is constructed by $\Delta u(k) = bl.diag\{L_1(0)', \ldots, L_p(0)'\} \cdot \eta$, that is only the first instance of the total control trajectory.

4.3. Controller Tuning

Except the weight matrices Q and R, the main design parameters that affect the control performance are: i) the Prediction Horizon (N_p), which is recommended to be selected as large as possible to ensure stability and it is directly related with the the desired settling time of the output signal; ii) the Laguerre Factor (a), which affects the closed-loop response speed and corresponds to the traditional control horizon N_c; iii) the Laguerre order (N), which defines the number of terms that are used to capture the future control signal.

In the predictive design algorithm for the TSE process we have used the following values: $N_p = 24$; $a_1 = a_2 = 0.6$; $N_1 = N_2 = 4$; $Q = C^T C$ and $R = diag(0.01, 0.01)$. A brief summary of the results is given next.

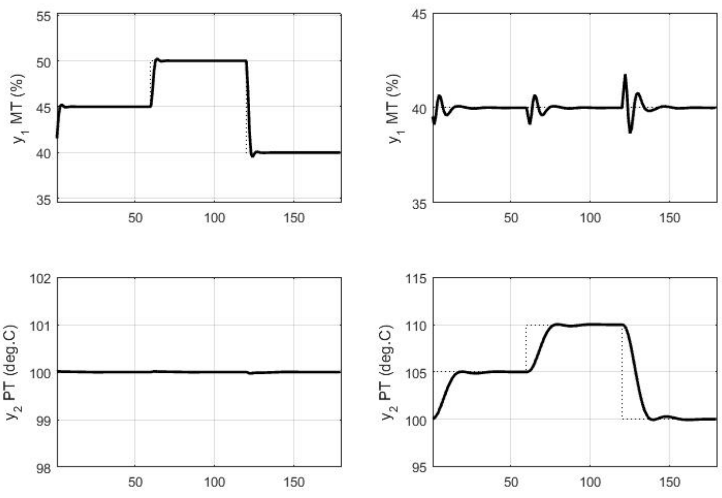

Figure 1: TSE Process Outputs with MPC. Left column: Step response on channel y_1; Right column: Step response on channel y_2.

5. Simulation Results

Various simulations have been performed to test the ability of the predictive controller in both regulator and tracking mode. Due to limited space, we present the simulation results only for the reference following control (Fig. 1), where the left column shows the tracking when a step response applied in channel y_1 and the right column in channel y_2. The same reference signal, $\underline{r}(k_i)$, was applied to both channels for a full cycle, i.e. 180 sampling instants, which is equal to 180 sec. More specifically, $\underline{r}(k_i) = [5\ 0]^T$ for $0 \leq k \leq 60$, $\underline{r}(k_i) = [10\ 0]^T$ for $61 \leq k \leq 120$ and then brought back to its steady-state values, $y_{ss} = [MT_{ss}\ PT_{ss}]^T = [40\ 100]^T$. As we can see the process under MPC control automatically adjust its outputs to the new set-points with fast settling times and by eliminating cross-couplings. Also, the MPC controller rejects the disturbances occur due to uncertain material properties, or variations in the feed rate and regulate the process outputs at the desired operating conditions.

6. Conclusions

In this work, experimental identification tests were performed first to estimate a process model for a TSE processing polymers. Then, a model-based predictive control strategy was developed to regulate the extruder processing conditions. The predictive control law was evaluated by simulations and the results have shown good tracking capabilities and adequate control performance for a range of operating conditions together with improved disturbance rejection properties. The identification and predictive design strategy demonstrated here may be applied to similar large scale and complex plants in the process industry with promising results.

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