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Application of Model Predictive Control suitable for closed-loop re-identification to a polymerization reactor

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ABSTRACT

Recently, a linear Model Predictive Control (MPC) suitable for closed-loop re-identification was proposed, which solves the potential conflict between the persistent excitation of the system (necessary to perform a suitable identification) and the control, and guarantees recursive feasibility and attractivity of an invariant region of the closed-loop. This approach, however, needs to be extended to account for a proper robustness to moderate-to-severe model mismatches, given that re-identifications are necessary when the system is not close to the operating point where the current linear model was identified. In this work, new results on robustness are presented, and an exhaustive application of the new MPC suitable for closed-loop re-identification to a nonlinear polymerization reactor simulator is made to explore the difficulties arising from a real life identification. Furthermore, several closed-loop re-identification are performed in order to clearly show that the proposed controller provides uncorrelated input–output data sets, which together with the guaranteed stability, constitute the main controller benefit.

1. Introduction

Multivariable model-based control techniques, which use a prediction model to optimize systems performance, are control strategies widely used in industry. In particular, linear Model Predictive Control (MPC) has shown to be extremely useful in this context, since it bases its formulation on a simplified linear model of the plant, explicitly considers constraints on the variables, handles the complete process with many manipulated and controlled variables as a whole, and it optimizes the process performance [3,27].

One of the key point of an MPC formulation is the model used for prediction. This point, however, is not so simple to analyze/understand, given that in most applications, good performances are obtained by using only a simplified linear model of the complex nonlinear system under control. First, the fact – usually disregarded by the industrial practitioners – that a crucial part of the model employed by an MPC strategy is the knowledge of the constraints on the variables, should be emphasized. Second, the other fundamental aspect to be taken into account in an MPC formulation, is the accuracy of the linear model parameters (mainly the gain, to perform a suitable economic optimization). In this context, it becomes clear that an updating of the model should be done every time the process is moved to an operating point far from the one used to identify the model currently used by the controller. And more important, it would be desirable to perform this updating in closed-loop, since disconnecting the controller any time an identification is needed, is not a practical solution [20,24,30,16,7,15].

The general topic of system identification is a vast area of research, which involves the problem of handling the collected data from real process, and how to extract the valuable information from these data [28,20]. Although the focus of this article is not put on the identification itself, but on the design of a controller formulation that permits an easy closed-loop identification, a brief discussion on the literature related to the closed-loop identification method is necessary. Roughly speaking, identification methods can be characterized into the following main groups [20,28]: (i) The direct approach ignores the feedback law and identifies the open-loop system using measurements of the input and the output. (ii) The indirect approach identifies the closed-loop transfer function and determines the open-loop parameters subtracting the controller dynamic. To do that, the controller dynamic must be linear and known. (iii) The joint input–output approach takes the input and

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output, jointly, as the output of a system produced by some extra input or setpoint signal. Since the last two methods need the exact knowledge of a linear controller, they are not directly applicable for closed-loops under constrained MPC.

If now the classification is circumscribed to the closed-loop re-identification *under MPC controllers*, then the following approaches should be mentioned. Genceli and Nikolaou [9] proposed a controller named Model Predictive Control and Identification (MPCI) where a persistent excitation condition is added by means of an additional constraint in the optimization problem. This strategy, which has been explored later in [2], turns the MPC optimization problem non-convex, and so, most of the well-known properties of the MPC formulation cannot be established. Zacekova et al. [29] presented a two-step controller approach: the first stage is devoted to optimize the control trajectory – as usual in MPC – while the second stage is devoted to generate the persistent excitation (PE) input signal by maximizing the minimal eigenvalue of the information matrix (a matrix describing the input variability). The link between these two stages is the optimal cost of the first one, which is used as constraint of the second one. The second optimization problem, however, is nonlinear and difficult to solve. Potts et al. [26] made a study of several MPC re-identification methods, focusing on the so-called MPC Relevant Identification (MRI). This method does not only take into account the identified model accuracy, but also the model aptitude for predictions, i.e., the model aptitude from the controller point of view. Marafioti [22] presents a new MPC-type formulation, defined as Persistently Exciting Model Predictive Control (PE-MPC). This formulation incorporates the persistent excitation (PE) signal by including a constraint into the MPC optimization problem, as it was made in [9]. The main difference between these two works is that the former allows the constraint to be inactive in the transient regime, and so, the MPC controller is not forced to obtain identification results at each sampling time. An enhanced formulation is presented in [23]. Similar results are presented in [18], where the time domain constraints are fulfilled while the identification criterion is taken into account. Heirung et al. [13] proposed the inclusion of an additional term in the MPC cost, and the use of a recursive (and modified) least square algorithm to obtain the on-line closed-loop identification. This way, the persistent excitation condition is no longer necessary, given that the excitation level is increased according to the estimated model parameters. Finally, [25] proposed to generate a PE signal by means of the maximization (instead of the minimization) of the MPC cost function. This way, the variance (variability) of the signal is maximized while the process variables fulfill the constraints. Neither the external excitation signal nor the dither signal are required in this approach. Also, the excitation signal depends – through the output noise – on the feedback signal, which means that the so obtained input and output signals will be highly correlated.

In general, none of these works pay attention to the formal feasibility and attractivity/stability of the MPC formulated for re-identifying the system. Recently, [10] has proposed a novel MPC suitable for re-identification that ensures feasibility and stability, and performs a safe closed-loop re-identification. The main idea in this paper is to extend the concept of equilibrium-point-stability to the invariant-set-stability, and to propose an MPC that drives the system into that invariant set, when outside, and persistently excites the system, when inside. This way, the method avoids the potential conflict between persistent excitation and control.[1] The MPC problem formulation is based on the concept of generalized distance from a point (the state and input trajectory) to a set (target invariant set and input excitation set). So, it guarantees the attractivity/stability of the target invariant set and also the feasible persistent excitation of the system, since both tasks are developed separately in the state space.

The method proposed in [10], however, involves some theoretical definitions which are model-dependent: invariant sets and distance functions to the invariant set. Then, two issues arise: (1) if the method could be adapted to reach a sufficient degree of robustness to properly account for moderate-to-severe model mismatches and changes of the operating points, and (2) if the model identification performed with the data obtained in closed-loop gives accurate models in every desired scenario. The first question is of interest since the invariant set used as a target by the MPC may be invariant in a region of the nonlinear system (precisely, in the proximity of the equilibrium where the current linear model was obtained) but not in other ones (when the nonlinear system may be steered, by a disturbance or by a change of operating conditions, far from the original equilibrium). The second question, on the other hand, is related to the quality of the collected data for identification, which in turn depends on the degree of correlation between inputs and outputs (noise) that the controller produces.

The objective of this work is then to extend the MPC suitable for re-identification to properly account for the robustness to moderate-to-severe plant-model mismatches. In this regard, the controller is applied to a nonlinear styrene polymerization reactor simulator, and several closed-loop re-identifications are performed to test both, the robustness and identification abilities of the proposed strategy. By means of the simulations it is shown that in most of the cases it is possible to compute proper robust invariant sets (according to new theoretic results) – and hence, it is possible to design a proper MPC for re-identification. Also, it is shown how to practically compute the invariant sets according to the regions of the nonlinear state space, where frequent re-identifications are needed. Finally, several identifications are performed to show that the collected input–output noise data are not correlated by the controller. This means that good identifications could be made under the proposed robust scheme.

The paper is organized as follows. After an Introduction in Section 1, Section 2 presents the problem statement and the MPC controller formulations suitable for closed-loop re-identification. Then, in Section 3, new results related to MPC robustness are given. In Section 4, a description of the styrene polymerization reactor is presented, while Section 5 describes the linear models for predictions and the constraint sets involved in the problem. Section 6 presents a detailed description of the simulation results, showing the pros and cons of the MPC in different scenarios. Finally, Section 7 provides some conclusions of the work.

2. Problem statement and controller formulation

2.1. Model and constraints assumptions

Consider a system described by a linear time-invariant discrete-time model

$$x^+ = Ax + Bu, \quad y = Cx \tag{1}$$

where $x \in \mathbb{R}^n$ is the system state, x^+ is the successor state, $u \in \mathbb{R}^m$ is the current control, and $y \in \mathbb{R}^p$ is the system output. The system is subject to hard constraints on state and input, $x(k) \in \mathcal{X} \subset \mathbb{R}^n$ and $u(k) \in \mathcal{U} \subset \mathbb{R}^m$, for all $k \geq 0$. Furthermore, it admits soft output constraints in the form of output zones, $y(k) \in \mathcal{Y}$, where $\mathcal{Y}$ is intended as an output set of appropriated dimension to perform a system identification. It is assumed, for simplicity, that matrix A has all its eigenvalues strictly inside the unit circle, the pair (A, B) is controllable, the set $\mathcal{X}$ is convex and closed, the sets $\mathcal{U}$ and $\mathcal{Y}$ are convex and

[1] It should be remarked that this kind of natural duality of the control task was first highlighted in [5].