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A framework for hybrid model predictive control in mineral processing ☆

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ABSTRACT

Model Predictive Control (MPC) is an advanced technique for process control that has seen a significant and widespread increase in its use in the process industry since its introduction. In mineral processing, in particular, several applications of conventional MPC can be found for the individual processes of crushing, grinding, flotation, thickening, agglomeration, and smelting with varying degrees of success depending on the variables involved and the control objectives. Given the complexity of the processes normally found in mineral processing, there is also great interest in the design and development of advanced control techniques which aim to deal with situations that conventional controllers are unable to do. In this aspect, Hybrid MPC enables the representation of systems, incorporating logical variables, rules, and continuous dynamics. This paper firstly presents a framework for modeling and representation of hybrid systems, and the design and development of hybrid predictive controllers. Additionally, two application examples in mineral processing are presented. Results through simulation show that the control schemes developed under this framework exhibit a better performance when compared with conventional expert or MPC controllers, while providing a highly systematized methodology for the analysis, design, and development of hybrid MPC controllers.

1. Introduction

Model predictive control (MPC) refers to a class of computer algorithms for process control that rely on the use of dynamic models to make predictions of the evolution of the process. Using this predictions, a MPC algorithm performs an optimization of predefined control objectives to compute the control sequence needed to drive the process to the optimal operating point. Only the first action in the control sequence is sent into the plant, and the optimization is repeated on the next control interval with the most recent state information (García, Prett, & Morari, 1989).

Predictive control is being increasingly applied in the process industry, mainly due to its ability to handle multi-variable plants naturally and incorporate constraints on operating variables (Maciejowski, 2002). Additionally, the tuning of the controller parameters is relatively easy and intuitive, making it particularly attractive to staff with limited knowledge of control theory (Camacho & Bordons, 2002).

In the mineral processing industry, several applications of MPC can be found for the individual processes. For instance, Ramasamy, Narayanan, and Rao (2005) performed a comparative analysis between a MPC strategy and a multi-loop PI control scheme applied to a mineral grinding plant. A similar comparison was performed by Chen, Zhai, Li, and Li (2007). In Suichies, Leroux, Dechert, and Trusiak (2000), a single-input/single-output (SISO) MPC algorithm and a AutoRegressive eXogeneous (ARX) model identification routine were implemented in several sulfide flotation circuits. In Gatzke and Doyle (2001), two control methods based on predictive control, soft output constraints, and prioritized control objectives were tested on a simulated granulation process.

The organization of this paper is as follows. Section 2 presents a review of conventional MPC applications in mineral processing. Section 3 describes the hybrid modeling of dynamic systems. The design and implementation of Hybrid Model Predictive Control (HMPC) is detailed in Section 4. In Section 5, the proposed HMPC framework is described. Section 6 presents two new applications of HMPC in mineral processing. Finally, conclusions are presented in Section 7.

2. Conventional MPC applications

Even though PID controllers are the most usual approach to feedback control found in mineral processing plants (Hodouin, 2011),

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several implementations of model-based controllers, tested through simulation and in real plants, can be found in the literature.

In Muller and Vaal (2000), a model predictive controller for a milling circuit was developed. Additionally, an optimizing algorithm was used to automatically tune the controller parameters. The controller was implemented and tested on a milling simulator, which was programmed using Microsoft Visual C++. Similarly, in Cortés and Cerda (2010), a MPC scheme was complemented with an expert rules module and implemented in a real grinding circuit. The expert module was designed to handle certain situations where conventional MPC fails, such as overloads on Semi-Autogenous Grinding (SAG) mills, opening and closing hydrocyclones, large disturbances in the feedback of pebbles, and blockage of lines. The predictive controllers and the expert module were implemented as a coordinated control system. In Salazar, Valdés-González, Vyhmeister, and Cubillos (2014), a multi-variable MPC strategy was developed for a SAG device. The controller performance showed a suitable behavior, independent of the system deviation from its set point.

Similarly, several applications of model-based control for the processes of granulation, flotation, and froth thickening can be found. A linear MPC scheme was developed by Adetayo, Pottman, and Ogunnaike (1997) and applied to a pan granulation process, using black-box, input–output models. Hodouin, Bazin, Gagnon, and Flament (2000) implemented an application of model-based control for flotation. The proposed control strategy combines feedforward and feedback actions and it was tested on a simulated linear flotation bank. Results show that the proposed strategy attenuates the effect of typical flotation feed disturbances. In Foroush, Gaulocher, and Gallestey (2009), a froth thickness control strategy with the goal of improving the concentrate mineralurgical characteristics was implemented. In Rojas and Cipriano (2011), two multi-variable MPC strategies based on tailing and concentrate grade measurements, and intermediate cell grade estimates were implemented and applied to a rougher flotation circuit.

Most conventional MPC strategies use linear models to characterize the dynamical systems to be controlled. While these linear models may provide an accurate representation in the vicinity of an operating point, if the controlled system deviates from the operating point, the accuracy of linear models will decrease, lowering the performance of the controller. In highly non-linear systems, linear approximations may not be sufficiently accurate to represent the real process. Additionally, conventional MPC strategies are unable to represent logical variables such as discrete events or rules. To address these issues, hybrid MPC is used.

3. Hybrid modeling of dynamic systems

Hybrid dynamic models are used to describe the evolution of dynamic systems that present both continuous and logical components. Several subclasses of hybrid systems are found in the literature: Linear Complementarity (LC) systems, Mixed Logical Dynamical (MLD) systems, PieceWise Affine (PWA) systems, among others.

PWA systems are a composition on linear time-invariant dynamic models that can approximate non-linear dynamics with arbitrary accuracy by increasing the number of linearization at appropriate operating points (Heemels, Schutter, & Bemporad, 2001). A PWA dynamic system is defined by

$$\begin{matrix} \mathbf{x}(k+1)=\mathbf{A}_i\mathbf{x}(k)+\mathbf{B}_i\mathbf{u}(k)+\mathbf{f}_i \\ \mathbf{y}(k)=\mathbf{C}_i\mathbf{x}(k)+\mathbf{g}_i \end{matrix} \quad \text{for} \begin{bmatrix} \mathbf{x}(k) \\ \mathbf{u}(k) \end{bmatrix} \in \mathcal{X}_i \tag{1}$$

where $\mathcal{X}_i$ is a subset of the state/input set, typically defined by the physical constraints of the process. Both state and input variables can take continuous or discrete values. Each subsystem $i \in \{1,2,\ldots,s\}$ defined by matrices $\mathbf{A}_i$, $\mathbf{B}_i$, and $\mathbf{C}_i$; and vectors $\mathbf{f}_i$ and $\mathbf{g}_i$, corresponds to one linearization of the original system at the operating point contained in $\mathcal{X}_i$. The transitions between linear models are determined at each sampling interval based on the value of the states and inputs.

MLD systems are a class of hybrid systems where physical laws, logic rules, and operating constraints are interdependent (Bemporad & Morari, 1999). A MLD system is described by the following linear relations:

$$\mathbf{x}(k+1)=\mathbf{A}\mathbf{x}(k)+\mathbf{B}_1\mathbf{u}(k)+\mathbf{B}_2\boldsymbol{\delta}(k)+\mathbf{B}_3\mathbf{z}(k) \tag{2a}$$

$$\mathbf{y}(k)=\mathbf{C}\mathbf{x}(k)+\mathbf{D}_1\mathbf{u}(k)+\mathbf{D}_2\boldsymbol{\delta}(k)+\mathbf{D}_3\mathbf{z}(k) \tag{2b}$$

$$\mathbf{E}_2\boldsymbol{\delta}(k)+\mathbf{E}_3\mathbf{z}(k)\le\mathbf{E}_1\mathbf{u}(k)+\mathbf{E}_4\mathbf{x}(k)+\mathbf{E}_5, \tag{2c}$$

where $\mathbf{x}(k)$ is the state of the system, $\mathbf{u}(k)$ is the input vector, and $\mathbf{y}(k)$ is the output vector. Any one of this vectors can include both continuous and discrete variables. Additionally, $\boldsymbol{\delta}(k)$ and $\mathbf{z}(k)$ are auxiliary logical and continuous variables, respectively. Eq. (2a) describes the evolution of the states through the state matrix $\mathbf{A}$ and the input matrices $\mathbf{B}_1$, $\mathbf{B}_2$, and $\mathbf{B}_3$. Similarly, (2b) describes the evolution of the outputs of the system through the output matrix $\mathbf{C}$ and the feedforward matrices $\mathbf{D}_1$, $\mathbf{D}_2$, and $\mathbf{D}_3$. The constraints in (2c) defined by the matrices $\mathbf{E}_1$ through $\mathbf{E}_5$ are a translation of the logical rules and statements into mixed-integer linear inequalities.

The MLD system representation is useful for expressing several types of systems involving discrete variables, as shown in Bemporad and Morari (1999). Additionally, given its structure, this representation is also useful for the development of control strategies.

Under some assumptions, PWA systems and MLD systems are completely equivalent. A well-posed PWA system, that is, $\mathbf{x}(k+1)$ and $\mathbf{y}(k)$ are uniquely determined for a given $\mathbf{x}(k)$ and $\mathbf{u}(k)$, can be rewritten as a MLD system, assuming a bounded set of feasible states and inputs. Conversely, a well-posed MLD system, that is, $\mathbf{x}(k+1)$, $\mathbf{y}(k)$, $\boldsymbol{\delta}(k)$, and $\mathbf{z}(k)$ are uniquely determined for a given $\mathbf{x}(k)$ and $\mathbf{u}(k)$, can be rewritten as a PWA system (Heemels et al., 2001).

In this study, PWA systems were used to develop hybrid models of mineral processes via piecewise linear identification. When considering real processes, such as the ones found in a mining plant, there are two main situations where hybrid models may be applicable, namely, the presence of variables that are intrinsically discrete, such as on-off switches, speed selectors, and number of active units; and the use of piecewise linear models to approximate nonlinearities. Both these situations can be accurately represented using PWA models.

Once the PWA system was formulated, an equivalent MLD system was obtained. To find the MLD representation, the HYbrid System DEscription Language (HYSDEL; see Torrisi & Bemporad, 2004) was used. HYSDEL is a modeling language designed to describe Discrete Hybrid Automata (DHA), which are the combination of a Finite State Machine (FSM) and a Switched Affine System (SAS) through a mode selector and an event generator.

The PWA models developed in this study, as described in (1), were represented in HYSDEL as DHA systems, which then were compiled and translated into equivalent MLD systems. The structure of the MLD representation is suitable for the formulation of hybrid predictive controllers, as shown in the next section.

4. Predictive control of hybrid systems

The next section describes the implementation of the predictive controller for hybrid systems based on the MLD representation (2). Additionally, a hybrid state estimator is presented. This estimator is based on the PWA representation (1) and simultaneously estimates the value of the continuous state of the system and the current active subsystem.

Hybrid model predictive control has been successfully implemented in several areas. In Nandola and Rivera (2013), an