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Reference trajectory tuning of model predictive control

André Shigueo Yamashita [a,*], Paulo Martin Alexandre [c], Antonio Carlos Zanin [b], Darci Odloak [a]

[a] Department of Chemical Engineering, University of São Paulo, Av. Prof. Luciano Gualberto, trv 3 380, 05424-970 São Paulo, Brazil
[b] Petrobras S.A., Center of Excellence for Technology Application in Industrial Automation, São Paulo, SP, Brazil
[c] Electrical Engineering, Maua School of Engineering, Praça Maua, São Caetano do Sul 01-09530-701, Brazil

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ABSTRACT

An approach to minimize tuning effort of nominal Model Predictive Control algorithms is proposed. The algorithm dynamically calculates output set points to accommodate user-defined output importance, which is more intuitive than selecting values for the MPC weighing matrices. Instead of tuning the weights on the outputs deviations from their set points, weights on the input values and input increments, which are the usual tuning parameters of MPC, the desired output control performance of the MPC can be specified by performance factors. The proposed method extends the existing methods that consider a reference trajectory for the output tracking to the case of zone control and input targets. The proposed method also assumes that, as in most commercial MPC packages, the controller has two layers: a static layer and an extended dynamic layer. The method is illustrated by three case studies, contemplating both SISO and MIMO systems. It is observed that: the output set point tracking performance can be changed without modifying the MPC tuning weights, the approach is capable of achieving similar performance to conventional MPC tuned by multiobjective optimization techniques from the literature, with a fraction of computer effort, and it can be integrated with Real Time Optimization algorithms to control complex systems, always respecting output constraints.

1. Introduction

Model Predictive Control (MPC) is a well-established process control strategy both in industry and academia. The main idea is to predict the future values of the system outputs based on a system model and minimizing the error between the predictions and reference values, or set points, over a prediction horizon. The control problem is posed in terms of a constrained optimization problem, in which optimum control actions are calculated minimizing the aforementioned goal, subject to constraints on the inputs and outputs and control action values. Extensive reviews of MPC algorithms and applications were addressed in the literature (Garcia, Prett, & Morari, 1989; Morari & Lee, 1999; Qin & Badgwell, 2003).

In the usual formulation, the cost function with input targets and output control zones is given in (1). The first term takes into account the sum of square errors along the prediction horizon between the predicted system output and the output set point, which is a decision variable of the control problem in the control zone strategy. The second and third terms penalize the total control moves and the deviation between the inputs and input targets over the control horizon, respectively

$$\min_{\Delta u_k, y_{sp,k}} V_k = \sum_{j=0}^{p} \left\| y(k+j/k) - y_{sp,k} \right\|_{Q_y}^2 + \sum_{j=0}^{m-1} \|\Delta u(k+j/k)\|_R^2 + \sum_{j=0}^{m-1} \|u(k+j/k) - u_{des}\|_{Q_u}^2 \quad (1)$$

where $\boldsymbol{Q_u} \in \Re^{nu \times nu}$, $\boldsymbol{Q_y} \in \Re^{ny \times ny}$, $\boldsymbol{R} \in \Re^{nu \times nu}$ are positive definite weighting matrices, p is the prediction horizon, m is the control horizon, $\boldsymbol{u}_{des}$ is the vector of input targets, $\boldsymbol{y}(k+j/k)$ is the output prediction at time instant $k+j$, $\boldsymbol{y}_{sp,k}$ is the output set point, $\Delta\boldsymbol{u}(k+j/k)$ is the vector of input increments at time instant $k+j$, $\Delta\boldsymbol{u}(k+j/k) = \boldsymbol{u}(k+j|k) - \boldsymbol{u}(k+j-1|k)$, and $\boldsymbol{u}(k+j/k)$ is the input value at time instant $k+j$, nu is the number of inputs and ny is the number of outputs of the system. The control problem with the objective defined in (1) is subject to constraints on $\boldsymbol{\Delta u}(k)$, $\boldsymbol{u}(k)$ and $\boldsymbol{y}(k)$ that represent physical constraints on control actions, input and output values, respectively

$$-\Delta\boldsymbol{u}_{max} \le \Delta\boldsymbol{u}(k+j|k) \le \Delta\boldsymbol{u}_{max}, \quad j = 0, 1, \ldots, m-1 \quad (2)$$

$$\boldsymbol{u}_{min} \le \boldsymbol{u}(k+j|k) \le \boldsymbol{u}_{max}, \quad j \in \mathbb{N} \quad (3)$$

* Corresponding author.
E-mail addresses: andre.yamashita@usp.br (A.S. Yamashita), pauloalexandre@maua.br (P.M. Alexandre), zanin@petrobras.com.br (A.C. Zanin), odloak@usp.br (D. Odloak).

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$$\boldsymbol{y}_{min} \leq \boldsymbol{y}_{sp,k} \leq \boldsymbol{y}_{max} \tag{4}$$

The decision variables of the optimization problem defined through (1)–(4) are the control sequence $\Delta\mathbf{u}_k = [\Delta\mathbf{u}(k|k)^T \ \ \Delta\mathbf{u}(k+1|k)^T \ \cdots \ \Delta\mathbf{u}(k+m-1|k)^T]^T$ and $\mathbf{y}_{sp,k}$ is a variable set point that must lie inside the control zone as defined in (4).

The set of parameters defined by $\boldsymbol{Q}_y$, $\boldsymbol{R}$, m and p are the usual tuning parameters that affect closed-loop MPC performance

Choosing the tuning parameters appropriately is not trivial and many strategies to obtain the optimal set of parameters have been developed in the literature. Garriga and Soroush (2010) reviewed the available tuning methods. Tuning strategies for p, m, $\boldsymbol{Q}_y$, $\boldsymbol{R}$, as well as the parameters related to a state observer (the covariance matrix and the Kalman filter gain) were compared. Reliable guidelines for m and p were established, however selection of $\boldsymbol{Q}_y$ and $\boldsymbol{R}$ is still open for discussions. For example, Shridhar and Cooper (1997, 1998) derived an analytical expression for $\boldsymbol{R}$, by approximating the system model by first-order-plus-dead-time transfer functions and setting the conditioning number of the hessian matrix of the control problem, posed as a quadratic programming problem, to 500. This value indicates an acceptable tradeoff between performance and robustness, but the tuning method cannot contemplate output tracking performance goals directly.

A multiobjective tuning technique was proposed in Exadaktylos and Taylor (2010). The tuning goals are defined as the minimization of the integral of the absolute errors between the closed-loop system output responses and first-order-plus-dead-time reference trajectories. In their approach, two optimization problems are solved simultaneously: one master problem that optimizes the tuning parameters $\boldsymbol{Q}_y$ and $\boldsymbol{R}$ and a secondary problem that internally solves the MPC problem, to calculate the closed-loop responses. The technique is computationally expensive, even though it was designed for offline MPC tuning. Another multiobjective technique designed for robust tuning was introduced by Júnior, Martins, and Kalid (2014). The tuning goals contemplate both the output deviations from their set points and the summation of the control effort over a simulation horizon. Assuming an additive uncertainty scenario, tuning is performed for the worst-case model, which is chosen based on the system transfer function matrix condition number and the Morari Resilience Index (Morari, 1982). The approach contemplates $\boldsymbol{Q}_y$, $\boldsymbol{R}$, p and m since the optimization problem is posed as a mixed-integer nonlinear problem.

Some effort has been directed to force the predictive controllers to follow reference output trajectories, instead of set points. In Charest and Dubay (2014), the authors employ continuous linear trajectories multiplied by a correcting factor that eliminates tracking offset. The performance superiority over Generalized Predictive Control and Dynamic Matrix Control is demonstrated through simulation and experimental results, however the technique is still dependent on the tuning of both the correcting factor and parameters Q_y and R. Piecewise continuous reference trajectories were utilized in Ren and Beard (2004) to derive controllers based on Lyapunov functions for time-varying input constraints.

In the control of batch processes, besides the issue of following set point trajectories, measurements regarding product quality are usually not immediately available, and models based on previous batch data are utilized to establish relationships between readily available measurements and manipulated variables and batch quality variables. Golshan, MacGregor, Bruwer, and Mhaskar (2010) proposed a system model based on Principal Component Analysis whereas Wan, Marjanovic, and Lennox (2012) utilized a projection to latent structures model to predict the behavior of critical variables. In batch processes, it is important to forecast the batch product quality and be able to make corrections through variable manipulation if the predicted result is not sufficiently close to the expected result. Thus, trajectory tracking predictive controllers play an important role in batch processes. However, the control strategy is still dependent on the appropriate selection of tuning parameters. Regarding the control of batch processes, it has been reported in the literature a different approach to achieve a specified product quality by means of a data-driven predictive control framework (Aumi, Corbett, & Mhaskar, 2012; Corbett, Macdonald, & Mhaskar, 2013). Non-linear models derived from detailed first-principle models predict the batch reactor behavior more accurately than the linear models in MPC, yielding significant less error in the number average and molecular weight average of key components (Corbett et al., 2013).

Trajectory tracking is also an important topic in the robot control area. Klančar and Škrjanc (2007) defined the reference trajectory as a smooth twice-differentiable function of time with known dynamics. Experimental results showed that on one hand, the proposed approach is more flexible than the conventional state-tracking controller, thus allowing better control but on the other hand, its performance is dependent on the tuning variables. Farrokhsiar, Pavlik, and Najjaran (2013) developed a dual control strategy in which the optimum control moves are calculated by a MPC and an ancillary control with inner feedback robustifies the desired trajectory to account for uncertainty. The control performance is still prone to parameter tuning.

In this paper, an extension of a state-space model based MPC (Santoro & Odloak, 2012) is proposed, in which closed-loop performance is defined in terms of the desired behavior of system outputs instead of the selection of $\boldsymbol{Q}_y$ and $\boldsymbol{R}$. The latter are only necessary for numeric conditioning of the control problem, posed as a constrained optimization problem as in the conventional MPC literature. The main contribution of this work is to extend the existing methods that consider a reference trajectory for the output tracking (Richalet, Rault, Testud, & Papon, 1978; Rossiter & Kouvaritakis, 1998) to the case of zone control and input targets. The approach assumes that, as in most commercial MPC packages, the control function is displaced in two layers, a static layer that optimizes the predicted steady-state and a dynamic layer that incorporates the concept of zone control and input targets. The approach also provides a MPC embedded with straightforward tuning guidelines, in which the behavior of its closed-loop performance is determined by a performance factor, independent of $\boldsymbol{Q}_y$ and $\boldsymbol{R}$. Wallace, Pon Kumar, and Mhaskar (2016) propose a MPC tuning strategy, based on a two-tier control structure in which the first tier calculates the best achievable performance subject to input constraints and the second tier implements the control actions related to the previously obtained performance. However, their method was not devised for MPC with zone control.

The paper is structured as follows: Section 2 describes the finite horizon MPC with output zone control and input targets formulation, based on an incremental state-space model. Section 3 presents case studies to demonstrate the efficiency of the proposed approach, and how it makes MPC tuning easier and more straightforward. The third case study illustrates the integration of a MPC with the proposed tuning approach and the Real Time Optimization through the inclusion of the static layer that, at each sampling time, calculates input targets that are as close as possible to the original input targets produced by the RTO layer but respecting the input and output constraints at the current operating point of the system (Marlin & Hrymak, 1997). Finally, some conclusions are drawn in Section 4.

2. Finite horizon reference tracking MPC

It is assumed that the system with ny outputs and nu inputs can be represented by a linear state-space model as in (5)