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Generalized predictive control tuning by controller matching

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ABSTRACT

This paper presents a tuning method for the model predictive control (MPC) based on the transfer function formulation, also known as generalized predictive control (GPC). The aim of the method is to find the tuning parameters of GPC to obtain the same behavior as an arbitrary linear-time-invariant (LTI) controller (favorite controller). The approach consists of two steps. The first step matches GPC gain to that of the favorite controller by equating the respective coefficients of the transfer function of the control law to those of the favorite controller. This step is followed by finding the weighting matrices in the cost function that will result in the GPC gain which is obtained in the first step. This proposed tuning approach does not require either loop-shifting techniques to deal with non-strictly-proper favorite controllers or equal prediction and control horizons as in conventional inverse optimality problems. In this paper, we also extend the method to the feed-forward case, which is seldom considered in standard reverse-engineering tuning methods. The feasibility conditions of the matching of a GPC with a favorite controller are analyzed and the limitation in control space the GPC can span with different tuning settings is shown. The proposed tuning method is demonstrated on a binary distillation column example.

1. Introduction

Model predictive control (MPC) is an established advanced process control technology and has been a standard tool for implementing multivariable constrained control in process industries. Broadly speaking, MPC technology refers to a class of control algorithms which solve an optimization problem subject to system constraints and explicitly uses a process model. Since its introduction in [1], theoretical developments and practical applications have progressed steadily and the technology has also been adopted by application domains other than traditional process industries [2,3].

Despite its flexibility in formulating the control problem and its broad and growing number of applications, MPC as a technology exhibits an uneven success rate across the process industry [4]. One of the major reasons for this is the lack of monitoring and maintenance of MPC systems leading to performance deterioration [5]. There could be several reasons for performance degradation such as model deterioration, change of operating conditions and disturbance characteristics. The shortage of skilled process engineers who can provide maintenance support is also a contributing factor. Factors like these, in most cases, lead to switching off MPC completely and returning to manual operation. In order to circumvent such shortcomings, a support strategy addressing the performance-related aspects of MPC in a systematic way is critical.

The performance of MPC and maintaining this performance require successful completion of several steps ranging from control structure selection to model adaptation as well as the MPC tuning [4]. For example, the closed-loop performance could be affected by a change in the plant dynamics [6] or disturbance characteristics. In such cases, re-tuning or auto-tuning the MPC can be considered as a solution to the restoration of performance [7,8] as obtaining a new model can be costly. This paper contributes to the MPC tuning problem which is currently addressed by practitioners in an ad-hoc manner.

The tuning of MPC involves selecting the parameters in the cost function, the disturbance model and the state observer if the state-space formulation is used. There are various approaches to the tuning of MPC. Garriga and Soroush [9] report that majority of the studies on MPC tuning fix the prediction horizon at a value that covers the main dynamics of the open-loop system, and select the control horizon based on computational capacity. Garriga, Trierweiler, and Lee and Yu [10–12] tackle the tuning problem by analyzing the performance

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specifications of MPC such as closed-loop poles, robustness and sensitivity functions. Maurath et al. [13] and Shridhar and Cooper [14] find the tuning parameters by considering the conditioning of the control law.

A very active research topic in MPC tuning is controller matching, which aims to compute the tuning parameters such that MPC matches an arbitrary LTI controller, also referred to as the favorite controller. The motivation for this approach is to interpret the available degrees of freedom in the MPC cost function while the constraints are inactive, which is not straightforward [15]. When MPC operates closely to the constraints and when active constraints occur frequently, the system will take advantage of the traditional ability of MPC. When MPC operates away from the constraints (e.g. at commissioning), the system can inherit the characteristics of an LTI controller, e.g. its robustness.

The matching of MPC with an LTI controller when MPC is formulated based on the state-space models has been investigated by several authors [15–20]. In such a formulation, the unconstrained solution of MPC can be written as a state feedback control law and the aim of the matching is to minimize the error between the state feedback gain of the favorite controller and that of MPC. The foundation of this approach is the inverse problem of linear optimal control, laid by Kalman [21] and Anderson and Moore [22]. This problem aims at finding the weighting matrices of the linear quadratic regulator (LQR) in order to match a given linear feedback gain. The inverse optimality problem is extended to a more general cost function in [23] with a cross-product term between the state and the control input. In [17], a matching method based on formulating an optimization problem with linear matrix inequality (LMI) or bilinear matrix inequality (BMI) constraints is proposed. The cost function of the optimization problem is the error between the control action of the MPC and the favorite controller. The above matching methods based on the inverse problem of linear optimal control usually consider the case in which the MPC is equivalent to an LQR and the states of the system are available.

In many applications, the states of the system are not measurable and the use of a state observer is required. In [16], the observer is designed with the loop-shaping procedure introduced in [24] and the tuning parameters of MPC are found by investigating the inverse problem of the normalized left co-prime factorization (NLCF) optimal control. In [20], separate designs of the robust observer and state feedback gain are used for the matching purpose, and non-convex optimization techniques are employed to perform the matching when the terminal weight is not used. Chmielewski and Manthanwar [19] investigate the inverse optimality with Kalman filter augmentation and shows how to make MPC match the minimum variance covariance constrained control (MVC).

In [25], it is shown that robustness is not guaranteed even when one attempts to design a “good” observer and a state feedback gain. Based on this observation, Hartley and Maciejowski [15] make use of the observer realization techniques described in [26] to divide a favorite controller into the observer part and state feedback part before performing the matching. A major drawback of this approach is that if a favorite output feedback controller contains a feed-through term from the outputs to the control inputs (i.e. a non-strictly-proper controller), loop-shifting techniques must be used to “transfer” the feed-through term to the dynamics of the plant so that the matching is feasible. Introducing some assumptions, Hartley and Maciejowski [18] have proposed a solution to the problem by considering the feed-through term in the framework of reference tracking.

Due to the nature of the inverse optimality problem [21–23], the controller matching is often studied with a state-feedback MPC law and an observer design. Nevertheless, MPC can also be formulated by transfer functions and this formulation is also well adopted by several MPC providers in process industry [27]. The MPC based on transfer function models (GPC) was introduced in [28,29] and further developed in [30]. Although there is certain equivalence between the GPC and the state-feedback MPC, there are differences in formulating the cost function and computing the solution.

Several studies have also been reported in literature for the tuning of GPC. Shah and Engell [31,32] proposed a tuning method such that the poles and zeros of the closed-loop system approximate certain desired ones. Shah and Engell [33] make use of optimization techniques to find an output feedback gain that minimizes the difference between the closed-loop behavior of the GPC and the desired behavior in the frequency domain. In that work, the tuning parameters are found by solving a convex optimization problem with LMI constraints. The approach is limited to the case where the control horizon is 1. Other tuning rules for the weighting matrices in GPC in literature are quite heuristic. Clarke and Mohtadi [34] show how the horizons and weighting factors affect the stability of GPC. They suggest choosing an input weight of 0 or a small value and augmenting the plant with an auxiliary model to achieve robustness and to perform pole-placement. This tuning approach is applied to a paper machine benchmark in [35]. Yoshitani and Hasegawa [36] heuristically set the input weight to 0.6 in the GPC for their heating furnace in continuous annealing to achieve a satisfactory performance. Karacan et al. [37] use the default values in [34] for the horizons of the GPC and varies the input weight to compare the simulated output error of the system at different tuning settings. Yamamoto et al. [38] fixes a long horizon and a control horizon of 1 and heuristically chooses the input weight based on the corresponding complementary sensitivity function. The criterion for finding a suitable input weight is based on small gain theorem [39] and therefore information on the model uncertainty is required. Banerjee and Shah [40] show that by increasing the input weight, the controller is de-tuned and becomes more sluggish and robust. Therefore, an input weight higher than 1 and lower than 2 is proposed to guarantee some level of robustness while guaranteeing the closed-loop nominal performance.

The focus of this paper is to propose a systematic tuning method for GPC that matches a GPC with a favorite controller when the constraints are inactive. Instead of using optimization techniques, we solve a set of linear equations to find the output feedback gain of GPC. To this end, the rank conditions of coefficient matrices are investigated. Once the rank conditions are fulfilled, an output feedback gain that guarantees the matching can always be found. Then, a convex optimization problem with LMI constraints similar to [17] is used to find the tuning parameters which provide the computed output feedback gain. The degrees of freedom of the convex optimization problem are increased by extending the objective function of the GPC with cross-product terms between the outputs and inputs. The proposed approach does not require any loop-shifting technique to tackle the feed-through term from output to input in the controller and also allows a control horizon greater than 1.

Moreover, in many studies on reverse-engineering tuning methods [15–17,20,31–33], the measurable disturbances in MPC are not considered. The observer realization in [26] did not tackle the feed-forward control either, which may pose limitations on the matching of the state-space MPC. In this work, the matching of the transfer functions can also be used for matching the feed-forward control in the favorite controller.

This paper is organized as follows. Section 2 presents the formulation and notations used throughout the paper. Section 3 presents the problem formulation and Section 4 provides the method to find the output feedback gain for the matching. The approach to the computation