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Development and application of a model-plant mismatch expression for linear time-invariant systems☆

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ABSTRACT

When a plant and its controller are sufficiently linear and time-invariant so that they can be represented by transfer functions, and this plant is under classical control (meaning the controller can also be represented by a transfer function), the model-plant mismatch (MPM) that often plagues industrial processes can be written as a closed-form expression. This includes a variety of controllers, among which the ubiquitous Proportional, Integral and Derivative (PID) controller. The MPM expression can then be used to identify a representative transfer function of the "true plant" from the currently available plant model. The MPM expression works for single-input single-output as well as multiple-input multiple-output systems. The closed-loop data required for application of the expression has to be sufficiently exciting. If significant disturbances perturb the plant their values need to be available. In this article the expression is applied to industrial data to show its applicability.

1. Introduction

The situation where only poor process models are available for control is a common one. When there is a notable difference between a process and the available model of the process, it is said that model-plant mismatch (MPM) is present. This situation is not only common, but will usually contribute to deteriorated controller performance. The availability of poor process models is known to be a source of poor control performance, in fact this is listed as one of the most significant reasons for poor control performance in the minerals-processing industry by [1]. The fact that MPM is however not limited to the minerals-processing industry is a reason why research into this area has received some focus in the recent past [2].

For processes where only poor models are available, [1] states that the peripheral control tools are as important as the controller itself. Peripheral control tools constitute all the elements in the control loop, other than the controller itself, that function to improve controller performance. These include fault detection and isolation, data reconciliation, observers, soft sensors, optimisers and model parameter tuners. Some of these peripheral tools are addressed for an ore grinding mill circuit in [3–5].

Many controller design methods make use of a plant model. A good plant model usually helps to improve controller performance, but the dynamics of industrial processes can change significantly over time (as is shown for the example of a milling circuit in [6]). As soon as the plant dynamics change, MPM is present and the controller designed based on the original model will produce sub-optimal control moves. Examples of the sources of changes in plant dynamics are maintenance or equipment changes as well as changes in operating conditions or parameters. In order to restore the controller performance the process needs to be re-identified and the controller redesigned, which is a costly and time-consuming exercise [7]. Apart from the formerly mentioned problems, process re-identification also often involves intrusive plant tests that disturb the normal operation of the plant [2].

An alternative to full process re-identification is to firstly identify the elements in the process transfer function matrix that contain significant mismatch and to only re-identify these. Algorithms for MPM detection have been proposed by [2] and [8]. These algorithms identify the transfer function matrix elements that contain mismatch as well as the significance of the mismatch. This is useful information that can be used to help assess the need for process re-identification. These algorithms do however not supply any

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additional information about the “true plant”, hence there is still a need for process re-identification (although not as expensive as full process re-identification) and ad-hoc controller re-tuning.

Model identification techniques that make use of closed-loop data have been introduced some time ago (see for example [9] and [10]). A good overview of closed-loop identification is given by [11] in which different closed-loop identification techniques are discussed and their characteristic properties are compared. The methods described by [11] are mostly based on statistical approaches and do not make explicit use of the transfer functions representing the system, unlike the method presented in this article. A more recent approach to on-line closed loop identification is given in [12]. Here the joint plant and controller model is identified using subspace model identification, and thereafter the plant model is separated assuming the controller model is known *a priori*.

This paper presents a closed-form expression for the model-plant mismatch (as first derived in [13]), which can be used to update the model such that it may be representative of the actual plant. This expression is shown to work for multiple-input multiple-output (MIMO) systems. The main difference between this article and [13] is the application of the MPM expression to industrial data.

Although this method is related to closed-loop identification, it does make use of the explicit expression for the mismatch to identify the representative plant model. This implies that the model structure is known *a priori* and can simply be updated through the mismatch expression.

The most common form of advanced control in the process industry is linear model predictive control [14]. Implementing a linear MPC requires a linear process model, typically in the form of an LTI transfer function. Most plants that use advanced control will therefore at some point have a good, representative model of the process. Making the previously known transfer function the starting point for the method is therefore a justified decision, as this is commonly available.

The sources of mismatch mentioned earlier are either due to discrete events (such as plant shut-downs) or e.g. slowly degrading instruments that cause the model to slowly drift over time. It is therefore sufficient to make use of this method after such events (depending on their frequency) or at certain times when the control performance has deteriorated. This supervised approach is preferable for processes where this is the case, rather than on-line model tracking, which would be preferable in processes where the model may change drastically at a high frequency.

The newly identified model may then be used to update the controller, such that it can perform in an optimal manner. The expression is however only valid for systems that contain a controller and plant model that can be expressed by means of transfer functions. This does include an array of controllers, but probably most importantly it includes PID controllers.

PID control is still very predominant in the processing industry. An industrial survey on grinding mill circuits by [15] found that more than 60% of the respondents make use of PID control, which implies a large scope for implementation of the presented expression.

Another limitation on the expression is that it requires the input signals to be sufficiently exciting in order to make the implementation sensible. This limitation is however also present for the MPM detection algorithms presented by [2] and [8], and also for most plant identification methods.

The requirement for sufficient excitation means that either sufficiently large (and known) changes are required for the independent variables (such as achieved with sizeable set-point changes) or sufficiently large (and known) disturbances should be present, or both. The expression handles known disturbances directly, but does not handle unknown disturbances. If it is unavoidable to use data without the presence of large unmeasured disturbances their values should first be estimated for example by making use of a Kalman filter ([16]). If this is not possible, the MPM expression described in this paper may not yield the desired results.

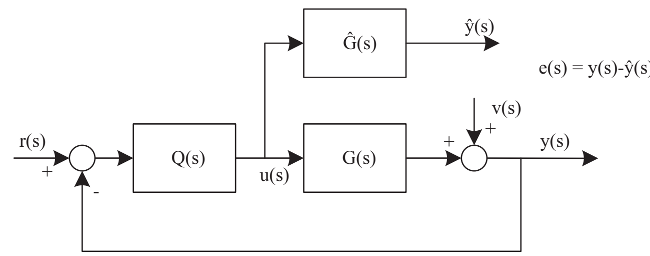

Fig. 1. Block diagram of a control loop with model outputs being generated.

Identifying the mismatch in the manner proposed in this paper is equivalent to identifying the additive uncertainty in the model [17], where the additive model uncertainty is also expressed as the difference between the plant and the model. Another possibility is presented by [18] where the output multiplicative uncertainty is explicitly defined by matching the output of the uncertainty model to the outputs of a set of known models.

The paper firstly presents the derivation of the MPM expression and shows how the representative transfer function model of the true plant may be obtained from it. Thereafter the expression is used in a MIMO application example to show its usefulness. Finally the expression is applied to industrial data and the representative plant transfer function is calculated by means of the MPM expression.

2. Model-plant mismatch expression

Consider the one degree of freedom, negative feedback control loop shown in Fig. 1 in which all signals and transfer functions are represented in the Laplace domain. G is the plant that generates the true output $y(s)$, $\hat{G}$ is the model of the plant that generates the model output $\hat{y}(s)$, Q is the controller, $v(s)$ is any disturbance that may be present and $r(s)$ is the reference signal (set-point).

The derivation of the MPM expression which follows is done for a general MIMO system in which all signals may be vectors and all transfer functions may be matrices. G, $\hat{G}$ and Q are all continuous-time, linear time-invariant (LTI) systems, represented in the Laplace domain. G and $\hat{G}$ have the dimensions $n_y \times n_x$ and Q has the dimensions $n_x \times n_y$. y, $\hat{y}$, r and v are $n_y \times 1$ vectors and u is an $n_x \times 1$ vector. For this derivation the number of manipulated variables in the controller must equal the number of controlled variables in the plant, and consequently $n_x = n_y$.

The reference to the Laplace operator (s) will be dropped for ease of representation. Let the residual (e) be the difference between the actual output and the model output as

$$e = y - \hat{y}, \tag{1}$$

$$e = Gu + v - \hat{G}u, \tag{2}$$

$$e = \Delta_M u + v, \tag{3}$$

where $\Delta_M = G - \hat{G}$ is the mismatch. This definition for the mismatch is equivalent to the definition for additive uncertainty presented by [17,p. 293]. During this derivation however Δ_M is used to represent uncertainty of any magnitude, as opposed to the weighted uncertainty with a restriction on the maximum singular value in [17] $(\bar{\sigma}(\Delta(j\omega)) \leq 1)$. The control signal $(u(s))$ is given by

$$u = Q\,(r - y)\,, \tag{4}$$

$$u = Q\,(r - [Gu + v])\,, \tag{5}$$