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Impact of model plant mismatch on performance of control systems: An application to paper machine control

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ABSTRACT

Model-based controllers based on incorrect estimates of the true plant behaviour can be expected to perform poorly. This work studies the effect of model plant mismatch on the closed loop behaviour and system performance for a certain class of MIMO systems. Performance is measured using a minimum variance index and a closely related user-specified criterion. We study the effect of model plant mismatch on the output variance and performance indices. Under mild assumptions, the performance of each output in a MIMO system can be analysed independently. Moreover, we propose an approach to distinguish the effect of model–plant mismatch from the effect of changes in disturbance characteristics on closed-loop performance. We define a sensitivity measure that relates system performance to model–plant mismatch, and use it to explore this sensitivity for three realistic types of parametric modelling errors. Next, we suggest a quantitative method that compares a system's actual output to its desired response in a transient setting. The performance of the transient response is demonstrably more sensitive to the model–plant mismatch than the steady state performance. The results are illustrated on industrial paper machine data.

1. Introduction

Performance of industrial control systems must be monitored continuously to maintain product quality. In this work, the term performance refers to the magnitude of perturbations in process outputs. In process industry, these perturbations are mainly caused by stochastic unmeasured disturbances and the control objective is to minimize the effect of the disturbances on process outputs. Harris, Seppala, and Desborough (1999), Huang and Shah (1999) and Joe Qin (1998) present comprehensive surveys of performance assessment techniques for both univariate and multivariable systems. The most popular benchmarks are based on (a) minimum variance control (MVC) and (b) user-specified control benchmarking. These techniques are widely used in industry. Applications of performance assessment techniques to pulp and paper processes are given by Lynch and Dumont (1996), Desborough and Harris (1994), Jofriet and Bialkowski (1996) and Owen, Read, Blekkenhorst, and Roche (1996). These approaches are used to detect poor performance of control systems by comparing the actual output variance with a specific benchmark defined based on the type of performance monitoring algorithm. Model–plant mismatch (MPM) is one of the causes of deterioration in performance of control systems; especially, model based control systems, e.g., model predictive control (MPC). Therefore, the sensitivity of the performance indices to MPM, which shows the ability of the indices to reveal MPM, is of utmost importance.

It is easy to observe that the typical performance indices depend on the model used to design a controller. However, there is scant literature on understanding the effect of MPM on minimum variance and user-specified performance indices. For instance, Yousefi et al. (2014) analyse the sensitivity of the various performance indices to different types of parametric MPM. They show that mismatch in different parameters influences the indices differently. However, there is a lack of explanation for their observations.

There are also few articles on MPM detection in control systems using other approaches. For instance, in Wang, Hagglund, and Song (2012), where Wang et al. analyse the influence of model–

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plant mismatch on control loop behaviour. They introduce Integral Absolute Error (IAE) index to measure performance of control systems to detect MPM. They claim that the smaller the index the better the performance. Indeed, they show that MPM increases IAE index. However, they do not define any benchmark to compare the index with. In fact, it is not clear what the index should be under normal operating conditions.

Badwe, Patwardhan, Shah, Patwardhan, and Gudi (2010) define a Relative Sensitivity Index (RSI) by comparing an actual sensitivity function with a designed sensitivity function to quantify the impact of model plant mismatch. This index is defined as follows:

$$RSI = \left\| \frac{S_a}{S_d} \right\|_\infty \quad (1)$$

where S_a is the actual sensitivity function and S_d is the designed sensitivity function. To calculate the above index, we only need to estimate S_a. They (Badwe et al., 2010) show that in the presence of MPM in a closed loop system, the *RSI* is greater than 0 db. They use closed loop information to estimate the actual sensitivity function. To do so, there must be set-point changes in the closed loop system. However, in industry, set-point changes do not happen often and most control systems work in regulatory mode. So, RSI cannot be reliably estimated online to monitor the closed loop performance.

The main objective of this work is to quantify the sensitivity of the performance indices to mismatch between a multivariable plant and the MIMO model used in its controller. Yousefi et al. (2014) performed similar analysis for SISO systems. In this paper, we show that MPM affects the closed-loop sensitivity function, and consequently, the output variance as well. We address the question of why the performance indices are more sensitive to certain types of MPM than others. In principle, the performance of each output in a MIMO system can be affected by modelling errors in every single element of the transfer function matrix representing the process model. In this paper, we identify conditions under which MPM in an element of the transfer matrix only deteriorates the performance of the associated output but does not effect the performance of other outputs. In such cases, the performance of each output can be analysed independently.

For a given controller, the sensitivity analysis lets us assess the effectiveness of the performance indices in detecting model–plant mismatch of various types. Since the indices are calculated using the steady-state response (regulatory mode) of control systems, they turn out to be insensitive to certain types of parametric mismatch, such as mismatch in time constants. However, we observe that model–plant mismatch has a stronger effect on a system's transient response (servo control mode). We propose a technique that uses transient response to measure controller performance. This analysis provides diagnostic information that helps identify the type of mismatch between the plant and the model. Such diagnostic information on the cause of poor performance can provide useful guidance for intervention, perhaps by focussing the goals of a re-identification experiment. The sensitivity of the performance assessment techniques to model–plant mismatch is analyzed through simulations on a model predictive controller operating on a paper machine.

This paper is organized as follows. In Section 2, we briefly review two widely used performance assessment techniques for MIMO systems, namely, minimum variance benchmarking and user specified benchmarking. In Section 3, we describe how MPM changes the sensitivity function and affects the output variance. In Section 4, we describe the possible decoupling between both performance criteria for different output components. In Section 5, we discuss the effect of changes in disturbance characteristics on a system's performance and propose a technique to distinguish the effect of MPM from the effect of disturbance on performance. In Section 6, we define a sensitivity function to quantify the sensitivity of the performance indices to model–plant mismatch. Also, we suggest a technique that measures the performance of control systems in servo control mode. Finally, in Section 7, we present the results of simulations and compare them with our theoretical formulations.

2. Assessment of multi-input/multi-output systems

2.1. Minimum variance benchmarking

Huang, Shah, and Kwok (1996) and Harris, Boudreau, and MacGregor (1996) use the minimum variance approach to measure performance of MIMO systems. In Harris (2009), Harris provides some interpretations of the performance bounds for such systems. Huang and Shah (1999) use a statistical signal processing approach, called the filtering and correlation (FCOR) algorithm, to estimate the minimum variance index (MVI) from raw data. In this approach, the only information needed to calculate the MVI is the measured output and the time delay of the system. As shown in Fig. 1, for a multivariable process the output vector Y_t, of dimension n, satisfies

$$Y_t = P(q^{-1})U_t + N(q^{-1})e_t. \quad (2)$$

Here U_t is the input vector in R^m, e_t is a noise vector in R^n with zero mean and $Var(e_t) = \Sigma_e$, $P(q^{-1})$ is a $n \times m$ transfer matrix representing the process model, $N(q^{-1})$ is a disturbance transfer matrix (assumed diagonal, $n \times n$), and q^{-1} is the back shift operator:

$$q^{-1}U_t = U_{t-1}. \quad (3)$$

For the sake of simplicity, the dependence on q^{-1} is not shown explicitly for most transfer functions in this paper. We decompose the matrix P in (2) as

$$P = D^{-1}\tilde{P}, \quad (4)$$

where the "interactor matrix" D^{-1} is the diagonal transfer matrix consisting of the time delays in the diagonal terms of P, and $\tilde{P}$ is the resulting delay-free transfer matrix. The interactor matrix was introduced by Wolovich and Elliott (1983), Wolovich and Falb (1976) and Goodwin and Sin (2013) for MVC and other purposes. Huang and Shah (1999) present a comprehensive survey on the characteristics of the interactor matrix.

The minimum variance control law is obtained by choosing the transfer matrix C so that the controller $U_t = -CY_t$ minimizes the objective function

$$J = E\left[(Y_t - E[Y_t])^T(Y_t - E[Y_t])\right]. \quad (5)$$

Proposition. *For any linear time invariant system with the transfer function shown in (2), the minimum value of J is*

$$J_{min} = \mathrm{tr}(Var(Fe_t)), \quad (6)$$

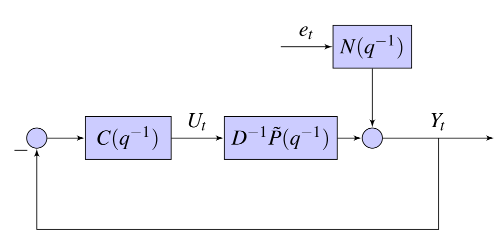

Fig. 1. The block diagram of a feedback control system.