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Detection and diagnosis of model-plant mismatch in multivariable model-based control schemes☆

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ABSTRACT

The extent of approximation in modelling a given process, characterized by the model-plant mismatch (MPM), amongst other factors, critically determines the performance of a model-based control scheme. It is necessary therefore to carry out model maintenance and correction on a regular basis. However, a complete re-identification is usually a costly exercise. Therefore, it is highly desirable to precisely determine the specific elements that are in mismatch and re-identify only those parameters. In the recent times, the plant-model ratio (PMR) was proposed as an effective metric for diagnosing MPM in single-input single-output (SISO) systems from closed loop data. The PMR facilitates unique detection of mismatch in gain, dynamics and delay. A straightforward application of PMR to multivariable closed-loop systems is challenging primarily due to the confounding effects of other inputs and loop-to-loop interactions under closed-loop conditions. Furthermore, the metric requires high-frequency excitation for identification of delay mismatch. In this work, we first present a method to overcome the latter requirement using Hilbert transform relation and partial cross-spectral densities. Subsequently, we present the key contribution of this work, that of generalizing the PMR approach to multivariable control systems. Two threshold-based hypothesis tests are presented for diagnosing mismatch in gain and dynamics. Three simulation case studies are presented to demonstrate the efficacy of the proposed method.

1. Introduction

Models are critical to the design of model-based control schemes [16] since their performance, amongst other factors, is significantly influenced by the predictions generated by the model and take corrective action accordingly. When a model is developed, usually at the commissioning stage, it is understood that the model is not exact, i.e., a non-zero model-plant mismatch (MPM) exists, due to neglected process dynamics, unmeasured disturbances, noise and/or time-varying system characteristics [5]. Moreover, these models are usually linearized approximations of non-linear processes and hence maybe valid over limited operating conditions. However, the deviations or approximation errors in modelling can grow due to changing process characteristics, operating conditions and sensor/equipment degradation. The MPM then naturally becomes a significant detriment in the closed-loop performance. It is, therefore, necessary to detect MPM on a regular basis and correct it through a re-identification exercise. However, the associated tasks can be usually *expensive* in terms of time and effort,[1] particularly for systems with large number of inputs, as it would require intrusive plant tests. Therefore, it is of value to develop a method that determines the source(s) of MPM (which result in poor loop performance) using routine operating data and re-identify only the concerned subsystems or elements of the models. Such a method should take into consideration its suitability to the control system's objectives (the information content), its plant-friendliness (causing minimum process disruption), and its complexity (computational effort and a priori process knowledge) [8].

Performance of control loops depends on several factors such as controller tuning, actuator non-linearities, sensor/equipment degradation, changing disturbance characteristics and extent of model-plant mismatch. Control loop performance monitoring is a rich area with nearly three decades of literature that spans metrics for benchmarking to diagnosis of poor control loop performance

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[1] To the best knowledge of the authors, no work in literature has attempted to objectively quantify cost for re-identification. Any metric defined for this purpose should take into account several factors such as invasiveness, process economics, computational costs, etc.

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[9,3,10]. There exist also methods capable of isolating the source in presence of other causes. Diagnosis of performance degradation caused by model-plant mismatch is a rather nascent but evolving field. Literature in the last fifteen years points to some interesting results on this topic that range from studying the impact of MPM on control loop performance to identifying channels with significant mismatch in multivariable systems. A brief review of literature follows. Patwardhan and Shah [19] presented a benchmark specific to model predictive controllers, which compares the achieved and designed objective functions. However, this benchmark does not distinguish between model-plant mismatch and unmeasured disturbance characteristics. The impact of MPM on the achieved controller performance was studied by Badwe et al. [2], wherein the root cause of controller performance degradation is isolated by analyzing certain key closed-loop sensitivities. It was also shown that the impact of MPM on control quality depends also on the direction of setpoint change. However attempts to identify the subset of models which need re-identification are not made. A state-space domain formulation of the MPM problem for multivariable processes controlled by MPC controllers was presented by Jiang et al. [11]. The objective of their work was to determine the state-space matrices that have significant mismatch. A major shortcoming of the approach therein is that there exists no unique mapping between mismatch in specific subsystems or elements of their models and the state-space matrices. Furthermore, delay mismatch cannot be detected by such an approach since changes in delays manifest as increase/decrease in the order of discrete-time state-space models.

Input–output model representations provide a suitable framework for directly mapping poor control-loop performance to changes in process characteristics. Stanfelj et al. [25] examined the correlation between model residuals and the input/setpoint (dither signal) for detecting MPM in SISO systems for the cases of output corrupted by white and coloured noise, respectively. The method was extended to MIMO systems Webber and Gupta [27] in order to detect those rows and columns of the transfer function matrix that have significant mismatch. Badwe et al. [1] proposed a method for detecting channels with significant mismatch in MIMO systems from routine-operating data using partial correlation functions between the model residuals and inputs. Computing partial correlations is equivalent to decoupling an $n \times n$ MIMO system into n^2 SISO systems, thereby allowing one to detect the mismatch in each of the subsystems. In the work by Kano et al. [12], the MPM problem is formulated in terms of an impulse-response model, where a mismatch score is computed to select those sub-models of the system that suffer from significant MPM.

A significant shortcoming of the aforementioned works is that they do not attempt to identify the type of mismatch (mismatch in gain, dynamics, or delay) within each input–output channel, i.e., a finer zoom-in capability is missing. This can be attributed to the fact that in all the works, MPM is represented as an additive uncertainty. Such a representation is conventional and useful in robust control design [24]. However, its utility in diagnosing the source of MPM is limited as the mapping between different types of mismatch, i.e., gain, dynamics and delay mismatches, and the additive uncertainty is mathematically complicated. Representing the MPM as multiplicative uncertainty, in contrast, provides a simpler and unique way of identifying the type of mismatch. Furthermore, it is natural to work in the frequency-domain since the gain, dynamics and delay characteristics of an LTI system are nicely decoupled in the frequency response function. With this viewpoint, Selvanathan and Tangirala [22] introduced a quantity known as the plant-model ratio (PMR) for SISO systems based on multiplicative uncertainty in the frequency domain. The PMR is, in fact, another transfer function that relates the process output to model predictions. The main feature of a PMR is that there exists a unique mapping between the frequency-domain properties of PMR, namely, the magnitude and phase of PMR, and the mismatch in gain, time constant, and delay. Based on this mapping, a methodology for diagnosis of mismatch in the frequency domain was developed. A estimation procedure for estimating PMR from closed-loop data was also proposed. The method requires *sufficient excitation* in the setpoint and is based in the internal model control setting. The PMR-based approach was further refined by Kaw et al. [13] to (i) design a sinusoidal setpoint dither signal with minimal excitation for the estimation of PMR and (ii) to develop a rigorous assessment procedure based on the theoretical properties of PMR.

The PMR methodology, albeit its benefits, has two important shortcomings. Firstly, detecting and diagnosing delay mismatch requires setpoint excitation in the high frequency regimes, mainly because the effects of dynamics on the phase of PMR is saturated at high-frequencies and it is only the delay mismatch that is the primary contributor. Secondly, the PMR methodology as developed for SISO systems cannot be applied in a straightforward manner to MIMO control systems for two reasons, (i) lack of a clear definition of PMR for multivariable systems (to be explained shortly) and (ii) difficulties in estimating PMR (for each channel) due to confounding from inputs in other channels (may be also viewed as interactions between loops).

The proposed work addresses the aforementioned limitations using ideas from systems theory, signal processing and statistics. We first propose a method that estimates delay mismatch from only low-frequency setpoint excitation. Furthermore, the method does not require the knowledge of mismatch in gain and dynamics. The method is based on the Hilbert transform relation-based approach combined to delay estimation in LTI systems [7,14,23]. The main idea underneath is to break up the phase of an LTI system into contributions from delay-free portion and the delay, where the former is estimated from the magnitude of cross-spectral density estimates using the Hilbert-transform relation. With this improvement over the existing PMR, we address the main objective of this paper, which is to extend the concept and methodology for diagnosing MPM in MIMO systems. A definition for MIMO systems is presented first. Subsequently, we develop a method to estimate the MPM in each channel. A major challenge encountered in estimating MPM from operating data is the confounding of input effects in a given output channel. We propose to overcome this challenge by numerically decoupling the channels using partial coherence functions. This idea has been implemented earlier in delay estimation of multivariable systems and in a different form in the work by [1]. Herein, we propose a different estimation procedure that is based on regression. Two hypothesis tests are subsequently developed to statistically determine the presence of significant MPM in each channel. The focus of this work is on parametric uncertainties; however, the proposed method can be potentially extended to the case of unstructured uncertainties.

The rest of this article is organized as follows. A brief review of PMR with a discussion of its shortcomings is presented in Section 2. The improved methodology for diagnosing delay mismatch using PMR is discussed in Section 3. In Section 4, we present the mainstay of this work, that of extending the definition and estimation methodology of PMR to multivariable systems. The proposed method is demonstrated on three simulation case-studies in Section 5. Concluding remarks with a few directions for future work appear in Section 6.

2. Preliminaries

In this section we review the concept of PMR and its estimation from closed-loop data. Subsequently, we highlight the limitations of its definition (w.r.t. MIMO systems) and the estimation method.