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IFAC-PapersOnLine 49-1 (2016) 266–271

Detection and diagnosis of model-plant mismatch in MIMO systems using plant-model ratio

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Abstract: The performance of any model-based controller depends on the quality of the model and hence on the model-plant mismatch (MPM). Model maintenance and correction is necessary to achieve desired performance. However, a complete re-identification of the model is usually a costly exercise. Therefore, it would be highly desirable to detect the precise location of the mismatch and update only those parts. The recently introduced plant-model ratio (PMR) was found to be effective in detecting and diagnosing MPM from closed loop operation data for SISO systems. The PMR facilitates a unique identification of the source of mismatch - namely gain, dynamics and delay mismatches. However, direct application of PMR to MIMO systems is a challenge due to the presence of interactions between the various input-output channels. In this paper, the PMR approach is extended to MIMO control systems. It is assumed that the control loop is driven through broadband excitation in the set-points. The key step in the proposed methodology involves decoupling interactions using partial cross-spectral density. The proposed methodology is able to detect the input-output channels with significant mismatch as well as identify the source of mismatch within these channels. The efficacy of this method is demonstrated through two simulation case studies.

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Keywords: model-plant mismatch, MIMO, frequency domain, plant-model ratio, partial cross-spectral density, model-based control

1. INTRODUCTION

Process models play an important role in any control system design. Classical control schemes use models offline in combination with well-defined tuning guidelines. On the other hand, model-based controllers (Maciejowski, 2002) use the model on-line to generate output predictions and take corrective action accordingly. Therefore, the quality of the model significantly affects the closed loop performance. It is widely accepted that uncertainties always exist in the model. Moreover, the models identified are generally linear while the processes themselves are non-linear. Therefore, the models are valid only over limited operating conditions. Over time, several changes can occur in the process, which may widen the *mismatch* with the model. This model-plant mismatch (MPM) can cause degradation in controller performance, as the predictions are no longer accurate. It is therefore necessary to periodically detect MPM and perform re-identification of the model. However, this exercise is usually costly, particularly for systems with large number of inputs, as it would require intrusive plant tests. Therefore, it would be desirable to locate the source of mismatch and re-identify only the concerned subsystems.

The diagnosis of poor control loop performance that occurs due to model-plant mismatch is an evolving field. Patwardhan and Shah (2002) presented a benchmark specific to model predictive controllers, which compares the achieved and designed objective functions. Badwe et al. (2010) studied the impact of MPM on the achieved controller performance by analyzing certain key closed loop sensitivities. The above methods indicate the presence of MPM but do not attempt to specify which subset of models need re-identification. In Jiang et al. (2004), the MPM problem is formulated in the state-space domain. The specific issue addressed here was to find elements in the state-space matrices with significant mismatch. Three MPM detection indices (MDIs) were proposed to solve this problem. Webber and Gupta (2008) extended the concept of finding correlations between the model residuals and the input (Stanfelj et al., 1991) to MIMO systems in order to detect which element of the transfer function matrix has significant mismatch. Badwe et al. (2009) proposed a method which detects channels with significant mismatch in MIMO systems from routine-operating data, using partial correlations between the model residuals and inputs. The partial correlation analysis essentially decouples the $n \times n$ MIMO system into n^2 SISO systems, and hence the mismatch in each of these sub-systems can be individually assessed. Kano et al. (2010) proposed a mismatch score to select those sub-models of a MIMO MPC system which contain significant MPM.

A major shortcoming of the above works is that they do not attempt to identify the type of mismatch (mismatch in gain, dynamics or delay) within each input-output channel. This is because their methods intrinsically represent MPM as additive uncertainty. This representation is useful for robust control design (Skogestad and

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10.1016/j.ifacol.2016.03.064

Postlethwaite, 2005). However its utility in the problem of interest is limited as the different types of mismatch manifest in a complex way and it is very difficult to identify them. On the other hand, quantifying MPM as multiplicative uncertainty provides a way of identifying the type of mismatch from the MPM. Keeping this in mind, Selvanathan and Tangirala (2010) defined a quantity known as the plant-model ratio (PMR) based on multiplicative uncertainty. They have theoretically shown that there exists a unique mapping between the properties of the PMR and the source of mismatch - namely gain, time constant and delay mismatch. They have also proposed a closed loop estimation procedure for the PMR, which requires sufficient excitation to be present in the set-point. For those systems which have no set-point excitation by default, Kaw et al. (2014) proposed a sinusoidal set-point design with minimal excitation. They have also proposed a rigorous assessment procedure based on the theoretical properties of the PMR. Notwithstanding its benefits, the PMR methodology is applicable to only SISO systems. Extension to MIMO systems is not straightforward due to the presence of closed-loop interactions.

The current work extends the PMR concept to MIMO systems for diagnosing MPM. The major challenge is to reliably estimate PMR in the presence of interactions. When the control loop is driven through broadband excitation in the set-points, the proposed method decouples these interactions using the partial cross-spectral density. While the primary focus is on parametric uncertainty, the proposed method can be potentially extended to the case of unstructured uncertainties.

The article is organized as follows. We present a review of PMR and discuss the problem statement in Section 2. Section 3 reviews the concept of the partial cross-spectral density and deals with the extension of PMR to MIMO systems. Section 4 discusses the proposed methodology to detect and diagnose MPM. The method is demonstrated through two simulation studies in Section 5. The paper concludes in Section 6.

2. PRELIMINARIES

2.1 Plant-model ratio

For SISO systems, plant-model ratio (Selvanathan and Tangirala, 2010) is defined as the ratio of the frequency response function of the plant to the frequency response function of the model:

$$\Pi_G(\omega) = \frac{G(\omega)}{\hat{G}(\omega)} = M(\omega)e^{j\Delta P(\omega)} \tag{1}$$

PMR can be interpreted as the transfer function between the model output ($\hat{y}$) and the plant output (y), as shown in Figure 1.

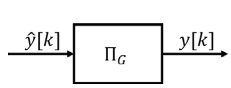

Fig. 1. Interpretation of PMR as a transfer function

Mismatch in gain affects only the magnitude of the PMR, while the mismatch in delay affects only the phase. Mismatch in dynamics (time constants) on the other hand

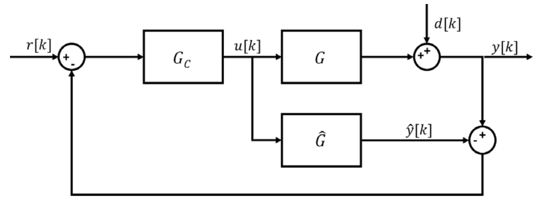

Fig. 2. Closed loop system - IMC structure

affects both the PMR signatures. In the absence of mismatch, $\Pi_G(\omega) = 1$, or, $M(\omega) = 1$ and $\Delta P(\omega) = 0$. The following assessment procedure based on the PMR signatures can be used to diagnose MPM:

(1) For no mismatch in gain: $M(\omega)|_{\omega=0} = 1$
(2) For no mismatch in dynamics: $M(\omega)$ must be flat
(3) For mismatch in delay: $\Delta P(\omega)$ must be linear

This signature-based method also identifies the sign of the mismatch: whether the actual parameter is greater or less than the corresponding model parameter.

2.2 Estimation from closed-loop data

Consider the closed loop internal model control (IMC) structure shown in Figure 2. The control loop is driven through set-point excitation. The expressions for the plant and model outputs respectively are:

$$Y(\omega) = G(\omega)U(\omega) + D(\omega) \tag{2}$$

$$\hat{Y}(\omega) = \hat{G}(\omega)U(\omega) \tag{3}$$

To efficiently estimate PMR, it is necessary to mitigate the effects of the noise. This is done by first correlating the plant and model outputs with the set-point (which is usually uncorrelated with the noise), and then calculating their ratio in the frequency domain. Therefore,

$$\hat{\Pi}_G(\omega) = \frac{\hat{\gamma}_{y,r}(\omega)}{\hat{\gamma}_{\hat{y},r}(\omega)} \tag{4}$$

where $\hat{\gamma}_{y,r}(\omega)$ is the estimated cross-spectral density between the plant output y and the set-point r.

2.3 Problem statement

For MIMO systems, the plant and model transfer functions are matrices, whose elements are individual transfer functions of the various input-output channels. The objective of the work is to identify the channels with significant mismatch and isolate the mismatch within each of these channels, when it is known that MPM is the *only* cause for performance degradation. The extension of PMR to the MIMO case is dealt in the next section.

3. EXTENSION TO MIMO SYSTEMS

The definition of PMR for SISO systems is clearly inadequate for the MIMO case. We begin by defining PMR for MIMO systems.

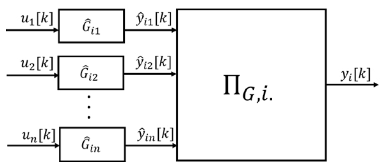

Fig. 3. Interpretation of PMR for the MIMO case

3.1 Definition

For a $n \times n$ MIMO system, the PMR matrix is defined as the element-wise division quotient between the transfer function matrices of the process and the model:

$$\mathbf{\Pi}_{\boldsymbol{G}}(\omega) = \begin{bmatrix} \frac{G_{11}(\omega)}{\hat{G}_{11}(\omega)} & \frac{G_{12}(\omega)}{\hat{G}_{12}(\omega)} & \cdots & \frac{G_{1n}(\omega)}{\hat{G}_{1n}(\omega)} \\ \frac{G_{21}(\omega)}{\hat{G}_{21}(\omega)} & \frac{G_{22}(\omega)}{\hat{G}_{22}(\omega)} & \cdots & \frac{G_{2n}(\omega)}{\hat{G}_{2n}(\omega)} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{G_{n1}(\omega)}{\hat{G}_{n1}(\omega)} & \frac{G_{n2}(\omega)}{\hat{G}_{n2}(\omega)} & \cdots & \frac{G_{nn}(\omega)}{\hat{G}_{nn}(\omega)} \end{bmatrix} \tag{5}$$

Remark: An alternate definition for PMR is $\mathbf{G}\hat{\mathbf{G}}^{-1}$. While this definition provides a convenient interpretation of PMR as a transfer function, it is difficult to identify the type of mismatch from this representation.

Before providing an interpretation for the PMR matrix, we examine the expression for the plant output y_i, and try to express it in terms of model output $\hat{y}_i$.

$$\begin{aligned} Y_i(\omega) &= \sum_{k=1}^{n} G_{ik}(\omega)U_k(\omega) + D_i(\omega) \\ &= \sum_{k=1}^{n} \Pi_{G,ik}(\omega)\hat{G}_{ik}(\omega)U_k(\omega) + D_i(\omega) \\ &= \sum_{k=1}^{n} \Pi_{G,ik}(\omega)\hat{Y}_{ik}(\omega) + D_i(\omega) \end{aligned} \tag{6}$$

where $\hat{y}_{ik}$ is the k^{th} component of the i^{th} model output ($\hat{y}_i$), corresponding to the k^{th} input (u_k).

Therefore, the i^{th} row of the PMR matrix can be interpreted as the transfer function between the n components (corresponding to the n inputs) of the model output $\hat{y}_i$ and the plant output y_i. If the inputs are uncorrelated, a plausible estimate for the $(i,j)^{th}$ element of the PMR matrix is given by

$$\hat{\Pi}_{G,ij}(\omega) = \frac{\hat{\gamma}_{y_i,\hat{y}_{ij}}(\omega)}{\hat{\gamma}_{\hat{y}_{ij},\hat{y}_{ij}}(\omega)} \tag{7}$$

However, the inputs have significant correlations due to the closed-loop interactions. These interactions can be decoupled through the partial cross-spectral density, which is reviewed in the next sub-section.

3.2 Partial cross-spectral density

The partial cross-spectral density or the conditioned cross-spectral density is the frequency domain analogue of the partial covariance function. Conditioning in the frequency domain is equivalent to *fitting a linear filter* between the variable of interest and the confounding variable(s). The partial cross-spectral density (Priestley, 1981; Tangirala, 2015) between two variables v_1 and v_2, conditioned on the variable set Z, is given by

$$\gamma_{v_1,v_2|\mathbf{Z}}(\omega) = \gamma_{v_1,v_2}(\omega) - \boldsymbol{\gamma}_{v_1,\mathbf{Z}}(\omega)\boldsymbol{\gamma}^{-1}_{\mathbf{Z},\mathbf{Z}}(\omega)\boldsymbol{\gamma}_{\mathbf{Z},v_2}(\omega) \tag{8}$$

Equation (8) is equivalent to the following two steps:

(1) Construct residuals from the best linear predictors of v_1 and v_2, with the variables in set $\mathbf{Z}$ as the predictors.
(2) Compute the cross-spectral density between the residuals to obtain the partial cross-spectral density.

Partial cross-spectral density analysis has certain advantages over its time domain counterpart, which arise from the advantages of the frequency domain. Analysis can be performed over a specific band of frequencies. This allows efficiently handling of the noise spectrum, which has effects predominantly at high frequencies.

4. PROPOSED METHODOLOGY

In this section, we discuss the estimation of PMR from operation data, using partial cross-spectral density, and the mismatch diagnosis method for each channel.

4.1 Estimator for PMR from operating data

From Equation (6), it can be seen that the confounding variables between the plant output y_i and the j^{th} component $\hat{y}_{ij}$ are the other $(n-1)$ components of the model output. We can therefore use the partial cross-spectral density to remove the effects of these variables. The proposed estimate for the $(i,j)^{th}$ element of the PMR matrix is given by

$$\hat{\Pi}_{G,ij}(\omega) = \frac{\hat{\gamma}_{y_i,\hat{y}_{ij}|\mathbf{Z}}(\omega)}{\hat{\gamma}_{\hat{y}_{ij},\hat{y}_{ij}|\mathbf{Z}}(\omega)} \tag{9}$$

where $\mathbf{Z} = \{\hat{y}_{ik}|_{k\neq j}\}$

The partial cross-spectral density decouples the $n \times n$ MIMO system into n^2 SISO systems in the frequency domain. Each of the SISO sub-systems is characterized by a unique input-output channel. Therefore, the PMR analysis for SISO system can be applied to each of these subsystems.

Remark: If the system has measured disturbance variables (DVs), they should also be included in the set of the confounding variables to remove their effects on the channel.

4.2 Set-point excitation

Since the PMR needs to be estimated at multiple frequencies, sufficient broadband excitation must be available at the set-points. This assumption can be justified, particularly in the case of closed loop MIMO systems operating under MPC where the set-points are regularly computed (Seborg et al., 2004) by a real-time optimization (RTO) layer.

Remark: The partial cross-spectral density will not be able to isolate interactions when sinusoidal excitation is provided at the set-points. This is because the variables of interest are highly correlated with the confounding variables at the excited frequencies, and hence the resulting residuals will have very low power.

4.3 Diagnosing model-plant mismatch

The diagnostic analysis performed in the SISO case can now be directly extended to each input-output channel. The following assessment procedure is used for diagnosing MPM in the $(i,j)^{th}$ input-output channel:

(1) For no mismatch in gain: $M_{ij}(\omega)|_{\omega=0} = 1$
- If $M_{ij}(\omega)|_{\omega=0} > 1$, then the gain is under-estimated.
- If $M_{ij}(\omega)|_{\omega=0} < 1$, then the gain is over-estimated.

(2) For no mismatch in dynamics: $M_{ij}(\omega)$ must be flat
- If $M_{ij}(\omega)$ initially decreases before leveling off, then the time constant(s) may be under-estimated.
- If $M_{ij}(\omega)$ initially increases before leveling off, then the time constant(s) may be over-estimated.

(3) For mismatch in delay: $\Delta P_{ij}(\omega)$ must be linear
- If the slope is negative, then the delay is under-estimated.
- If the slope is positive, then the delay is over-estimated.

Remark: In practice, the size of the data is finite. The data also has random variations due to disturbances. Therefore, it is imperative to perform the diagnostic tests statistically, which requires the knowledge of the distribution of the estimates. This requires rigorous statistical analysis, a subject that is reserved for future work. For the current work, we use heuristic thresholds as proposed by Selvanathan and Tangirala (2010), which are reproduced in Table 1.

Table 1. Emperical Thresholds

	Assessment Procedure	Heuristic Thresholds
Magnitude Mismatch	$M(\omega)\|_{\omega=0} = 1$	$M(\omega)\|_{\omega=0} \geq 1.05$ or $M(\omega)\|_{\omega=0} \leq 0.95$
Dynamics Mismatch	Test of flatness (zero slope) of $M(\omega)$ before leveling off: $M(\omega) = \alpha_\tau \omega + \beta$	$\|\alpha_\tau\| \geq 0.001$
Delay Mismatch	Linearity of $\Delta P(\omega)$: $\Delta(\omega) = \alpha_D \omega$	$\|\alpha_D\| \geq 0.9$

5. SIMULATION STUDIES AND DISCUSSIONS

The proposed methodology is applied to two simulation case studies. In case study 1, we apply the methodology to the Wood-Berry distillation column, while in case study 2, we consider a designed 3x3 MIMO system. All the results are presented in the form of magnitude and phase spectra plots of the plant-model ratio. The simulations are performed under closed loop MPC, using the MPC toolbox in MATLAB. In each scenario, random type dither signals are added to the set-points. The outputs are corrupted with white noise disturbances, while maintaining the signal-to-noise ratio (SNR) at 10. The partial cross-spectral densities are computed using Equation (9). The cross-spectral densities are computed using the Welch's averaged periodogram method (Tangirala, 2015).

5.1 Case study 1: Wood-Berry distillation column

In this case study, we consider control of the Wood-Berry distillation column. Wood and Berry (1973) have reported transfer function models of a pilot-scale methanol/water column. This system has been used extensively in the literature for the comparison of multivariate control schemes. One characteristic of this column is the *presence of strong interactions.*

The model for this column is as follows:

$$\hat{\mathbf{G}} = \begin{bmatrix} \dfrac{12.8e^{-s}}{16.7s+1} & \dfrac{-18.9e^{-3s}}{21s+1} \\ \dfrac{6.6e^{-7s}}{10.9s+1} & \dfrac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \tag{10}$$

The system is discretized using ZOH with a sampling time of 1 min. The prediction and control horizons chosen for MPC are 30 and 10 respectively. We consider two scenarios, where there are mismatches in gains and time constants. Note that the control loop is unstable in the presence of delay mismatches, and hence they are not considered in this simulation study.

Scenario 1 - Mismatch in all channels: In this scenario, mismatch is introduced in all gains and time constants of the model. The extent and direction of this mismatch is varied to show the applicability of the methodology in the presence of strong interactions. The extent of mismatch is shown in Table 2.

Table 2. Mismatch added to the channel parameters

Mismatch/Channel	1-1	1-2	2-1	2-2
$\Delta K/K_m$	40%	-22%	30%	-15%
$\Delta\tau/\tau_m$	20%	30%	-25%	-15%

The magnitude and phase spectra plots are shown in Figures 4 and 5 respectively. The phase spectra plot correctly shows no delay mismatch.

Diagnosis of gain mismatches: The estimate of $\hat{M}(0)$ correct to 3 significant digits, for the four channels is as follows:

$$\hat{\mathbf{M}}(\mathbf{0}) = \begin{bmatrix} 1.39 & 0.781 \\ 1.29 & 0.842 \end{bmatrix} \tag{11}$$

Clearly, the direction of the mismatch is correctly identified. These estimates also provide a rough indication about the extent of mismatch in the respective directions.

Diagnosis of time constant mismatches: In channels 1-1 and 1-2, which have under-estimated time constants, the PMR magnitude decreases initially until leveling off. In channels 2-1 and 2-2, which have over-estimated time constant, the PMR magnitude increases initially until leveling off. Therefore the direction of the mismatch is correctly identified.

Scenario 2: No mismatch in channel 2-2 This scenario is similar to the previous one, except that there is no mismatch in channel 2-2. The extent and direction of mismatch in the other channels is the same as in the previous case (Table 2). This scenario is designed to show that the channels with significant mismatch do not

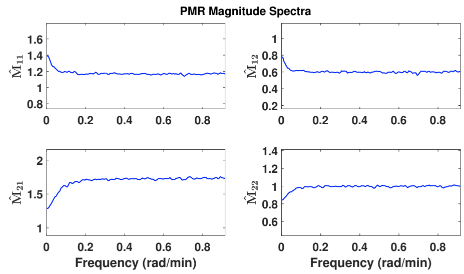

Fig. 4. Case study 1, Scenario 1: Estimated PMR magnitude spectra

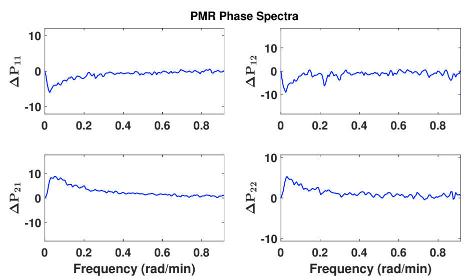

Fig. 5. Case study 1, Scenario 1: Estimated PMR phase spectra

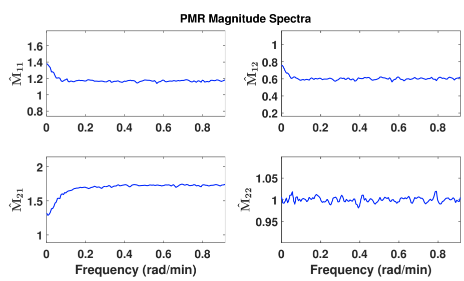

Fig. 6. Case study 1, Scenario 2: Estimated PMR magnitude spectra

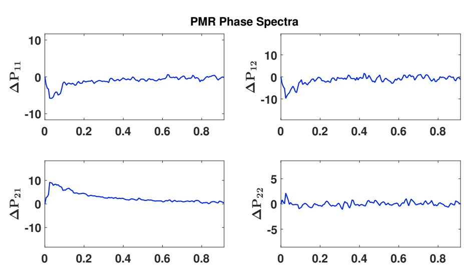

Fig. 7. Case study 1, Scenario 2: Estimated PMR phase spectra

confound the diagnosis of mismatch in the other channels. The magnitude and phase spectra plots are shown in Figures 6 and 7 respectively.

The diagnosis of mismatch in the other three channels is similar to that in the previous scenario. The only difference is in channel 2-2, where the lack of mismatch in any parameter is correctly identified.

5.2 Case study 2

In this case study, we consider a MIMO system, whose model is as follows:

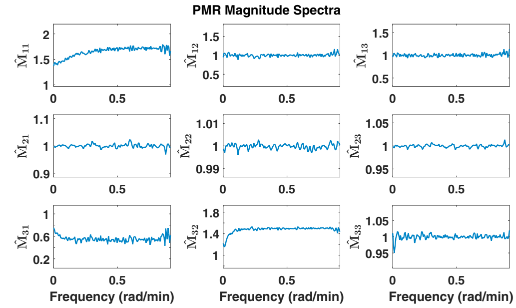

Fig. 8. Case study 2, Scenario 1: Estimated PMR magnitude spectra

$$\hat{\mathbf{G}} = \begin{bmatrix} \frac{5e^{-5s}}{4s+1} & \frac{3.6e^{-s}}{10.4s+1} & \frac{6.08}{8s+1} \\ \frac{2.8e^{-4s}}{8s+1} & \frac{6e^{-3s}}{10s+1} & \frac{4.06e^{-s}}{7.6s+1} \\ \frac{3.4e^{-6s}}{12s+1} & \frac{4.1e^{-2s}}{15s+1} & \frac{6.9e^{-4s}}{4.8s+1} \end{bmatrix} \tag{12}$$

The system is discretized using ZOH with a sampling time of 1 min. The prediction and control horizons chosen for MPC are 20 and 5 respectively. Three scenarios are considered - one with no mismatch and two with mismatches in some parameters.

Scenario 1 - Mismatch in channels 1-1, 3-1, and 3-2: In this case, mismatch is added to channels 1-1, 3-1, and 3-2 in all the three parameters. The extent of mismatch in each of these channels is shown in Table 3.

Table 3. Mismatch added to the channel parameters

Channel	$\frac{\Delta K}{K_m}$	$\frac{\Delta \tau}{\tau_m}$	$\frac{\Delta D}{D_m}$
1-1	40%	-19%	-20%
3-1	-25%	40%	33.3%
3-2	20%	-20%	50%

The magnitude and phase spectra plots of the PMR are shown in Figures 8 and 9 respectively. A quick visual inspection of the plots shows mismatch in channels 1-1, 3-1 and 3-2 alone. Thus, the absence of mismatch in the other channels is correctly identified.

Diagnosis of gain mismatch: The estimates of $\hat{M}(0)$ for channels 1-1, 3-1 and 3-2 are 1.41, 0.788 and 1.21 respectively, correct to 3 significant digits. The second estimate indicates a over-estimated gain in channel 3-1, while the other two estimates indicate under-estimated gains in their respective channels.

Diagnosis of dynamics' mismatch: The PMR magnitude in channels 1-1 and 3-2 increase initially before leveling off. This indicates that the time constants in these channels are over-estimated. The PMR magnitude in channel 3-1 decreases initially before leveling off, thereby indicating an under-estimated time constant in this channel.

Diagnosis of delay mismatch: The PMR phase plots of channel 1-1 shows an upward slope, indicating an over-estimated delay. The PMR phase plots of the other two channels show a downward slope, thereby indicating under-estimated delays.

Scenario 2 - Mismatch in all channels: Here, mismatch is introduced in such a way that all the model parameters

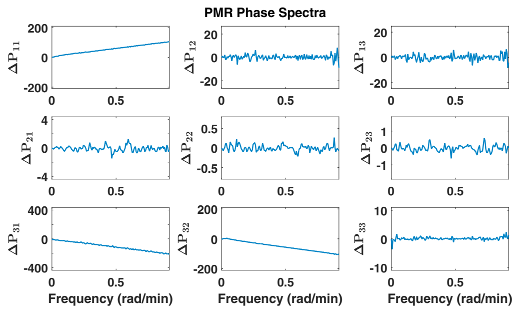

Fig. 9. Case Study 2, Scenario 1: Estimated PMR phase spectra

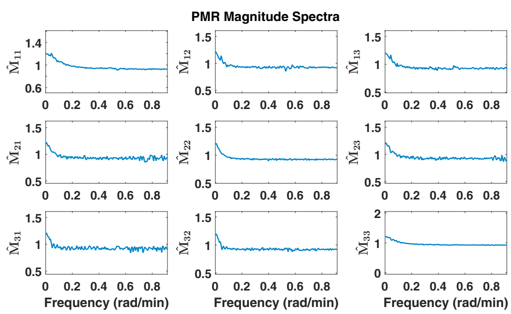

Fig. 10. Case study 2, Scenario 2: Estimated PMR magnitude spectra

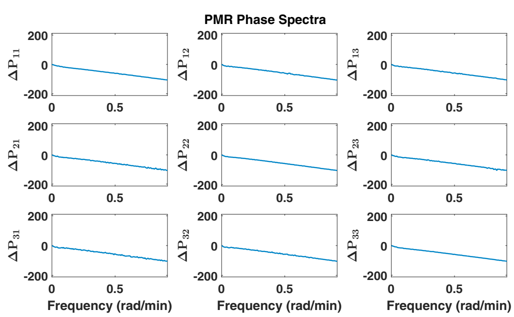

Fig. 11. Case study 2, Scenario 2: Estimated PMR phase spectra

are under-estimated. The actual gains and time constants are larger by 20% and 30% respectively, while the delays are larger by 1 sample.

The magnitude and the phase spectra plots are shown in Figures 10 and 11 respectively. The estimates of $\hat{M}(0)$ for all channels are roughly equal to 1.21, correct to 3 significant digits, thereby indicating that all the gains are under-estimated. The magnitude initially decreases before leveling off, thereby indicating under-estimated time constants. The downward slope in the phase plot indicates that all the delays are under-estimated.

6. CONCLUSIONS

In this work, we have extended the PMR methodology for detection and diagnosis of MPM to MIMO systems. The proposed method not only detects the channels with significant mismatch but also identifies the source of mismatch within the respective channels. The efficacy of this method is demonstrated through two simulation case studies. The theoretical analysis of the statistical properties of the estimates requires a rigorous treatment, a subject that is reserved for future study.

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