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An Iterative, Direct Closed Loop Identification Method For Model Refinement: Application to Interaction Estimation.

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Abstract: This paper addresses the problem of model refinement under closed loop conditions. Updating of both the direct and interaction dynamics in decentralized control schemes is considered here. While the direct dynamics are indeed crucial in determining local loop control performance, accurate identification of interaction relationships is important for the deployment of coordinated, decentralized control schemes. The proposed methodology is based on the direct method of closed loop identification and requires dithering. An iterative strategy, that sequentially updates both the direct and the interaction dynamics, is proposed as part of the identification methodology. Representative validation studies are presented to demonstrate the practicality of the proposed methodology.

Keywords: Closed loop identification, interaction estimation, model refinement.

1. INTRODUCTION

Multivariable systems can be controlled using either centralized or decentralized control structures. Centralized control schemes that are based on a complete description of the cause and effect relationships yield optimized control performance for multivariable systems. However, for optimization and control of large-scale systems, partitioning and decentralized control schemes have been eminently recommended over centralized approaches (Siljak, 1996). Amongst other factors cited for this choice, an important limitation for centralized control of large-scale systems is from a modeling and identification perspective. It is widely recognized that identification of the dynamic, cause-effect relationships in large-scale systems is a relatively difficult task. While such relationships are identified easily at a local level, for example at a unit level in a chemical or power generation plant, the interaction between such levels is usually associated with a lot of uncertainty. Often times, such interactions are also not perceivable during direct modeling, but manifest when the local control loops are closed. Identification of such interaction dynamics is a critical requirement for implementing coordinated decentralized schemes, which are known to yield closed loop performance that approaches that of a centralized control scheme.

The direct and interacting dynamics are identifiable when all available control inputs for the large scale system are perturbed for identification. This perturbation, when performed in open-loop, is a huge and expensive exercise involving long experimental times and is usually not practical if the interaction structure is not full. Therefore, a preferred alternative would be to partition the overall multivariable system into smaller sub-systems and implement local controllers that are based initially on an approximate identification of the local plant dynamics (obtained say from open loop step tests). This task can be done relatively easily owing to smaller sizes, and is also intuitive because these dynamics typically pertain to a particular unit such as the FCCU in a large plant. The control performance can be enhanced via refinement of the direct models and also by implementing higher-level co-ordinators or peer-level communication (Mesarovic *et al.* 1970, Katebi and Johnson (1997), Venkat et al. (2004)). These co-ordination mechanisms require knowledge of the interaction to achieve the desired level of co-ordination. This interaction thus also needs to be identified under controlled conditions using closed-loop identification methodologies along with the refinement of the direct dynamics described earlier.

Closed-loop identification strategies have been extensively proposed in the literature and an excellent review of the state of the art can be found in Forssell and Ljung (1999). The primary motivation in these strategies has been towards identifying direct models between the inputs and outputs using closed loop data, when for example, the plant is open loop

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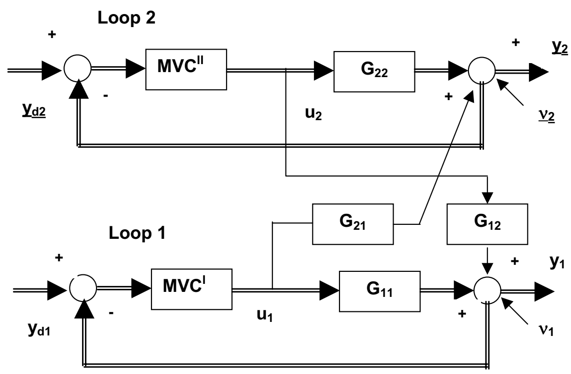
unstable or there are inherent feedback mechanisms implemented for safety reasons. Another important reason for identifying such direct models has been towards obtaining reduced order models with a view to achieve better control(Gevers and Ljung, 1986). Broadly, three different approaches to closed loop identification of the direct dynamics, viz (i) the direct, (ii) the indirect and (iii) the joint input-output methods, have been proposed. These methods differ in terms of apriori knowledge assumed about the nature of the controller and the assumptions made regarding the noise models. The relative merits of these strategies, in terms of consistency of estimates and the applicability of these methods (depending on the accuracy of the noise models) are discussed in Ljung (1999), Forssell and Ljung (1999). One key aspect that is particularly relevant to the work considered in this paper is that the presence of a nonlinear controller (that results for example when a model based controller is constrained) helps in minimizing bias errors resulting from input-noise correlation, and facilitates the use of the direct method of closed loop identification.

The identification problem considered in this paper involves both the issues discussed above, viz. the refinement of the direct model as well as characterization of the interaction dynamics between decentralized control loops. These tasks are proposed to be performed using closed loop data. The challenges encountered are similar to those one would expect for identification of the direct plant in closed loop, discussed in the earlier paragraph. Firstly, as is the case with closed loop identification, lack of informative data for identification is a key problem. This problem is overcome in regular closed loop identification, via the use of a dither signal applied either at the controller output or at the setpoint. For the tasks of direct model refinement and interaction estimation, this dither signal needs to be carefully designed and frugally implemented to balance the requirements of minimum closed loop variability as well as richness for identification. Secondly, prior to closed loop model updating, apriori but approximate knowledge on the direct (local loop) dynamics is usually available based on which the controller is designed. This apriori knowledge has typically not been considered in earlier works on closed loop identification, but does provide useful starting points for model updation of the direct and estimation of the interacting dynamics. In earlier works (Gudi et al. (2004), Gudi and Rawlings (2006)), we proposed a method to isolate interaction channels based on the use of partial correlation analysis and evaluated methods of estimating the interaction in these channels. The approach presented in the above earlier works was based on the indirect methods of closed loop identification. In this paper, we propose an iterative scheme that is based on the direct method. The approach proposed here relaxes assumptions made regarding the sparsity of the interaction structure and as such is applicable to a wider class of multivariable systems. The approach presented here is oriented towards identification of the interaction dynamics for use in co-ordinated control schemes. As discussed earlier, it also addresses the additional issue of refinement of the direct model towards enhanced, local control performance.

This paper is structured as follows: Section 2 analyzes the above mentioned problems encountered in identifying the interaction dynamics in large scale systems, with a view to achieving co-ordinated decentralized control. The approach proposed here to identify the interaction is based on using closed loop data and is discussed in Section 3. Identification results involving the multivariable, polymerization reactor of Congalidis *et al.* (1989) are presented in Section 4, followed by a summary of the work.

2. PROBLEM DEFINITION

The identification problem that we seek to address in the paper is shown in Figure 1. For purposes of explanation, we consider the case of two decentralized loops and seek to identify the interacting dynamics $\mathbf{G_{12}}$ **and** $\mathbf{G_{21}}$ between them as well as refine the estimates of the direct models $\mathbf{G_{11}}$



and $\mathbf{G_{22}}$.

Figure 1: Schematic of interacting multivariable controllers

Each of the individual loop outputs is assumed to be affected by noise and unmeasured disturbances. For purposes of explanation again, we assume that the controllers involved with loop I and loop II are multivariable and of size nu x nu. These controllers are designed based on the local dynamics $\mathbf{G_{11}}$ and $\mathbf{G_{22}}$**,** which are assumed to be approximately known from simple, open-loop plant tests. In general, no other apriori knowledge is assumed about the interaction dynamics; however the channels in which they exist are assumed to be known using methods presented earlier (Gudi et al. (2004)). We seek to estimate the interacting dynamics ($\mathbf{G_{ij}}$, $\mathbf{i \neq j}$) and update the direct dynamics ($\mathbf{G_{ii}}$, $\forall$ **i,j**) under closed loop conditions. The intent is to then use knowledge of the interacting dynamics in co-ordinated control schemes so as to achieve centralized performance but by using decentralized control structures as shown above.

In general, closed loop data is known to be less informative from an identification viewpoint. Hence a dither signal **d** at the controller output is commonly employed. For a general, decentralized loop I, Figure 2 shows the block diagram with the introduction of the dither signal.

3. IDENTIFICATION METHODOLOGY

Consider the block diagram shown in Figure 2.

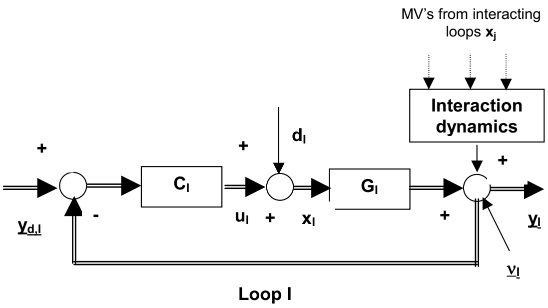


Figure 2: Signals associated with a single loop.

The dynamic relationship between the plant output and all the other inputs affecting it can be written as,

$$y_I = G_I\, x_I + \sum_{K=1}^{n_{\text{int}}} G_{kI}\; x_k + v_I \qquad (1)$$

where x_k are the manipulated variables (MV) from the other controllers and n_{int} is the number of such interacting MVs. Let us assume that an approximate estimate of the direct dynamics $\hat{G}_I$ is available based on which the controller C_I is initially designed. We next consider the term ε_I defined as the prediction errors as,

$$\varepsilon_I = y_I - \hat{G}_I\, x_I \qquad (2)$$

Using Equation (1),

$$\varepsilon_I = (G_I - \hat{G}_I)\, x_I + \sum_{K=1}^{n_{\text{int}}} G_{KI}\; x_K + v_I \qquad (3)$$

Due to the presence of the multivariable controller, u_I itself is related to all k^{th} interacting MVs through its interacting dynamics G_{kI} as,

$$u_I = R^i{}_{0,I} \sum_{k=1}^{n_{\text{int}}} G_{kI} x_k \qquad (4)$$

where $R^i{}_0$ is the loop sensitivity defined as,

$$R^i{}_{0,I} = (I + C_I G_I)^{-1} C_I \qquad (5)$$

The above expressions in Equations (4) and (5) are applicable for the linear controller case. When the model-based controller C_I is non-linear, as would be the case when the controller is constrained, the linear correlation between u_I and all the other interacting MVs would be broken. The expression for the prediction error represented in Equation (2) can then be used to setup an identification problem.

Let the error in the approximate estimate of the direct dynamics $\hat{G}_I$ is:

$$\Delta = G_I - \hat{G}_I \qquad (6)$$

Then from equation (3)

$$\varepsilon_I = \Delta x_I + \sum_{k=1}^{n_{\text{int}}} G_{kI} x_k + e_I \qquad (7)$$

Equation (7) above provides a multi-input, single-output form for identification of the Δ and G_{kI}. In the above equation, it is evident that if the signals x_I and x_k are designed to be linearly uncorrelated, unbiased, estimates of both Δ and G_{kI} can be generated. In relation to Figure (2), if the controller is nonlinear, any dithering in the interacting channels u_K (k = 1, 2 … n_{int}) and the signal u_I would be uncorrelated and therefore unbiased estimates of both Δ and G_{KI} can be obtained. It must be added that if there are more that one interacting channels, the dither in each of them should also be designed to be uncorrelated. Let us denote the estimate of error in the direct model as Δ and the dynamics of the interacting term as $\hat{G}_{kI}$. Since the error signal ε_I is generated from an approximate identification of direct model G_I, we could refine this estimate in an iterative fashion, using the same perturbation data. We achieve this direct updating by using an estimate of the direct error model $\hat{\Delta}$ as follows:

Let $\hat{G}_I^{(L)}$ denote the L^{th} iterative estimate of $\hat{G}_I$ and further let $\varepsilon^{(L)}$, $\Delta^{(L)}$ and $G_{KI}^{(L)}$ denote the estimate of prediction error, error in direct dynamics and the interacting dynamics respectively, also at L^{th} iterate. To generate estimate of $\hat{G}_I^{(L+1)}$, we correct $\hat{G}_I^{(L)}$, using the estimate of its error i.e. $\Delta^{(L)}$ as

$$\hat{G}_I^{(L+1)} = \hat{G}_I^{(L)} + \hat{\Delta}^{(L)} \qquad (8)$$

Since, this would lead to higher order of the model at the L+1th iteration, we propose to obtain the best lower order estimate of the RHS term of equation (8) by restricting the model order to be same as that at L^{th} instant. The steps involved in this reduced order approximation can be shown diagrammatically in Figure 3.

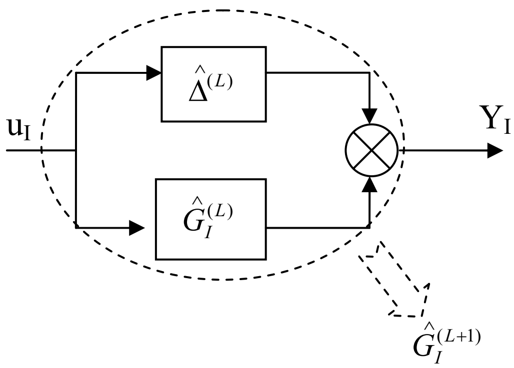


Figure 3: Illustration of method for generating reduced order approximation of $\hat{G}_I^{(L)}$

The overall iterations in the framework to generate a refined model of $\hat{G}_I$ as well as the interaction dynamics can be written as follows:

a) Start with an initial approximate model with L = 0 as $\hat{G}_I^{(0)}$ design uncorrelated perturbation signals u_{kI} ; k = 1, 2 … L and d_i (See Figure 2).

b) Using Equation (2) generate the sequence $\varepsilon_I^{(L)}$.

c) Using Equation (7), generate an estimate of $\hat{\Delta}^{(L)}$ and $\hat{G}_{kI}^{(L)}$ by solving the concerned identification problem.

d) Use Equation (8) to update $\hat{G}_{kI}^{(L)}$ *to* $\hat{G}_{kI}^{(L+1)}$ and go to step (2). Iterate till no appreciable changes in the estimate of $\hat{\Delta}^{(L)}$ and $\hat{G}_{kI}^{(L)}$ are seen.

Remarks:

1) *The iterations involving Equations 2 and 7 are necessary because prior information about the local model dynamics (G_I) needs to be exploited.*

2) *An alternate way of direct, closed loop model identification is to start from Equation 1 and generate estimates of the direct and local models. However, when the local dynamics are multivariable and large in size, it is preferable to exploit prior knowledge of the local dynamics and implement the iterative methodology.*

4. CASE STUDY: POLYMERIZATION REACTOR CASE STUDY (Congalidis *et al.* 1989)

In this section we validate the proposed methodology on 4x5 system involving a polymerization reactor considered by Congalidis, Richards and Ray (1989).

The concerned dynamics of the system are given as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \end{bmatrix} = \begin{bmatrix} \frac{0.34}{0.85s+1} & \frac{0.21}{0.42s+1} & \frac{0.5(0.5s+1)}{0.12s^2+0.4s+1} & 0 & \frac{6.46(0.90s+1)}{0.07s^2+0.30s+1} \\ \frac{-0.41}{2.41s+1} & \frac{0.66}{1.51s+1} & \frac{-0.30}{1.45s+1} & 0 & \frac{-3.72}{0.80s+1} \\ \frac{0.30}{2.54s+1} & \frac{0.49}{1.54s+1} & \frac{-0.71}{1.35s+1} & \frac{-0.2}{2.71s+1} & \frac{4.71}{0.08s^2+0.41s+1} \\ 0 & 0 & 0 & 0 & \frac{1.03(0.23s+1)}{0.07s^2+0.31s+1} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{bmatrix}$$

An RGA analysis leads to pairing $y_1 - u_3$, $y_2 - u_2$, $y_3 - u_4$, and $y_4 - u_5$ and thus controllers are designed based on the local dynamics $\mathbf{G_{13}}$, $\mathbf{G_{22}}$, $\mathbf{G_{34}}$ and $\mathbf{G_{45}}$. We restrict the application of our methodology for brevity to identifying direct and interaction dynamics for the second loop involving the direct dynamics G_{22} and the interacting dynamics G_{23} and G_{25} as shown in Figure 4.

Starting with the initial approximation for G_{22} as $\hat{G}_I^{(0)}$ = 1.66 / (2.51 s + 1) and using the iterative method described above, the direct model gets refined to G_{22} = 0.623 / (1.37 s + 1), and the interaction dynamics are G_{23} = – 0.292 / (1.369 s + 1) and G_{25} = – 3.358 / (0.758 s + 1). Figure 5 shows the step responses of G_{22} and includes all the three, i.e. the responses of the initial, approximate guess, the final refined model and the true model. The figure shows that the direct model is iteratively refined to the true model in three iterations. In Figure 6, we show the step responses for the interacting terms G_{23} and G_{25}; again both the responses, i.e. the true as well as the identified model are shown.

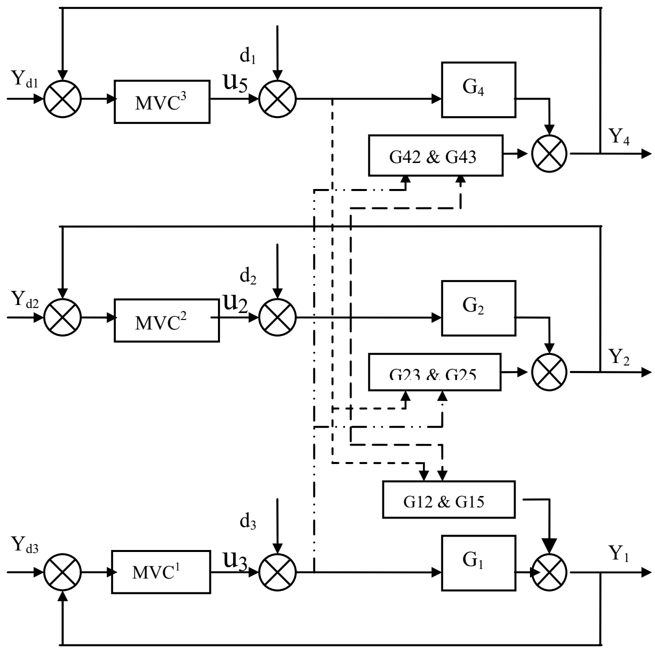


Figure 4 Signals associated with system considered for validation.

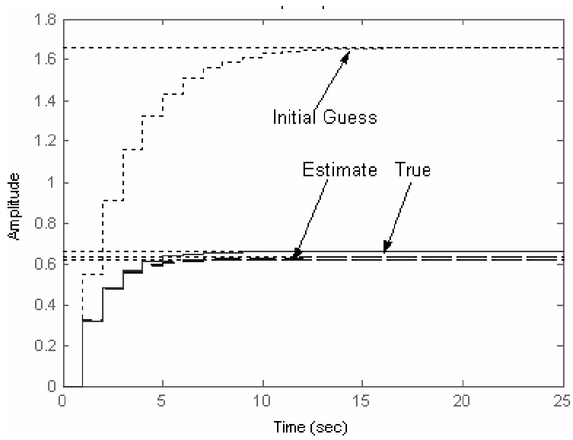
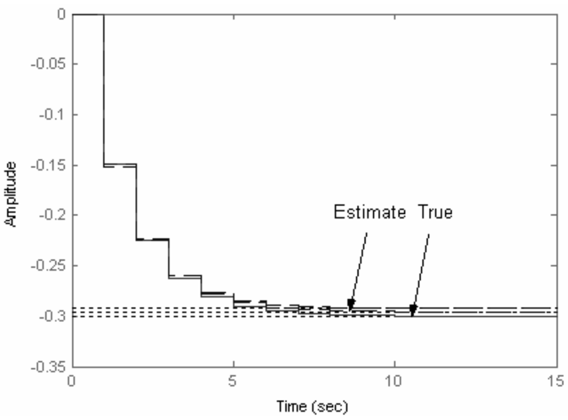
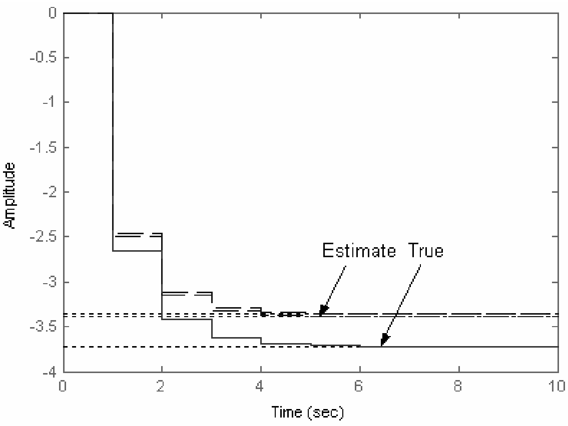


Figure 5 Step response for the direct dynamics G_{22}.

It can be seen that the estimated models agree with the true models fairly well with respect to the dynamics but there is a small mismatch in the estimation of the steady state gain.



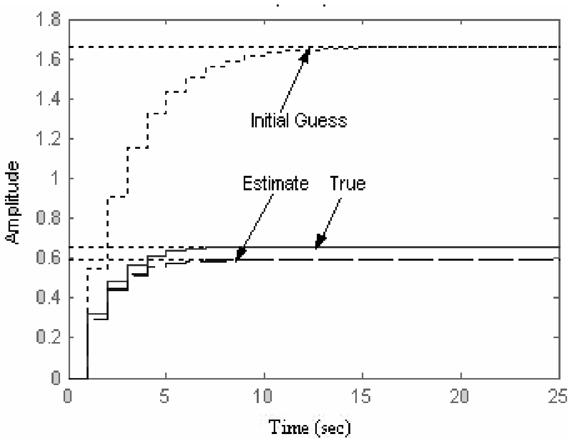
(a)



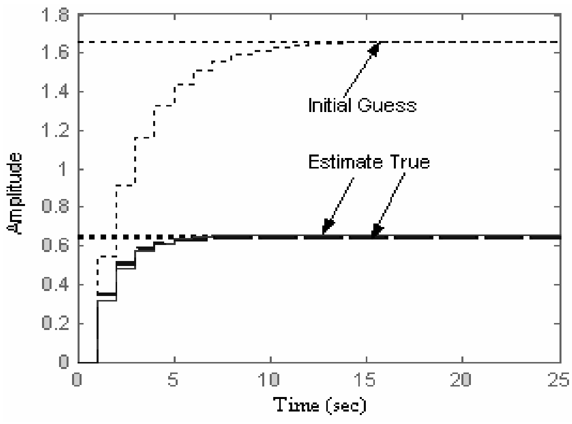
(b)

Figure 6 Comparison of the step responses of the estimated interaction models with the true interaction dynamics. (a) G_{23} and (b) G_{25}.

To examine the role of the MPC constraints in decorrelating the concerned signals, we repeat the runs by further tightening the saturation bounds on the MVs.



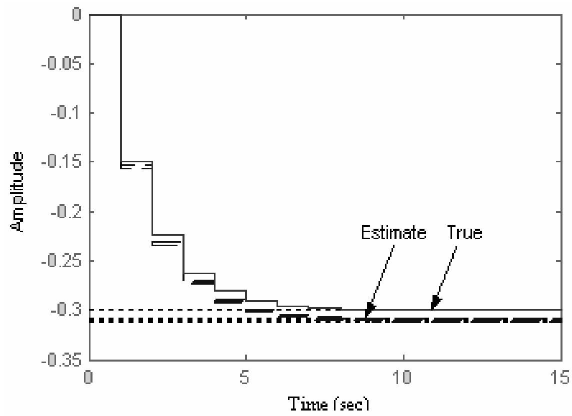
(a)



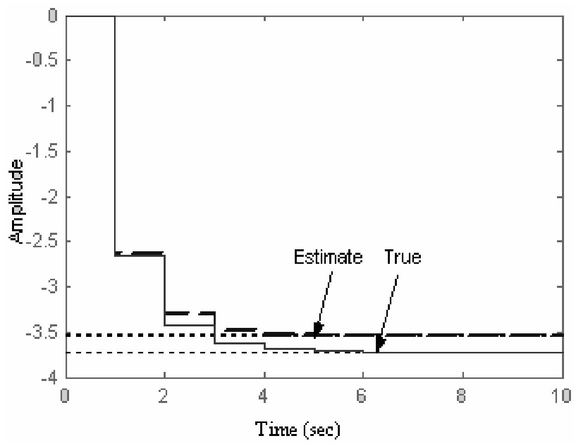
(b)

Figure 7 Step response for the direct dynamics G_{22}, when saturation bounds (a) relaxed (b) tightened.

Figure 7 shows that the direct dynamics are identified more accurately, as there is negligible mismatch in gain of true and identified model when the saturation bounds are tightened.



(a)



(b)

Figure 8 Comparison of the step responses of the estimated interaction models with the true interaction dynamics for tightened saturation bounds. (a) G_{23} and (b) G_{25}.

In Figure 8, we show the step responses for the interacting terms for the case of tightened saturation limits. It can be seen that the estimated models agree with the true models fairly well with respect to the dynamics but there is relatively a small mismatch in the estimation of the steady state gain than that in previous case (see Figure 6). Thus, it can be inferred that the presence of a nonlinear controller would improve the estimates using the proposed direct method.

There could be two possible mechanisms by which the accuracy of identification could be improved by the presence of a constrained controller. Firstly, the presence of constraints makes the controller nonlinear and hence the linear correlation between the noise/ interacting signals and the manipulated variables of the local loop is destroyed, and this results in smaller biases in the estimates. (Forsell and Ljung, 1999). A second possible explanation for the improvement in the estimation of the steady state gain for the tighter saturation case could be that the low frequency content in the concerned signals would be enhanced due to low variability in the inputs due to tighter constraints.

5. CONCLUSIONS

The focus of this paper was on the use of the direct, closed loop identification methods, for the estimation of interacting dynamics in large decentralized multivariable controllers. The proposed methodology is based on an iterative scheme to update both the direct local dynamics and estimate the interacting dynamics. The presence of a nonlinear controller, that is typically expected in a industrial environment, yields more accurate estimates of both the dynamics (direct and interacting) due to its decorrelating effect on the closed loop signals. The proposed estimation methodology has been validated on a representative case study and has been shown to function satisfactorily. The proposed methodology would be useful in on-line estimation of the interacting dynamics for use in coordinated control schemes.

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