Identification of MIMO Magnetic Bearing System Using Continuous Subspace Method with Frequency Sampling Filters Approach

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Abstract - **This paper presents a system identification of multi input multi output (MIMO) magnetic bearing system. It comprises of two steps. The first step employs a MIMO frequency sampling filters, in which, the raw data will be analyzed in order to obtain a meaningful multivariable parameters that describe the empirical model of the analyzed data. Then, the information of the empirical model will be used in the second step, in which, the MIMO continuous time subspace method will be used to obtain the state space model of the system. The application based on magnetic bearing system apparatus data will be used to demonstrate the efficacy of the developed MIMO algorithms and the approach used. Based on result, the MIMO two steps identification provide significant performance as compared to direct identification approach.**

I. Introduction

As mentioned in NASA spinoff, "magnetic bearings support moving machinery without physical contact. They can levitate a rotating shaft and permit relative motion without friction or wear. Long considered a promising advancement, they are now moving beyond promise into actual service in such industrial applications as electric power generation, petroleum refining, machine tool operation and natural gas pipelines" [1]. The overwhelming demands have raised so much interest with respect to advanced design specification, precision control, vibration control, flexibility of degree of freedom, high speed endurance and reliability of the system to sustain under extreme condition.

Magnetic bearing (MB) is a mechatronics system that can be regarded as a highly nonlinear, open loop unstable and multivariable system. To control engineers and researchers, this system offers lots of research opportunities especially in the areas of modeling, control system design, precision control, optimization, and many more. Till now, there are numbers of publications being published with respect to magnetic bearing system and technology. See recent examples for the implementation of MB in system design and control as in [2,3,4] and the application of MB as in [5,6,7].

The successful operation of a magnetic bearing application needs for an accurate system model. This is due to its unstable characteristics, coupled with complex vibration and comprises of multivariable system in nature. Therefore, the derivation of the mathematical model based on first principle approach seems difficult to achieve. The empirical approach via system identification is somehow more practical to be used in this sense. In general, system identification is based on study and analysis of the input and output data collected from the system. System identification procedures consist of experiment design, data acquisition, model selection, model estimation and model validation [8].

For real systems, it is mostly deal with multi-input-multi-output (MIMO) data. MIMO systems typically contain complex dynamic characteristics. It is difficult to establish a dynamic model of a MIMO system accurately and subsequently. The traditional model based on single-input-single-output (SISO) scheme requires extensive computation that renders it nearly impossible to adapt correctly to the complexity of MIMO systems. Therefore, the development of MIMO algorithm is attracting much interest.

In addition, data acquisition process from real system typically yields large amounts of data. This may lead to unacceptable computational time during the identification process. The raw data may also contain complex system disturbance information, which may require a sophisticated optimization algorithm in order to achieve desirable results.

In this paper, a MIMO Frequency Sampling Filter (FSF) is introduced within the first stage of the identification process. This approach involves the use of Finite Impulse Response (FIR) model and the maximum likelihood method which play a role in eliminating the bias and noise effects of the data collected from closed-loop systems. In addition, the Prediction Error Sum of Square (PRESS) technique is also employed. This tool will determine the precise value of the model and to ensure the final FSF model has the greatest predictive capability among all the prescribed candidates. This stage is also referred as data compression stage as the raw data will be analyzed in order to obtain only an important and meaningful parameter that describes the empirical model of the analyzed data. From here, the step response estimates is obtained. This data will be next used on the second step, in which, a continuous time subspace identification will be conducted in order to get the state-space model of the magnetic bearing system.

The idea of using FSF approach is originally obtained from Wang and Cluett [9,10,11]. It has been successfully applied for example in food extruder process [12], Shell distillation column plant [13], underwater glider system [14], and during estimation of physical parameters of stable and unstable system [15]. However, all these applications are treated in

SISO manner. As for the magnetic bearing system application, it has also being applied in SISO configuration as in [16,17] and MISO configuration as in [18]. In this paper, this approach is further extended to MIMO FSF model.

In the other hand, the MIMO continuous time subspace identification approach is also adopted in order to obtain the MIMO state-space model [19]. Here, the use of Laguerre filter network and an instrumental variable method in the time domain will be utilized. The overall two steps MIMO identification approach will guarantee a better performance as compared to direct identification process with respect to time and accuracy. As a result, this paper carries the following contributions:

- New MIMO FSF identification to be applied for MIMO magnetic bearing system.
- A two stage identification assist the closed-loop system data, in which, during first step the use of FIR model and the maximum likelihood method have eliminated the bias and noise effects of the data collected from closed-loop systems. Having this first stage of identification, the second stage can now be treated in open loop manner.
- The use of instrumental variable method to eliminate the noise (if any) during the second stage of identification.

Briefly, this paper is organized as follow. Section II will elaborate on MIMO continuous time state-space problem formulation. Section III and IV provides information of identification using FSF and continuous subspace approach in details. Section V demonstrates the performance of the developed model in identifying the magnetic bearing system. Finally, section VI concludes the paper.

II. PRELIMINARIES

Consider the state-space model of the continuous-time system in Laplace domain

$$\begin{aligned} sX(s) &= AX(s) + BU(s) \\ Y(s) &= CX(s) + DU(s) \end{aligned} \tag{1}$$

where $U(s) \in R^m, Y(s) \in R^l, X(s) \in R^n$ are the Laplace transform of the system inputs, outputs and state variables respectively, and $A \in R^{nxn}, B \in R^{nxm}, C \in R^{lxn}$ and $D \in R^{lxm}$ are the system matrices. The transfer function can be expressed as

$$G(s) = C(sI_n - A)^{-1}B + D \tag{2}$$

Where I_n denotes the $n \times n$ identity matrix.

The continuous time identification problem is to consistently estimates the system order, $\hat{n}$ and system matrices of A, B, C and D.

III. FSF FRAMEWORK

The FSF approach for the step response identification is carried out according to [10,11]. The description of the system using frequency sampling filters is described as

$$y(t_k) = G(z)u(t_k) \tag{3}$$

where $u(t_k)$ is the input signal, $y(t_k)$ is the output signal and $G(z)$ is defined as

$$G(z) = \sum_{i=0}^{n-1} \frac{1}{\mathrm{N}} \sum_{m=-\frac{n-1}{2}}^{\frac{n-1}{2}} G\left(e^{j\frac{2\pi m}{\mathrm{N}}}\right) e^{j\frac{2\pi mi}{\mathrm{N}}} z^{-i} \tag{4}$$

where N is the model order, n is the effective order of the FSF model, and z^{-1} is the backward shift operator for all impulse response sampling instant i, $i = 0,1,\ldots,n-1$ and frequency response sampling instant m, $m = 0,\pm1,\ldots,\pm\frac{n-1}{2}$.

The FSF approach approximates the transfer function $\overline{G}(z)$ as

$$\overline{G}_{fsf}(z) = \sum_{m=-\frac{n-1}{2}}^{\frac{n-1}{2}} \theta_m \overline{H}_m(z) \tag{5}$$

$$\overline{H}_m(z) = \frac{1}{\mathrm{N}} \frac{1 - z^{-N}}{1 - e^{j\Omega m} z^{-1}} \tag{6}$$

where n is odd and the frequency sampling interval $\Omega = \frac{2\pi}{T}$, $\overline{H}_m(z)$ is the m-th FSF and θ_m is the corresponding (complex) parameter. For the frequency range of $0 \le \omega \le \mathrm{N}\Omega$ choosing $n = \mathrm{N}$ gives an exact match $\overline{G}_{fsf}(z) = \overline{G}(z)$ and choosing $n < \mathrm{N}$ gives an approximate match $\overline{G}_{fsf}(z) \approx \overline{G}(z)$ [10,11].

The FSF of (5) can be rewritten in compact form as

$$\overline{G}_{fsf}(z) = \theta^{\mathrm{T}} \overline{F}(z) \tag{7}$$

where

$$\overline{F}(z) = \begin{bmatrix} \overline{H}_0(z) \\ \overline{H}_{-1}(z) \\ \overline{H}_1(z) \\ \vdots \\ \overline{H}_{-\frac{n-1}{2}}(z) \\ \overline{H}_{\frac{n-1}{2}}(z) \end{bmatrix}; \qquad \theta = \begin{bmatrix} \theta_0 \\ \theta_{-1} \\ \theta_1 \\ \vdots \\ \theta_{-\frac{n-1}{2}} \\ \theta_{\frac{n-1}{2}} \end{bmatrix}$$

Thus, Equation (3) can be rewritten as

$$y(t_k) = \theta^{\mathrm{T}} f(t_k) * u(t_k) \tag{8}$$

For N data measurement, Equation (8) can also be written in matrix form as

$$Y_N = \Theta_N^{\mathrm{T}} \Phi_N \tag{9}$$

Then, the estimate of Θ is obtained over least squares solution given by

$$\hat{\Theta} = (\Phi_N^{\mathrm{T}} \Phi_N)^{-1} \Phi_N^{\mathrm{T}} Y_N \tag{10}$$

which minimize the performance index of the form

$$J(N, \hat{\Theta}) = \sum_{k=0}^{N} | Y - \Theta\Phi |^2 \tag{11}$$

PRESS Computation

The least squares model estimates based on PRESS computation is used to obtain a proper FSF parameter optimization. It act to minimize the prediction error as well as determine the most suitable candidate for dynamic model structure [9]. Define the prediction error as

$$e_{-k}(k) = y(k) - \hat{\theta}^{\mathrm{T}} \phi(k) = y(k) - \hat{y}_{-k}(k) \tag{12}$$

where $e_{-k}(k), k = 1,2,...,N$ are called the PRESS residuals and $\hat{\theta}$ has been estimated according to (10) without including $\phi(k)$ and $y(k)$. The PRESS residuals $e_{-k}(k)$ represent the true prediction errors, since $y(k)$ and $\hat{y}_{-k}(k)$ are independent. The PRESS residuals $e_{-k}(k)$ can be calculated according to the following equation

$$e_{-k}(k) = \frac{e(k)}{1 - \phi(k)^{\mathrm{T}} \Phi^{\mathrm{T}} \Phi^{-1} \phi(k)} \tag{13}$$

The PRESS statistic is defined as

$$\mathrm{PRESS} = \sum_{k=1}^{N} e_{-k}(k)^2 \tag{14}$$

The average PRESS is calculated as

$$\mathrm{PRESS}_{av} = \sqrt{\frac{\sum_{k=1}^{N} e_{-k}(k)^2}{N-1}} \tag{15}$$

MIMO FSF Model

In order to take full advantages of the orthogonal decomposition algorithm for parameter estimation, the MIMO system is chosen to be identified. For p inputs denote as $u_1(k), u_2(k), \ldots, u_p(k)$ and q outputs denote as $y_1(k), y_2(k), \ldots, y_q(k)$, the times to steady state for each subsystem are given by $\mathrm{N}_1, \mathrm{N}_2, \ldots, \mathrm{N}_p$, and the reduced orders for each subsystem represented by its own FSF model are chosen to be $n_1, n_2, \ldots, n_p$. For the MIMO system, the matrix representation is dictated as follow.

- The first input $u_1(k)$ is passed through a set on n_1 FSF based on N_1, to form the first n_1 columns in the data matrix.
- The next input is passed accordingly to form the next columns in the data matrix.
- The associated parameters comprise of all the subsystems will be justified in the multivariable form.
- The least squares algorithm is then applied to estimate the FSF model parameters with respect to each subsystem.

Although the FSF approach is cast in discrete time domain, the resultant model can be used to obtain continuous time step response [11]. The system impulse response $\hat{g}(t)$ can be approximately computed using the continuous time equivalent as

$$\hat{g}(t) \approx \hat{g}_{fsf}(t) = \sum_{m=-\frac{n-1}{2}}^{\frac{n-1}{2}} \hat{\theta}_m \hat{h}_m(t) \tag{16}$$

and

$$\hat{h}_m(t) = \frac{1}{T} e^{j\frac{2\pi mt}{T}} \qquad \text{for} \qquad t < T\Delta \tag{17}$$

where T is a sampling period. The step response is determined as

$$y_{step}(t) = \int_0^t \hat{g}(\tau) d\tau \tag{18}$$

IV. MIMO SUBSPACE IDENTIFICATION

For completeness of two stage identification approach, this section elaborates a MIMO continuous time subspace identification method using step response data as proposed in [19]. The input (unit step), $u_{step}(t)$ and the output $y_{step}(t)$ will be used to developed a continuous time state-space model.

The i-th continuous time Laguerre filter is defined as

$$L_i(s) = \sqrt{2p} \frac{(s-p)^i}{(s+p)^{i+1}} \tag{19}$$

where $p > 0$ is the scaling factor to ensure that the filters are stable. Introduce a w-operator that corresponds to the all-pass Laguerre filter,

$$w(s) = \frac{s-p}{s+p}, \qquad s = p\frac{1+w}{1-w} \qquad p > 0 \tag{20}$$

The transformation of the 0-th Laguerre filter $L_o(s) = \frac{\sqrt{2p}}{s+p}$ gives $\sqrt{2p} w_0$. By repetitively multiplying with w, a bank of Laguerre filters is obtained with filter orders denotes as

$(l_o(t), l_1(t), ..., l_i(t))$. Therefore, the model description in (1) is transformed into

$$[wx](t) = A_w x(t) + B_w [l_0 u_s](t) \quad (21)$$
$$[l_0 y_s](t) = C_w x(t) + D_w [l_0 u_s](t) \quad (22)$$

with

$$A_w = (A + pI_{\hat{n}})^{-1}(A - pI_{\hat{n}})$$
$$B_w = \sqrt{2p}(A + pI_{\hat{n}})^{-1} B$$
$$C_w = \sqrt{2p} C (A + pI_{\hat{n}})^{-1}$$
$$D_w = D - C(A + pI_{\hat{n}})^{-1} B \quad (23)$$

and

$$A = p(I_{\hat{n}} - A_w)^{-1}(I_{\hat{n}} + A_w)$$
$$B = \sqrt{2p}(I_{\hat{n}} - A_w)^{-1} B_w$$
$$C = \sqrt{2p} C_w (I_{\hat{n}} - A_w)^{-1}$$
$$D = D_w + C_w (I_{\hat{n}} - A_w)^{-1} B_w \quad (24)$$

where $[l_i y_s](t)$ denotes the convolution of $y_s(t)$ with $l_i(t)$ and $[l_i y_s](t) = \int_0^t l_i(t-\tau) y_s(\tau) d\tau$ (same implementation to $[l_i u_s](t)$). With the transformed system description, the continuous time data equation is defined to be

$$\begin{bmatrix} [l_0 y_s](t) \\ [l_1 y_s](t) \\ \vdots \\ [l_{i-1} y_s](t) \end{bmatrix} = \begin{bmatrix} C_w \\ C_w A_w \\ \vdots \\ C_w A_w^{i-1} \end{bmatrix} x(t) + \begin{bmatrix} D_w & 0 & \cdots & 0 \\ C_w B_w & D_w & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ C_w A_w^{i-2} B_w & \cdots & C_w B_w & D_w \end{bmatrix} \begin{bmatrix} [l_0 u_s](t) \\ [l_1 u_s](t) \\ \vdots \\ [l_{i-1} u_s](t) \end{bmatrix} \quad (25)$$

Introduce the notation

$$Y_{i,j}^f(t) = \begin{bmatrix} [l_i y_s](t) \\ [l_{i+1} y_s](t) \\ \vdots \\ [l_{i+j-1} y_s](t) \end{bmatrix}; \quad O_j = \begin{bmatrix} C_w \\ C_w A_w \\ \vdots \\ C_w A_w^{j-1} \end{bmatrix};$$

$$\Gamma_j = \begin{bmatrix} D_w & 0 & \cdots & 0 \\ C_w B_w & D_w & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ C_w A_w^{i-2} B_w & \cdots & C_w B_w & D_w \end{bmatrix}$$

$U_{i,j}^f(t)$ is defined similar to $Y_{i,j}^f(t)$. By this notation, the continuous time data equation is rewritten in a compact form as

$$Y_{i,j}^f = O_j x(t) + \Gamma_j U_{i,j}^f(t) \quad (26)$$

Using the sampled data at sampling times $t_1, t_2, ..., t_{N_c}$, the sampled data matrices are

$$Y_{i,j,N_c}^f = \begin{bmatrix} [l_i y_s](t_1) & \cdots & [l_i y_s](t_{N_c}) \\ [l_{i+1} y_s](t_1) & \cdots & [l_{i+1} y_s](t_{N_c}) \\ \vdots & \vdots & \vdots \\ [l_{i+j-1} y_s](t_1) & \cdots & [l_{i+j-1} y_s](t_{N_c}) \end{bmatrix} \quad (27)$$

$$X_{i,N_c} = \begin{bmatrix} x(t_1) & x(t_2) & \cdots & x(t_{N_c}) \end{bmatrix} \quad (28)$$

By these matrices, the sampled data equation becomes

$$Y_{i,j,N_c}^f(t) = O_j x(t) + \Gamma_j U_{i,j}^f(t) \quad (29)$$

Past and future output is constructing from the data matrices and it is represented by Y_{0,i,N_c}^f and Y_{i,j,N_c}^f respectively. Similar construction of data matrices is applied to past input, U_{o,i,N_c}^f and future input, U_{i,j,N_c}^f.

Three assumptions are made since the constructed data matrices available:

i) Assume that the input data is a noise-free input, therefore the projection on the null space of U_{o,i,N_c}^f is introduced as

$$\Pi_{U_{0,i,N_c}}^{\perp} = I - U_{0,i,N_c}^{\mathrm{T}} (U_{0,i,N_c}^{\mathrm{T}})^{-1} U_{0,i,N_c} \quad (30)$$

ii) Assume that if in case there still a process and measurement noise appear in the system, therefore the instrumental variable, which is constructed from future input and future output data is introduced as

$$P = \begin{bmatrix} U_{i,j,N_c}^f \\ Y_{i,j,N_c}^f \end{bmatrix} \quad (31)$$

and multiply (29) from right with projection matrix of $\Pi_{U_{0,i,N_c}}^{\perp}$ and later with P to obtain

$$\lim_{N_c \to \infty} \frac{1}{N_c} Y_{0,i,N_c} \Pi_{U_{0,i,N_c}}^{\perp} P^{\mathrm{T}} = \lim_{N_c \to \infty} \frac{1}{N_c} O_j X_{i,N_c} \Pi_{U_{0,i,N_c}}^{\perp} P^{\mathrm{T}} \quad (32)$$

where the second term tend to zero since $U_{0,i,N_c} \Pi_{0,i,N_c}^{\perp} = 0$, and the noise term will be eliminated due to uncorrelated between the noise term and the instrumental variable.

iii) If the initial condition is appeared in the state-space system, the effect will be reduced by introducing the filter defined as

$$\Phi_{i,j,N_c} = \begin{bmatrix} l_i(t_1) & \cdots & l_i(t_{N_c}) \\ l_{i+1}(t_1) & \cdots & l_{i+1}(t_{N_c}) \\ \vdots & \cdots & \vdots \\ l_{i+j-1}(t_1) & \cdots & l_{i+j-1}(t_{N_c}) \end{bmatrix} \quad (33)$$

Details on MIMO subspace identification algorithm can be referred in [16,19].

V. EXPERIMENTAL RESULTS

In this section, the performance of the proposed two steps MIMO system identification will be demonstrated, in which, the magnetic bearing data collected from the test stand of magnetic bearing system apparatus will be used. The bearing system available has two bearing actuators that are employed to support a shaft on which a disk is fixed at the middle point and two journals are fixed at the end of the shaft. As the magnetic bearing actuators are open-loop unstable, a control system needs to be implemented in order to suspend the shaft so as to facilitate the data acquisition procedure. It has been noted that a decentralized PD (Proportional-Derivative) control system is usually sufficient for this purpose. During the levitating mode (assuming zero shaft speed), the dynamics in the *x-z* plane *y-z* plane are assumed to be decoupled and identical. This will lead to two separate system dynamics. Each of the two systems has two inputs and two outputs and, therefore, can be modeled by a 2x2 transfer function matrix.

At $\Delta t = 0.002s$, about $N = 1000$ data is measured for each plane. In this paper, the observation will be on *x-z* plane only. The *y-z* plane can be treated in similar way and therefore, is omitted in this paper. The parameter is set to $p = 440, i = 10, \hat{n} = 8$ and the step response data, $N_c = 300$ is used in the second stage. The plot of input and output signal obtained from the *x-z* plane is shown in Fig. 1. The step response obtained from MIMO FSF is illustrated in Fig. 2. The result after performing the MIMO continuous time subspace identification is shown in Fig. 3. Based on the result, it demonstrates that the MIMO subspace model can identify the step response of the MB systems closely.

The analysis is further conducted into direct identification and with 2-stage identification for both SISO and MIMO observation. It leads to direct identification (using SISO subspace and MIMO subspace) and 2-stage identification (using SISO FSF with SISO subspace and MIMO FSF with MIMO subspace). As a measure of accuracy of the tested models, the Variance Accounted For (VAF) test, which is given by the following formula

$$\boldsymbol{VAF} = \left(1 - \frac{\mathbf{VAR}(y_{step} - \hat{y})}{\mathbf{VAR}(y_{step})}\right) x100$$

where y_{step} = step response output

$\hat{y}$ = estimated output

and Mean Squares Error (MSE) test given as

$$\boldsymbol{MSE} = \frac{1}{N} \sum_{i=1}^{N} | y_{step} - \hat{y} |^2$$

where y_{step} = step response output

$\hat{y}$ = estimated output

are calculated. The outcome of the analysis is tabulated in Table 1.

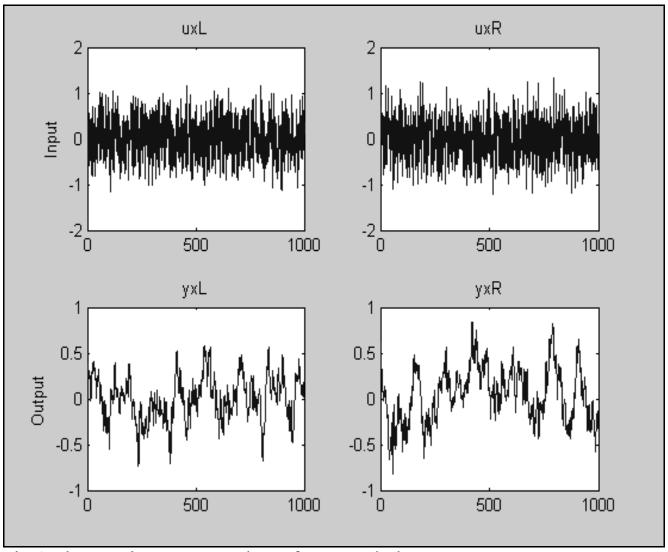

Fig.1.The MB input-output data of $x-z$ and plane

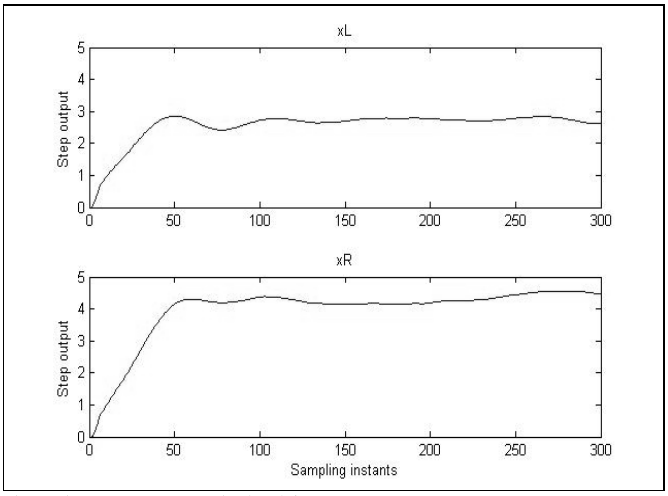

Fig.2.The step response obtained from MIMO FSF

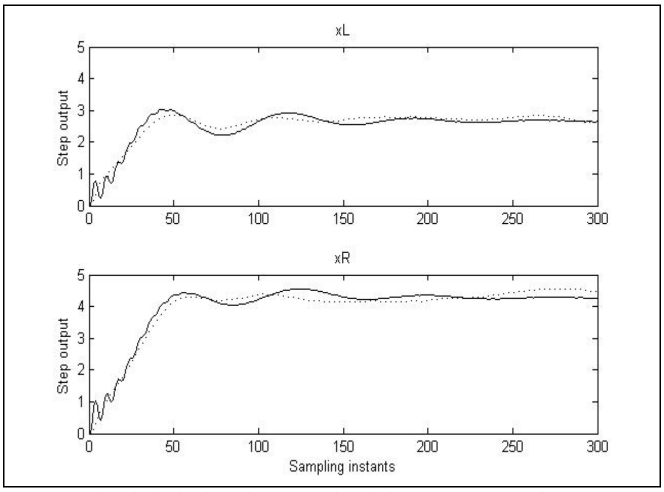

Fig.3.Simulated (dashed) and estimated (solid) step response of MB system

TABLE I
ACCURACY TEST RESULTS FOR DEVELOPED MODEL

Identification Approach	**Test**	**SISO**		**MIMO**	
		xL	***xR***	***xL***	***xR***
Direct ID Approach	***MSE***	0.0578	0.0895	0.0229	0.0692
	VAF(%)	0.2234	3.9737	61.2771	24.5139
2-Stage ID Approach	***MSE***	0.0113	0.0168	0.0219	0.0349
	VAF(%)	95.2946	98.0034	91.4290	95.9086

Based on TABLE I, it shows that two steps identification approach is able to identify the model of the system with low MSE and good percentage of accuarcy as compared to direct identification approach. In comparison between SISO and MIMO of 2-stage identification approach, the result shows about the same performance, which SISO comes slightly better. This result is expected as the MIMO model will integrate more complexity along with the process. However, the outcome based on MIMO identification will be more meaningful as all the variables are utilised together and the correlation within it is taking care of.

VI. CONCLUSION

MIMO frequency sampling filters and MIMO subspace identification approach have been proposed in this paper. The efficacy of the proposed approach is demonstrated to identify a real system taken from magnetic bearing apparatus. The result shows good performance as compared to direct identification using raw data. The MIMO FSF helps to provide cleaner step response data in reduced amount of samples. This has led to successful identification of MIMO continuous time subspace identification with less computational time.

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