Optimal Static Decoupling for the Decentralized Control: an Experimental Study

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Abstract: A three Degrees-Of-Freedom (DOF) vibration isolation system with a certain degree of symmetry shows significant cross coupling. The decentralized control is intended and it demands excellent decoupling performance. The Vaes optimization algorithm is applied to find the optimal static decoupling matrices. However, experiments show that the measured $\mu$ interaction measure is not consistent with calculation results and thus not optimized. An iterative procedure based on the Vaes algorithm is proposed to obtain the optimal static decoupling matrices. The Vaes algorithm is also modified to improve the numerical stability and to speed up the optimization process. The proposed iterative procedure and the modified Vaes optimization algorithm are validated on the 3-DOF vibration isolation system.

1. INTRODUCTION

The requirements on Active Vibration Isolation Systems (AVIS) are quite demanding in many high-precision mechatronic systems. Examples are photolithographic wafer scanners which are used to manufacture the integrated circuits up to nanometer details, and electron microscopes used for sub-micron imaging. The AVIS is used to support and isolate the payload from the seismic vibration which has a broad band spectrum and unpredictable waveform. As the payload is extremely sensitive to any disturbances, mechanical contacts between the payload and the environment are not desired. If the contactless AVIS is applied, not only the payload has to be stabilized at all six Degrees-Of-Freedom (DOF), but also the compensation of the payload gravity force (in the order of $10^4$ N) with low energy consumption becomes a challenge. The current contactless AVIS applied in the industry is based on pneumatic isolators, see Heertjes et al. (2005). The pressurized air is used to suspend the heavy payload with low energy consumption. However, the pressurized air has its own dynamics which are difficult for accurate modeling or control at high frequencies. The performance of the pneumatic AVIS is therefore limited. Besides, it is difficult to implement the pneumatic AVIS in vacuum.

According to Janssen et al. (2009), gravity compensation in the similar scales with dimension constrains using passive permanent magnetic force is feasible. Therefore, the AVIS based on contactless electromagnetic isolators is being developed as an alternative, see Ding et al. (2010). In order to test and validate control design for the final electromagnetic AVIS, a 3-DOF setup, which was initially designed to study precise positioning of the planar actuator with manipulator, see Gajdusek et al. (2008), is being modified to a 3-DOF AVIS.

According to experimental measurements, the 3-DOF system shows significant cross coupling. To avoid the cumbersome Multi-Input-Multi-Output (MIMO) parameter estimation and direct MIMO control design, the strategy of decentralized control which combines a diagonal MIMO controller with decoupling transformation is intended. Based on the measured Frequency Response Function (FRF) matrix, the decoupling transformation is designed to diagonalize the plant as much as possible. Subsequently, the decoupled system is treated as three Single-Input-Single-Output (SISO) systems and SISO identification and control design are applied.

For the non-dyadic systems, perfect decoupling in a wide frequency range is almost impossible in practice. As a result, the off-diagonal entries of the diagonalized plant, which are to be ignored in the decentralized control, are not zero. They might destroy the closed-loop performance or even destabilize the closed-loop system. Therefore, the performance of the decoupling is essential. There are two approaches to achieve decoupling. Compared with the dynamic decoupling approach, see Heertjes et al. (2010), static decoupling requires only constant real matrices which are easier to obtain and to implement. There are two issues concerned by static decoupling design.

- How to evaluate the decoupling performance. In other words, how to quantify the relative error between the diagonalized plant itself and the plant model with only the diagonal entries.
- How to derive the decoupling matrix.

Many criterions can be used to evaluate the decoupling performance, for example, the Relative Gain Array (RGA) defined by Bristol (1966), the diagonal dominance defined by Economou and Morari (1986), the $\bar{\sigma}$ interaction measure used in Vaes et al. (2004), and the $\mu$ interaction measure defined by Grosdidier and Morari (1986). Skogestad and Morari (1989) has found a tight stability condition for the decentralized control loop based on the $\mu$ interaction measure. Experiments by Vaes (2005) show that the improved $\mu$ interaction measure corresponds to an improved available control performance. Therefore, the $\mu$ interaction measure is chosen to evaluate the decoupling performance.

Many methods have been developed to decouple a MIMO plant. Model decomposition, see Heertjes et al. (2005); Zuo and Slo-
tine (2005), is based on the physical equation of the plant. But the performance is not as good as expected for the plant without the property of proportional damping. The well-known ALIGN-procedure, see MacFarlane and Kouvaritakis (1977), is based on eigenvalue decomposition of the measured FRF matrix. Both of the two methods share the same drawbacks: the limited decoupling performance due to the un-necessary constrains applied on the decoupling matrix parameters and the difficult stability analysis of the decentralized control loop due to the irrelevance to the \( \mu \) interaction measure. Vaes et al. (2003) modified the Owens method, see Owens (1978), which is only applicable to dyadic systems, in a way that it can be applied to the non-dyadic systems. Subsequently, Vaes et al. (2007) developed a numerical algorithm to find the optimized static decoupling matrices which minimizes \( \mu \) interaction measure. The initial values of the optimization process are chosen as the results of the modified Owens method to reduce the possibility to get the local optimum. The number of the optimization parameters are minimized without affecting the decoupling performance. However, the derived decoupling matrix does not give consistent experimental result if the original system is significantly cross coupled. Besides, there are still rooms to improve the Vaes algorithm on the perspective of numerical stability and optimization calculation time.

In this paper, an iterative procedure based on the modified Vaes algorithm is proposed to derive the optimal static decoupling matrices for a square MIMO plant with significant cross coupling. A few modifications are proposed to improve the Vaes algorithm. Proposed methods are validated by experiments on a 3-DOF AVIS. This paper is organized as follows. Section 2 reviews the previous methods to derive the static decoupling matrices. Section 3 describes the practical problems with the Vaes algorithm and subsequently proposes the iterative procedure and two modifications to the Vaes algorithm. Section 4 describes the 3-DOF AVIS and provides the experimental results. The conclusion is given in Section 5.

2. STATIC DECOUPLING REVIEW

2.1 Nomenclature

Static decoupling implies that the decoupling matrices employed are constant real matrices. For a \( n \)-DOF plant, \( P \) is the \( n \times n \) transfer function matrix. \( \tilde{P}(\omega) \) is the measured Frequency Response Function (FRF) matrix of the original plant at frequency \( \omega \). \( T_y \) and \( T_u \) are two constant real matrices to be determined to diagonalize \( \tilde{P}(\omega) \). \( P_d(\omega) \) is the decoupled FRF matrix calculated by applying some \( T_y \) and \( T_u \) to the measured FRF matrix.

\[
P_d(\omega) = T_y \tilde{P}(\omega) T_u.
\]

\( \tilde{P}_d \) is the measured FRF matrix of \( P_d \). \( P_{d,i}, i \in \{1,2,\ldots,n\} \) denote the diagonal entries of the system \( P_d \). \( \text{diag}\{P_{d,i}(\omega)\} \) represents the diagonal FRF matrix obtained by considering the diagonal entries of the FRF matrix \( P_d \) only. If the decoupling is perfect, \( \text{diag}\{P_{d,i}(\omega)\} = P_d \). \( E_P(\omega) \) is the relative error between the FRF matrix \( P_d(\omega) \) and \( \text{diag}\{P_{d,i}(\omega)\} \), defined as

\[
E_P(\omega) = (P_d(\omega) - \text{diag}\{P_{d,i}(\omega)\}) (\text{diag}\{P_{d,i}(\omega)\})^{-1}.
\]

\( \mu_\Delta(E_P(\omega)) \) is the \( \mu \) interaction measure for the FRF matrix \( P_d(\omega) \), which is defined as the structured singular value of the relative error matrix \( E_P(\omega) \) at the frequency \( \omega \). The subscript \( \Delta \) denote the structure of the decentralized controller, which is diagonal. Although the \( \mu \) can not be directly calculated, the upper and lower bounds of \( \mu \) calculated by Matlab are reasonably close. Therefore, we use the upper bound of the \( \mu \) as the practical \( \mu \) interaction measure. \( C \) denotes the diagonal decentralized controller and its diagonal entries are \( C_i, \forall i \in \{1,2,\ldots,n\} \). The complementary sensitivity function for the \( i^{th} \) loop is \( \tilde{H}_i = P_{d,i}C_i(1 + P_{d,i}C_i)^{-1}. \)

2.2 Stability of Decentralized Control

The off-diagonal entries of \( \tilde{P}_d(\omega) \) ignored during the decentralized control design could affect the stability of the closed-loop system. It is proved by Skogestad and Morari (1989) that the closed-loop system is stable if

\[
\tilde{\sigma}(\tilde{H}_i(\omega)) \leq \mu_\Delta^{-1}(E_P(\omega)), \forall \omega
\]

is feasible for each SISO loop. Therefore, \( \mu_\Delta(E_P(\omega)) \) has to be minimized to increase the stability robustness of the decentralized control loop.

2.3 Dyadic Transfer Function Matrices

In the theory of Dyadic Transfer function Matrices (DTM), a \( n \times n \) transfer function matrix \( P(s) \) is called dyadic if there exist constant \( n \times n \) matrices \( T_y \) and \( T_u \) such that \( T_yP(s)T_u \) is a diagonal rational transfer function matrix. Owens (1978) developed a procedure to determine \( T_y \) and \( T_u \) for dyadic systems:

- Select two constant numbers \( c_1 \) and \( c_2 \).
- \( T_y^{-1} \) is the eigenvector matrix of \( P(c_1)P(c_2)^{-1} \).
- \( T_u \) is the eigenvector matrix of \( P(c_2)^{-1}P(c_1) \).

This procedure can be easily understood. Since

\[
P(c_1) = T_y^{-1}P(c_1)T_u^{-1}, \quad P(c_2) = T_y^{-1}P(c_2)T_u^{-1}
\]

we have

\[
P(c_1)P(c_2)^{-1} = T_y^{-1}P(c_1)P(c_2)^{-1}T_y
\]

and

\[
P(c_2)^{-1}P(c_1) = T_u^{-1}P(c_2)^{-1}T_u^{-1}.
\]

As both \( P_d(c_1) \) and \( P_d(c_2) \) are diagonal, \( T_y^{-1} \) and \( T_u \) are eigenvector matrices of \( P(c_1)P(c_2)^{-1} \) and \( P(c_2)^{-1}P(c_1) \), respectively.

2.4 Modified Owens Method

The Owens method is only applicable to the dyadic systems. Vaes et al. (2003) modifies Owens method to adapt it to the measured FRF matrices of non-dyadic systems. The modified Owens method is described as follows.

- The two constants \( c_1 \) and \( c_2 \) are chosen as two frequencies \( \omega_1 \) and \( \omega_2 \) where the FRF matrices are measured.
- \( T_y^{-1} \) is the eigenvector matrix of \( \tilde{P}(\omega_1)\tilde{P}(\omega_2)^{-1} \).
- \( T_u \) is the eigenvector matrix of \( \tilde{P}(\omega_2)^{-1}\tilde{P}(\omega_1) \).

For non-dyadic systems, the calculated \( T_y \) and \( T_u \) are neither unique nor real. We can take either the absolute values or the real parts of the two complex matrices, whichever works better.

2.5 Vaes Optimization Algorithm

As there are limited number of the frequency pairs (\( \omega_1 \) and \( \omega_2 \)), the set formed by all the corresponding \( T_y \) and \( T_u \) is finite.
Even a search program is employed to find the best $\omega_1$ and $\omega_2$, it is still possible that there exist some $T_y$ and $T_u$ which are not in that set but gives better decoupling performance. Vaes et al. (2007) has developed a numerical algorithm to search for the optimal $T_y$ and $T_u$.

First, the two matrices $T_y$ and $T_u^{-1}$ are parameterized in such a way that the number of parameters are minimized without losing decoupling accuracy. Vaes et al. (2007) has explained that scaling of a row vector in matrices $T_y$ and $T_u^{-1}$ does not affect the $mu_3(E_p(\omega))$. Therefore, $T_y$ is parameterized as

$$
\begin{bmatrix}
\prod_{i=1}^{n-1} \cos(\alpha_{1,i}) & \cdots & \prod_{i=1}^{n-1} \cos(\alpha_{n,i}) \\
\sin(\alpha_{n-1,1}) \prod_{i=1}^{n-2} \cos(\alpha_{1,i}) & \cdots & \sin(\alpha_{n-1,n}) \prod_{i=1}^{n-2} \cos(\alpha_{n,i}) \\
\sin(\alpha_{1,1}) \prod_{i=1}^{n-2} \cos(\alpha_{i,1}) & \cdots & \sin(\alpha_{1,n}) \prod_{i=1}^{n-2} \cos(\alpha_{i,n}) \\
\sin(\alpha_{2,1}) \cos(\alpha_{1,1}) & \cdots & \sin(\alpha_{2,n}) \cos(\alpha_{1,n}) \\
\sin(\alpha_{1,1}) \\
\end{bmatrix}
$$

and $T_u^{-1}$ is parameterized as

$$
\begin{bmatrix}
\prod_{i=1}^{n-1} \cos(\beta_{1,i}) & \cdots & \prod_{i=1}^{n-1} \cos(\beta_{n,i}) \\
\sin(\beta_{n-1,1}) \prod_{i=1}^{n-2} \cos(\beta_{1,i}) & \cdots & \sin(\beta_{n-1,n}) \prod_{i=1}^{n-2} \cos(\beta_{n,i}) \\
\sin(\beta_{1,1}) \prod_{i=1}^{n-2} \cos(\beta_{i,1}) & \cdots & \sin(\beta_{1,n}) \prod_{i=1}^{n-2} \cos(\beta_{i,n}) \\
\sin(\beta_{2,1}) \cos(\beta_{1,1}) & \cdots & \sin(\beta_{2,n}) \cos(\beta_{1,n}) \\
\sin(\beta_{1,1}) \\
\end{bmatrix}
$$

such that the row vectors of $T_y$ and $T_u^{-1}$ are unit vectors. All the parameters $\alpha_{ij}$ and $\beta_{ij}$ are bounded within $[-\pi, \pi]$.

Second, the cost function

$$
\max_{\omega} \mu_3(E_p(\omega)W(\omega))
$$

is numerically minimized. $P_d$ is calculated by (1) with parameterized $T_y$ and the inverse of the parameterized $T_u^{-1}$, $W(\omega)$ is a weighting filter to enhance a certain frequency range. Note that $E_p(\omega)W(\omega)$ is calculated only for the frequencies where $\tilde{P}$ is measured. The results from the modified Owens method can be used to derive the initial parameter values so that the chances to get a local optimum is reduced.

### 3.1 Iterative Optimization Procedure

The Vaes algorithm does not lead to the true optimal decoupling for a significantly cross coupled plant. This is possibly because that the Vaes algorithm loses accuracy due to the unknown noises in the measurement channel. Therefore, for a significantly coupled $\tilde{P}$, an iterative procedure is proposed.

1. Apply the modified Owens method and derive the two decoupling matrices $T_y$ and $T_u$.
2. Measure $P_d$, the FRF matrix of the system $P_d$ decoupled by $T_y$ and $T_u$.
3. Apply the Vaes algorithm and derive the optimized decoupling matrices $T_{yo}$ and $T_{uo}$ based on $P_d$. The initial values of the decoupling matrices are set to the identity matrix.
4. $T_y = T_{yo} \times T_y$ and $T_u = T_{uo} \times T_u$.
5. Validate the optimized $T_y$ and $T_u$ by comparing the new $\mu_3(E_p(\omega)W(\omega))$ and $\mu_4(E_p(\omega)W(\omega))$.
6. If $\mu_3(E_p(\omega)W(\omega))$ and $\mu_4(E_p(\omega)W(\omega))$ are still not consistent, repeat the procedure from the second step. Otherwise, the iteration stops.

The initial $T_y$ and $T_u$ are derived using the modified Owens method because it is much simpler and faster than the Vaes algorithm and the result is fairly good for the approximately dyadic systems. But the Vaes algorithm is also applicable. Usually, a second iteration would have consistent $\mu_3(E_p(\omega)W(\omega))$ and $\mu_4(E_p(\omega)W(\omega))$.

### 3.2 Modified Vaes Algorithm

Two modifications to the Vaes algorithm are proposed to speed up the calculation and to improve the numerical stability.

First, the row vectors of $T_y$ and $T_u^{-1}$ are intended to be designed such as a mapping that they can access all the $n$ dimensional unit vectors when the parameters $\alpha_{ij}$ and $\beta_{ij}$ vary within their bounds. A one-to-one mapping would be the best choice but the parameter bounds proposed by Vaes is so loose that one or more combinations of $\alpha_{ij}$ and $\beta_{ij}$ are corresponding to a single vector. In fact, among all the parameters $\alpha_{ij}$ and $\beta_{ij}$, only $\alpha_{i,n-1}$ and $\beta_{i,n-1}$ should be bounded within $[-\pi, \pi]$. All the other parameters can have tighter bound $[-\frac{\pi}{2}, \frac{\pi}{2}]$ without losing accuracy. Obviously, reducing the parameter bounds would speed up the optimization process.

Second, the calculation of inverting $T_u^{-1}$ is not desired in the optimization process. The numerical process sometimes comes up with a $T_u^{-1}$ which is nearly singular. Inverse of this matrix induces calculation error which would stop the optimization process. Besides, inverse of a matrix costs extra calculation time. Therefore, instead of $T_u^{-1}$, $T_u$ is parameterized as

$$
\begin{bmatrix}
\prod_{i=1}^{n-1} \cos(\beta_{1,i}) & \cdots & \prod_{i=1}^{n-2} \cos(\beta_{n,i}) \\
\sin(\beta_{n-1,1}) \prod_{i=1}^{n-2} \cos(\beta_{1,i}) & \cdots & \sin(\beta_{n-1,n}) \prod_{i=1}^{n-2} \cos(\beta_{n,i}) \\
\sin(\beta_{1,1}) \prod_{i=1}^{n-2} \cos(\beta_{i,1}) & \cdots & \sin(\beta_{1,n}) \prod_{i=1}^{n-2} \cos(\beta_{i,n}) \\
\sin(\beta_{2,1}) \cos(\beta_{1,1}) & \cdots & \sin(\beta_{2,n}) \cos(\beta_{1,n}) \\
\sin(\beta_{1,1}) \\
\end{bmatrix}
$$

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so that the calculation of inverting $T_u^{-1}$ is no longer necessary. Vaes et al. (2007) has explained that scaling the column vector of $T_u$ does not affect $\mu_A(E_{\tilde{P}}(\omega))$. Therefore, this modification does not affect the decoupling accuracy.

4. EXPERIMENTS

4.1 The 3-DOF Setup

The experimental setup was originally designed to validate the control design for the contactless planar actuator with manipulator, see Gajdusek et al. (2008). With some of the unnecessary components (the H-bridge and the manipulator) removed, the photo of the setup is shown in Fig. 1. The payload is subjected to 3-DOF movements: the translation along the vertical axis ($z$) and the two rotations about the two horizontal axes (roll $\phi$ and pitch $\theta$). The rest of the DOFs are limited by the three leaf-springs connecting the payload and the base-frame. The leaf-springs can easily bend at their two ends but they can not shrink or extend. Therefore, the three DOFs have very low stiffness. Fig. 2 shows the drawings of the setup. Four mechanical hard-stops are installed at the four corner of the payload for safety. There are nine Voice Coil Actuators (VCA), labeled by numbers 1-9, providing the control force. As the 3-DOF system has nearly double-integrator properties, the controllers designed for identification. The controllers $C_1$, $C_2$, and $C_3$ take feedback signals ($\vec{y} = [y_1,y_2,y_3]^T$) from S-1, S-2, and S-3, and send the control signals ($\vec{u} = [u_1,u_2,u_3]^T$) to the 3-DOF plant and $C = \text{diag}(C_1,C_2,C_3)$ represents three PI controllers designed for identification. The controllers $C_1$, $C_2$, and $C_3$ take feedback signals ($\vec{y} = [y_1,y_2,y_3]^T$) from S-1, S-2, and S-3, and send the control signals ($\vec{u} = [u_1,u_2,u_3]^T$) to the system analyzer 'Siglab' (from Spectral Dynamics, Inc.), the three SISO loop are excited by white noise separately and subsequently, $P$ is calculated by

$$P(\omega) = \tilde{G}(\omega) \times |I - C(\omega)\tilde{G}(\omega)|^{-1},$$

(11)

where $I$ is the $3 \times 3$ identity matrix and $C(\omega)$ is the calculated FRF matrix of the three PI controllers at frequency $\omega$. The magnitude of the resultant FRF matrix $\tilde{P}$ is plotted in Fig. 4. The upper bound of the $\mu_A(E_{\tilde{P}}(\omega))$ is plotted in Fig. 5.
The modified Owens method is applied to the measured FRF matrix $P$ within the interested frequency range. The two constant frequencies are chosen as $\omega_1 = 1$ Hz and $\omega_2 = 10$ Hz. The decoupled FRF matrix derived by calculation ($P_d$) according to (1) and by measurement ($\tilde{P}_d$) are both obtained. Subsequently, the upper bounds of $\mu_\Delta(E_{P_d}(\omega))$ and $\mu_\Delta(E_{\tilde{P}_d}(\omega))$ are calculated and compared in Fig. 7.

Both the Vaes algorithm and the modified Vaes algorithm are applied to find the optimal static decoupling matrices. The initial values are both taken from the results of the modified Owens method. They yield almost the same performance but the modified Vaes algorithm saves about 40% calculation time. The upper bound of $\mu_\Delta(E_{P_d}(\omega))$ and $\mu_\Delta(E_{\tilde{P}_d}(\omega))$ using the result of the modified Vaes algorithm are compared in Fig. 8. Note that the resonant peak at 28 Hz and the noise peaks at high frequencies are filtered by the weighting filter.

Shown in both Fig. 7 and Fig. 8, the upper bound of $\mu_\Delta(E_{P_d}(\omega))$ is not consistent with that of $\mu_\Delta(E_{\tilde{P}_d}(\omega))$. Comparison of the $\mu_\Delta(E_{P_d}(\omega))$ in Fig. 7 and Fig. 8 shows that the modified Vaes optimization algorithm flattens $\mu_\Delta(E_{P_d}(\omega)W(\omega))$ which yields better decoupling performance the modified Owens method. However, this conclusion can hardly drawn comparing the $\mu_\Delta(E_{\tilde{P}_d}(\omega))$ in Fig. 7 and Fig. 8 due to the inconsistency of $\mu_\Delta(E_{P_d}(\omega))$ and $\mu_\Delta(E_{\tilde{P}_d}(\omega))$.

According to the iterative optimization procedure, the modified Vaes optimization algorithm is applied to $\tilde{P}_d$, the FRF matrix measured in the decoupling validation experiment for the modified Owens method. The decoupling matrices obtained by the iterative optimization procedure are

$$T_v = \begin{bmatrix} -0.6768 & 0.7343 & -0.0521 \\ 0.4528 & 0.4290 & 0.7832 \\ -0.4340 & -0.3135 & 0.8469 \end{bmatrix}, \quad (12)$$

$$T_w = \begin{bmatrix} -0.6780 & 0.4662 & -0.4394 \\ 0.7337 & 0.4441 & -0.3227 \\ -0.0439 & 0.7676 & 0.8448 \end{bmatrix}, \quad (13)$$

The upper bounds of the corresponding $\mu_\Delta(E_{P_d}(\omega))$ and $\mu_\Delta(E_{\tilde{P}_d}(\omega))$ are plotted in Fig. 9. It shows that the calculated curve and the measured curve coincide well and they are both flattened. The magnitude of the measured FRF matrix $\tilde{P}_d$ is plotted in Fig. 10. The off-diagonal entries have at least 20dB lower magnitude than the diagonal entries. Comparison of Fig. 10 and Fig. 4 shows that the decoupling is effective. Comparison of Fig. 9 and Fig 5 shows that the decoupling matrices greatly reduces the $\mu$ interaction measure.
The 3-DOF system shows significant cross coupling. The directly applied Vaes algorithm does not lead to the true optimal static decoupling matrices because \( \mu_3(E_p^0(\omega)) \) is not consistent with \( \mu_3(E_p^0(\omega)W(\omega)) \) which is calculated based on \( P_d \). The FRF matrix measured on decoupled plant. An iterative procedure based on the Vaes algorithm is proposed to achieve the optimal decoupling performance. It only requires the FRF matrix measurement and no MIMO parameter estimation is needed. Two modifications are proposed to the Vaes algorithm to speed up the optimization process and to improve the numerical stability. The proposed methods are experimentally tested on a 3-DOF system. The results show that proposed iterative procedure is effective to achieve the optimal static decoupling. \( \mu_3(E_p^0(\omega)) \) and \( \mu_3(E_p^0(\omega)W(\omega)) \) coincide reasonably well. The modified Vaes algorithm significantly saves the calculation time and improves the numerical stability of the optimization process.

5. CONCLUSION

The 3-DOF system shows significant cross coupling. The directly applied Vaes algorithm does not lead to the true optimal static decoupling matrices because \( \mu_3(E_p^0(\omega)W(\omega)) \) which is calculated based on \( P_d \), is not consistent with \( \mu_3(E_p^0(\omega)) \) which is calculated based on \( P_d \). The FRF matrix measured on decoupled plant. An iterative procedure based on the Vaes algorithm is proposed to achieve the optimal decoupling performance. It only requires the FRF matrix measurement and no MIMO parameter estimation is needed. Two modifications are proposed to the Vaes algorithm to speed up the optimization process and to improve the numerical stability. The proposed methods are experimentally tested on a 3-DOF system. The results show that proposed iterative procedure is effective to achieve the optimal static decoupling. \( \mu_3(E_p^0(\omega)) \) and \( \mu_3(E_p^0(\omega)) \) coincide reasonably well. The modified Vaes algorithm significantly saves the calculation time and improves the numerical stability of the optimization process.

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