the observer-based controller in Fig. 4, i.e., the block diagram inside the dotted-line box, can be written as follows:

\[
\begin{bmatrix}
\dot{x} \\
\dot{y}
\end{bmatrix} =
\begin{bmatrix}
A & B_2F + HC_2F & HD_22F \\
-C_2 & D_22F & 0
\end{bmatrix}
\begin{bmatrix}
x \\
y
z
\end{bmatrix} +
\begin{bmatrix}
0 & -I & 0 \\
1 & D_22 & 0
\end{bmatrix}
\begin{bmatrix}
u \\
\theta
\end{bmatrix},
\]

(3.11a)

where

\[
\begin{bmatrix}
u \\
\theta
\end{bmatrix} =
\begin{bmatrix}
\alpha_{11} & \alpha_{12} \\
\alpha_{21} & \alpha_{22}
\end{bmatrix}
\begin{bmatrix}
x \\
y
z
\end{bmatrix} +
\begin{bmatrix}
\beta_1 \\
\beta_2
\end{bmatrix} y.
\]

(3.11b)

Assume that the added dynamics \(K(s)\) is described by the following minimal relation:

\[
k = A k + B y
\]

(3.12a)

\[
u_2 = C k + D y.
\]

(3.12b)

The controller \(Q(s)\) is just a combination of (3.11) and (3.12). From (3.11) and (3.12), we have the dynamic equations of the controller \(Q(s)\) as follows:

\[
\begin{bmatrix}
\dot{x} \\
\dot{k}
\end{bmatrix} =
\begin{bmatrix}
\alpha_{11} & \alpha_{12} \\
\alpha_{21} & \alpha_{22}
\end{bmatrix}
\begin{bmatrix}
x \\
k
\end{bmatrix} +
\begin{bmatrix}
\beta_1 \\
\beta_2
\end{bmatrix} y +
\begin{bmatrix}
\gamma_1 & \gamma_2
\end{bmatrix}
\begin{bmatrix}
x \\
\theta
\end{bmatrix} + \dot{\theta}
\]

(3.13a)

\[
u = \begin{bmatrix}
\gamma_1 & \gamma_2
\end{bmatrix}
\begin{bmatrix}
x \\
\theta
\end{bmatrix} + \dot{\theta}
\]

(3.13b)

where

\[
\begin{align*}
\beta_1 &= -H - (B_2 + HD_22F)I (I - DD_22)^{-1} \dot{D} \\
\beta_2 &= B + BD_22(I - DD_22)^{-1} \dot{D} \\
\gamma_1 &= F + (I - DD_22)^{-1} \dot{D} C_2 + D_22 F \\
\gamma_2 &= -(I - DD_22)^{-1} \dot{C} \\
\alpha_{11} &= A + HC_2 + (B_1 + HD_22 F) \gamma_1 \\
\alpha_{12} &= A + B_2 F - \beta_2 (C_2 + D_22 F) \\
\alpha_{21} &= \beta_2 (C_2 + D_22 F) \\
\alpha_{22} &= A - BD_22 \gamma_2 \\
\dot{\theta} &= -(I - DD_22)^{-1} \dot{D}
\end{align*}

(3.14a-3.14j)

Now, assume that the state-space representation (3.13) of the controller \(Q(s)\) is unobservable. Then by the PBH test [6], there exists a nonzero vector \(\xi\) such that

\[
\begin{bmatrix}
\gamma_1 & \gamma_2 \\
\alpha_{11} & \alpha_{12} \\
\alpha_{21} & \alpha_{22}
\end{bmatrix}
\begin{bmatrix}
\xi_0 \\
\xi_1 \\
\xi_2
\end{bmatrix} = 0
\]

(3.15a)

\[
\lambda \begin{bmatrix}
\xi_0 \\
\xi_1 \\
\xi_2
\end{bmatrix} = 0
\]

(3.15b)

for some eigenvalue \(\lambda\) of (3.13). Note that it is the eigenvalue \(\lambda\) that is unobservable. From (3.15b), we get

\[
\alpha_{11} \xi_1 + \alpha_{12} \xi_2 = \lambda \xi_1
\]

(3.16a)

and

\[
\alpha_{21} \xi_1 + \alpha_{22} \xi_2 = \lambda \xi_2
\]

(3.16b)

which, by using (3.14c) and (3.14d), is rewritten as

\[
(A + HC_2) \xi_1 + (B_1 + HD_22 F) \gamma_1 \xi_1 + \gamma_2 \xi_2 = \lambda \xi_1
\]

(3.16b)

In view of (3.15a), the above equation reduces to

\[
(A + HC_2) \xi_1 = \lambda \xi_1
\]

(3.16c)

which clearly establishes that the unobservable eigenvalue belongs to \(S_{\text{unobservable}}\).

Proceeding similarly, it can be shown that if (3.13) is uncontrollable, then the uncontrollable eigenvalue belongs to \(S_{\text{uncontrollable}}\).

Note in the above development that \(\xi_0 = 0\) contradicts the minimality assumption of \(K(s)\). Thus,

\[
S_{\text{unobservable}} \subset S_{\text{observer}}
\]

(3.17a)

\[
S_{\text{uncontrollable}} \subset S_{\text{regulator}}
\]

(3.17b)

where \(S_{\text{unobservable}}\) is the set of all the unobservable poles of the controller \(Q(s)\), \(S_{\text{uncontrollable}}\) is defined similarly. This completes the proof of Theorem 3.2.

IV. CONCLUSION

The poles of the closed-loop system with the observer-based controller parameterization shown in Fig. 4 can be classified into three groups, and each group of poles can be independently determined. These three groups of poles are the regulator poles (the eigenvalues of \(A + B_1 F\)), the observer poles (the eigenvalues of \(A + HC_2\)), and the poles of the added dynamics \(K(s)\). \(F, H,\) and \(K(s)\) are free parameters to be chosen such that the closed-loop transfer function matrix \(\Phi(s)\) has some optimal performance subject to the following constraints: \(A + B_1 F\) and \(A + HC_2\) are stable and \(K(s)\) is proper stable with \(I - DD_22 K(s)\) invertible.

If the realization of the controller in Fig. 4 is not minimal, then the uncontrollable and/or unobservable controller poles can be removed and the order of the controller is minimized. The set of these removable controller poles is a subset of the regulator and the observer poles. The poles of the closed-loop system with the minimal order controller will include all the poles of the parameter matrix \(K(s)\) and some of the regulator and the observer poles which are not the removable controller poles.

REFERENCES


Model Reduction of Linear Conservative Mechanical Systems

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Abstract—A new approach for model reduction of linear conservative or weakly damped mechanical systems is proposed which is based on the balancing of an associated gradient system.

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1. Introduction

We consider linear conservative mechanical systems with external controls \( u \), written in Hamiltonian form as

\[
\begin{pmatrix}
q \\
p
\end{pmatrix} = \begin{pmatrix}
0 & P \\
-Q & 0
\end{pmatrix} \begin{pmatrix}
q \\
p
\end{pmatrix} + \begin{pmatrix}
0 \\
B
\end{pmatrix} u,
\]

\( P = P^T > 0, \ Q = Q^T > 0 \quad (1a) \)

with \( q = (q_1, \ldots, q_n)^T \) the vector of generalized configuration coordinates and \( p = (p_1, \ldots, p_n)^T \) the vector of generalized momenta. The expressions \( \frac{1}{2} P p p + \frac{1}{2} Q q q \) are the kinetic, respectively, potential, energy of the system. Although in applications the total energy \( \frac{1}{2} P p p + \frac{1}{2} Q q q \) is usually not strictly conserved (due to dissipation), often the conservative model \((1a)\) serves as a useful starting point, especially if the inherent damping in the system is negligible and/or difficult to quantify. In principle, the output map for a system \((1a)\) can be any function of \( q \) and \( p \) (or of \( q \) and \( p \) since \( p = P^{-1} q \)); see [15]. However, in the present paper, we concentrate on the case of collocated sensors and actuators for which the outputs are given as

\[
y = B^T q. \quad (1b)
\]

System \((1a), (1b)\) is called a Hamiltonian system, and is known to have some enjoyable properties (see, e.g., [3, 13, 14, 19]). The transfer matrix \( F_H(s) \) of \((1)\) is given as [14]

\[
F_H(s) = B^T (s I + P Q)^{-1} P B,
\]

and therefore satisfies the symmetry properties

\[
F_H(-s) = F_H(s) \quad (2)
\]

Conversely, it can be shown [13]; see also [4]) that if a transfer matrix \( F(s) \) satisfies (3), then there always exists a minimal realization of the form \((1)\), with det \( P \neq 0 \), but \( P \) and \( Q \) not necessarily positive definite. The assumption \( P > 0 \) and \( Q > 0 \) implies that the poles of the system are all on the imaginary axis and unequal to zero, and that the system is marginally (but not asymptotically) stable. In fact, it is well known (cf. [1]) that there always exists a state-space transformation \( \tilde{q} = S q, \tilde{p} = S^{-1} p \), det \( S \neq 0 \)

\[
\begin{pmatrix}
0 & P \\
-Q & 0
\end{pmatrix}
\]

for \((1)\) such that the system matrix

\[
\begin{pmatrix}
0 & I_n \\
-D & 0
\end{pmatrix}, \quad D = \text{diag}(\omega_1^2, \ldots, \omega_n^2)
\]

transforms into

\[
\begin{pmatrix}
0 & I \\
-D & 0
\end{pmatrix}.
\]

This is called modal analysis.

The problem investigated in the present paper is that of model reduction of a Hamiltonian system \((1)\). Most common approaches to model reduction are based on the above displayed modal analysis of the system matrix; indeed, the system is reduced to a simpler system by leaving out the eigenmodes corresponding to some of the eigenfrequencies (usually the higher ones). However, since modal analysis basically is only concerned with the system matrix, and not with the input and output matrix, the resulting model reduction may have disadvantages from a system and control theoretic point of view. For instance, it is clear that the omission of a particular high eigenfrequency for which the corresponding input component happens to be large will result in substantial control (and observation) spillover (cf. [2]). In this paper, we therefore wish to give an alternative approach using the joint knowledge of the system matrix and the input and output matrices of \((1)\). This approach is heavily motivated by the well-established technique of model reduction of asymptotically stable systems using balancing (cf. [6, 10, 12]).

Let us stress here that the balancing procedure itself cannot be applied to systems \((1)\) since \((1)\) is only marginally and not asymptotically stable, and hence the controllability and observability gramiens (cf. [10, 12]) for \((1)\) cannot be defined as improper integrals. Furthermore, also, an alternative definition of these gramiens as unique solutions of some well-defined Riccati equations (cf. [9]) is easily seen not to be feasible in this case. This problem was partially circumvented in [7, 8] by balancing weakly damped (and therefore asymptotically stable) mechanical systems, and by carrying out a limiting analysis for infinitely small damping. Although appealing, it is not clear if this approach is the most natural one; moreover, the numerical problems related to the computations of the gramiens of a weakly damped mechanical system seem not to be resolved [5, 7]. For other interesting approaches based on "closed-loop" balancing, respectively, modal cost analysis, we refer to [11, 17], respectively [16].

The key idea of the approach presented in this paper is to associate as in [3, 13] with the Hamiltonian system \((1)\) the gradient (or reciprocal) system

\[
x = -P Q x + P B u, \quad P = P^T > 0, \ Q = Q^T > 0 \quad (6a)
\]

\[
y = B^T x \quad (6b)
\]

or, equivalently,

\[
P^{-1} x = -Q x + B^T u, \quad P = P^T > 0, \ Q = Q^T > 0 \quad (6a')
\]

\[
y = B^T x \quad (6b')
\]

with inner product \( P^{-1} \) and potential function \( \frac{1}{2} x^T Q x \). (If the Hamiltonian system \((1)\) is physically realized by masses and springs, then the gradient system \((6)\) is obtained by replacing the springs by dampers.)

The above transition from Hamiltonian to gradient system is a basis-free operation, as already explained in [3, 14]. Indeed, a basis transformation \( \tilde{q} = S q, \det S \neq 0 \) induces the symplectic transformation (4), transforming the Hamiltonian system \((1)\) into

\[
\begin{pmatrix}
\dot{\tilde{q}} \\
\dot{\tilde{p}}
\end{pmatrix} = \begin{pmatrix}
0 & S P S^T \\
-S^{-T} Q S^{-1} & 0
\end{pmatrix} \begin{pmatrix}
\tilde{q} \\
\tilde{p}
\end{pmatrix} + \begin{pmatrix}
0 \\
S^{-T} B
\end{pmatrix} u \quad (7)
\]

\[
y = B^T S^{-1} \tilde{q}. \quad (8)
\]

The associated gradient system of \((7)\) is given as

\[
(S^{-T} P^{-1} S^{-1}) \tilde{x} = -S^{-T} Q S^{-1} \tilde{x} + S^{-T} B u
\]

\[
y = B^T S^{-1} \tilde{x} \quad (8)
\]

and thus is obtained from \((6')\) by the state-space transformation \( \tilde{x} = S x \). (Notice that the inner product \( P^{-1} \) and potential function \( \frac{1}{2} x^T Q x \) both transform in the right, covariant way.)

Clearly, the transfer matrix \( F_G(s) \) of \((6)\) is related to \( F_H(s) \) [see (2)] as

\[
F_H(s) = F_G(s^2) \quad (9)
\]

and thus satisfies \( F_G(s) = F_G(\frac{s^2}{s}) \) (Conversely, it can be shown, see, e.g., [18], that a transfer matrix \( F(s) \) satisfying \( F(s) = F(s)^2 \) always has a minimal realization of the form \((6)\), with det \( P \neq 0 \) but \( P \) and \( Q \) not necessarily positive definite.) Also, the following relation is easily proven.

Proposition 1 [13, 14]: The Hamiltonian system \((1)\) is controllable (respectively, observable) if and only if its associated gradient system \((6)\) is controllable (respectively, observable). Furthermore (by collocation of sensors and actuators), the Hamiltonian (respectively, gradient) system is controllable iff the Hamiltonian (respectively, gradient) system is observable.

Indeed, as already remarked in [3], there are physical reasons which suggest that controllability (observability) of the Hamiltonian system \((1)\) is closely related to controllability (observability) of the associated gradient system \((6)\). Since model reduction by balancing is based on exploiting the controllability and observability properties of the system, this partly motivates the consideration of the associated gradient system for model reduction of the Hamiltonian system.
From now on, we shall assume that the Hamiltonian system (1) is minimal. Since, as we have seen, the poles of $F(s)$ are all purely imaginary and nonzero, it then immediately follows from (9) and Proposition 1 that the gradient system (6) is minimal and all its eigenvalues are all real and strictly negative. In particular, the associated gradient system is asymptotically stable.

II. Model Reduction of Hamiltonian Systems via Pseudobalancing

Since the associated gradient system (6) is asymptotically stable, we can apply balancing [10] to it. This is done by comparing the controllability and observability gramians $W$ of (6), as defined as the unique solution of the Riccati equation

$$(-PQ)W + W(-PQ)^T = -(PB)PB^T$$

(10)

to its observability gramian $M$, as defined as the unique solution of the Riccati equation

$$(-PQ)^TM + M(-PQ) = -BB^T$$

(11)

If we apply a coordinate transform $x = Sx$ to the gradient system (6), then the gramians $W$ and $M$ transform as

$$W ightarrow SWS^T, \quad M ightarrow S^{-T}MS^{-1}$$

(12)

It follows from the theory of balancing [10], [11] that there always exist coordinate transformations $x = Sx$ such that

$$SWS^T = S^{-T}MS^{-1} = \text{diag}(\alpha_1, \ldots, \alpha_r) := \Sigma$$

(13)

with $\alpha_1 \geq \alpha_2 \geq \cdots \geq \alpha_r > 0$. Actually, the argument is similar to the one underlying the existence of a transformation (4) resulting in (5). Furthermore, $\alpha_1, \ldots, \alpha_r$ are input-output invariants, and are given as the square roots of the eigenvalues of $MW$. Let us call them the singular values of the system (6). The system in such coordinates satisfying (13) is said to be balanced. Model reduction of a balanced system is achieved by omitting the last $n - k$ state-space variables corresponding to the singular values $\alpha_{r+1}, \ldots, \alpha_r$ where $\alpha_r \gg \alpha_{r+1}$ (see [10], [11]).

In the case of balancing of gradient systems (6), we additionally have the following.

**Lemma 2:** The controllability and observability gramians $W$ and $M$ for (6) are related as

$$W = PMP^T$$

(14)

**Proof:** $W$ and $M$ are given as the unique solutions of (10), respectively, (11). On the other hand, pre- and postmultiplication of (11) with $P$ yields $-PQPMP - PMPQP = -BB^TP$, and hence, PMP also satisfies (10).

**Proposition 3:** Let (6) be balanced. Then

$$P = I_r$$

(15)

Furthermore, suppose $\alpha_1 > \alpha_{r+1}$, and write

$$x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}, \quad Q = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{pmatrix}, \quad B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}$$

(16)

with $\dim x_1 = k$, and $Q_{11}$ a $k \times k$ and $B_1$ a $k \times m$ matrix. Then the reduced system

$$\dot{x}_1 = -Q_{11}x_1 + B_1u$$

$$\dot{x}_2 = B_2x_1 + B_2u$$

is a gradient system which is minimal, balanced, and asymptotically stable with $Q_{12} > 0$.

**Proof:** Since the system is balanced, we have $M = W = \Sigma$ with $\Sigma$ diagonal. By Lemma 2, this implies

$$\Sigma = P\Sigma P^T$$

(18)

Since the $i$th row of $\Sigma P$ equals the $i$th row of the matrix $P$ premultiplied with the positive factor $\alpha_i$, it follows that the product of the $j$th column of $P$ with the $i$th row of $P$ equals the zero matrix for $i \neq j$. Hence, $PP^T = \Sigma$, and in diagonal, and $P^T = I_r$. Since $P > 0$, the eigenvalues of $P$ are real and positive. Together with $P^2 = I$, this implies that the eigenvalues of $P$ are all 1, and $P = I_r$. Clearly, (17) is a gradient system. The fact that (17) is minimal, balanced, and asymptotically stable follows from standard balancing theory [12].

**Remark:** A gradient system (6) for which $P = I$ and $Q > 0$ is called a relaxation system in [18]. It thus follows from Proposition 3 that a balanced gradient system is always a relaxation system. This can be seen as the analog of [12, Theorem 3.1]. (A relaxation system has purely oscillatory behavior converging to the origin.) A related result for single-input, single-output systems for $P$ indefinite was obtained in [7].

Now let us see how this translates to the original Hamiltonian system (1). As we saw before [cf. (7), (8)], a basis transformation $x = Sx$ for the gradient system (6) corresponds to the symplectic transformation (4) for the Hamiltonian system (1), transforming it into (7).

In particular, if $\bar{x} = Sx$ is a coordinate transformation which brings the gradient system (6) into balanced form, then by Proposition 3 [cf. (15)], $S$PS$^T = I_r$, and thus the induced symplectic transformation (4) transforms the Hamiltonian system (1) into

$$\begin{pmatrix} \dot{\tilde{q}} \\ \dot{\tilde{p}} \end{pmatrix} = \begin{pmatrix} 0 & I_r \\ -Q & 0 \end{pmatrix} \begin{pmatrix} \tilde{q} \\ \tilde{p} \end{pmatrix} + \begin{pmatrix} 0 \\ B \end{pmatrix} u$$

$$y = B^T \tilde{q}$$

(19)

where $Q := S^{-T}QS^{-1}$, $B := S^{-T}B$. We shall call (19) a pseudobalanced Hamiltonian system. Formally, we have the following.

**Definition 4:** The Hamiltonian system (1) is said to be pseudobalanced if the associated gradient system is balanced.

Model reduction of a pseudobalanced Hamiltonian system (19) will now be based on model reduction of the associated balanced gradient system. Indeed, suppose that the singular values $\alpha_1 \geq \cdots \geq \alpha_r$ of the gradient system satisfy $\alpha_r \gg \alpha_{r+1}$, and write [compare (16)]

$$\tilde{q} = \begin{pmatrix} \tilde{q}_1 \\ \tilde{q}_2 \end{pmatrix}, \quad \tilde{p} = \begin{pmatrix} \tilde{p}_1 \\ \tilde{p}_2 \end{pmatrix}, \quad \bar{Q} = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \end{pmatrix}, \quad B = \begin{pmatrix} B_1 \\ B_2 \end{pmatrix}$$

(20)

with $\dim \tilde{q}_1 = \dim \bar{q}_1 = k$, $Q_{11}$ a $k \times k$ matrix, and $B_1$ a $k \times m$ matrix. Then a reduced-order model of (19) is given as

$$\begin{pmatrix} \dot{\bar{q}}_1 \\ \dot{\bar{p}}_1 \end{pmatrix} = \begin{pmatrix} 0 & I_r \\ -Q_{11} & 0 \end{pmatrix} \begin{pmatrix} \bar{q}_1 \\ \bar{p}_1 \end{pmatrix} + \begin{pmatrix} 0 \\ B_1 \end{pmatrix} u$$

$$y = B_1^T \bar{q}_1,$$

(21)

**Proposition 5:** Suppose $\alpha_1 > \alpha_{r+1}$ for the pseudobalanced Hamiltonian system (19). Then (21) is a Hamiltonian system which is pseudobalanced, minimal, and marginally stable with $Q_{12} > 0$.

**Proof:** Clearly, (21) is Hamiltonian (with dimension of its state space equal to $2k$). By Proposition 3, the associated gradient system of (21) is balanced, minimal, and has $Q_{12} > 0$. Thus, (21) is pseudobalanced (Definition 4), minimal (Proposition 1), and the total energy $\frac{1}{2}P_1^T \bar{p}_1 + \frac{1}{2}Q_1 \bar{q}_1$ is positive, implying that (21) is marginally stable.

Recall that the eigenfrequencies $\omega_1, \ldots, \omega_k$ of the full-order system (19) are obtained by calculating an orthonormal matrix $R$ such that $RQR^T = \text{diag}(\omega_1^2, \ldots, \omega_k^2)$ (indeed, the symplectic transformation (4) with $S$ replaced by $R$ will transform the system matrix of (19) into the form (5)), and thus equal the square roots of the eigenvalues of $Q$. Similarly, the eigenfrequencies $\omega_{k+1}^2, \ldots, \omega_n^2$ of the reduced-order system (21) are the square roots of the eigenvalues of $Q_{11}$. We immediately obtain the following relationship.

**Proposition 6:** The eigenfrequencies of the system (19) and (21) satisfy

$$\min_{i \in \mathbb{R}} \omega_i \leq \min_{i \in \mathbb{R}} \omega_i' \leq \max_{i \in \mathbb{R}} \omega_i' \leq \max_{i \in \mathbb{R}} \omega_i$$

(22)
be a subset of the set of eigenfrequencies of the original system (in fact, and similarly for the second inequality. of eigenfrequencies $U_1;,$ usually "better" and never "worse" than the approximations resulting have a full theoretical answer to this question. In all numerical examples sense the reduced-order Hamiltonian system to the full-order Hamiltonian system (19) or from the reduced-order models obtained by modal analysis (by leaving some of the eigenmodes of the system). Here, "better" has to be understood in the naive sense of impulse responses and Bode plots being closer to the corresponding figures for the full-order system.

In order to show the main characteristics of our method, we now give a simple toy example of a mechanical system consisting of two masses $m_1, m_2$ attached to springs with spring constants $k_1, k_2$ (see Fig. 1).

The control $u$ acts on mass $m_2,$ and the position of mass $m_1,$ (relative to rest position) is observed as output $y.$ The impulse response and the Bode plot (amplitude) of the system are depicted in Figs. 2 and 3.

The singular values of the associated gradient system are computed as $\sigma_1 = 0.0488,$ $\sigma_2 = 0.0012.$ It is clear from the impulse response of the system (Fig. 2) that no second-order system will satisfactorily approximate the full fourth-order system. This conclusion is enforced by the fact that the singular values of the Hamiltonian system should be taken as $\sqrt{\sigma_1}$ and $\sqrt{\sigma_2},$ and since $\sqrt{\sigma_1} = 6.3, \sqrt{\sigma_2},$ these singular values are too close to each other to have a good model reduction. However, if we do apply pseudobalancing and leave out the components corresponding to $\sigma_1,$ then we obtain the reduced-order system

$$\dot{x} = \begin{pmatrix} 0 & 1 \\ -1.9952 & 0 \end{pmatrix} x + \begin{pmatrix} 0 \\ 0.4415 \end{pmatrix} u, \quad y = (0.4415 \quad 0) x$$

which has an impulse response and Bode diagram as depicted in Figs. 2 and 3 (dotted lines), and which reasonably approximates the fourth-order system.

On the other hand, if we would reduce the model by modal analysis, then we obtain a second-order system with frequency equal to the first or the second eigenfrequency of the system, and with amplitude in both cases approximately 0.7, which clearly is very unsatisfactory. Notice also that modal analysis does not a priori tell us which eigenmode has to be left out, contrary to our pseudobalancing approach which is based upon the calculation of the singular values.

**III. AN EXAMPLE**

The fundamental question raised by the previous section is in what sense the reduced-order Hamiltonian system (21) is a good approximation to the full-order Hamiltonian system (19) or (1). Up to now, we do not have a full theoretical answer to this question. In all numerical examples we tried so far, it was found that the reduced-order models obtained with our approach give approximations to the full-order system which are usually "better" and never "worse" than the approximations resulting from the reduced-order models obtained by modal analysis (by leaving out some of the eigenmodes of the system). Here, "better" has to be understood in the naive sense of impulse responses and Bode plots being closer to the corresponding figures for the full-order system.

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**IV. CONCLUSION**

We have given an alternative approach to model reduction of a fairly large class of linear conservative mechanical systems, which in numerical examples looks promising. If we would have a general dependence of the outputs of the configuration coordinates, i.e., instead of (18) an equation $\gamma = C\theta,$ then our procedure could still be applied, mutatis mutandis, but the basic Proposition 5 will not hold anymore in this noncollocated case.

The approach taken in this paper raises two fundamental questions. First, we do not yet know what kind of "norm" is underlying our approach of pseudobalancing and reducing a Hamiltonian system (contrary to the balancing procedure for asymptotically stable systems, which is related to the Hankel norm of the system). Possibly, a clue of this problem is the following observation, due to an anonymous referee. The mapping $\lambda \mapsto \lambda^T$ maps the $45^\circ$ radials in the complex plane onto the imaginary axis. In view of (9), this implies that transfer matrix error bounds along the imaginary axis for the reduced gradient system (see, e.g., [4]) translate into error bounds along the $45^\circ$ radials for the reduced Hamiltonian system. Second, it would be nice to have some physical interpretation of the reduced-order model (21). Finally, our approach can be also applied to nearly conservative (weakly damped) systems by first leaving out the damping in the model reduction process, and then adding it again to the reduced-order model, and to infinite-dimensional (nearly) conservative systems by first reducing the system to a high- but finite-dimensional (nearly) conservative system by modal analysis (omitting the high eigenfrequencies) (compare [5]).

**REFERENCES**

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