

State-Space System Identification with Identified Hankel Matrix

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Abstract

In state-space system identification theory, the Hankel matrix often appears prior to model realization. Traditionally, one identifies from input-output data the Markov parameters from which the Hankel matrix is built. This paper examines the strategy where the Hankel matrix itself is identified from input-output data. Various options are examined along this direction where the identification of the Hankel matrix can be carried out directly or indirectly. Advantages and drawbacks associated with each option are examined and discussed. Extensive evaluation both with simulated and experimental data indicates that the new approach is effective in detecting the “true” or effective order of the system, hence it is capable of producing relatively low-dimensional state-space model. The interactive matrix formulation plays a key role in the development of the proposed identification technique.

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1. Introduction

The problem of state-space system identification has received considerable attention in recent years. Within the aerospace community, the Eigensystem Realization Algorithm (ERA),¹ an extension of the work of Ho and Kalman,² has become an accepted and widely used method. In this or other state-space realization methods³ the Hankel matrix plays a critical role because a state-space model can be obtained from a factorization of the Hankel matrix via its singular value decomposition (SVD) for example. The Hankel matrix comprises of the Markov parameters arranged in a specific Toeplitz pattern. Much efforts have been placed on the problem of obtaining the Markov parameters from input-output data by time or frequency domain approaches.^{4,5} Once the Markov parameters are determined, they become entries in the Hankel matrix for state-space identification.

It is well known that the rank of the Hankel matrix is the order of the system. With perfect noise-free data, the minimum order realization can be easily obtained by keeping only the non-zero Hankel singular values. With real or noise-contaminated data, however, the Hankel matrix tends to be full rank, thus making the problem of determining a minimum-order state-space model non-trivial. In this case, one would hope for a significant drop in the singular values that signals the “true” order of the system, but while this can happen with low-noise simulated data, it rarely happens with real data. A reduced-order model obtained by retaining only “significant” singular values tends to be poor in accuracy. Indeed, this issue remains one of the most unsatisfactory

discrepancy between what is expected in theory and what is actually observed in practice. One may argue that real systems are both non-linear and infinite dimensional. While this is certainly true in many cases it is not to blame in all cases. A common procedure is to keep all Hankel singular values at the expense of a high-dimensional state-space model and use a separate post-identification procedure such as model reduction to reduce the dimension of the identified model. However, any time model reduction is invoked, some accuracy is lost. It is preferable to have an identification method that produces a “true” or effective order model directly in the first place.

While detailed analysis that explains the above phenomenon is difficult because the relationship between the Hankel matrix and the final state-space realization is quite non-linear, some heuristic arguments may provide insights into the problem. In the presence of noise, the identified Markov parameters that are the building blocks of the Hankel matrix are invariably in error. Since the Hankel matrix has a very specific Toeplitz pattern, this error pattern is built in the Hankel matrix and subsequent non-linear decomposition during the realization step does nothing to undo it. Furthermore, the Markov parameters themselves are usually not directly identified from input-output data, but computed indirectly via an identified auto-regressive or transfer function model. This leads to the idea of identifying the Markov parameters directly from input-output data as done in Refs. 6, 7 through the use of ARMarkov models. In this paper, we go one step further in trying to identify the Hankel matrix itself directly from input-output data. The motivation here is that by skipping intermediate steps, an identified Hankel matrix does not suffer from having the error pattern that is associated with a Hankel matrix that is

built from the Markov parameters which are directly or indirectly identified. Since the Hankel matrix consists of the Markov parameters, an identified Hankel matrix essentially has the Markov parameters themselves directly identified from input-output data as well.

In this paper we will first provide a generalization of the ARMarkov model development through the use of interaction matrix. Next, we will develop equations that allow the Hankel matrix to be identified from input-output data. Several options will be examined where the Hankel matrix identification is carried out directly, or indirectly, or both. Following the theoretical development, extensive results using both simulated and real data will be used to examine the utility of the identified Hankel approach in comparison with other methods.

2. Auto-Regressive Model with Markov Parameter Coefficients (ARMarkov)

In the following we will derive the ARMarkov models via the use of an interaction matrix. This development is a generalization of the ARMarkov model first derived in Ref. 6 for adaptive neural control, and later in Ref. 7 for system identification, and Ref. 8 for predictive control. Consider an n -th order, r -input, m -output discrete-time model of a system in state-space format

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) + Du(k) \end{aligned} \tag{1}$$

By repeated substitution, we have for some $p \geq 0$,

$$\begin{aligned} x(k+p) &= A^p x(k) + \mathbf{e}_p u_p(k) \\ y_p(k) &= \mathbf{O}x(k) + \mathbf{\tau}u_p(k) \end{aligned} \quad (2)$$

where $u_p(k)$ and $y_p(k)$ are defined as column vectors of input and output data going p steps into the future starting with $u(k)$ and $y(k)$, respectively,

$$u_p(k) = \begin{bmatrix} u(k) \\ u(k+1) \\ \vdots \\ u(k+p-1) \end{bmatrix}, \quad y_p(k) = \begin{bmatrix} y(k) \\ y(k+1) \\ \vdots \\ y(k+p-1) \end{bmatrix} \quad (3)$$

For a sufficiently large p , \mathbf{e}_p in Eq. (2) is an $n \times pr$ controllability matrix, \mathbf{O} a $pm \times n$ observability matrix, $\mathbf{\tau}$ a $pm \times pr$ Toeplitz matrix of the system Markov parameters,

$$\mathbf{e}_p = [A^{p-1}B, \dots, AB, B], \quad \mathbf{O} = \begin{bmatrix} C \\ CA \\ \vdots \\ CA^{p-1} \end{bmatrix}, \quad \mathbf{\tau} = \begin{bmatrix} D & 0 & 0 & \dots & 0 \\ CB & D & \ddots & \ddots & \vdots \\ CAB & CB & D & \ddots & 0 \\ \vdots & \ddots & \ddots & \ddots & 0 \\ CA^{p-2}B & \dots & CAB & CB & D \end{bmatrix} \quad (4)$$

As long as $pm \geq n$, it is guaranteed for an observable system that an interaction matrix M exists such that $A^p + M\mathbf{O} = 0$. The existence of M ensures that for $k \geq 0$ there exists an expression for $x(k+p)$ where the state variable is completely eliminated from Eq. (2),

$$x(k+p) = (\mathbf{e}_p + M\boldsymbol{\tau})u_p(k) - My_p(k) \quad (5)$$

From the point of view of system identification, Eq. (5) is significant for two reasons. It is independent of the unknown initial conditions $x(0)$, and it is independent of the system stability. Although we invoke the interaction matrix in this derivation, it needs not be known nor identified during the course of system identification. To derive the ARMarkov model, first note that

$$x(k+q) = A^q x(k) + \mathbf{e}_q u_q(k) \quad (6)$$

By shifting the time indices in Eq. (5) back by p time steps, and then substituting it into Eq. (6) we have for $k \geq p$ an expression for the state $x(k+q)$,

$$x(k+q) = A^q (\mathbf{e}_p + M\boldsymbol{\tau})u_p(k-p) - A^q My_p(k-p) + \mathbf{e}_q u_q(k) \quad (7)$$

Substituting Eq. (7) into $y(k+q) = Cx(k+q) + Du(k+q)$, we arrive at an ARMarkov model representation,

$$y(k+q) = CA^q (\mathbf{e}_p + M\boldsymbol{\tau})u_p(k-p) - CA^q My_p(k-p) + [C\mathbf{e}_q, D]u_{q+1}(k) \quad (8)$$

We observe that the expression for $y(k+q)$ involves past p input values from $u(k-1)$ to $u(k-p)$, past p output values from $y(k-1)$ to $y(k-p)$, the present input $u(k)$, and q

future input values from $u(k+1)$ up to $u(k+q)$. Moreover, the expression for $y(k+q)$ assumes the general form

$$y(k+q) = \sum_{i=1}^p \alpha_i y(k-i) + \sum_{i=1}^p \beta_i u(k-i) + \sum_{i=0}^q \gamma_i u(k+i) \quad (9)$$

whose coefficients are related to the original space-space model A, B, C, D by

$$\begin{aligned} [\alpha_p, \dots, \alpha_2, \alpha_1] &= -CA^q M \\ [\beta_p, \dots, \beta_2, \beta_1] &= CA^q (\mathbf{e}_p + M\boldsymbol{\tau}) \\ [\gamma_0, \gamma_1, \dots, \gamma_{q-1}, \gamma_q] &= [C\mathbf{e}_q, D] \end{aligned} \quad (10)$$

The coefficients γ_i in Eq. (10) are precisely the first q system Markov parameters, $CA^k B$, $k = 0, 1, \dots, q-1$, and D ,

$$[C\mathbf{e}_q, D] = [CA^{q-1}B, \dots, CAB, CB, D] \quad (11)$$

For this reason, these auto-regressive models are referred to as ARMarkov models. Having justified the structure of the ARMarkov model, the Markov parameters can be identified directly from a set of input-output data along with $\rho_1 = -CA^q M$ and $\rho_2 = CA^q (\mathbf{e}_p + M\boldsymbol{\tau})$ as follows,

$$\begin{bmatrix} \rho_1 & \rho_2 & [C\mathbf{e}_q, D] \end{bmatrix} = Y_1 V_1^+ \quad (12)$$

where V_1^+ denotes the pseudo-inverse of V_1 which can be computed via its singular value decomposition where zero or insignificant singular values are truncated, and

$$Y_1 = \begin{bmatrix} y(p+q) & y(p+q+1) & \cdots & y_p(p+q+\ell) \end{bmatrix} \quad (13)$$

$$V_1 = \begin{bmatrix} u_p(0) & u_p(1) & \cdots & u_p(\ell) \\ y_p(0) & y_p(1) & \cdots & y_p(\ell) \\ u_{q+1}(p) & u_{q+1}(p+1) & \cdots & u_{q+1}(p+\ell) \end{bmatrix} \quad (14)$$

To identify the Markov parameters uniquely, the data set must be sufficiently long and rich so that the rows of V_1 associated with input data are linearly independent. These identified Markov parameters can then be used to build the Hankel matrices

$$\bar{\mathbf{H}}(0) = \begin{bmatrix} CB & \cdots & CA^{n_1}B \\ \vdots & \vdots & \vdots \\ CA^{n_2}B & \cdots & CA^{n_1+n_2}B \end{bmatrix}, \quad \bar{\mathbf{H}}(1) = \begin{bmatrix} CAB & \cdots & CA^{n_1+1}B \\ \vdots & \vdots & \vdots \\ CA^{n_2+1}B & \cdots & CA^{n_1+n_2+1}B \end{bmatrix} \quad (15)$$

The procedure to obtain a state-space model is straightforward from this point on. An s -th order state-space model is $\bar{A} = \Sigma_s^{-1/2} U_s^T \bar{\mathbf{H}}(1) V_s \Sigma_s^{-1/2}$, \bar{B} is the first r columns of $\Sigma_s^{1/2} V_s^T$, \bar{C} is the first m rows of $U_s \Sigma_s^{1/2}$, and $s \leq \min(r(n_1+1), m(n_2+1))$. The matrix U_s and V_s are made up of s left and right singular vectors of $\bar{\mathbf{H}}(0)$, respectively. The diagonal matrix Σ_s is made up of s corresponding singular values of $\bar{\mathbf{H}}(0)$. With perfect data $\bar{\mathbf{H}}(0)$ has exactly n positive singular values (all remaining singular values are identically zero), where n is the true minimum order of the system, $s = n$. Otherwise, the user can

specify the order of the state-space model by s , the number of Hankel singular values that he or she wishes to retain. The readers are referred to Ref. 1 for further details.

The ARMarkov model is a generalization of the standard Auto-Regressive model with eXogenous input (ARX) because it results in an ARX model when q is set to zero in Eq. (10). The coefficients of the ARX model are related to those of the original state-space model by the same interaction matrix M . In the ARX model, the Markov parameters don't appear explicitly as coefficients but they can be recovered from the ARX model coefficients.^{4,5} With ARMarkov models the Markov parameters are identified directly from input-output data. This is accomplished at the expense of having to identify additional (extraneous) coefficients $\alpha_i, \beta_i, i = 1, 2, \dots, p$. Thus it would be beneficial to minimize the number of these extraneous terms. The interaction matrix formulation allows us to do just that because it separates $p, pm \geq n$, from q which is number of Markov parameters that one desires to identify.

To put the ARMarkov model in perspective, it is known that the pulse response model also relates input-output data through the Markov parameters,

$$y(k) = CA^k x(0) + Du(k) + CBu(k-1) + CABu(k-2) + \dots + CA^{k-1}Bu(0) \quad (16)$$

This model, however, suffers from many difficulties from the point of view of system identification: (1) The initial condition $x(0)$ is typically unknown. (2) The number of Markov parameters in the model increases with k . (3) Even with stable systems so that

the initial condition response can be neglected when steady-state data is used, one must keep all “non-zero” Markov parameter coefficients in the model and this number can be quite high for a lightly damped system. With the ARMarkov model, one can solve for any desired number of Markov parameters without having to wait for steady-state data and without concern for the initial condition effect.

3. Hankel-Toeplitz Model

Instead of building the Hankel matrix from the Markov parameters which can be identified directly via an ARMarkov model, or indirectly via an ARX model, one may look for a way to identify the Hankel matrix itself directly from input-output data. To accomplish this task, an input-output model that involves the Hankel matrix must be derived. We obtain this equation by combining Eq. (7) with Eq. (2),

$$\begin{aligned} y_p(k+q) &= \mathbf{O}x(k+q) + \mathbf{\tau}u_p(k+q) \\ &= \mathbf{O}A^q(\mathbf{e}_p + M\mathbf{\tau})u_p(k-p) - \mathbf{O}A^qMy_p(k-p) + \mathbf{H}u_q(k) + \mathbf{\tau}u_p(k+q) \end{aligned} \quad (17)$$

where \mathbf{H} has the following structure

$$\mathbf{H} = \mathbf{O}\mathbf{e}_q = \begin{bmatrix} CA^{q-1}B & CA^{q-2}B & \dots & CB \\ CA^qB & CA^{q-1}B & \dots & CAB \\ \vdots & \vdots & \vdots & \vdots \\ CA^{p+q-2}B & CA^{p+q-3}B & \dots & CA^{p-1}B \end{bmatrix} \quad (18)$$

Normally, the Hankel matrix is arranged with Markov parameters of increasing order going from left to right as shown in Eq. (15). All it takes to put \mathbf{H} in the standard form is a simple rearrangement of its elements. Also, for a sufficiently large size \mathbf{H} , one can extract $\bar{\mathbf{H}}(0)$ and $\bar{\mathbf{H}}(1)$ for state-space identification. The matrix $\mathbf{\tau}$ is often referred to as a Toeplitz matrix, hence we call Eq. (17) a Hankel-Toeplitz model.

4. Identification and Construction of Hankel Matrix

In the following we describe three methods by which the Hankel matrix can be obtained directly or indirectly from a set of input-output data. We then discuss the advantages or drawbacks associated with each approach

Direct Method

The simplest method is to identify the Hankel matrix directly from input-output data using Eq. (17). Define $\mathcal{A}_1 = \mathbf{O}A^q(\mathbf{e}_p + M\mathbf{\tau})$, $\mathcal{A}_2 = -\mathbf{O}A^qM$, Eq. (17) becomes

$$y_p(k+q) = [\mathcal{A}_1 \quad \mathcal{A}_2 \quad \mathbf{H} \quad \mathbf{\tau}] \begin{bmatrix} u_p(k-p) \\ y_p(k-p) \\ u_q(k) \\ u_p(k+q) \end{bmatrix} \quad (19)$$

Given a set of sufficiently rich input-output data, \mathbf{H} can be computed from

$$[\mathcal{A}_1 \quad \mathcal{A}_2 \quad \mathbf{H} \quad \mathbf{\tau}] = Y_2 V_2^+ \quad (20)$$

where

$$Y_2 = \begin{bmatrix} y_p(p+q) & y_p(p+q+1) & \cdots & y_p(p+q+\ell) \end{bmatrix} \quad (21)$$

$$V_2 = \begin{bmatrix} u_p(0) & u_p(1) & \cdots & u_p(\ell) \\ y_p(0) & y_p(1) & \cdots & y_p(\ell) \\ u_q(p) & u_q(p+1) & \cdots & u_q(p+\ell) \\ u_p(p+q) & u_p(p+q+1) & \cdots & u_p(p+q+\ell) \end{bmatrix} \quad (22)$$

One obvious drawback of this direct Hankel matrix identification method is that the high number of extraneous terms that must be solved for while solving for \mathbf{H} . Unlike the ARMarkov models, we cannot use p to minimize the number of extraneous terms because p itself (together with q) governs the size of the Hankel matrix to be identified. We thus see that although it is possible to identify the Hankel matrix directly from input-output data, this simplest strategy is not efficient. In fact, there is Hankel-related information hidden in the extraneous terms, but for the sake of simplicity, this issue will be revisited in a later section.

Indirect Method

Next we look for a method where no identified information is left out in recovering the Hankel matrix. Consider the case where $q=0$ in Eq. (17). Define $\mathcal{B}_1 = \mathbf{O}(\mathbf{e}_p + M\boldsymbol{\tau})$, $\mathcal{B}_2 = -\mathbf{O}M$, it becomes

$$y_p(k) = \begin{bmatrix} \mathcal{B}_1 & \mathcal{B}_2 & \boldsymbol{\tau} \end{bmatrix} \begin{bmatrix} u_p(k-p) \\ y_p(k-p) \\ u_p(k) \end{bmatrix} \quad (23)$$

The interaction matrix reveals the internal structures of \mathcal{B}_1 and \mathcal{B}_2 . This information is used to extract the “square” Hankel matrix $\mathbf{H}_0 = \mathbf{O}\mathbf{C}_p$ without having to know M ,

$$\mathbf{H}_0 = \mathcal{B}_1 + \mathcal{B}_2\boldsymbol{\tau} \quad (24)$$

The matrices \mathcal{B}_1 , \mathcal{B}_2 , and $\boldsymbol{\tau}$ themselves can be identified from input-output data as

$$\begin{bmatrix} \mathcal{B}_1 & \mathcal{B}_2 & \boldsymbol{\tau} \end{bmatrix} = Y_3 V_3^+ \quad (25)$$

where

$$Y_3 = \begin{bmatrix} y_p(p) & y_p(p+1) & \cdots & y_p(p+\ell) \end{bmatrix} \quad (26)$$

$$V_3 = \begin{bmatrix} u_p(0) & u_p(1) & \cdots & u_p(\ell) \\ y_p(0) & y_p(1) & \cdots & y_p(\ell) \\ u_p(p) & u_p(p+1) & \cdots & u_p(p+\ell) \end{bmatrix} \quad (27)$$

The indirect method makes use of all identified information to extract \mathbf{H}_0 . The needed extra step is quite simple since it involves only matrix multiplication and addition. In this sense, it is the most efficient approach.

Once \mathbf{H}_0 is (indirectly) identified, an “adjacent” $\mathbf{H}_1 = \mathbf{O}A^p\mathbf{C}_p$ can be easily computed by recognizing that $A^p = -M\mathbf{O}$,

$$\mathbf{H}_1 = \mathbf{O}A^p\mathbf{C}_p = \mathbf{O}(-M\mathbf{O})\mathbf{C}_p = (-\mathbf{O}M)\mathbf{O}\mathbf{C}_p = \mathcal{B}_2\mathbf{H}_0 \quad (28)$$

In fact, any other adjacent \mathbf{H}_i can be computed in a similar manner,

$$\mathbf{H}_i = \mathbf{O}(A^p)^i \mathbf{e}_p = \mathbf{O}(-M\mathbf{O}) \cdots (-M\mathbf{O}) \mathbf{e}_p = (-\mathbf{O}M) \cdots (-\mathbf{O}M) \mathbf{O} \mathbf{e}_p = (\beta_2)^i \mathbf{H}_0 \quad (29)$$

Using $\mathbf{H}_0, \mathbf{H}_1, \dots$ as building blocks, a Hankel matrix of any size can be constructed.

Combined Direct and Indirect Method

In this scheme, the Hankel matrix \mathbf{H}_0 is identified directly, and all other Hankel matrices $\mathbf{H}_1, \mathbf{H}_2, \dots$ are identified indirectly. For convenience we set $q = p$, and re-visit the direct method to determine if useful information can be recovered from the “extraneous” terms. Define $\mathcal{C}_1 = \mathbf{O}A^p(\mathbf{e}_p + M\boldsymbol{\tau})$, $\mathcal{C}_2 = -\mathbf{O}A^pM$, Eq. (17) becomes

$$y_p(k+p) = [\mathcal{C}_1 \quad \mathcal{C}_2 \quad \mathbf{H}_0 \quad \boldsymbol{\tau}] \begin{bmatrix} u_p(k-p) \\ y_p(k-p) \\ u_p(k) \\ u_p(k+p) \end{bmatrix} \quad (30)$$

It is obvious that the Hankel matrix \mathbf{H}_0 can be directly identified along with $\mathcal{C}_1, \mathcal{C}_2$, and $\boldsymbol{\tau}$ from a set of input-output data as

$$[\mathcal{C}_1 \quad \mathcal{C}_2 \quad \mathbf{H}_0 \quad \boldsymbol{\tau}] = Y_4 V_4^+ \quad (31)$$

where

$$Y_4 = [y_p(2p) \quad y_p(2p+1) \quad \cdots \quad y_p(2p+\ell)] \quad (32)$$

$$V_4 = \begin{bmatrix} u_p(0) & u_p(1) & \cdots & u_p(\ell) \\ y_p(0) & y_p(1) & \cdots & y_p(\ell) \\ u_p(p) & u_p(p+1) & \cdots & u_p(p+\ell) \\ u_p(2p) & u_p(2p+1) & \cdots & u_p(2p+\ell) \end{bmatrix} \quad (33)$$

Making use of the internal structure of the identified parameters as revealed by the interaction matrix, $\mathbf{H}_1 = \mathbf{O}A^p\mathbf{e}_p$ can be computed indirectly from \mathcal{C}_1 , \mathcal{C}_2 , and $\boldsymbol{\tau}$ as

$$\mathbf{H}_1 = \mathcal{C}_1 + \mathcal{C}_2\boldsymbol{\tau} \quad (34)$$

To compute all other “adjacent” Hankel matrices, we next show that the “even” \mathbf{H}_2 , \mathbf{H}_4 , ... can be computed from \mathbf{H}_0 and \mathcal{C}_2 , and the “odd” \mathbf{H}_3 , \mathbf{H}_5 , ... can be computed from \mathbf{H}_1 and \mathcal{C}_2 . For example,

$$\begin{aligned} \mathbf{H}_2 &= \mathbf{O}(A^p)^2\mathbf{e}_p = \mathbf{O}(-M\mathbf{O})(-M\mathbf{O})\mathbf{e}_p = (-\mathbf{O}M)(-\mathbf{O}M)\mathbf{O}\mathbf{e}_p \\ &= (-\mathbf{O}M)^2\mathbf{H}_0 = \mathcal{C}_2\mathbf{H}_0 \end{aligned} \quad (35)$$

The last equality holds because $\mathcal{C}_2 = -\mathbf{O}A^pM = -\mathbf{O}(-M\mathbf{O})M = (-\mathbf{O}M)^2$. Similarly,

$$\begin{aligned} \mathbf{H}_3 &= \mathbf{O}(A^p)^3\mathbf{e}_p = \mathbf{O}(-M\mathbf{O})(-M\mathbf{O})A^p\mathbf{e}_p = (-\mathbf{O}M)(-\mathbf{O}M)\mathbf{O}A^p\mathbf{e}_p \\ &= (-\mathbf{O}M)^2\mathbf{H}_1 = \mathcal{C}_2\mathbf{H}_1 \end{aligned} \quad (36)$$

By induction, $\mathbf{H}_i = (\mathcal{C}_2)^{i/2} \mathbf{H}_0$ for even $i = 2, 4, \dots$ and $\mathbf{H}_i = (\mathcal{C}_2)^{(i-1)/2} \mathbf{H}_1$ for odd $i = 3, 5, \dots$. Again using $\mathbf{H}_0, \mathbf{H}_1, \dots$ as building blocks, a Hankel matrix of any size can be constructed. Thus we see that it is possible to make use of the “extraneous” terms to recover additional Hankel matrices indirectly. However, high dimensionality in the identification places this method at a disadvantage when compared with the indirect method.

5. Illustrations with Simulated and Experimental Data

In this section, we examine the quality of identification results obtained from an identified Hankel matrix with those from a Hankel matrix that is built from the Markov parameters. The Markov parameters themselves can be identified indirectly through auto-regressive or transfer function models by a method such as OKID,^{4,9,10} or directly through the use of ARMarkov models. The Observer/Kalman filter Identification (OKID) algorithm also identifies from input-output data an observer or Kalman filter gain for observer-based controller design, but this information is not needed in our present application.

The outcome of each identification method (labeled as Hankel, OKID, or ARMarkov in the illustrations) is a complete state-space model of the system. With perfect noise-free data, all methods identify the system exactly, so that difference among these methods can only be seen with noise-contaminated or real data. It is not uncommon to have an identification method that works well with simulated data under ideal

conditions, but fails to perform with real data which may be affected by non-linearities, aliasing, poor resolution, among other factors. For this reason, extensive numerical simulation is used to establish the relative performance pattern among these different methods, and then real data is used to develop a sense of how well this expected pattern holds up in practice.

To present a very large amount of results compactly, the combination of model order and prediction error is used to represent the quality of an identified model. In this sense, the “best” method is the one that produces the smallest order state-space model while reproducing the data most accurately. The prediction error is defined as the difference between the actual output and the reconstructed output of the identified model when driven by the same input. The norm of this prediction error over the entire data record is used to indicate the accuracy of the model, and this value is plotted as a function of model order. For example, if the order increment is 2 then a plot of the norm of the prediction error versus model order going from 2 to 100 succinctly represents the results of 50 individual state-space models. Furthermore, to compare different methods, we have one such plot for each method tested.

Numerical Example

We first examine the performance of each method with simulated data on a 3 degree-of-freedom system,

$$\begin{bmatrix} m_1 & 0 & 0 \\ 0 & m_2 & 0 \\ 0 & 0 & m_3 \end{bmatrix} \begin{bmatrix} \ddot{x}_1 \\ \ddot{x}_2 \\ \ddot{x}_3 \end{bmatrix} + \begin{bmatrix} c_1 + c_2 & -c_2 & 0 \\ -c_2 & c_2 + c_3 & -c_3 \\ 0 & -c_3 & c_3 \end{bmatrix} \begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} + \begin{bmatrix} k_1 + k_2 & -k_2 & 0 \\ -k_2 & k_2 + k_3 & -k_3 \\ 0 & -k_3 & k_3 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} u_1 \\ 0 \\ 0 \end{bmatrix}$$

where $m_1 = 0.5 \text{ Kg}$, $m_2 = m_3 = 1 \text{ Kg}$, $k_1 = k_2 = k_3 = 10 \text{ N/m}$, $c_1 = c_2 = c_3 = 0.35 \text{ N sec/m}$.

The sampling interval is 0.1 sec. The outputs are the positions of the last two masses, $y_i = x_i, i = 2, 3$. The data is corrupted by moderate plant and measurement noise (3–18% standard deviation). Extensive simulation was carried out, and representative results are shown in Figs. 1 and 2, one for each output. The computation of, say V_1^+ , is computed as $V_1^T (V_1 V_1^T)^+$ where the SVD is used to compute $(V_1 V_1^T)^+$ with zero or insignificant singular values truncated. Note that these singular values are associated with least squares parameter estimation, they are not Hankel singular values associated with model order selection. Let us first examine OKID result identified with $p = 30$. As expected, the smallest prediction error is associated with the maximum order state-space model where all Hankel singular values are kept, Ref. 9. When a smaller order is chosen by truncating Hankel singular values, significant accuracy is lost. This problem is described earlier in the introduction. Let us now examine the identified Hankel result where a $2pm \times pr$ Hankel matrix $\bar{\mathbf{H}}$ is formed from identified \mathbf{H}_0 and \mathbf{H}_1 , each of dimensions $pm \times pr$ where $p = 30$, $m = 2$, $r = 1$. For state-space model realization, $\bar{\mathbf{H}}(0)$ and $\bar{\mathbf{H}}(1)$, each of dimensions $(2p-1)m \times pr$, are extracted from $\bar{\mathbf{H}}$. Observe that the prediction error drops sharply to the minimum when 6 is selected as the order of the state-space model, which is exactly the true order of the system. Furthermore, this error remains at the same level if a larger order is selected. Result obtained with the

ARMarkov approach where $q = 61$ Markov parameters are identified with $p = 30$ follows the same pattern. For a fair comparison, in this and all other test cases, the number of identified Markov parameters q is chosen so that a Hankel matrix of the same dimension as an identified Hankel matrix can be formed. At higher model orders the ARMarkov result is sporadic due to numerical ill-conditioning associated with including the “smaller” Hankel singular values in $\Sigma_s^{-1/2}$ that should have been discarded. This is not necessarily a problem because it may simply indicate that the maximum order has been reached. Thus we see that both the identified Hankel matrix and the ARMarkov approaches produce the correct minimum order state-space model directly by Hankel singular value truncation. The prediction quality of these models is comparable to the full (high-dimensional) OKID model where all Hankel singular values are kept.

Identification of HST

We now examine if the pattern observed in the simulation holds up with real data through a series of tests. The first test involves a three-input three-output data from the Hubble Space Telescope (HST) in orbit, Fig. 3. The system is operating in closed-loop, hence it is highly damped. For this reason the problem of order determination may be difficult. The HST has six gyros located on the optical telescope assembly which are used mainly to measure the motion of the primary mirror. The outputs are expressed in terms of the three angular rates in the vehicle coordinates. The input commands excite the telescope mirror and structure and they are given in terms of angular acceleration in the three rotational vehicle axes. The data record is 620 seconds long, and sampled at a relatively low rate of 10 Hz. The identification results are shown in Figs. 4-6, one for

each output. The identified Hankel matrix approach produces a 3-mode model that reproduces the data quite accurately. This result is in agreement with that obtained with a more substantial set of data sampled at a higher resolution.⁹ The ARMarkov result obtained with $q = 61$ identified Markov parameters arrives at the same conclusion, although the result is somewhat more sporadic for higher order models. Indeed, the highest order that the ARMarkov method can produce with this data is 18, beyond which the incorporation of additional singular values gives rise to inaccurate results due to the reason explained earlier. The prediction quality of these low-dimensional models is similar to the full OKID model for the first two outputs, but a bit worse for the third output. We thus see that the general pattern observed with simulation data is reproduced here with this set of experimental data.

Identification of SPINE

The second set of single-input single-output data is obtained from a compact yet very lightly damped and flexible apparatus (SPINE) at Princeton, Figs. 7, 8. SPINE consists of a series of parallel steel rods mounted on a thin center wire. In its 10-rod configuration, an actuator controls the vertical position of the tip of the first rod. A laser-based optical sensing system detects the torsional motion of the third rod, and the tenth rod is clamped to a rigid support. Since the tip of the first rod is a controlled input and the last rod is fixed, the “effective” order of the system should be around 16 (for 8 flexible modes). With this set of data we have an opportunity to see how well each method produces a state-space model of this expected order. The system is excited by a random input for 80 seconds and the resultant output is recorded at a sampling rate of 200

Hz. The identification results are reported in Fig. 9. As expected, the prediction error drops sharply and then flattens out at the chosen order of 16 for the identified Hankel method. The ARMarkov result (with $q = 201$ identified Markov parameters) also detects this model order but the prediction error is slightly worse. The prediction error of the identified Hankel approach is virtually identical to that of the full OKID model. Again the expected pattern is observed for this set of data, with the identified Hankel matrix approach holding a slight edge over the ARMarkov approach.

Identification of a Truss

The third set of data is obtained from a two-input two-output truss developed for vibration control of flexible space structures at NASA Langley Research Center, Fig. 10. The inverted L-shape structure consists of nine bays on its vertical section, and one bay on its horizontal section, extending 90 inches and 20 inches respectively. The shorter section is clamped to a steel plate which is rigidly attached to the wall. At the tip of the truss are two cold air jet thrusters, and two accelerometers. For identification, the structure is excited using random inputs to both thrusters. The data record is 8 seconds long and is sampled at 250Hz. This data record is relatively short and the system is more difficult to be identified because besides a small number of dominant modes it also has a large number of less dominant but still significant modes. The identification results are shown in Figs. 11 and 12. Among the three methods, the identified Hankel method produces the smallest order model that is comparable in accuracy to a much higher order OKID model. The ARMarkov method with 76 identified Markov parameters fails to produce comparable results although it suggests an order of around 30 with a sharp drop

in the prediction error. One possible source of difficulty of the ARMarkov method is that one does not know in advance the number of Markov parameters q that should be solved for. Since the Markov parameters are the system pulse response samples, they will eventually converge to zero for a damped system. If q is too small then damping estimate may be in error. If q is too large then it is possible that many higher order Markov parameters are essentially zero which need not be identified. While it is not necessary to solve for all non-zero Markov parameters, the total number depends on the system stability. This is in contrast to the other two methods where the specification of the order of the auto-regressive model or the size of the Hankel matrix is essentially a specification of an upper bound on the order of the system, and this specification is independent of the system stability. Another distinction between the identified Hankel matrix approach and the ARMarkov approach is that the former is based on the Hankel-Toeplitz model which can be thought of as a family of ARMarkov models. Hence for a given set of data, the Markov parameters in the identified Hankel matrix are required to satisfy a much larger number of constraints than those in a single ARMarkov model.

In view of the above results and others not reported here due to space limitation, a number of general observations can be made. OKID is consistent in producing a high order model with low prediction error. However, model reduction by Hankel singular value truncation tends to be poor in prediction quality. For this reason, the best strategy for OKID is to keep the full order model and use a separate procedure for model reduction. In contrast, the identified Hankel matrix approach is quite consistent in detecting a true or effective order of the system through Hankel singular value truncation.

Thus we can combine these two methods by using OKID to establish the minimum prediction error level at the expense of high dimensionality, and then use the identified Hankel matrix method to find a lower dimensional model with the same level of prediction accuracy as the full OKID model. As a possible third source of confirmation, the ARMarkov method can be used to corroborate the identified Hankel result in terms of order confirmation, but this method may not be as consistent as the other two methods.

6. Conclusions

In this paper we examine in details the strategy of using an identified Hankel matrix for state-space system identification. The standard method is to identify from input-output data the Markov parameters which are the building blocks of the Hankel matrix instead of going directly after the Hankel matrix itself. Several options are examined including schemes where the Hankel matrix is identified directly and indirectly from input-output data. Advantages and drawbacks associated with each option are explained. Both simulated and real data are used to perform an extensive evaluation of this approach. Our results indicate that this approach of identifying the Hankel matrix is effective in terms of its ability to detect the true or effective order of the system, and to produce relatively low-dimensional state-space model by Hankel singular value truncation.

This paper has also shown the utility of the interaction matrix approach in providing a transparent connection between the state-space model and various input-

output models. The interaction matrix serves two primary purposes in this work. First, it justifies the existence of certain input-output maps that are relevant for the task at hand (Hankel matrix identification). Second, it reveals the relationship among the identified coefficients or matrices from which the Hankel matrix can be computed. Interestingly, this task can be accomplished without having to compute explicitly the system-dependent interaction matrix itself.

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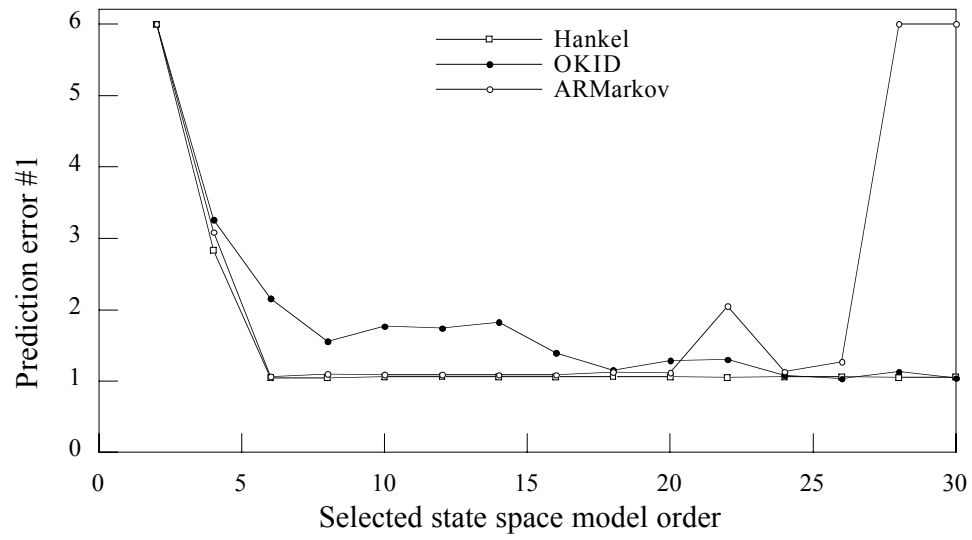


Fig. 1. Hankel, OKID, and ARMarkov identification of a 6-th order system (Output 1)

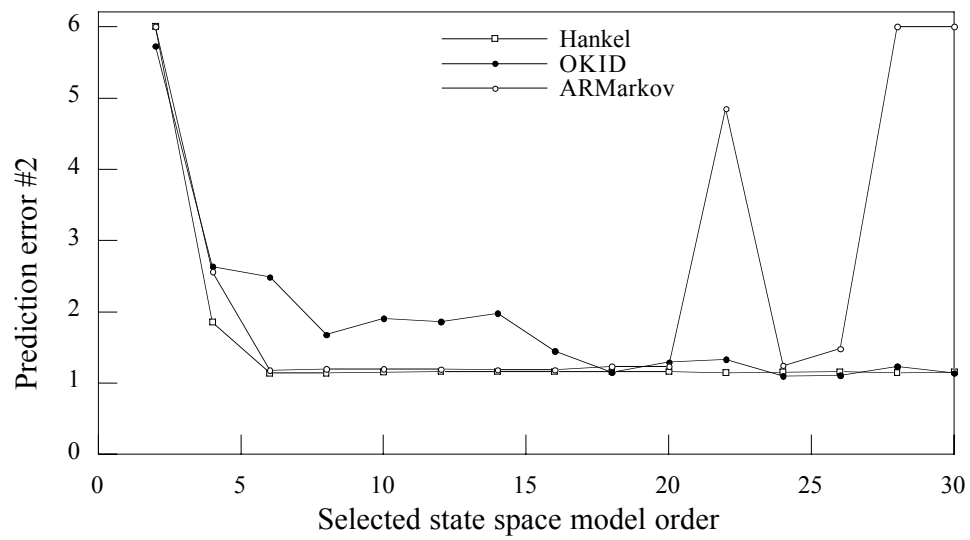


Fig. 2. Hankel, OKID, and ARMarkov identification of a 6-th order system (Output 2)

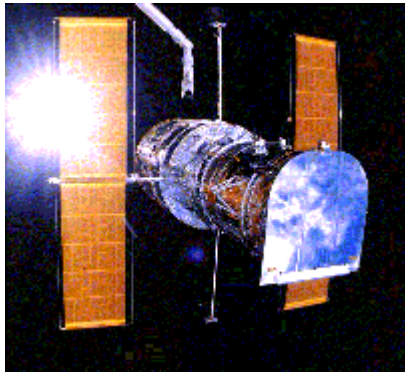


Fig. 3. Hubble Space Telescope

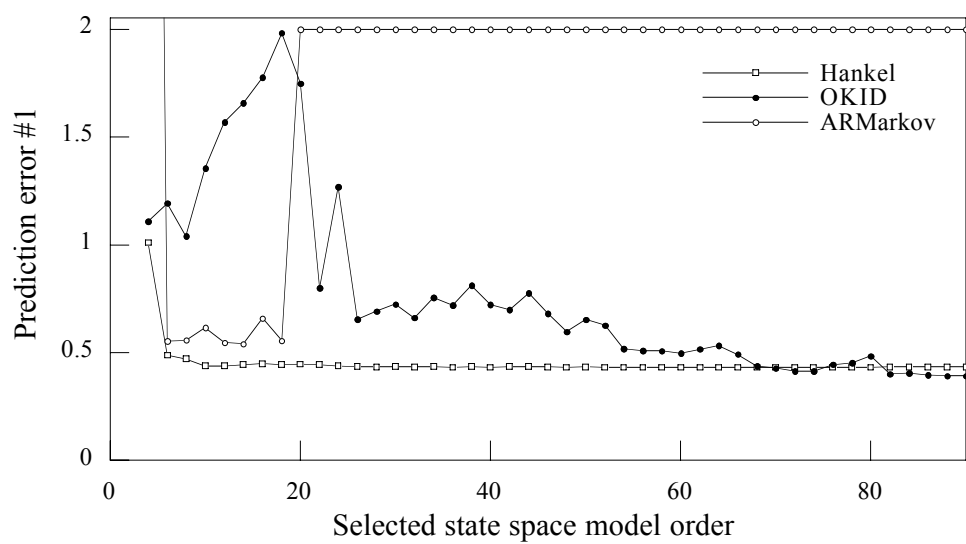


Fig. 4. Hankel, OKID, ARMarkov identification of HST (Output 1)

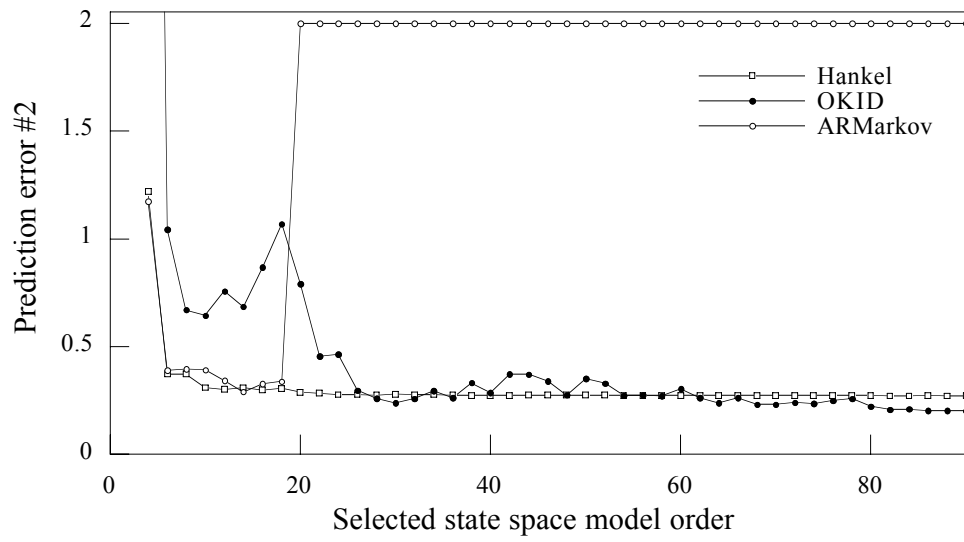


Fig. 5. Hankel, OKID, ARMarkov identification of HST (Output 2)

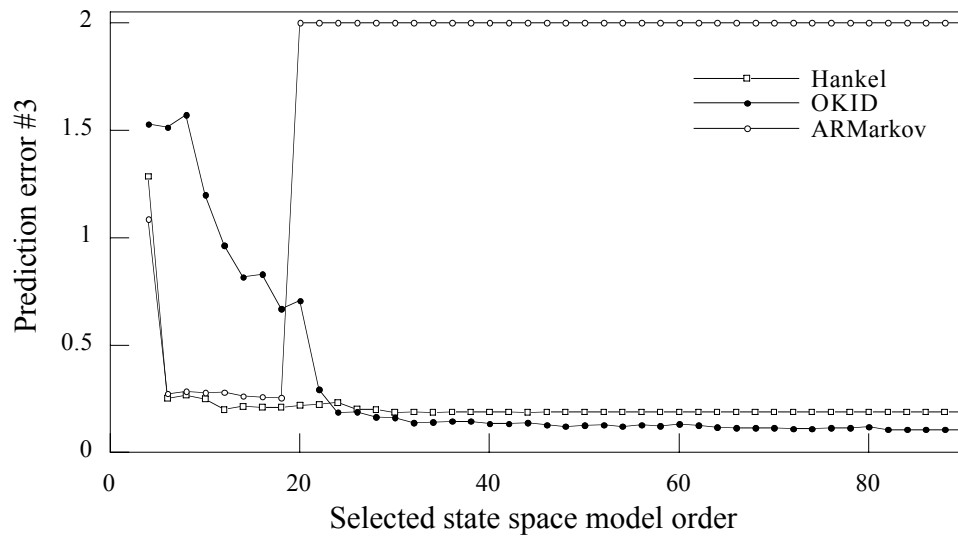
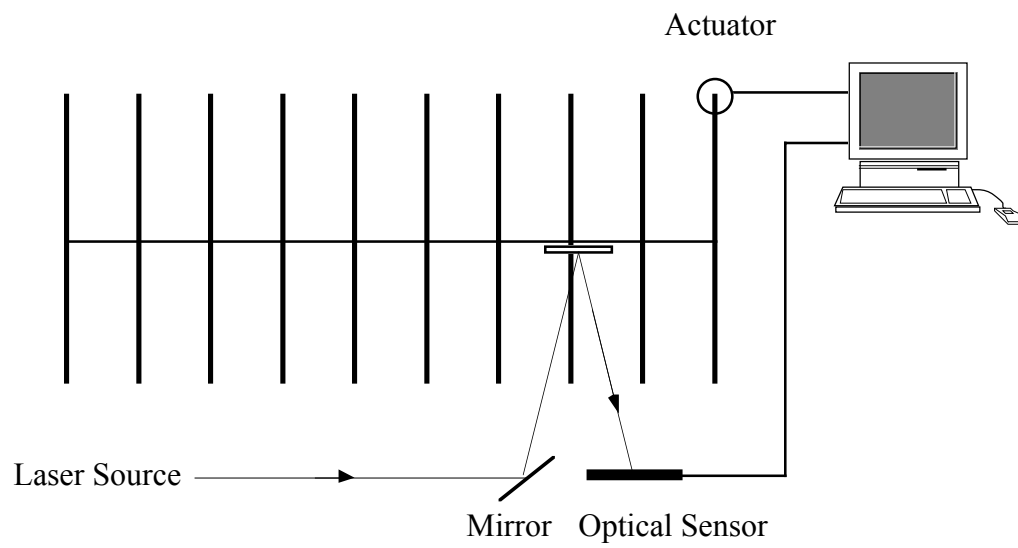
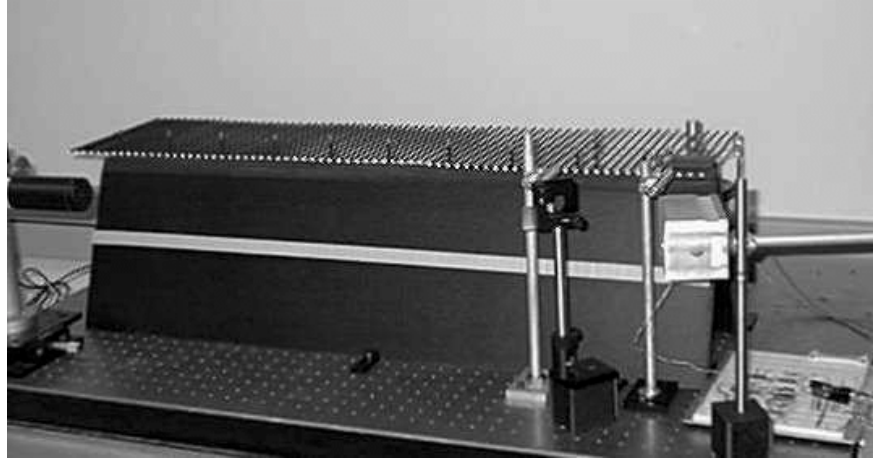


Fig. 6. Hankel, OKID, ARMarkov identification of HST (Output 3)



Figs. 7,8. SPINE and a 10-rod configuration

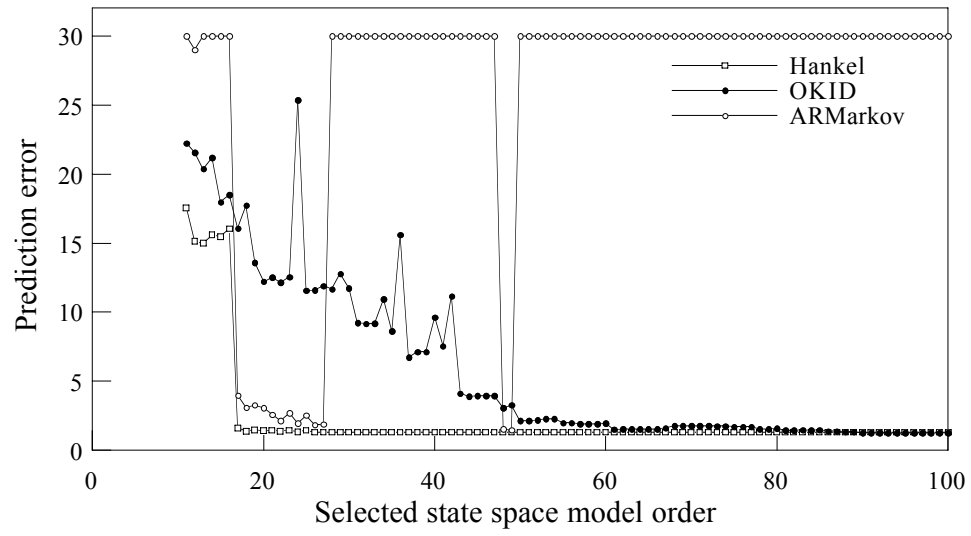


Fig. 9. Hankel, OKID, ARMarkov identification of SPINE

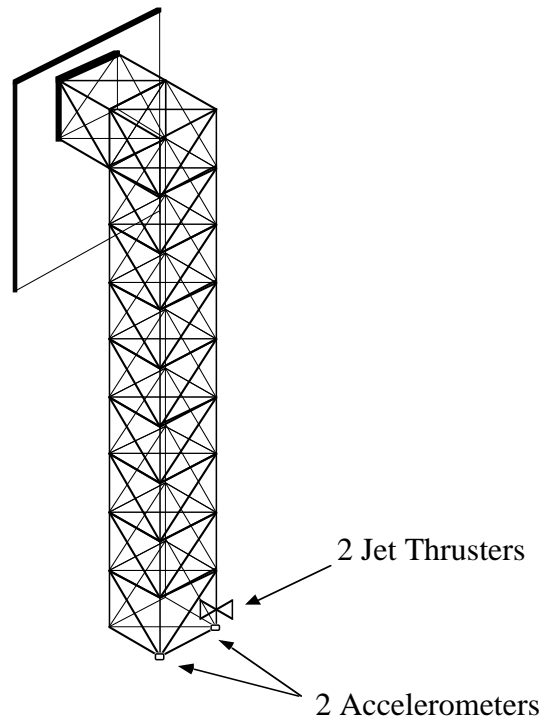


Fig. 10. A truss structure

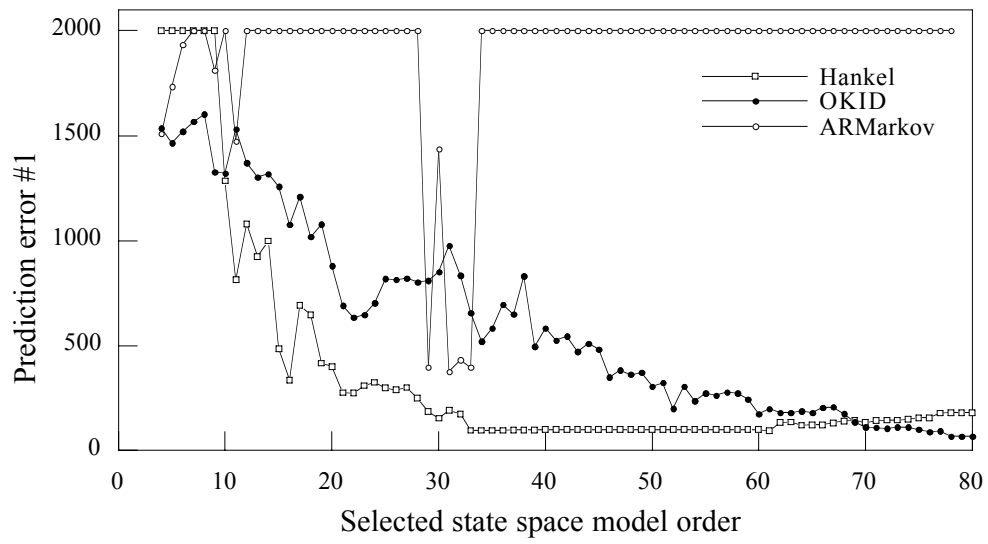


Fig. 11. Hankel, OKID, ARMarkov identification of truss (Output 1)

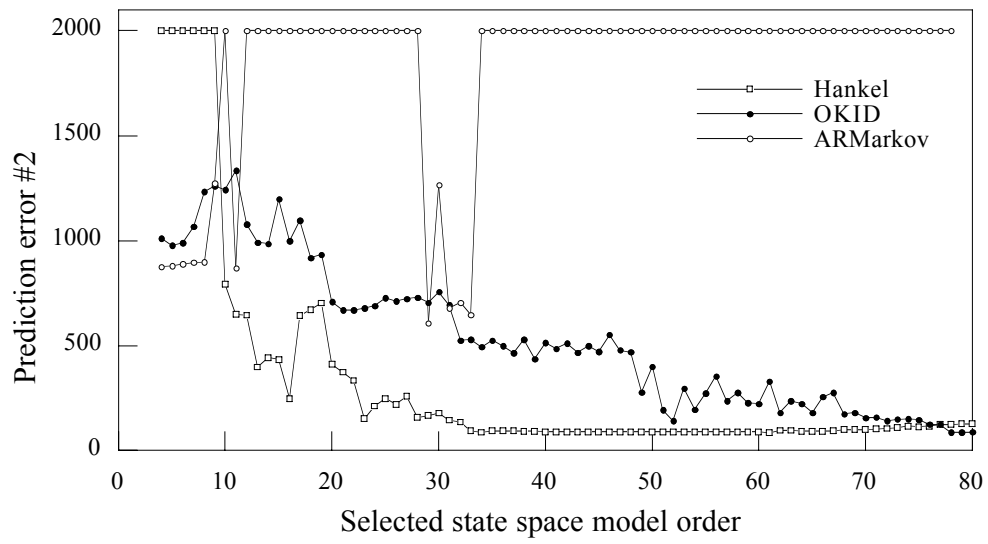


Fig. 12. Hankel, OKID, ARMarkov identification of truss (Output 2)