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ORDER REDUCTION OF LARGE-SCALE LINEAR OSCILLATORY SYSTEM MODELS

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MASTER

ORDER REDUCTION OF LARGE-SCALE LINEAR OSCILLATORY SYSTEM MODELS

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Abstract: Eigenanalysis and signal analysis techniques of deriving representations of power system oscillatory dynamics result in very high-order linear models. In order to apply many modern control design methods, the models must be reduced to a more manageable order while preserving essential characteristics. Presented in this paper is a model reduction method well suited for large-scale systems. The method searches for the optimal subset of the high-order model that best represents the system. An Akaike information criterion is used to define the optimal reduced model. The method is first presented, and then examples of applying it to Prony analysis and eigenanalysis models of power systems are given.

Key Words: Model order reduction, oscillatory system models, eigenanalysis, Prony analysis.

1.0 INTRODUCTION

Extensive research and development have been conducted on the use of eigenanalysis and time-series analysis to represent oscillatory dynamics (e.g., see the papers in [1]). Because a modern power system is very large, these models are of very high order (often hundreds to thousands of states). For a given input/output combination, certain dynamic characteristics dominate, allowing the effective transfer function to be of much lower order. Development of a low-order model from a high-order one has received little attention in the power system literature. The purpose of this paper is to present a model order reduction algorithm well suited to the power system problem. The method is applied to both signal analysis and eigenanalysis results.

One primary objective in the development of linear models is to provide a basis for damping control-system design (e.g., power system stabilizer (PSS) units and static var compensator (SVC) modulation). Many advanced and emerging control system design methodologies (such as the state-space methods) require relatively low-order models for numerically stable and/or realistic solutions. For example, H_2 and *H-infinity* methods often result in a feedback controller with an order equal to that of the design model [2]. If the model is of order 100 or more, such a controller is unrealistic. An obvious option is to use a reduced-order model for the appropriate steps of the design.

Using the parsimony principle [3], the best model of a system is defined as the one that accurately represents a transfer function with a minimal number of parameters. With the power system problem it is important that certain system characteristics are preserved in a reduced-order model. For example, because their damping and frequency directly represent electromechanical stability conditions, the dominant pole locations should be preserved. Also, the mode phase must be preserved because this represents modal shape and is critical in control system design.

Various techniques have been proposed for deriving reduced-order models from high-order counterparts. A well-known method for linear system reduction is the Balanced Realization Method (BRM) [4,5]. With the BRM, system states are removed by preserving the controllability and observability of other states. The BRM is not well suited for the power system problem because system pole locations are not preserved, it requires computationally expensive numerics, and the high-order model must be stable.

The model reduction algorithm proposed here employs a search technique to find the reduced-order model that best fits the high-order model's time and frequency domain impulse responses. It preserves the critical high-order modes and their associated phasing. Also, the optimum order of the reduced model is identified. The optimum model is judged using the Akaike information criterion (AIC) which ensures that the model order is large enough to accurately represent the given input/output pair [3,6].

The remainder of the paper is organized as follows. System dynamic models are discussed in Section 2.0. The model reduction algorithm is presented in Section 3.0, and a discussion of key elements of the algorithm is contained in Section 4.0. In Sections 5.0 and 6.0 the method is applied to Prony and eigenanalysis examples, and conclusions are drawn in Section 7.0.

2.0 SYSTEM DYNAMIC MODELS

The electromechanical dynamics of a power system can be linearized about an operating point and written as

$$\dot{x}=Ax+bu \qquad y=c^T x \tag{1}$$

where A is a square state matrix of order n, x is the state vector, u is a single input, and y is a single output [7]. Let P and Q be nxn matrices whos columns are the right and left eigenvectors of A, respectively. It is well known that if the eigenvalues of A are distinct, then $Q^TP=I$ (where I is the identity matrix and superscript T denotes the conjugate transpose) [8]. Using the transformation $x_d=Q^Tx$, (1) can be represented as

$$\dot{x}_d=A_d x_d+b_d u \qquad y=c_d^T x_d \tag{2}$$

where

$$A_d=Q^TAP=[diag(\lambda_i)] \qquad b_d=Q^Tb \qquad c_d^T=c^TP \tag{3}$$

and λ_i, $i=1,2,...,n$, are the eigenvalues of A.

Reverting to the Laplace domain, (2) is written as

$$G(s)=\frac{y(s)}{u(s)}=c_d^T(sI-A_d)^{-1}b_d \tag{4}$$

Because A_d is diagonal, (4) becomes

$$G(s)=\sum_{i=1}^{n}\frac{c^Tp_iq_i^Tb}{s-\lambda_i}=\sum_{i=1}^{n}\frac{R_i}{s-\lambda_i} \tag{5}$$

where p_i and q_i are the ith right and left eigenvectors, respectively. R_i is termed the transfer function residue associated with λ_i. The diagonal of matrix $p_iq_i^T$ is the well-known participation-factor vector for λ_i [7].

When considering model-order reduction for linear power system models, (5) is of special form. This is demonstrated by considering (5) as an open-loop transfer function and $\varepsilon H(s)$ as a negative feedback function. The closed-loop poles are determined by the roots of

$$1+\varepsilon\sum_{i=1}^{n}\frac{R_iH(s)}{s-\lambda_i}=0 \tag{6}$$

At small ε, the open-loop λ_i's are shifted by

$$\Delta\lambda_i=-\varepsilon R_iH(\lambda_i) \tag{7}$$

An interpretation of (7) is that the angle of departure for λ_i in a root locus is governed by the phase of R_i. Also, the magnitude of shift is directly related to the magnitude of R_i. These residue properties are discussed in detail in [9]. To reflect control design effects, a reduced-order model of (5) should preserve the phase and magnitude effects of the full-order model residues.

3.0 MODEL REDUCTION ALGORITHM

The model-order reduction technique proposed here is essentially a method of selecting the smallest subset of (R_i,λ_i) terms in (5) that accurately represent the system. The obvious criterion is to select the larger residue terms and neglect the smaller. But, this is not a feasible method because a lightly damped term with a small residue can be a much more important element to the model than a heavily damped term with a large residue. A better criterion is to select the subset that best represents the impulse response of the high-order model in both the time and frequency domains while maintaining a minimal order.

Let the high-order model be represented as (5), the model reduction is performed using the following steps:

1. Calculate the impulse time and frequency responses of the actual high-order system.

2. Search for the smallest subset of residue/eigenvalue terms that accurately fit a linear combination of the high-order time and frequency domain data calculated in step 1.

The impulse responses are directly calculated from the high-order model using

$$g(t_k)=\sum_{i=1}^{n}R_ie^{t_k\lambda_i};\ k=0,1,...,N_T-1$$
$$G(j\omega_k)=\sum_{i=1}^{n}\frac{R_i}{j\omega_k-\lambda_i};\ k=1,2,...,N_\omega \tag{8}$$

where t_k = kT and $\omega_k=(2\pi k)/(N_\omega\Delta\omega)$. Parameters T, N_T, $\Delta\omega$, and N_ω are selected to reflect system bandwidth characteristics.

The search step starts by calculating impulse time and frequency domain responses of the n individual residue/eigenvalue pairs, i.e.,

$$g_i(t_k)=R_ie^{t_k\lambda_i};\ k=0,1,...,N_T-1$$
$$G_i(j\omega_k)=\frac{R_i}{j\omega_k-\lambda_i};\ k=1,2,...,N_\omega \tag{9}$$

for $i=1,2,...,n$. The one (R_i,λ_i) that minimizes the Akaike information criterion (AIC) defined by

$$\Gamma = \alpha\left(N\log\left(\frac{\|g_i-g\|^2}{N\|g\|^2}\right)+4n_i\right) + \beta\left(N\log\left(\frac{\|G_i-G\|^2}{N\|G\|^2}\right)+4n_i\right) \tag{10}$$

is termed $(R_{m(1)}, \lambda_{m(1)})$ and the corresponding AIC is Γ_1. In (10) $\|\cdot\|$ is the 2-norm and n_i is the order of G_i. The (α,β) are nonnegative real constants, with α emphasizing the time domain and β emphasizing the frequency domain data.

After $(R_{m(1)}, \lambda_{m(1)})$ and the corresponding AIC Γ_1 have been determined, the following n-1 impulse responses are calculated:

$$\begin{aligned} g_i(t_k) &= R_{m(1)}e^{t_k\lambda_{m(1)}} \\ &\quad + R_i e^{t_k\lambda_i};\ k=0,1,\ldots,N_T-1 \\ G_i(j\omega k) &= \frac{R_{m(1)}}{j\omega_k-\lambda_{m(1)}} \\ &\quad + \frac{R_i}{j\omega_k-\lambda_i};\ k=1,2,\ldots,N_\omega \end{aligned} \tag{11}$$

for $i=1,2,\ldots,n$, $i\neq m(1)$. The one (R_i,λ_i) from (11) that corresponds to a minimum (10) is termed $(R_{m(2)}, \lambda_{m(2)})$ and the corresponding AIC is Γ_2.

Now the n-2 impulse responses

$$\begin{aligned} g_i(t_k) &= R_{m(1)}e^{t_k\lambda_{m(1)}} + R_{m(2)}e^{t_k\lambda_{m(2)}} \\ &\quad + R_i e^{t_k\lambda_i};\ k=0,1,\ldots,N_T-1 \\ G_i(j\omega_k) &= \frac{R_{m(1)}}{j\omega_k-\lambda_{m(1)}} + \frac{R_{m(2)}}{j\omega_k-\lambda_{m(2)}} + \\ &\quad + \frac{R_i}{j\omega_k-\lambda_i};\ k=1,2,\ldots,N_\omega \end{aligned} \tag{12}$$

where $i=1,2,\ldots,n$, $i\neq m(1)$, $i\neq m(2)$ are tested to determine the one (R_i,λ_i) that results in (10) being minimized. This pair is termed $(R_{m(3)}, \lambda_{m(3)})$ and the corresponding AIC is Γ_3. The process is continued until the residue/eigenvalue pairs have been reordered as $(R_{m(i)}, \lambda_{m(i)})$ with corresponding AICs Γ_i, for $i=1,2,\ldots,n$-r. Integer r is adjusted so that n-r is an upper limit on the reduced-model order. Also, in the above search, complex conjugate pairs are considered simultaneously.

The reduced order model is determined by the minimum of Γ_i, $i=1,2,\ldots,n$-r. Let Γ_v be the minimum of all Γ's. Then the reduced-order model is

$$G(s)=\sum_{i=1}^{v}\frac{R_{m(i)}}{s-\lambda_{m(i)}} \tag{13}$$

4.0 DISCUSSION

Two important issues in the reduction algorithm merit further discussion: a theoretical basis for the AIC; and a basis for the search algorithm.

To formulate a best reduced-order model, one must define a criterion for measuring a model. This is done using the well-known parsimony principle: the best model of a system is the one that accurately represents a transfer function with a minimal number of parameters [3]. A statistical basis for measuring the best model is the prediction error variance (PEV) of a given model. It is shown in [3] that the PEV is estimated by the AIC, which was first proposed in [6] as a statistical model identification measurement.

The AIC has been applied to various parameter reduction problems (e.g. see [3,10,11]). These applications have demonstrated that because of finite convergence, the AIC often results in a conservative estimate of the reduced-order model in that further reduction is possible. This is not a disadvantage, as it is better to have a reduced model that contains extra terms than one that does not include all critical parameters. The examples to follow demonstrate this conservativeness.

Formulating the AIC for the problem addressed in this paper results in (10). The terms within the *log* penalize the reduced-order model fit while the $4n_i$ terms penalize the order of the reduced model. As n_i increases, the *log* terms decrease and $4n_i$ increases; the minimum of (10) represents an optimal tradeoff between the two terms. The $\|g_i-g\|$ and $\|G_i-G\|$ terms estimate the variance between the impulse responses of the high-order and reduced-order models, while the $N\|g\|$ and $N\|G\|$ terms simply normalize Γ.

The ideal solution to searching for the best subset of (R_i,λ_i)'s is to test every possible combination. For the power system problem, this is not feasible as it would require 2^{n-r}-1 tests. Therefore, the simple search procedure employed by the reduction algorithm is used. It is shown in [12] that this method ensures that the proper subset is selected while having to conduct at most $\sum_{i=1}^{n-r} i$ tests, which, for large n-r, is much less than 2^{n-r}-1.

In Section 3.0 the criterion for determining the optimal reduced-order model is the minimum of the AIC in (10). Due to the conservative nature of the AIC, practical experience has suggested that a better criterion is to use the model order at which the AIC first stops decreasing (in theory this is also the minimum). This further reduces the number of tests, making the problem relatively computationally trivial.

5.0 MODEL REDUCTION IN PRONY ANALYSIS

A developing method for analyzing power system dynamics is Prony analysis (e.g., see [13-18]). It is a method of fitting a linear model to a disturbance ring-down signal. If the input is known, a transfer function in the form of (5) is obtained [18]. It has demonstrated uses in field-data analysis [13,14], transient stability program analysis [17], and control system design [15,16].

In using Prony analysis to identify a model, terms representing true dominant system effects and system noise are identified. Removing the terms associated with noise is often based on engineering judgement and can be difficult [19]. For numerical robustness, n is chosen to be near $N_T/2$ (typically 30 to 100), while in many cases the order representing true system effects is closer to 20 to 40.

To separate noise and system effects from a Prony analysis solution, the proposed reduction algorithm is being incorporated into the latest version of the Bonneville Power Administration (BPA) Prony analysis code. The following two examples demonstrate the usefulness of the algorithm in Prony analysis.

Example 1

Consider the 9th-order transfer function

$$G(s)=\frac{15.38\pm j55.37}{s+0.5\pm j0.7\pi}+\frac{-18.59\mp j16.82}{s+0.25\pm j0.9\pi}+\frac{-1.00\pm j2.83}{s+0.1+1j1.6\pi}+\frac{-2.74\pm j2.06}{s+0.05\pm j2\pi}+\frac{44.06}{s+3.2\pi} \tag{14}$$

where "±" indicates complex conjugate pairs. A unit impulse is applied to the input of the system and white noise is added to the output so that the signal-to-noise ratio (SNR) of the first 10 seconds is 15 db. A Prony analysis is performed on the data, resulting in a 60th-order model that includes estimation of the actual system terms in (14) within 10% error. Fig. 1 shows the AIC for the reduced model orders. The solid line is for the case where $\beta=0$, $T=0.1$, $N_T=100$ (testing time-domain impulse only), and the dotted line shows the case where $\alpha=0$, $\Delta\omega=0.04\pi$, $N_{\Delta\omega}=150$ (testing frequency domain only). The solid line indicates a 10th-order reduced model and the dotted indicates a 12th-order. In both cases, the reduced models contain the identified Prony terms corresponding to (14). The remaining few terms are highly damped and have little relative effect.

Figs. 2, 3, and 4 show the full-order model and 10th-order reduced-model impulse responses. In the time domain, the response is smoothed because of the removal of noise terms. In the frequency domain, the gain and phase response fits very well at the high gains. At lower gains, the signal is dominated by noise terms; therefore, the fit is not as good.

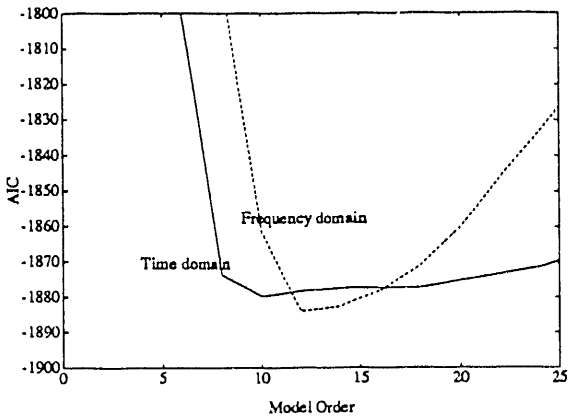

Fig. 1: Akaike information criterion (AIC) for example 1.

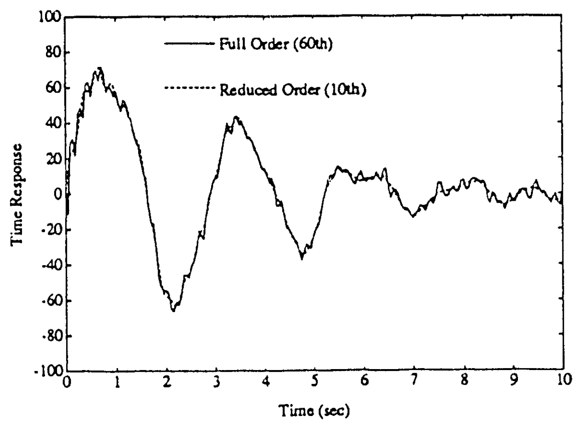

Fig. 2: Impulse time-domain response for example 1.

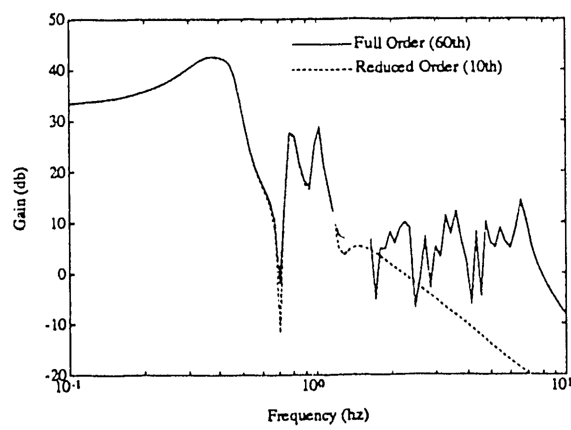

Fig. 3: Impulse frequency-domain response for example 1 (gain).

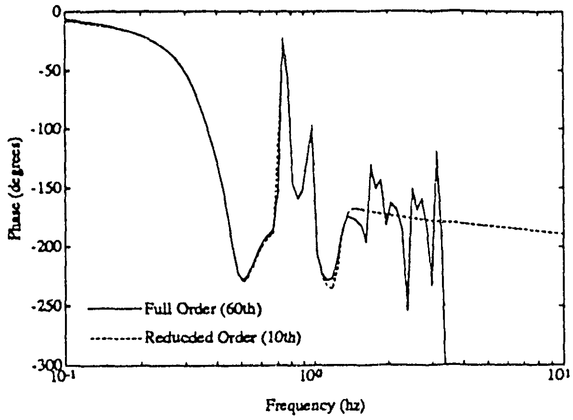

Fig. 4: Impulse frequency-domain response for example 1 (phase).

6.0 MODEL REDUCTION IN EIGENANALYSIS

Extensive work has been done in the linear model-based analysis of power system dynamics using eigenanalysis [1]. Methods for calculating transfer function residues and zeros are in [20] and [21]. Eigenanalysis of a modern power system results in a very high-order linear system (often hundreds of states). But, for a given input/output pair, only a few terms dominate, which allows it to be represented by a reduced-order model. The following example demonstrates how the reduction method can be applied to eigenanalysis problems.

Example 2

Consider the five-machine system in Fig. 5; it is a version of the one presented in [22]. Each machine is represented by a 5th-order q-d axis model and a first-order exciter, resulting in a 30th-order model (see data in [22]).

An eigenanalysis is performed on the system, revealing one dominant unstable mode. The transfer-function residues are then calculated for each mode from the reference voltage to the speed-error at generator 4, resulting in a 30th-order transfer function. The impulse response of this transfer function is dominated by the unstable mode; but, it also has a secondary dominant mode and many other terms. The question to be answered is how many of these terms are required to accurately represent the transfer function?

Model reduction is then performed on the 30th order model. Fig. 6 shows the AIC for three cases: 1) $\alpha=1$, $\beta=0$, $T=0.1$, $N_T=100$ (testing time-domain data only); 2) $\alpha=0$, $\beta=1$, $\Delta\omega=0.03\pi$, $N_\omega=150$ (frequency domain data only); and 3) $\alpha=0.5$, $\beta=0.5$, $T=0.1$, $N_T=100$, $\Delta\omega=0.03\pi$, and $N_\omega=150$. Cases 1 and 2 indicate 8th-order models; case 3 indicates a 10th-order model. Each reduced model is the same up to the 6th order. Terms after this are highly damped. This likely indicates that the minimum reduced model is 6th-order.

Fig. 7 shows the impulse response of the 30th- and 10th-order models. Both give nearly the same exact response. The frequency responses of the two are also very similar. Fig. 8 shows the root-locus of the high-order model's dominate modes, and the root-locus for the 8th-order model is in Fig. 9. Both models show the same path for dominant mode loci, indicating similar control system response characteristics.

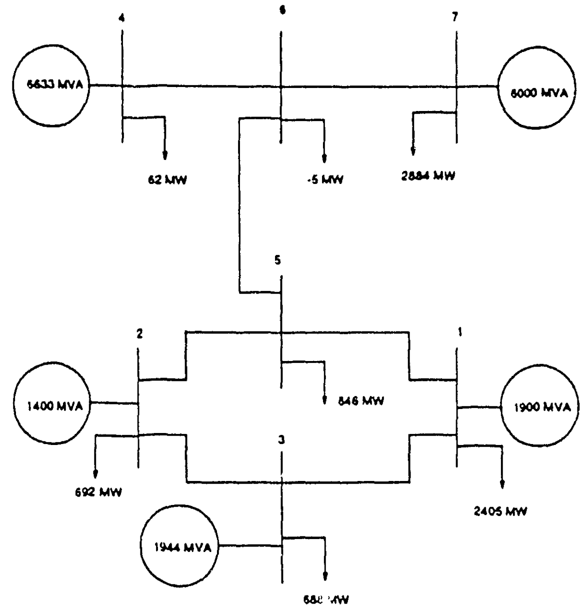

Fig. 5: Five-machine test system.

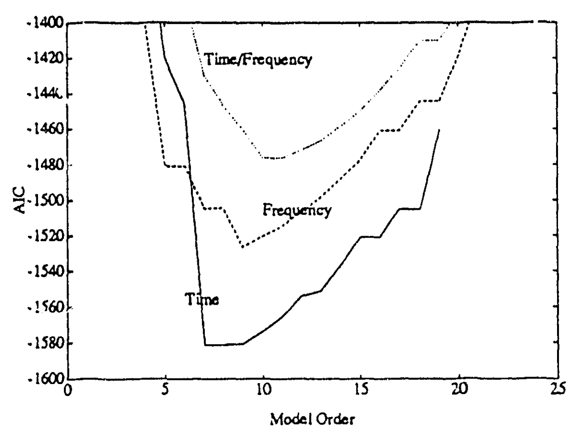

Fig. 6: AIC for example 2.

7.0 CONCLUSION

An algorithm for reducing the order of large-scale systems has been presented. The algorithm basically finds the one subset of the large-scale system that best represents the given transfer function's impulse response. The criterion incorporates both time and frequency domain information. In the cases investigated, the reduced-order model appears to be a conservative estimate of a smaller one, but this issue is not of major concern as it is better not to underestimate.

The algorithm is not numerically intensive and is easily implemented as a computer program.

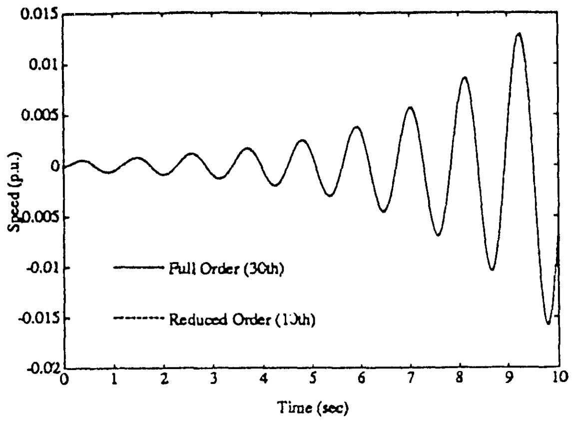

Fig. 7: Impulse response for example 2.

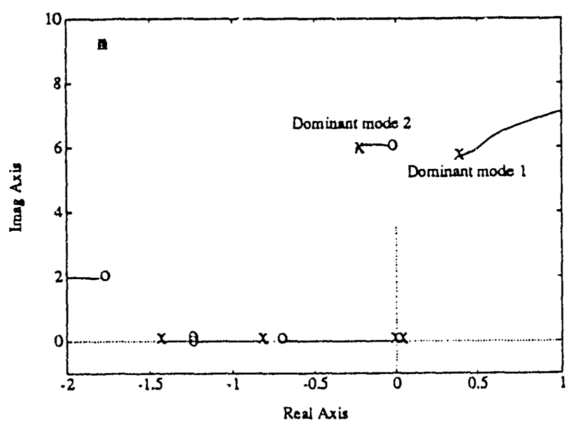

Fig. 8: Root-locus for high-order (30th) model in example 3.

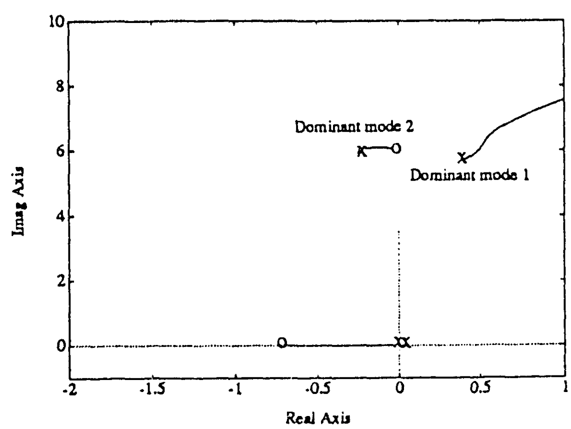

Fig. 9: Root-locus for reduced-order (10th) model in example 2.

In developing a reduced-order model, one should not depend solely on an algorithm such as presented here. Engineering judgement should always be used in conjunction. For example, in many cases one may only consider system terms in a given bandwidth or force the reduced-order model to include certain terms. These issues are difficult to generalize as they are very problem specific.

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BIOGRAPHY

Daniel J. Trudnowski (M'91) received the B.S. degree in engineering science from Montana College of Mineral Science and Technology (Montana Tech) in 1986, and the M.S. and Ph.D. degrees in electrical engineering from Montana State University (MSU) in 1988 and 1991, respectively.

From 1985 through 1986, he worked at Mountain States Energy, Inc. designing a video instrumentation system for a magnetohydrodynamic generator. Since 1991, he has been a research engineer at the Pacific Northwest Laboratory where he conducts research on control system and power system dynamic problems. Current research topics include identification and control of oscillatory systems including power systems and flexible robotic manipulators.

In 1991, Dr. Trudnowski was awarded the MSU Graduate Achievement Award given to MSU's outstanding Ph.D. graduate. He is a member of the IEEE Control Systems and Power Engineering societies.

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