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Power System Analysis and Controller Design Using System Identification Techniques

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ABSTRACT

In this study, Subspace System Identification (SSI) is used for power system analysis and controller design. It is too difficult to apply analytic method for analysis and controller design of an operating power system, since there are several power system components which can be modeled by high order differential equations. On the other hand, components parameter may vary during normal operation of power system. Therefore, there is a gap between the real-time behavior and analytical behavior of power systems. In this study, the difficulties that may arise when using the analytical studies are investigated using different power system models. Moreover, it is suggested to use SSI algorithms for power systems analysis and controller design. The benefits and drawbacks of subspace identification methods are studied for different power systems. An Linear Quadratic Gaussian (LQG) controller design scheme is also presented based on subspace system identification. Several comparisons investigated using computer simulations, the results expresses usefulness and easiness of proposed methods.

Key words: Small signal, subspace identification, power system, controller design

INTRODUCTION

Power system is a complicated system. It is consist of several main parts which can be arranged as following; generation, transmission, distribution and loads. Each of these parts contains several complex structures and components (Kouzou *et al.*, 2010; Samimi and Golkar, 2012). The need for controlling and providing continuous and secure operation of power system causes many researchers to devote their investigations to such a large nonlinear system (Radaideh, 2003; Belhadj *et al.*, 2007; Sabahi *et al.*, 2008). However, there are some documents which still reveal the need for more effective methods to analysis and monitor the undesirable happenings of power systems (Al-Odienat, 2006; Zribi and Rifai, 2006; Haidar *et al.*, 2007). In order to get rid of such problems, the parameters of power system should be identified using online measurements of signals. In this case, the role of identification methods becomes important. In this study, It is supposed to use Subspace System Identification (SSI) methods for improving the power system operation.

Numerous investigators have worked on SSI methods. They used different SSI algorithms for different applications (Katayama, 2005; Keyvaani *et al.*, 2010; Jamaali *et al.*, 2011). The first footsteps of SSI applications in power systems may be seen in Kamwa *et al.* (1996). The study provided low order model of large power system using N4SID algorithm of SSI. Results of the study express that SSI based model is in lower orders, more optimized and more suitable for controller design in comparison with classical system identification and modeling.

A Heffron-Phillips model of synchronous generator was identified by Karrari and Malik (2004) using subspace identification algorithms and online measurements. According to Soliman *et al.* (2008), the parameters of a Heffron-Phillips model of a synchronous generator was extracted from closed loop data using SSI algorithms. It divides identification problem of a closed loop system to two open loop identification and then it uses SSI algorithms to identify each open loop transfer function. Using some mathematical processing of provided transfer function, it provides a transfer function as generator model. Wu and Malik (2006) discussed a model predictive controller design for multi-machine power system using SSI algorithms. The design uses a recursive subspace system identification algorithm in order to provide a MIMO self-tuning adaptive controller; therefore it can be used for online applications.

Zhou *et al.* (2006) mentions use of different types of power system signals applicable to SSI algorithms. It uses such signals to provide identification data. Modal analysis of power system was developed using subspace system identification methods and provided data. Ghasemi *et al.* (2006) also discussed modal analysis and oscillatory stability study of power systems based on SSI methods. It provided a voltage stability measure using identified critical modes of power system. Cai *et al.* (2009) discusses a PSS using stochastic subspace system identification approaches. It also mentions small signal analysis of power systems.

In this study, draw-backs of classical methods for power system analysis and controller design are investigated. Moreover, Subspace System Identification is used to extract beneficial properties of power system for analysis and controller designs. A Linear Quadratic Gaussian (LQG) controller is designed based on the information provided by subspace system identification methods.

SUBSPACE SYSTEM IDENTIFICATION (SSI) METHODS

The considered system is:

$$\begin{aligned} x_{t+1} &= Ax_t+Bu_t+w_t \\ y_t &= Cx_t+Du_t+v_t \end{aligned} \tag{1}$$

where:

$$E\left[\begin{pmatrix} w_p \\ v_p \end{pmatrix}\begin{pmatrix} w_q^T & v_q^T \end{pmatrix}\right] = \begin{pmatrix} Q & S \\ S^T & R \end{pmatrix}\delta_{pq} \geq 0 \tag{2}$$

and $u_t \in \Re^{n_u}, y_t \in \Re^{n_y}, x_t \in \Re^{n}$ are samples of input, output, state vectors and $v_t \in \Re^{n_y}, w_t \in \Re^{n}$ are static, zero average state noise and output noise vectors. Subspace system identification problem can be formulated as below:

There are N samples of input vectors $u = [u_0\, u_1\, u_2 .. u_{N-1}]$ and output vectors $y = [y_0\, y_1\, y_2 .. y_{N-1}]$ from a system of order n. Find A, B, C, D, Q, R, S matrices and n for the structure defined in Eq. 1.

There are two basic subspace system identification algorithm expressed in Table 1. They use the same measurements, same block Hankel matrices, different types of projections, SVD of different matrices, the same method for extraction of system order and different extended observability matrices. MOESP does not need to estimate future states of system but N4SID provides future state vectors by using a weighting matrix. MOESP uses extended observability

Table 1: Comparison of two basic SSI algorithms, MOESP (MIMO output-error state space) algorithm and N4SID (numerical algorithm for subspace state space system) algorithm

Step	Operation	MOESP algorithm	N4SID algorithm
1	Model	$x_{k+1} = Ax_k + Bu_k + w_k$ $y_k = Cx_k + Du_k + v_k$ $E\left\{\begin{bmatrix} w(t) \\ v(t) \end{bmatrix}\begin{bmatrix} w^T(s) & v^T(s) \end{bmatrix}\right\} = \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix}\delta$.	$x_{k+1} = Ax_k + Bu_k + w_k$ $y_k = Cx_k + Du_k + v_k$ $E\left\{\begin{bmatrix} w(t) \\ v(t) \end{bmatrix}\begin{bmatrix} w^T(s) & v^T(s) \end{bmatrix}\right\} = \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix}\delta$.
2	Measured data	$u = [u_0\ u_1\ u_2 \dots u_{N-1}]$ $y = [y_0\ y_1\ y_2 \dots y_{N-1}]$	$u = [u_0\ u_1\ u_2 \dots u_{N-1}]$ $y = [y_0\ y_1\ y_2 \dots y_{N-1}]$
3	Block Hankel matrices	$U_{0,k-1} = \begin{bmatrix} u_0 & u_1 & \cdots & u_{N-1} \\ u_1 & u_2 & \cdots & u_N \\ \vdots & \vdots & \vdots & \vdots \\ u_{k-1} & u_k & \cdots & u_{k+N-2} \end{bmatrix} \in \Re^{kn_u \times N}$ $Y_{0,k-1} = \begin{bmatrix} y_0 & y_1 & \cdots & y_{N-1} \\ y_1 & y_2 & \cdots & y_N \\ \vdots & \vdots & \vdots & \vdots \\ y_{k-1} & y_k & \cdots & y_{k+N-2} \end{bmatrix} \in \Re^{kn_y \times N}$	$U_{0,k-1} = \begin{bmatrix} u_0 & u_1 & \cdots & u_{N-1} \\ u_1 & u_2 & \cdots & u_N \\ \vdots & \vdots & \vdots & \vdots \\ u_{k-1} & u_k & \cdots & u_{k+N-2} \end{bmatrix} \in \Re^{kn_u \times N}$ $Y_{0,k-1} = \begin{bmatrix} y_0 & y_1 & \cdots & y_{N-1} \\ y_1 & y_2 & \cdots & y_N \\ \vdots & \vdots & \vdots & \vdots \\ y_{k-1} & y_k & \cdots & y_{k+N-2} \end{bmatrix} \in \Re^{kn_y \times N}$
4	Extra predefined matrices	$U_p = U_{0,k-1}$, $U_p = Y_{0,k-1}$	$U_p = U_{0,k-1}$, $Y_p = Y_{0,k-1}$, $U_f = U_{k,2k-1}$, $Y_f = Y_{k,2k-1}$ $W_p = \begin{bmatrix} U_p \\ Y_p \end{bmatrix}$, $W_f = \begin{bmatrix} U_f \\ Y_f \end{bmatrix}$
5	LQ decomposition	$\begin{bmatrix} U_p \\ Y_p \end{bmatrix} = \begin{bmatrix} L_{11} & 0 \\ L_{21} & L_{22} \end{bmatrix}\begin{bmatrix} Q_1^T \\ Q_2^T \end{bmatrix}$	$\begin{bmatrix} U_f \\ W_p \\ Y_f \end{bmatrix} = \begin{bmatrix} L_{11} & 0 & 0 \\ L_{21} & L_{22} & 0 \\ L_{31} & L_{32} & 0 \end{bmatrix}\begin{bmatrix} Q_1^T \\ Q_2^T \\ Q_3^T \end{bmatrix}$
6	Projection	$\dfrac{Y_p}{U_p^{\perp}} = L_{22}Q_2^T$	$Y_f /_{U_f} W_p = L_{32}L_{22}^{\dagger}W_p$
7	Singular value decomposition (SVD)	$L_{22} = \begin{bmatrix} U_1 & U_2 \end{bmatrix}\begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}$	$L_{32}L_{22}^{\dagger}W_p = \begin{bmatrix} U_1 & U_2 \end{bmatrix}\begin{bmatrix} \Sigma_1 & 0 \\ 0 & 0 \end{bmatrix}\begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix}$
8	System order	$n = \dim(\Sigma_1)$	$n = \dim(\Sigma_1)$
9	Extended observability matrix	$O_k = U_1 \Sigma_1^{1/2}$	$O_k = U_1 \Sigma_1^{1/2} T,\ \lvert T \rvert \neq 0$
10	Future state estimation	---------	$X_f = T^{-1}\Sigma_1^{1/2}V_1^T \in \mathbb{R}^{n\times N}$ $X_k = X_f = \begin{bmatrix} x_k & x_{k+1} & \cdots & x_{k+N-1} \end{bmatrix} \in \mathbb{R}^{n\times N}$
11	Estimation of state space matrixes	$C = O_k(1:n_y, 1:n)$ $A = O_k^{\dagger}(1:n_y(k-1), 1:n)O_k(n_y+1:kn_y, 1:n)$ Solving a least square problem to estimate B and D	$\begin{bmatrix} \hat{A} & \hat{B} \\ \hat{C} & \hat{D} \end{bmatrix} = \left(\begin{bmatrix} X_{k+1} \\ Y_{k,k} \end{bmatrix}\begin{bmatrix} X_k \\ U_{k,k} \end{bmatrix}^T\right)\left(\begin{bmatrix} X_k \\ U_{k,k} \end{bmatrix}\begin{bmatrix} X_k \\ U_{k,k} \end{bmatrix}^T\right)^{-1}$

matrix to extract system matrices but N4SID uses future states and through a least square problem estimates system matrices.

Table 1 expresses the following advantages for subspace system identification algorithms; SSI Algorithms are the only system identification methods that can easily and extensively be applied to all MIMO and SISO systems. Estimation of system order is one of the steps of SSI algorithms. This advantage reduces amount of time, cost and calculations. SSI methods can handle big packages of data. Online operations of SSI methods are easier and can easily be applied to MIMO systems. SSI methods use robust mathematical tools such as SVD, LQ decomposition, least square and QR decomposition. They also don't need nonlinear optimization. Some SSI algorithms only use output data to identify a model. This is a considerable advantage.

Since, the algorithms expressed in Table 1 use exogenous inputs, they are called deterministic subspace identification algorithms. Those SSI algorithms that don't use exogenous inputs are stochastic. To full fill the comparison, a stochastic SSI algorithm is provided in a stochastic SSI algorithm uses output data and provide A and C matrices. They also provide an innovation model in order to estimate future states.

APPLICATION OF SSI METHODS FOR SMALL SIGNAL ANALYSIS OF POWER SYSTEMS

Power system is generally a nonlinear system. Therefore, one should follow the following stages to achieve small signal properties of a power system; (i) Finding the details of all included elements (Generator constants, Transformer and line parameters, ...), (ii) Finding nonlinear model of power system using constant, parameters and theoretical relations of variables for different power system elements, (iii) Solving a load flow problem in order to provide an operating point, (iv) Linearization of nonlinear model using the provided operating point and (v) Application of modern small signal methods to provide small signal properties.

Providing an operating point, a nonlinear modeling and linearizing the model are all tough works in application, especially when the system is large. There is always a big gap between the analysis done on a piece of paper and the system behavior. Such a method is not applicable for monitoring of power system and this is a considerable draw-back for a scientific method.

Classical identification methods are useful in many applications. When using a classical system identification method, the biggest difficulty origins from Single-Input/Single-Output (SISO) structure of such methods. Classical system identification methods may fall into whirlpool of over parameterization. Coping with such problems is itself a new problem.

Our suggestion for overcoming such problems is to use Subspace System Identification (SSI) methods. SSI methods are good solution for Multi-Input/Multi-Output (MIMO) systems. They can be considered as the bridge for passing over the gap between real world system and theoretical analysis. The next section investigates SSI methods to glorify their useful advantages for small signal analysis of power systems.

The SSI advantages expressed in previous section can be used to overcome the difficulties with classical small signal analysis of power systems. The above five steps can be reduced to the following three steps Using SSI methods; (i) Measuring input/output signals of power system, (ii) Identification of a linear model for power system using SSI algorithms and (iii)Application of modern small signal methods to provide small signal properties.

As it can be seen, the four first steps vanished and two other steps replaced them. The fifth step left with no change. Therefore, one can provide small signal analysis of power systems in an easier and faster way.

Signal measuring is the starting point of system identification. The most effective inputs must be used since measured signals should have enough persistent excitement. In attention to differential equations of a single machine power system (Kundur and Balu, 1998), mechanical torque and field voltage are proper inputs.

Suppose that input vector u and output vector y of a power system have been measured. As an identification problem, goal is to find small signal properties of power system (Modes, Damping Ratios, Oscillation Frequencies, Participation Factors) using several samples of u and y.

It is announced that having N samples of input/output vectors and utilizing a subspace system identification algorithm, one can identify the following state space linear model:

$$\begin{aligned} \dot{x}_t &= Ax_t + Bu_t \\ y_t &= Cx_t + Du_t \end{aligned} \tag{3}$$

One can find system modes and as a result damping factors and damping frequencies by digging matrix A. But the state vector x of model is not that of real power system obtained using analytical methods, since the state vector x is not unique. Therefore, mode in state participation factors can't be utilized using identified A.

In order to cope with such a problem, it is proposed to use modal canonical realization of Eq. 3. Using T as a similarity transform matrix, one can provide the following modal canonical realization:

$$\begin{cases} \dot{z} = \Lambda z + \bar{B}u \\ y = \bar{C}z + \bar{D}u, \qquad z_{n\times 1}, u_{n\times n_u}, y_{n_y\times n} \end{cases}$$
$$x = Tz,\ \Lambda = T^{-1}AT,$$
$$\bar{B} = T^{-1}B,\ \ \bar{C} = CT,\ \bar{D} = D \tag{4}$$

Generally, Λ is in Jordan and block diagonal structure. Mode in state participation factor (p_{ki}) is defined as:

$$p_{ki} = \frac{\partial \lambda_i}{\partial a_{kk}} \tag{5}$$

where, a_{kk} is the diagonal element of system matrix. Since, in Eq. 4, the system matrix is diagonal with modes as its diagonal elements:

$$p_{ki} = \frac{\partial \lambda_i}{\partial a_{kk}} = \frac{\partial \lambda_i}{\partial \lambda_i} = 1 \tag{6}$$

Therefore, modal canonical realization can maximize (100%) mode in state participation factor of model. In order to clarify the point, suppose that u is zero and z^0 is initial condition vector of modal canonical realization. Therefore:

$$\dot{z} = \Lambda z \ \Rightarrow z_i = e^{-\lambda_i t} z_i^0,\ i = 1, 2, \cdots, n \tag{7}$$

Therefore, the only participated mode in state z_i is γ_i, so the participation factor of mode γ_i in state z_i is 100% and each mode is mapped to a state.

Considering above point and output equation of Eq. 3, one can write:

$$y = \bar{C}z \Rightarrow y_k = \sum_{i=1}^{n} \bar{c}_{ki} z_i = \sum_{i=1}^{n} \bar{c}_{ki} z_i^0 e^{-\lambda_i t},\quad k = 1, \cdots, n_y \tag{8}$$

Therefore, output y_k is affected by mode γ_i and mode in output participation factor (p_{ki}) is proposed as:

$$p_{ki} = \bar{c}_{ki} z_i^0, k = 1, \cdots, n_y \ \text{ and } i = 1, \cdots, n \tag{9}$$

In order to provide participation factors, one may need z^0 which can be provided through following relation:

$$z^0 = T^{-1} x^0 \tag{10}$$

x^0 is the initial condition vector of identified state space model which is also provided by SSI algorithms.

Some investigators (Hashlamoun *et al.*, 2009) discuss another kind of participation called state in mode participation factor. In most of literatures state in mode and mode in state participation factors are the same and they have been used interchangeably, however, there is a discussion on some differences by Hashlamoun *et al.* (2009).

TEST CASES

Single machine three bus system: Power system shown in Fig. 1 is a three bus single machine power system with no control and exciter. The parameters of the system are those used in (Kundur and Balu, 1998). It is supposed to extract all small signal properties of system using SSI Algorithms and the methods illustrated in previous sections.

Identification process should be provided with measured input/output signals. Computer simulations have been conducted using the system shown in Fig. 1 in order to measure input/output data. It is recommended to use mechanical torque as input and rotor speed or its angle as output signals since the extraction of small signal properties of generator angle and speed is desired to be achieved. Mechanical power can be used as input signal since in a per-unit system, torque and power are the same.

In order to have enough persistence excitation in input signals, one may add a white noise to input signals. To provide more realistic operating conditions, one may add a white noise to output signals, as well. Effect of noises will be investigated later.

300 samples of input/output data acquired through a 30 sec simulation. Using the SSI algorithms presented in Table 1, some linear models were identified and results are presented in Table 2. It is clear that to investigate performance of noises, the noise average cannot be manipulated because the operating point may vary which is not applicable in this study. Each noise variance was altered separately in order to see its effect.

In Table 3, one can see that an increase in input noise variance may lead to a better model from the view of FPE measure but one should be conservative when estimation of small signal properties is under consideration. Actually, a large increase in input noise variance may alter the operating point or its absorption area and may lead to instability.

Comparison of SSIM4 and SSIM5 with SSIM2 in Table 2, one can see that output noise has no effect on subspace system identification. The point is something related to application of consistence linear algebra tools in SSI. Left eigenvectors of a wide matrix are not sensitive to additive white noise considerably (Katayama, 2005). Therefore, the identification is not sensitive to output noise.

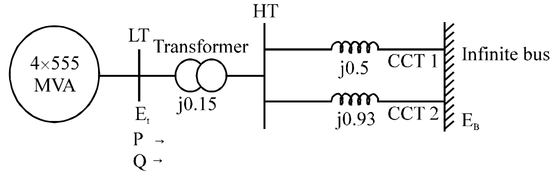

Fig. 1: Single Machine 3 bus power system

Table 2: A stochastic subspace system identification algorithm

Step	Operation	Stochastic algorithm
1	Model	$\begin{cases} x_{t+1} = Ax_t + w_t \\ y_t = Cx_t + v_t \end{cases}, \; E\left\{\begin{bmatrix} w_{(t)} \\ v_t \end{bmatrix}\begin{bmatrix} w_s^T & v_s^T \end{bmatrix}\right\} = \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix}\delta_{ts}$
2	Measured data	$f(t) = \begin{bmatrix} y_t & y_{t+1} & \cdots & y_{t+k-1} \end{bmatrix}^T, p(t) = \begin{bmatrix} y_{t-1} & y_{t-2} & \cdots & y_{t-k} \end{bmatrix}^T$
3	Block Hankel matrices	$\begin{cases} \left\{\Lambda_l = E\{y_{t+l}y^T{}_l\}, \quad l = 0,1,\cdots,L\right\} \\ 2k-1 \le L \;, \quad k > n \end{cases}, \; H_{k,k} = E\{f_t p_t^T\} = \begin{bmatrix} \Lambda_1 & \Lambda_2 & \cdots & \Lambda_k \\ \Lambda_2 & \Lambda_3 & \cdots & \Lambda_{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ \Lambda_k & \Lambda_{k+1} & \cdots & \Lambda_{2k-1} \end{bmatrix}$
4	Extra predefined matrices	
5	LQ decomposition	
6	Projection	
7	Singular value decomposition (SVD)	$H_{k,k} = \begin{bmatrix} U_s & U_n \end{bmatrix}\begin{bmatrix} \Sigma_s & 0 \\ 0 & \Sigma_n \end{bmatrix}\begin{bmatrix} V_s^T \\ V_n^T \end{bmatrix} \approx U_s \Sigma_s V_s^T$
8	System order	$n = \dim(\Sigma_S)$
9	Extended observability matrix	$O_k = U_s \Sigma_s^{1/2}$
10	Controllability matrix	$C_k = \Sigma_s^{1/2} V_s^T$
11	Future state estimation	
12	Estimation of state space matrixes	$A = O_{k-1}^{\dagger} O_k(p+1:kn_y, 1:n), C = O_k(1:n_y, 1:n), \bar{C}^T = C_k(1:n, 1:n_y)$
13	Riccati algebraic equation	$\Pi_{k+1} = A\Pi_k A^T + (\bar{C}^T - A\Pi_k C^T)(\Lambda(0) - C\Pi_k C^T)^{-1}(\bar{C} - C\Pi_k C^T), \;\; \Pi_* = \lim_{k\to\infty} \Pi_k$
14	Estimation of variance matrixes	$Q = \Pi_* - A\Pi A^T, S = \bar{C}^T - A\Pi_* C^T, R = \Lambda(0) - C\Pi_* C^T$
15	Estimation of Kalman gain matrix	$K = (\bar{C}^T - A\Pi_* C^T)(\Lambda(0) - C\Pi_* C^T)^{-1}$
16	Innovation model for state estimation	$x_{t+1} = Ax_t + Ke_t, \; y_t = Cx_t + e_t, \; \mathrm{cov}\{e_t\} = R$

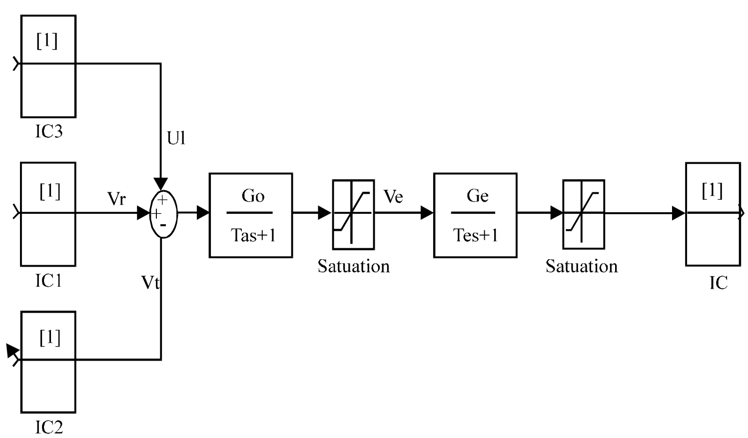

Fig. 2: Voltage regulator model

Since, applied input noise is too weak, the identification process has no effect on normal operating conditions of power system.

State estimation and LQG controller design: The single inertia model of a turbine generator connected to an infinite bus is represented by an 11th order nonlinear state space set of equations. Its state vector is $x = [\delta, \dot{\delta}, \omega_0\Psi_d, \omega_0\Psi_f, \omega_0\Psi_q, \omega_0\Psi_{kq}, V_e, A_p, T_m]^T$ where $d, \dot{d}$ are the rotor load angle relative to the infinite bus-bar and its differential, $\omega_0\Psi_d, \omega_0\Psi_f, \omega_0\Psi_q, \omega_0\Psi_{kq}$ are the electromagnetic states, v_e and v_f are voltage regulator states defined in Fig. 2 and A_p and T_m (pu torque) are governor states defined in Fig. 3.

Table 3: Small signal analysis of power system using ssi algorithms; abriviations are: classical model (CM), subspace system identified model (SSIM), subspace system identification algorithm (SSIA) and final prediction error (FPE).

	σ_u input noise variance	σ_y output noise variance	λ eigen values	ω_d (Hz) damping frequency	ξ damping factor	ω_n (Hz) natural frequency	|P| participation matrix	FPE
CM	-	-	λ = -0.714±j6.35	1.0101	0.112	1.0165	$\begin{bmatrix} 0.503 & 0.503 \\ 0.503 & 0.503 \end{bmatrix}$	-
SSIM01	0.0001	0	λ = -0.7975±j6.2443	0.9906	0.1276	0.9988	$\begin{bmatrix} 0.5037 & 0.5037 \\ 0.5037 & 0.5037 \end{bmatrix}$	7.43536e-5
SSIM02	0.001	0	λ = -0.7192±j6.3203	1.0039	0.1139	1.0105	$\begin{bmatrix} 0.5028 & 0.5028 \\ 0.5028 & 0.5028 \end{bmatrix}$	8.55596e-5
SSIM03	0.01	0	λ = -0.7727±j6.1330	0.9747	0.1253	0.9825	$\begin{bmatrix} 0.5033 & 0.5033 \\ 0.5033 & 0.5033 \end{bmatrix}$	11.1083e-5
SSIM04	0.001	0.01	λ = -0.7192±j6.3203	1.0039	0.1139	1.0105	$\begin{bmatrix} 0.5028 & 0.5028 \\ 0.5028 & 0.5028 \end{bmatrix}$	0.594847
SSIM05	0.001	0.01	λ = -0.7192±j6.3203	1.0039	0.1139	1.0105	$\begin{bmatrix} 0.5028 & 0.5028 \\ 0.5028 & 0.5028 \end{bmatrix}$	0.596223

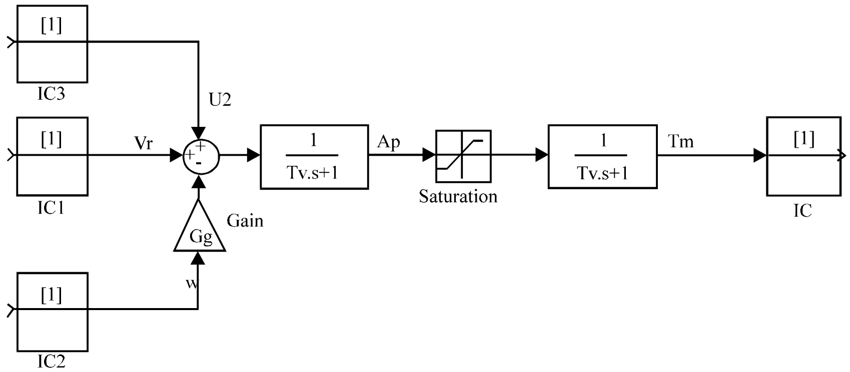

Fig. 3: Governor states

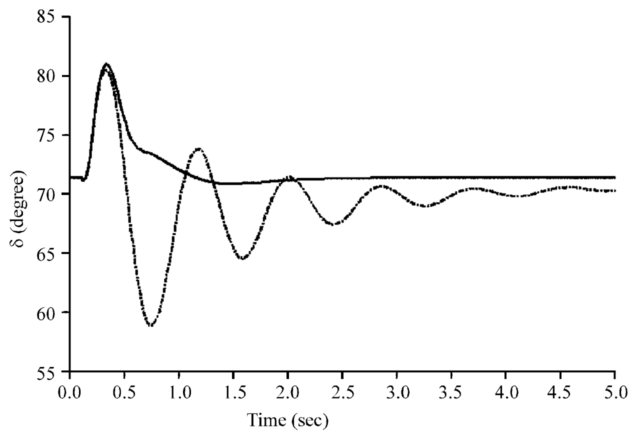

Fig. 4: Performance of subspace based LQG control (solid) of nonlinear power system and the response without LQG (dashed)

The voltage regulator model, for a very fast excitation system, is a simplified representation of an IEEE Type AC4 aimed to give the transient performance. Field current can be forced up or down but cannot reverse. The governor model is a 2 time-constant approximation and represents main and interceptor values being governed in parallel to give a fast response. It is assumed that opening and closing speeds are the same which is not typical of present practice, opening being comparatively slow.

To validate the proposed approach to state estimation and controller design for nonlinear power systems, some simulations have been arranged using matlab7/simulink software. We used the nonlinear power system model described in above. It means that the power system is a turbine generator connected to an infinite bus through a line. The sampled signals were used to identify a linear model of power system. Then the state space matrices of the model were applied to design an LQG. The LQG can be redesign in any time instances which is more suitable.

Figure 4 and 5 show the load angle response of system following a 3-phase fault of 100 msec, with two controller designs compared with performance without supplementary control. The fault is assumed to be at the high voltage terminals of the generator transformer when the generator is at 0.8 pu power, unity power factor and the tie-line impedance is assumed to be unchanged. Load angle to the infinite bus and field voltage are measured and used as a basis of estimation.

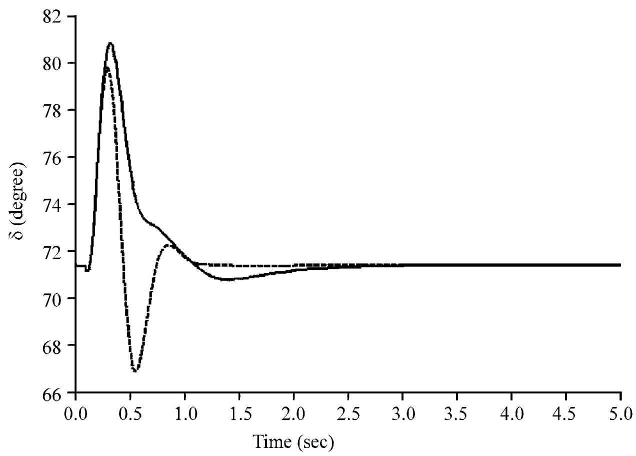

Fig. 5: Performance comparison of analytic LQG (dashed) and subspace based LQG (solid)

An illustration of the performance of a subspace based LQG controller of nonlinear power system is shown in Fig. 5. The LQG performance is very good. An 11th order linear model of nonlinear power system has been used to design a usual LQG controller. The performance of subspace based LQG and analytical LQG have been compared in Fig. 5. Both LQG controllers are the same in all common parameters. It is clear that the proposed SSI based LQG controller can successfully cope with damping of the second swing while there is a little increase in the first swing.

CONCLUSIONS

In this study, it is shown that system identification can be very helpful for analysis and controller design of power systems. Moreover, different models can be identified for different applications based on sampled signals of power systems. The pitfalls of analytic methods for power systems can also be avoided using models identified by system identification tools.

The study proposed that subspace system identification is a useful tool for small disturbance analysis and controller design of power systems. In this case, a state space multi-input/multi-output model of system was identified using the sampled data and subspace system identification algorithms. Furthermore, extraction of modes and their participation factors were easily investigated using SSI methods. However, it was a need to apply some modification in SSI algorithms. Additionally, It was shown that linear controller design based on the online system identification was very easy to implement.

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