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An intelligent based LQR controller design to power system stabilization

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Abstract

This paper presents an intelligent model, named as free model, approach for a closed-loop system identification using input and output data and its application to design a power system stabilizer (PSS). The free model concept is introduced as an alternative intelligent system technique to design a controller for such dynamic system, which is complex, difficult to know, or unknown, with input and output data only, and it does not require the detail knowledge of mathematical model for the system. In the free model, the data used has incremental forms using backward difference operators.

A linear transformation is introduced to convert the free model into a linear model so that a conventional linear controller design method can be applied. Also, it is shown that the free model is controllable, observable, and robust to disturbance.

In this paper, the feasibility of the proposed method is demonstrated in a three-machine nine-bus power system. The linear quadratic regulator (LQR) method is applied to the free model to design a PSS for the system, and compared with the conventional PSS and LQR controller based on the ARMA-model. The free-model based (FMB) PSS is robust in different loading conditions and system failures such as the outage of a major transmission line or a three phase to ground fault which causes the change of the system structure.

Keywords: Free model; Intelligent control; Power system stabilization; Linear quadratic regulator

1. Introduction

The main object of power system control is to provide every single customer an electric supply with tight ranges of frequency and voltage magnitude irrespective of the load variation. Customers also expect a reliable and secure supply of electric energy despite the fact that power systems consist of extensive network of lines, cables, and transformers, and power is supplied from distant power stations.

Traditionally, a power system stabilizer (PSS) with the excitation system is the most common tool used to enhance the damping of low frequency oscillations of a power system. Considerable effort has been made to design PSS for power systems, most of which is based on deMello and Concordia's pioneering work [1]. They use a linearized model to find a proper set of parameters in a fixed structure PSS. Linear optimal control and modern control theories are also introduced to improve the dynamic performance of power systems under the uncertainty of power system models [2–5]. These techniques, however, depend on the accuracy of the model, which is less reliable as the power system becomes larger. Adaptive techniques are also employed in the PSS design for a wide range of operations [6–12]. Recently, intelligent control, so called artificial neural networks and fuzzy logic, has attracted the attention of power system engineers. There has been a great deal of research that reports on artificial neural network and fuzzy logic and its application to control and power systems [13–23].

In this paper, based on the free model concept, an alternative intelligent system technique is presented and demonstrated in a power system that is very complex and hard to know. Moreover, the proposed method uses input and output data only, which implies no detail knowledge of mathematical model for the system. Incremental forms using backward difference operators are applied in the free model. Such data forms are from the concept of the free model, in that a system can be identified if the differences, such as position, velocity, and acceleration, are known. The parameters of the

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free model can be obtained by least square method. The free model is then transformed to a linear state space model and the linear quadratic regulator (LQR) method [24] is used to design a controller. The accuracy of the free-model approximation can be improved by increasing the observation window for estimation and the order of the free model. In this study, a three-machine and nine-bus power system given in Appendix A [25,26] is studied to demonstrate the feasibility of the proposed method.

The LQR method is applied to the free model to design a PSS for the system, and LQR controller based on free model, FMB PSS, is compared with the conventional PSS and the LQR controller based on the ARMA model [27]. The FMB PSS shows robustness in different loading conditions and system failures such as the outage of a major transmission line or a three phase to ground fault which causes the structure changes in the power system.

2. Description of the free model

Consider a nonlinear time-invariant discrete-time system, represented by

$$y(k+1) = f(y(k), y(k-1), \ldots, y(k-N), u(k), u(k-1), \ldots, u(k-M)), \tag{1}$$

where and $y(k-i)$, and $u(k-j)$, $i = 0, 1, \ldots, N$, $j = 0, 1, \ldots, M$ denote the delayed outputs and inputs, respectively. It can be shown that the delayed signals are made of increments or differences. For this purpose, the backward difference operator [28] is defined as

$$\begin{array}{l} \Delta^n f(k) = \Delta^{n-1} f(k) - \Delta^{n-1} f(k-1), \quad n \geq 1 \\ \Delta^0 f(k) = f(k) \end{array}. \tag{2}$$

Using the difference operator (2), the system (1) can be represented as

$$y(k+1) = f(y(k), \Delta y(k), \ldots, \Delta^N y(k), u(k), u(k-1), \Delta u(k-1), \ldots, \Delta^M u(k-1)). \tag{3}$$

The right hand side of (3) can be expanded into the Taylor series around the state at $k-1$:

$$\begin{aligned} y(k+1) &= f(y(k), \Delta y(k), \ldots, \Delta^N y(k), u(k), u(k-1), \Delta u(k-1), \ldots, \Delta^M u(k-1)) \\ &= f(y(k-1), \ldots, \Delta^N y(k-1), u(k-1), u(k-2), \ldots, \Delta^M u(k-2)) \\ &\quad + \left(\frac{\partial f}{\partial y(k-1)}\right)(y(k) - y(k-1)) + \cdots \\ &\quad + \left(\frac{\partial f}{\partial \Delta^N y(k-1)}\right)(\Delta^N y(k) - \Delta^N y(k-1)) \\ &\quad + \left(\frac{\partial f}{\partial u(k-1)}\right)(u(k) - u(k-1)) \\ &\quad + \left(\frac{\partial f}{\partial u(k-2)}\right)(u(k-1) - u(k-2)) + \cdots \\ &\quad + \left(\frac{\partial f}{\partial \Delta^M u(k-2)}\right)(\Delta^M u(k-1) - \Delta^M u(k-2)) + O(k) \\ &= y(k) + \sum_{i=1}^{N} a_i \Delta^i y(k) + b_0 \Delta u(k) + \sum_{i=1}^{M} b_i \Delta^i u(k-1) + O(k), \end{aligned} \tag{4}$$

where $a_i = \partial f/\partial(\Delta^i y(k-1))$, $b_0 = \partial f/\partial(u(k-1))$, $b_i = \partial f/\partial(\Delta^i u(k-2))$, and $O(k)$ represents the high order terms. By subtracting $y(k)$ from (4), the above equation is represented as following:

$$\Delta y(k+1) = \sum_{i=1}^{N} a_i \Delta^i y(k) + b_0 \Delta u(k) + \sum_{i=1}^{M} b_i \Delta^i u(k-1) + O(k). \tag{5}$$

Neglecting the high order terms

$$\Delta \hat{y}(k+1) = \sum_{i=1}^{N} a_i \Delta^i y(k) + b_0 \Delta u(k) + \sum_{i=1}^{M} b_i \Delta^i u(k-1), \tag{6}$$

and dividing both sides with Δ, and then the free model is defined as following:

$$\hat{y}(k+1) = \sum_{i=1}^{N} a_i \Delta^{i-1} y(k) + b_0 u(k) + \sum_{i=1}^{M} b_i \Delta^{i-1} u(k-1) \tag{7}$$

where and N and M are the orders of the free model for output and input, respectively. The least squares method [28] is applied for the parameters a_i, b_0, and b_i based on minimizing J, that is a sum of squares:

$$\min J = \sum_{i=0}^{n} (y(k-i+1) - \hat{y}(k-i+1))^2 \tag{8}$$

where and y and $\hat{y}$ indicate the system output and the estimated output, respectively. The procedure is in Appendix B.

3. State-space realization

Free model can be easily adapted to design controllers with conventional design methods. In this study, the linear quadratic regulator is applied to design a controller that is called the free-model based optimal controller (FMBOC). First, a linear transformation is introduced to convert the free model into a linear state-space model so that the linear quadratic regulator design method can be applied. The state variables are defined by the following linear transformation:

$$\begin{aligned} x_1(k) &= y(k) \\ x_2(k) &= \Delta^1 y(k) + \beta_1 u(k-1) \\ x_3(k) &= \Delta^2 y(k) + \beta_2 u(k-1) + \beta_1 \Delta^1 u(k-1) \\ &\vdots \\ x_N(k) &= \Delta^{N-1} y(k) + \beta_{N-1} u(k-1) + \cdots \\ &\quad + \beta_1 \Delta^{N-2} u(k-1). \end{aligned} \tag{9}$$

From the linear transformation (9), the ith state variable is defined by

$$x_i(k) = \Delta^{i-1} y(k) + \sum_{m=0}^{i-2} \beta_{i-m-1} \Delta^m u(k-1), \tag{10}$$

where $i = 1, 2, \ldots, N$, and $\beta_0 = 0$. Solving for the output increments:

$$\begin{aligned} y(k) &= x_1(k) \\ \Delta^1 y(k) &= x_2(k) - \beta_1 u(k-1) \\ \Delta^2 y(k) &= x_3(k) - \beta_2 u(k-1) - \beta_1 \Delta^1 u(k-1) \\ &\vdots \\ \Delta^{i-1} y(k) &= x_i(k) + \beta_{i-1} u(k-1) - \beta_{i-2} \Delta^1 u(k-1) \\ &\quad - \beta_{i-3} \Delta^2 u(k-1) - \cdots - \beta_1 \Delta^{i-2} u(k-1). \end{aligned} \tag{11}$$

Then applying (11) into (7) and replacing $\hat{y}(k+1)$ with $y(k+1)$,

$$\begin{aligned} y(k+1) &= \sum_{i=1}^{N} a_i \Delta^{i-1} y(k) + b_0 u(k) \\ &\quad + \sum_{i=1}^{N-1} b_i \Delta^{i-1} u(k-1), \end{aligned} \tag{12}$$

which can be represented as the following equation:

$$\begin{aligned} x_1(k+1) &= \sum_{i=1}^{N} (a_i (x_i(k) - \beta_{i-1} u(k-1) \\ &\quad - \beta_{i-2} \Delta^1 u(k-1) - \beta_{i-3} \Delta^2 u(k-1) - \cdots \\ &\quad - \beta_1 \Delta^{i-2} u(k-1)) \\ &\quad + b_0 u(k) + \sum_{i=1}^{N-1} b_i \Delta^{i-1} u(k-1), \end{aligned}$$

or

$$\begin{aligned} x_1(k+1) &= \sum_{i=1}^{N} a_i x_i(k) + b_0 u(k) + (b_1 - a_2\beta_1 - a_3\beta_2 - \cdots \\ &\quad - a_N \beta_{N-1}) u(k-1) + (b_2 - a_3\beta_1 - a_4\beta_2 - \cdots \\ &\quad - a_N \beta_{N-2}) \Delta^1 u(k-1) + (b_3 - a_4\beta_1 - \cdots \\ &\quad - a_N \beta_{N-3}) \Delta^2 u(k-1) + \cdots \\ &\quad + (b_{N-1} - a_N \beta_1) \Delta^{N-2} u(k-1). \end{aligned} \tag{13}$$

Choose β_i so that the coefficients of $\Delta^i u(k-1)$ become zeros, i.e.

$$\begin{bmatrix} a_2 & a_3 & \cdots & a_N \\ a_3 & a_4 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ a_N & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{N-1} \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{N-1} \end{bmatrix}. \tag{14}$$

Then, (13) becomes

$$x_1(k+1) = \sum_{m=1}^{N} a_m x_m(k) + b_0 u(k). \tag{15}$$

Now, it remains to derive the $x_i(k+1)$ for $i \geq 2$. From the definition of the backward difference operator, and (9)

$$\begin{aligned} \Delta x_{i-1}(k+1) &= x_{i-1}(k+1) - x_{i-1}(k) \\ &= \left\{ \Delta^{i-2} y(k+1) + \sum_{m=1}^{i-2} \beta_{i-m-1} \Delta^{m-1} u(k) \right\} \\ &\quad - \left\{ \Delta^{i-2} y(k) + \sum_{m=1}^{i-2} \beta_{i-m-1} \Delta^{m-1} u(k-1) \right\}, \end{aligned}$$

so that,

$$\begin{aligned} \Delta x_{i-1}(k+1) &= x_{i-1}(k+1) - x_{i-1}(k) \\ &= \Delta^{i-1} y(k+1) + \sum_{m=1}^{i-2} \beta_{i-m-1} \Delta^m u(k). \end{aligned} \tag{16}$$

From (16)

$$\begin{aligned} \Delta^{i-1} y(k+1) &= x_{i-1}(k+1) - x_{i-1}(k) \\ &\quad - \sum_{m=1}^{i-2} \beta_{i-m-1} \Delta^m u(k). \end{aligned} \tag{17}$$

From (10), the state equation of the ith state variable is defined as:

$$x_i(k+1) = \Delta^{i-1} y(k+1) + \sum_{m=0}^{i-2} \beta_{i-m-1} \Delta^m u(k). \tag{18}$$

Substituting (17) into (18),

$$x_i(k+1) = x_{i-1}(k+1) - x_{i-1}(k) + \beta_{i-1} u(k), \tag{19}$$

By using (19) recursively,

$$x_i(k+1) = \begin{cases} x_{i-2}(k+1) - x_{i-2}(k) - x_{i-1}(k) + \beta_{i-2} u(k) \\ \quad + \beta_{i-1} u(k) \\ x_{i-3}(k+1) - x_{i-3}(k) - x_{i-2}(k) - x_{i-1}(k) \\ \quad + \beta_{i-3} u(k) + \beta_{i-2} u(k) + \beta_{i-1} u(k) \\ \vdots \\ x_1(k+1) - x_1(k) - x_2(k) - \cdots - x_{i-1}(k) \\ \quad + \beta_1 u(k) + \beta_2 u(k) + \cdots + \beta_{i-1} u(k). \end{cases}$$

Using (15),

$$x_i(k+1) = \sum_{m=1}^{i} a_m x_m(k) + \sum_{m=1}^{i-1} x_m(k) + b_0 u(k) + \sum_{m=1}^{i-1} \beta_m u(k), \quad \text{for } 2 \le i \le N. \tag{20}$$

In a matrix form, the state-difference Eqs. (15) and (19) of the linear model is then transformed into the following linear system:

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k), \end{aligned} \tag{21}$$

where

$$A = \begin{bmatrix} a_1 & a_2 & \cdots & a_N \\ a_1 - 1 & a_2 & \cdots & a_N \\ \vdots & \vdots & \ddots & \vdots \\ a_1 - 1 & a_2 - 1 & \cdots & a_N \end{bmatrix},$$

$$B = \begin{bmatrix} b_0 \\ b_0 + \beta_1 \\ \vdots \\ b_0 + \beta_1 + \cdots + \beta_{N-1} \end{bmatrix}, \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{N-1} \end{bmatrix}$$

$$= \begin{bmatrix} a_2 & a_3 & \cdots & a_N \\ a_3 & a_4 & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ a_N & 0 & 0 & 0 \end{bmatrix}^{-1} \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_{N-1} \end{bmatrix}, \qquad C[1\,0\,\ldots\,0].$$

In this paper, the LQR technique is applied to the free model to design a power system stabilizer. The object of the LQR design is to determine the optimal control law u which can transfer the system from its initial state to the final state such that a given performance index is minimized. The performance index is given in the quadratic form

$$J = \sum_{k=0}^{\infty} (x^T(k)Q(k)x(k) + u^T(k)R(k)u(k)) \tag{22}$$

where $Q(k)$ is positive semi-definite, and $R(k)$ is positive-definite. To design the LQR controller, the first step is to select the weighting matrices Q and R. The value R weight inputs more than the states while the value of Q weight the state more than the inputs. Then, the feedback gain K can be computed and the closed-loop system responses can be found by simulation. This method has an advantage of allowing all control loops in a multi-loop system to be closed simultaneously, while guaranteeing closed-loop stability.

The LQR controller is given by

$$u(k) = -Kx(k) \tag{23}$$

where K is the constant feedback gain obtained from the solution of the discrete algebraic Ricatti equation:

$$\begin{aligned} K &= (B^T SB + R)^{-1} B^T SA \\ S &= A^T SA - A^T SBK + (C^T QC) \end{aligned} \tag{24}$$

In conventional method to design LQR controller, the controller requires all state variables and often an observer is needed. However, the free-model based realization (21) is observable since all the states are constructed from the input–output data via (7). Therefore, an observer is not required for state feedback control. Since the realization is linear, any linear controller design method can be used.

4. Simulation studies

The free-model based PSS is designed for a three-machine nine-bus power system [25,26]. In this power system, the *d*–*q* axis generator model, the IEEE type-1 excitation system, and turbine and governor models are used.

The input–output data set are collected with sampling time of 0.01 s. To see the modeling accuracy of the free model and ARMA model, the root mean square (RMS) of the error is calculated as

$$\text{RMS} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y(i) - \hat{y}(i))^2} \tag{25}$$

where n is the number of samples, and $y(i)$ and $\hat{y}(i)$ are the system output and the free-model output, respectively.

Since the main purpose of using the free model is its simplicity, the simplest case is selected to design the controller, i.e., the free model is estimated with the order $N = 2$ and the data window of 100 samples. Tables 1 and 2 show the parameters and the error for the free model and ARMA model. Table 1 show the parameters of the free model and ARMA model for the second order models, respectively. Table 2 shows the RMS error for various free model and ARMA model order. The error decreases as the order of the free model and ARMA model increases. The LQR weights factors are as: R_1, R_2, and R_3 are 0.0001, 0.0005, and 0.0005,

Table 1
Parameter of free and ARMA model

	Machine 1	Machine 2	Machine 3
Free model ($N = 2$, data = 100)			
a_1	0.99901	0.99912	0.99910
a_2	0.97528	0.97649	0.97837
b_0	1.6740×10^{-3}	1.6602×10^{-3}	1.6598×10^{-3}
b_1	-1.4278×10^{-3}	-1.4196×10^{-3}	-1.4234×10^{-3}
ARMA model ($N = 2$, data = 100)			
a_1	1.97430	1.9759	1.9773
a_2	−0.97532	−0.97675	−0.97822
b_0	1.6695×10^{-3}	1.6640×10^{-3}	1.6529×10^{-3}
b_1	-1.4274×10^{-3}	-1.4241×10^{-3}	-1.4173×10^{-3}

Table 2
RMS error of free model and ARMA model (data = 100 ($\times 10^{-5}$))

Machine	$N = 2$	$N = 3$	$N = 4$	$N = 5$
The order of the free model				
1	0.4046	0.4041	0.4039	0.4038
2	3.9055	3.8942	2.3054	2.2757
3	2.4778	2.2376	2.0327	1.6743
The order of the ARMA model				
1	0.4069	0.4061	0.4053	0.4047
2	3.9583	3.9108	2.5702	2.2928
3	2.6823	2.4376	2.1373	1.8656

Table 3
LQR gains

Machine	Torque deviation	Fault
Free model		
1 (K_1)	[91.38, 423.3]	[92.051, 402.13]
2 (K_2)	[62.781, 381.18]	[66.467, 368.58]
3 (K_3)	[33.662, 306.45]	[34.445, 301.92]
ARMA model		
1 (K_1)	[196.45 −96.949]	[200.67 −98.630]
2 (K_2)	[131.46 −64.977]	[134.96 −66.548]
3 (K_3)	[66.905 −33.105]	[70.386 −34.760]

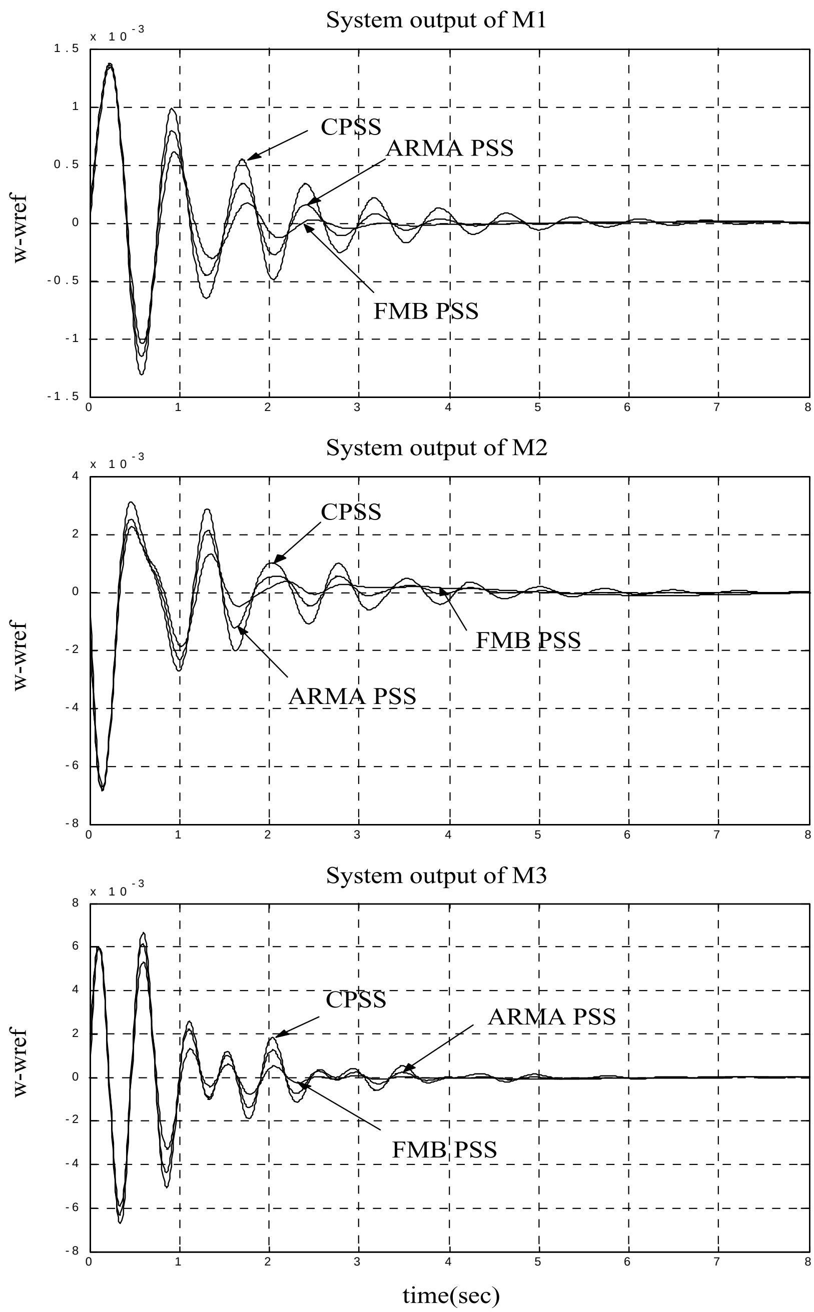

Fig. 1. Comparison of the CPSS, FMB PSS, and ARMA PSS in normal loading ($N = 2$, data = 100, sampling time = 0.01 s).

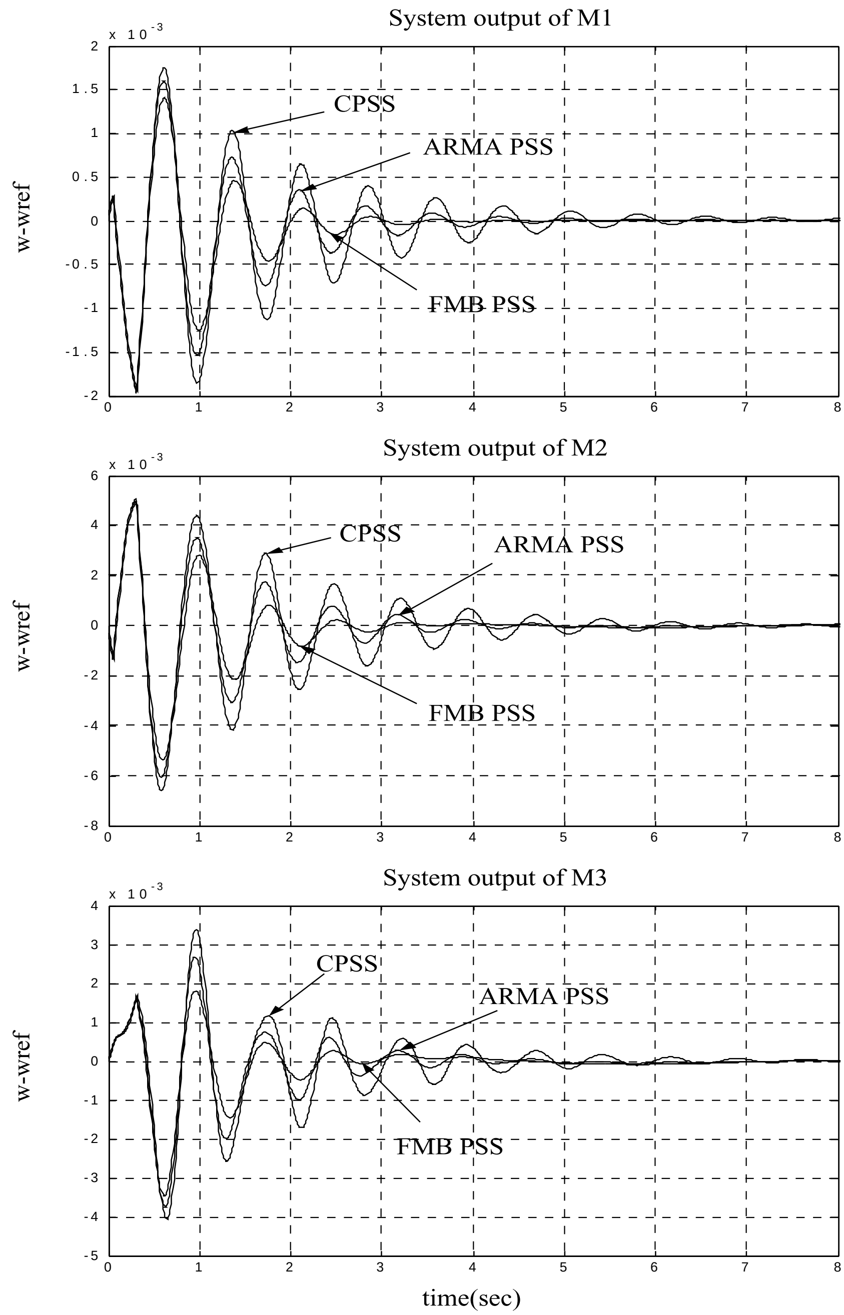

Fig. 2. Comparison of the CPSS, FMB PSS, and ARMA PSS in three phase fault ($N = 2$, data = 100, sampling time = 0.01 s).

respectively, and Q_1, Q_2, and Q_3 are all 1. Table 3 shows the LQR gains for each machine.

The FMB PSS controller and ARMA PSS are designed for the power system using the second-order free model and ARMA-model. Fig. 1 shows the comparison of angle speed deviations among the conventional PSS (CPSS), FMB PSS, and ARMA PSS in the case of the torque angle deviations: 15% is decreased in Machine 1, 35% is decreased in Machine 2, and 10% is increased in Machine 3. Three-phase fault occurred at 0 s, lasted 0.09 s and faulted lines are disconnected until 1 s when faulted lines are reclosed. Fig. 2 shows this robustness testing of the free model because the three-phase ground fault is the severe disturbance and also implies the structure change of the power system. Therefore, these studies demonstrate that the free model based controller is robust for a wide range of operating conditions.

5. Conclusion

This paper presents the free model approach for system identification and its application to design a power system stabilizer. The free model concept is introduced as an alternative intelligent system technique to design a controller for a dynamic system, which is very complex or difficult to know, with only input and output data, and it does not require the knowledge of mathematical model for the system. The parameters in the free model can be estimated using input–output data and a controller can be designed based on the free model. The free model is transformed to a linear state-space model and the linear quadratic regulator technique is used to design a PSS. Observer is commonly required to implement LQR; however, the free model does not require an observer.

The free model thus developed is shown to be controllable, observable, and robust. It was demonstrated that the accuracy of the free-model approximation increases as the order of the free model increases and as the window of observation increases for parameter estimation. However, a low order free model and a relatively small window of observation were used in designing the free-model based PSS in order to make the design simple.

The FMB PSS was implemented in a three-machine nine-bus system. The FMB PSS was tested in various operating conditions and compared with the conventional PSS and ARMA PSS. In all cases, the FMB PSS out-performed the conventional PSS and ARMA PSS and thus demonstrated the usefulness of the free-model based controller design.

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Appendix A. Three-machine nine-bus power system

A.1. Differential equations

$$
\begin{aligned}
T'_{doi}\frac{dE'_{qi}}{dt} &= -E'_{qi} - (X_{di} - X'_{di})I_{di} + E_{fdi} \\
T'_{qoi}\frac{dE'_{di}}{dt} &= -E'_{di} + (X_{qi} - X'_{qi})I_{qi} \\
\frac{d\delta_i}{dt} &= \omega_b(\omega_i - \omega_0) \\
M_i\frac{d\omega_i}{dt} &= T_{Mi} - E'_{di}I_{di} - E'_{qi}I_{qi} \\
&\quad - (X'_{qi} - X'_{di})I_{di}I_{qi} - D_i(\omega_i - \omega_0) \\
T_{E_i}\frac{dE_{fd_i}}{dt} &= -(K_{E_i} + S_E(E_{fd_i}))E_{fd_i} + V_{R_i} \\
T_{A_i}\frac{dV_{R_i}}{dt} &= -V_{R_i} + K_{A_i}R_{F_i} - \frac{K_{A_i}K_{F_i}}{T_{F_i}}E_{fd_i} \\
&\quad + K_{A_i}(V_{\mathrm{ref}_i} - V_i + u(k)) \\
T_{F_i}\frac{dR_{F_i}}{dt} &= -R_{F_i} + \frac{K_{F_i}}{T_{F_i}}E_{fd_i}
\end{aligned}
\tag{A.1}
$$

where i is machine number ($i = 1, 2, 3$).

Table A.1
Excitation system data (IEEE Type 1)

Parameters	Machine 1 Hydro	Machine 2 Steam	Machine 3 Steam
K_A	400	400	400
K_E	−0.243	−0.17	−0.17
K_F	0.04	0.04	0.04
T_F	1	1	1
T_A	0.05	0.05	0.05
T_E	0.95	0.95	0.95
A_e	0.0245	0.027	0.027
B_e	1.0276	0.3857	0.3857
$S_{Ei}(E_{fdi}) = A_{ei}e^{B_{ei}E_{fdi}}$, $i = 1, 2, 3$			

Table A.2
Conventional power system stabilizer data

Machine	K_{stab}	T_w	T_1	T_2	T_3	T_4
2	8.255	10	0.201	0.05	0.137	0.05
3	0.082	10	0.631	0.05	0.629	0.05

Limitation: $C_{\mathrm{PSS}} \in [-0.2\ 0.2]$,, $E_{fd} \in [-0.64\ 0.73]$.

A.2. Stator algebraic equations

$$
\begin{aligned}
&E'_{di} - V_i\sin(\delta_i - \theta_i) + X'_{qi}I_{qi} = 0 \\
&E'_{qi} - V_i\cos(\delta_i - \theta_i) + X'_{di}I_{di} = 0 \quad \text{where } i = 1, 2, 3.
\end{aligned}
\tag{A.2}
$$

A.3. Network equations

$$
\begin{aligned}
&I_{di}V_i\sin(\delta_i - \theta_i) + I_{qi}V_i\cos(\delta_i - \theta_i) + P_{Li}(V_i) \\
&\quad - \sum_{k=1}^{n} V_iV_kY_{ik}\cos(\theta_i - \theta_k - \alpha_{ik}) = 0 \\
&I_{di}V_i\cos(\delta_i - \theta_i) - I_{qi}V_i\sin(\delta_i - \theta_i) + Q_{Li}(V_i) \\
&\quad - \sum_{k=1}^{n} V_iV_kY_{ik}\sin(\theta_i - \theta_k - \alpha_{ik}) = 0, \quad i = 1, 2, 3,
\end{aligned}
\tag{A.3}
$$

$$
\begin{aligned}
&P_{li}(V_i) - \sum_{k=1}^{n} V_iV_kY_{ik}\cos(\theta_i - \theta_k - \alpha_{ik}) = 0 \\
&Q_{li}(V_i) - \sum_{k=1}^{n} V_iV_kY_{ik}\sin(\theta_i - \theta_k - \alpha_{ik}) = 0, \\
&\qquad i = 4, 5, \ldots, 9.
\end{aligned}
\tag{A.4}
$$

Please see Fig. 3 and Tables A.1 and A.2.

Appendix B. Least square

Once (6) is obtained and then parameters are found as in the following scheme:

$$
\begin{aligned}
&\bar{Y} = \overline{PX} \\
&\bar{P} = [A\ B]
\end{aligned}
\tag{B.1}
$$

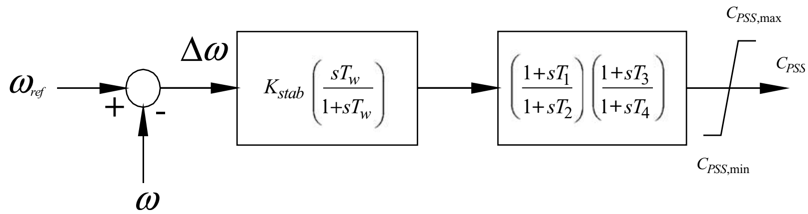

Fig. 3. Conventional power system stabilizer (CPSS).

where

$$A = \begin{bmatrix} \Delta^0 y(k) & \cdots & \Delta^{N-1} y(k-1) \\ & \vdots & \\ \Delta^0 y(k) & \cdots & \Delta^{N-1} y(k-n) \end{bmatrix},$$

$$B = \begin{bmatrix} u(k) & \Delta^0 u(k-1) & \cdots & \Delta^N u(k-1) \\ \vdots & & \vdots & \\ u(k-n) & \Delta^0 u(k-n-1) & & \Delta^N u(k-n-1) \end{bmatrix}$$

and

$$\bar{X} = \begin{bmatrix} a_1 \\ \vdots \\ a_N \\ b_0 \\ b_1 \\ \vdots \\ b_N \end{bmatrix} \in R^{[(2N+1)\times 1]},$$

$$\bar{Y} = \begin{bmatrix} y(k+1) \\ \vdots \\ y(k+1-n) \end{bmatrix} \in R^{[(N+1)\times 1]}.$$

Then using the measured data, $\bar{X}$ can be obtained as:

$$\bar{X} = (\bar{P}^{\mathrm{T}}\bar{P})^{-1}\bar{P}^{\mathrm{T}}\bar{Y} \quad \text{(B.2)}$$

where $\bar{P} \in R^{[(n+1)\times(2N+1)]}$.

References

[1] F.P. deMello, C.A. Concordia, Concept of synchronous machine stability as affected by excitation control, IEEE Trans. PAS PAS-103 (1969) 316–319.

[2] S.A. Doi, Coordinated synthesis of power system stabilizers in multimachine power systems, IEEE Trans. PAS 103 (1984) 1473–1479.

[3] T.L. Hwang, T.Y. Hwang, W.T. Yang, Two-level optimal output feedback stabilizer design, IEEE Trans. PWRS 6 (3) (1991) 1042–1047.

[4] M.R. Khaldi, A.K. Sarkar, K.Y. Lee, Y.M. Park, The Model performance measure for parameter optimization of power system stabilizers, IEEE Trans. Energy Convers. 8 (4) (1993) 660–666.

[5] K.T. Law, D.J. Hill, N.R. Godfrey, Robust controller structure for coordinate power system voltage regulator and stabilizer design, IEEE Trans. Control Syst. Technol. 2 (3) (1994) 220–232.

[6] A. Ghosh, G. Ledwich, O.P. Malik, G.S. Hope, Power system stabilizer based on adaptive control techniques, IEEE Trans. PAS 103 (1984) 1983–1989.

[7] S.J. Chang, Y.S. Chow, O.P. Malik, G.S. Hope, An adaptive synchronous machine stabilizer, IEEE Trans. PWRS 1 (1986) 101–109.

[8] A. Pierre, A Perspective on adaptive control of power systems, IEEE Trans. PWRS 2 (1987) 387–396.

[9] W. Gu, K.E. Bollinger, A Self-tuning power system stabilizer for wide-range synchronous generator operation, IEEE Trans. PWRS 4 (2) (1989) 1191–1199.

[10] J.Y. Fan, T.H. Ortmeyer, R. Mukundan, Power system stability improvement with multivariable self-tuning control, IEEE Trans. PWRS 5 (5) (1990) 227–234.

[11] A. Ghandakly, A.M. Farhoud, A parametrically optimized self-tuning regulator for power system stabilizer, IEEE Trans. PWRS 7 (1992) 1245–1250.

[12] O.P. Malik, C. Mao, An adaptive optimal controller and its application to an electric generating unit, Int. J. Electr. Power Energy Generating Unit 15 (1993) 169–178.

[13] Y. Zhang, O.P. Malik, G.S. Hope, G.P. Chen, Application of an inverse input/output mapped ANN as a power system stabilizer, IEEE Trans. Energy Convers. 9 (3) (1994) 433–441.

[14] Y.Y. Hsu, C.R. Chen, Tuning of power system stabilizers using an ANN, IEEE Trans. on Energy Convers. 6 (1991) 612–619.

[15] Q.H. Wu, B.W. Hogg, G.W. Irwin, A neural network regulator for turbogenerators, IEEE Trans. Neural Networks 3 (1) (1992) 95–100.

[16] K.Y. Lee, H.S. Ko, Power system stabilization using free-model based inverse dynamic neuro controller, Int. Joint Conf. Neural Network 3 (2002) 2132–2137.

[17] M.A.M. Hassan, O.P. Malik, G.S. Hope, A fuzzy logic based stabilizer for a synchronous machine, IEEE Trans. Energy Convers. 6 (3) (1991) 407–413.

[18] K.A. El-Metwally, O.P. Malik, Fuzzy logic power system stabilizer, IEE Proc. Generation Transmission Distribution 143 (3) (1996) 263–268.

[19] Y.Y. Hsu, C.H. Cheng, Design of fuzzy power system stabilizers for multi-machine power systems, IEE Proc. Generation Transmission Distribution 137 (Pt C 3) (1990) 233–238.

[20] C.-C. Su, Y.-Y. Hsu, Fuzzy dynamic programming: an application to unit commitment, IEEE Trans. Power Syst. 6 (3) (1991) 1231–1237.

[21] V. Miranda, J.T. Sarauva, Fuzzy modeling of power systems optimal load flow, IEEE Trans. Power Syst. 7 (2) (1992) 843–849.

[22] R. Hasan, T.S. Martis, A.H.M. Sadral Ula, Design and implementation of a fuzzy controller based automatic voltage regulator for a synchronous generator, IEEE Trans. Energy Convers. 9 (3) (1994) 550–557.

[23] T. Hiyama, Robustness of fuzzy logic power system stabilizers applied to multi machine power system, IEEE Trans. Energy Convers. 9 (3) (1994) 451–459.

[24] B.D.O. Anderson, J.B. More, Linear Optimal Control, Prentice Hall, New Jersey, 1990.

[25] P.W. Sauer, M.A. Pai, Power System Dynamics and Stability, Prentice Hall, New Jersey, 1998.
[26] P.M. Anderson, A.A. Fouad, Power Systems Control and stability, Iowa State University Press, USA, 1984.
[27] L. Ljung, System Identification, Prentice Hall, New Jersey, 1999.
[28] R.L. Burden, J.D. Faires, Numerical Analysis, PWS-KENT, 1989.

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