Power System Dynamic Stabilizer Design Using Adaptive Genetic Algorithm and Grey Prediction Fuzzy PID Control

Ting-Yu Wen Chih-Han Chang Tsong-Liang Huang
Department of Electrical Engineering, Tamkang University
#151,Ying-Chuan Rd. Tamsui, Taipei Hsien, Taiwan 25137, R.O.C
Tel：+886-2-26215656 Ext 2615
Fax：+886-2-26221565
e-mail：huang@ee.tku.edu.tw

***Abstract*—The paper combines the advantages of the grey prediction theory, fuzzy theory and genetic algorithm to design a dynamic grey prediction fuzzy PID controller for power system stabilizers (PSS). The design of a PSS can be formulated as an optimal linear regulator control problem; however, implementing this technique requires the design of estimators. This increases the implementation and reduces the reliability of control system. Therefore, favor a control scheme that uses the only desired state variable, such as speed.**

To deal with this problem, we employ the Grey Prediction Fuzzy PID Control to find control signal of each generator. Under considering the difficulty of establishing membership function and rule base of a Grey Prediction Fuzzy PID controller, we add a Genetic Algorithm (GA), which has an optimal searching method on the grey predictor, forecast step. The proposed method can reduce the oscillation and enhance the dynamic stability of the power system. Finally, the advantages of the proposed method are verified through a detailed simulation of a multimachine power system.

***Keywords:* Power System stability, Grey prediction, Fuzzy, PID, Genetic Algorithm**

I. INTRODUCTION

The design of PSSs can be formulated as an optimal linear regulator control problem whose solution is a complete state control scheme [l]. Thus, the implementation requires the design of state estimators. But, this increases the implementation and reduces the reliability of control system. These are the reasons that a control scheme uses the only desired state variable such as speed. It is used to design an output states feedback controller.

The traditional PSSs strategies adopt the previous information of the system to decide the control signal so that it is hard to control the power system before it going to change. In this paper, we use the Adaptive Genetic Algorithm and Fuzzy PID Control [3] to develop a prediction power system stabilizer [4][5]. We use the Fuzzy PID Controller to be our controller, to compute a grey predictor forecast step by Genetic Algorithm. It appears the proposed method reduces the oscillation and enhances the dynamic stability of the power system. Then, the proposed method will compare with optimal control method and optimal reduced order method [6][7][8].

II. THE PREDICTION POWER SYSTEM STABILIZER

The structure of the Adaptive Genetic Algorithm and Fuzzy PID Control power system stabilizer is shown in Fig.1. It is compose of three units:

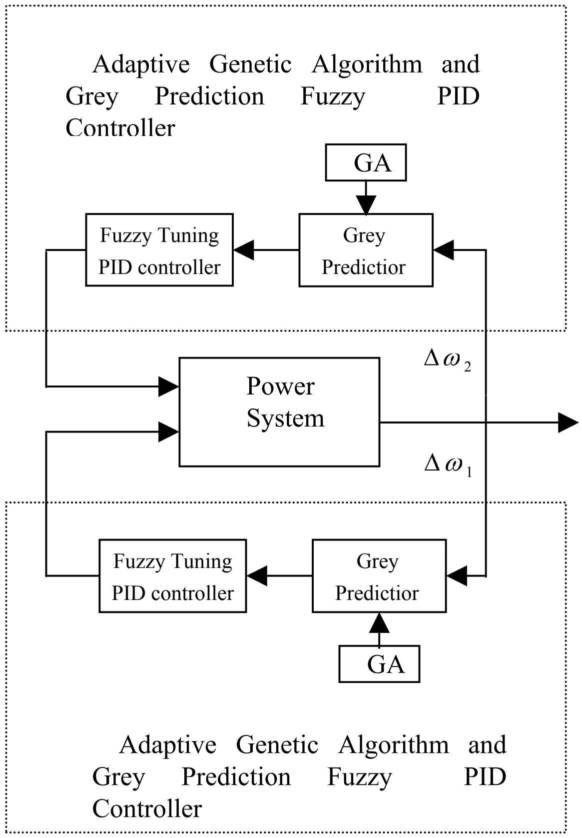

Fig.1. The structure of the Adaptive Genetic Algorithm and Grey Prediction Fuzzy PID Control power system stabilizer

A. Grey predictor unit:

The grey predictor is used to predict the forecasting values $\Delta\hat{\omega}$, these values are provided for power system.

B. GA operation unit:

We add a Genetic Algorithm, which has an optimal searching method on the Grey predictor step, and it is sure to find the best parameters that conform the controlled system.

C. Fuzzy Turning PID controller unit:

The fuzzy system is constructed from a set of Fuzzy IF-THEN rules that describe how to choose the PID gains under certain operation conditions. The control signal of power system is generated from this unit.

III. GREY PREDICTION

After the grey system theory was initiated by Deng in 1982 [2][3]; Cheng Bias proposed a grey prediction controller to control an industrial process without knowing the system model in 1986 [4]. In this paper, we build a dynamic model called the grey model GM(n,h) to approximate the system dynamic behaviour. The grey modelling procedure of GM(1,1) can be described as follows [10][11]:

Suppose $y^{(0)}$ be an original data sequence, which are denoted as

$$y^{(0)} = (y^{(0)}(1), y^{(0)}(2), \ldots, y^{(0)}(n)), \qquad n \geq 4 \qquad (1)$$

the accumulated generating operation (AGO) on $y^{(0)}$ is the first step in building grey model. AGO is denoted as

$$y^{(1)}(k) = AGO \bullet y^{(0)} = \sum_{m=1}^{k} y^{(0)}(m), \qquad k = 1,2,\ldots,n \qquad (2)$$

Let $z^{(1)}$ as the data sequence obtained by the following MEAN generating operation from $y^{(1)}$

$$z^{(1)}(k) = MEAN \bullet y^{(1)} = \frac{1}{2}[y^{(1)}(k) + y^{(1)}(k-1)], k = 2,3,\ldots,n \qquad (3)$$

Then the grey differential equation of GM(1,1) is

$$y^{(0)}(k) + az^{(1)}(k) = u \qquad (4)$$

The grey differential equation is

$$\frac{dy^{(1)}}{dt} + ay^{(1)}(k) = u \qquad (5)$$

The parameters a and u can be solved by means of least-square method as follows

$$\hat{\theta} = \begin{bmatrix} a \\ u \end{bmatrix} = (B^T B)^{-1} B^T y_N \qquad (6)$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \qquad (7)$$

and

$$y_N = (y^{(0)}(2), y^{(0)}(3), \ldots, y^{(0)}(n)), \qquad n \geq 4 \qquad (8)$$

Based on the solution of the whitening (4) is

$$y^{(1)}(t) = (y^{(0)}(1) - \frac{u}{a})e^{-at} + \frac{u}{a} \qquad (9)$$

the GM(1,1) model with respect to the data sequence $y^{(1)}$ can be expressed by

$$\hat{y}^{(1)}(n+p) = (y^{(0)}(1) - \frac{u}{a})e^{-a(n+p-1)} + \frac{u}{a}, \qquad n \geq 4 \qquad (10)$$

where the parameter p is the prediction step size and the upscript " Λ" means this value is a forecasting value.

The inverse accumulated generating operation (IAGO) is used to estimate the value of $y^{(0)}$, the corresponding IAGO sequence $\hat{y}^{(0)}$ is defined by

$$\hat{y}^{(0)} = IAGO. \ \hat{y}^{(1)} \qquad (11)$$

the forecasting value of $y^{(0)}(n+p)$ expressed as follows:

$$\hat{y}^{(0)}(n+p) = (y^{(0)}(1) - \frac{u}{a})(1-e^{a})e^{-a(n+p-1)}, n \geq 4 \qquad (12)$$

IV. GENETIC ALGORITHM

The first genetic algorithm (GA) was developed by Holland in 1975 [13]. Many studies have extended the application of GA'S in searching, optimizing, and machine learning [14], [15].GA's are both global and robust over a wide range of problems. The search procedures rely upon the mechanics of natural genetics. That all natural species can survive by adaptation is the underlying power of GA's. GA's combine a Darwinian survival-of-the-fittest strategy to eliminate unfit components and use random information exchange, with an exploitation of knowledge contained in old solutions, to affect a search mechanism with surprising power and speed. GA's employ multiple concurrent search points called "chromosomes" which process through three genetic operations, reproduction, crossover, and mutations, to generate new search points called "offspring" for the next iterations. Such operations ensure the discovery of an optimal solution to the problem in an appropriate manner.

V. THE FUZZY TUNING PID CONTROLLER

A. The PID Controller

Due to their simple structure and robust performance, proportional-integral-derivative (PID) controllers are the most commonly used controllers in industrial process control. The transfer function of a PID controller has following form：

$$G(s) = K_p + \frac{K_i}{s} + K_d s \qquad (13)$$

where K_p , K_i and K_d are called the prepositional, integral, and derivative gains, respectively.

B. Fuzzy Tuning PID Control

Consider a PID controller using the fuzzy system turns the PID gains in real time. The fuzzy system is constructed from a set of fuzzy IF-THEN rules that describe how to choose the PID gains under certain operation conditions.

Suppose that we can determine the ranges $[K_{p\min}, K_{p\max}] \subset R$ and $[K_{d\min}, K_{d\max}] \subset R$ such that the proportional gain $K_p \in [K_{p\min}, K_{p\max}]$ and derivative gain $K_d \in [K_{d\min}, K_{d\max}]$. For convenience, K_p and K_d are normalized toe the range between zero and five hundred by the following linear transformation：

$$K_p' = \frac{K_p - K_{p\min}}{K_{p\max} - K_{p\min}} \tag{14}$$

$$K_d' = \frac{K_d - K_{d\min}}{K_{d\max} - K_{d\min}} \tag{15}$$

Assume that the integral time constant is determined with reference to the derivative time constant by

$$T_i = \alpha T_d \tag{16}$$

from which we obtain

$$K_i = \frac{K_p}{\alpha T_d} = \frac{K_p^2}{\alpha K_d} \tag{17}$$

Hence, the parameters to be turned by the fuzzy system are K_p', K_d' and α. If we can determine these parameters, then the PID gains can be obtained form（14），（15）and（17）.

Assume that the inputs to the fuzzy system are $e(t)$ and $\dot{e}(t)$, so the fuzzy system turner consists of three two - input-output fuzzy system, as shown in Fig.2.

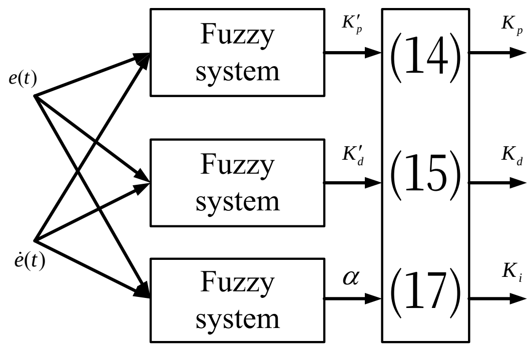

Fig.2 Fuzzy system turner for the PID gains

Let the fuzzy IF-THEN rules be of the following form:

IF $e(t)$ is A^l and $\dot{e}(t)$ is B^l, THEN K_p' is C^l, K_d' is D^l, α is E^l.

where A^l, B^l, C^l, D^l and E^l are fuzzy sets, and $l = 1,2,\cdots,M$。Suppose that the domains of interest of $e(t)$ 和 $\dot{e}(t)$ are $[e_M^-, e_M^+]$ and $[e_{Md}^-, e_{Md}^+]$, respectively, and we define 7 fuzzy sets , as shown in Fig. 3.

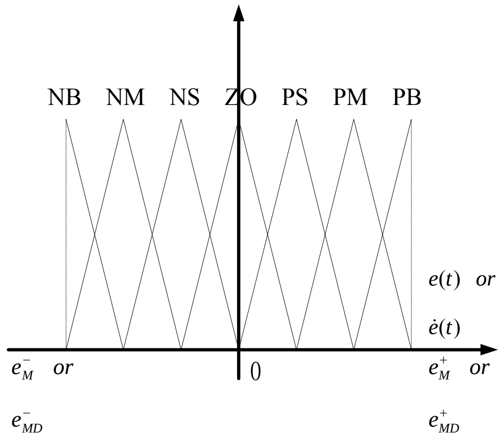

Fig. 3 Membership functions for $e(t)$ and $\dot{e}(t)$.

Thus, a complete fuzzy rule base consists of 49 rules. For simplicity assume that C^l and D^l are either the fuzzy set big or the fuzzy set small whose membership functions are show in Fig. 4.

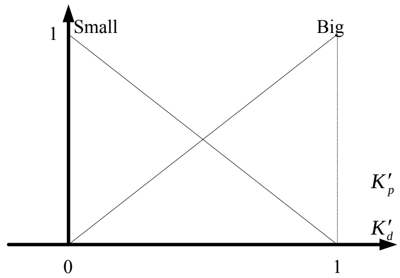

Fig.4 Membership functions for K_p' and K_d'.

Finally, assume that E^l can be the four fuzzy sets shown in Fig. 5. We are now ready to deriver the rules.

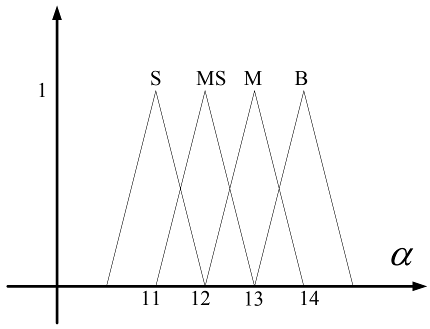

Fig.5 Membership functions for α.

		$\dot{e}(t)$						
		NB	NM	NS	ZO	PS	PM	PB
$e(t)$	NB	B	B	B	B	B	B	B
	NM	S	B	B	B	B	B	S
	NS	S	S	B	B	B	S	S
	ZO	S	S	S	B	S	S	S
	PS	S	S	B	B	B	S	S
	PM	S	B	B	B	B	B	S
	PB	B	B	B	B	B	B	B

Fig. 7 Fuzzy turning rules for K_p'.

		$\dot{e}(t)$						
		NB	NM	NS	ZO	PS	PM	PB
$e(t)$	NB	S	S	S	S	S	S	S
	NM	B	B	S	S	S	B	B
	NS	B	B	B	S	B	B	B
	ZO	B	B	B	B	B	B	B
	PS	B	B	B	S	B	B	B
	PM	B	B	S	S	S	B	B
	PB	S	S	S	S	S	S	S

Fig. 8 Fuzzy turning rules for K_d' .

		$\dot{e}$ (t)						
		NB	NM	NS	ZO	PS	PM	PB
$e(t)$	NB	S	S	S	S	S	S	S
	NM	MS	MS	S	S	S	MS	MS
	NS	M	MS	MS	S	MS	MS	M
	ZO	B	M	MS	MS	MS	M	B
	PS	M	MS	MS	S	MS	MS	M
	PM	MS	MS	S	S	S	MS	MS
	PB	S	S	S	S	S	S	S

Fig.9 Fuzzy turning rules for α .

VI. NUMERICL RESULTS

A. Full Order Model

The Two machine-infinite-bus power system full order model given in [8][9] is shown Fig. 8.

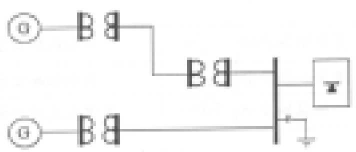

Fig.8 the two machine-infinite-bus power system

$$\dot{x} = Ax + Bu \qquad (18)$$

where

$$x = \begin{bmatrix} \Delta\omega_1 & \Delta\delta_1 & \Delta e'_{q1} & \Delta V_{F1} & \Delta\omega_2 & \Delta\delta_2 & \Delta e'_{q2} & \Delta V_{F2} \end{bmatrix}^T$$

Δ denotes deviation from operation point

ω speed

δ torque angle

e'_q voltage proportional to direct axis flux linkages

V_{FD} generation field voltage

$$A = \begin{bmatrix} -0.244 & -0.0747 & -0.1431 & 0 & 0 & 0.0747 & 0.0041 & 0 \\ 377 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.046 & -0.455 & 0.244 & 0 & 0.046 & 0.13 & 0 \\ 0 & -398.56 & -19498.8 & -50 & 0 & 398.58 & -3967 & 0 \\ 0 & 0.178 & -0.0433 & 0 & -0.2473 & -0.178 & -0.146 & 0 \\ 0 & 0 & 0 & 0 & 376.99 & 0 & 0 & 0 \\ 0 & 0.056 & \substack{0 \\ 0.1234} & 0 & 0 & -0.0565 & -0.3061 & 0.149 \\ 0 & -677.39 & -10234.22 & 0 & 0 & 677.78 & -13364.16 & -50 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & 2500 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 2500 \end{bmatrix}^T$$

The full model optimal controller is designed by solving the following linear regulator problem:

$$Minimize \;\; J = \frac{1}{2}\int_0^\infty \left\{ x^T(t)Qx(t) + u^T(t)Ru(t) \right\} dt \qquad (19)$$

Where

Q=*diagonal* (1, 1, 10, 10)

R=*diagonal* (1, 1)

The eigenvalues of the power system are given in Table 1.

Table 1. System eigenvalues

-0.0904±j9.843	-25.1741±j67.8187
-0.0006	-25.2392±j30.3072
-0.2443	

B. Grey predictor

From the (12) ,we use Ga's search the forecasting step size p=2 for each forecasting values ($\Delta\omega_1$, $\Delta\omega_2$).

C. Simulation results

In the grey system process, we suppose the original data sequence is shown Fig. 9. And the first or second order accumulated generating operation (AGO) is shown Fig. 10.

We will make simulations to verify that the different forecasting step-size in the grey predictor brings about the different effect that is shown in Fig. 11.

Finally, the transient responses of the angular frequencies with a 5% change in the mechanical torque of both machines are shown in Fig. 12-13. And the torque angle responses are shown in Fig. 14-15.

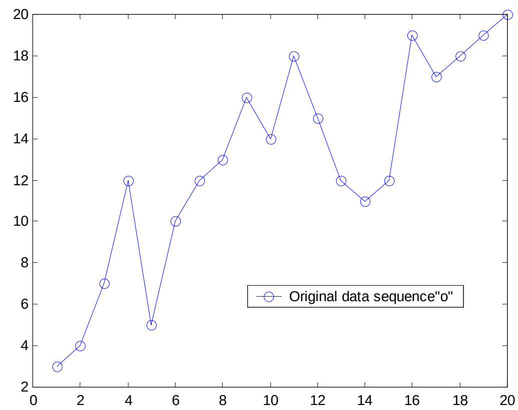

Fig. 9 The original data sequence

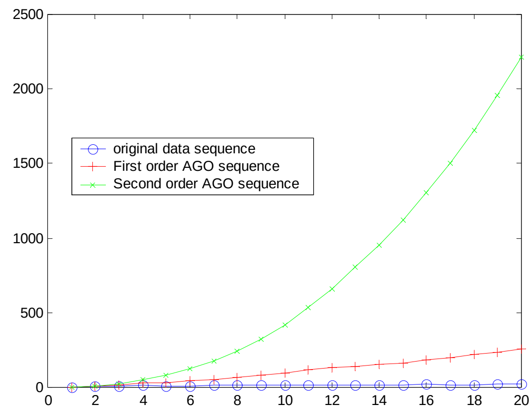

Fig. 10 The first and second order accumulated generating operation (AGO)

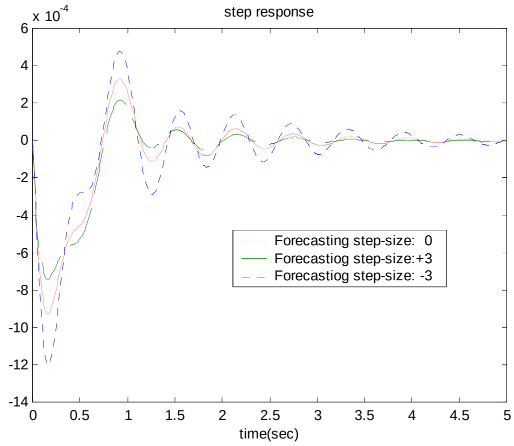

Fig. 11 The angular frequency response of machine1 in the two machine-infinite-bus power system

Δω1 (pu)

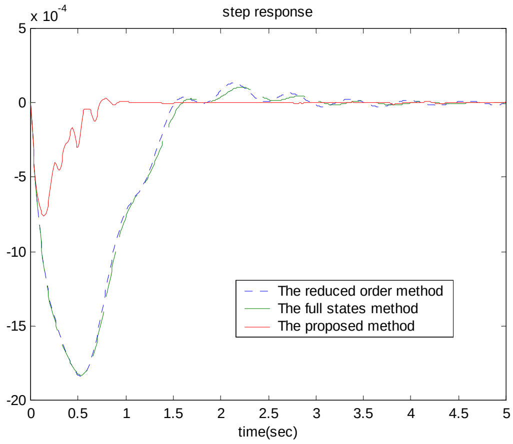

Fig. 12 The angular frequency response of machine1 in the two machine-infinite-bus power system

Δω2 (pu)

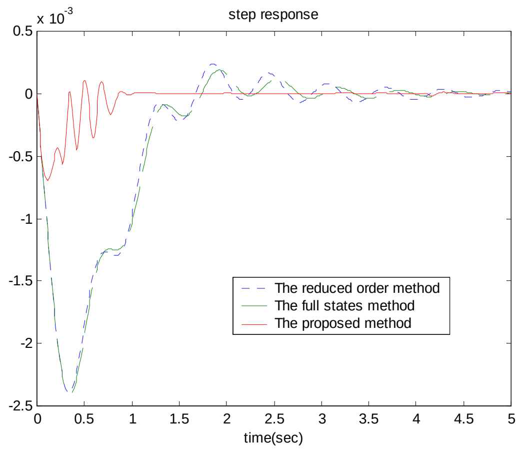

Fig. 13 The angular frequency response of machine2 in the two machine-infinite-bus power system

$\Delta\delta_1$ (pu)

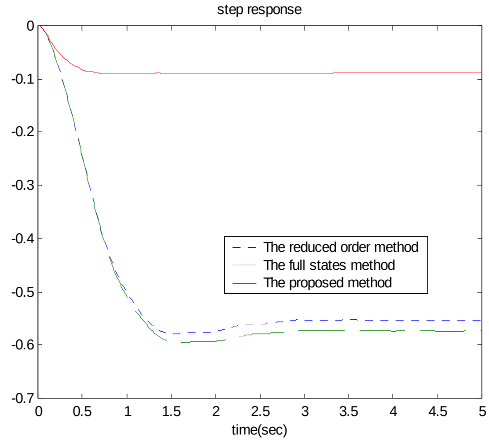

Fig. 14 The torque angle response of machine 1 in the two machine-infinite-bus power system

$\Delta\delta_2$ (pu)

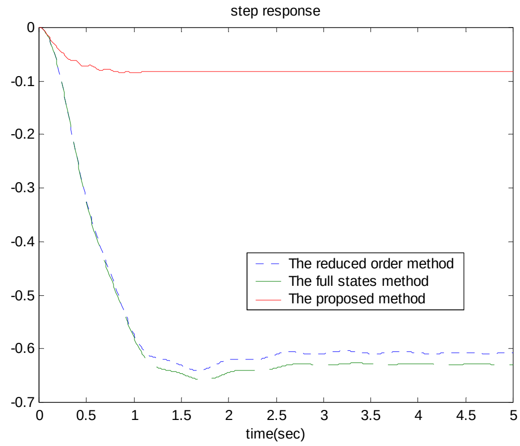

Fig. 15 The torque angle response of machine 2 in the two machine-infinite-bus power system

VII. CONCLUSIONS

In this paper we suggest a new design procedure for the power system stabilizer. The proposed method combines the genetic algorithm and grey system theorem, the fuzzy theorem and the PID control to replace the traditional full order optimal control method. A two machine-infinite-bus power system have been considered in this paper.

Finally, Comparison of the proposed method with the traditional optimal control and the optimal reduced method, the effectiveness of the Adaptive Genetic Algorithm and Grey Predictor Fuzzy PID Control power system stabilizer in enhancing the dynamic performance stability is verified through the simulation results.

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