Optimal Design for Power System Dynamic Stabilizer by Grey Prediction PID Control

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Abstract

In this paper, we proposed an effective method to design the 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 only some desired state variables, such as torque angle and speed.

To deal with this problem, we use the optimal reduced models to reduce the power system model into two state variables system by each generator and use grey prediction PID control to find control signal of each generator. Moreover, we will apply genetic algorithms (GAs) to find the appropriate parameter values for the desired system. Finally, the advantages of the proposed method are illustrated by numerical simulation of the two machines-infinite-bus power systems.

Keyword : Power Systems Stability, Grey Prediction, Genetic Algorithms

I. INTRODUCTION

The power system stabilizers[1] are added to the power system to enhance the damping of the electric power system. The design of PSSs can be formulated as an optimal linear regulator control problem whose solution is a complete state control scheme [2]. But, the implementation requires the design of state estimators. These are the reasons that a control scheme uses only some desired state variables such torque angle and speed. Upon this, a scheme referred to as optimal reduced order model whose state variables are the deviation of torque angles and speeds will be used. The approach retains the modes that mostly affect these variables. The model is used to design an output states feedback controller. By using only the output feedback, the control strategy can be implemented easily.

The traditional PSSs strategies adopts the previous information of the system to decide the control signal so that it is hard to control the power system before it is going to change. In this paper, we adopt a grey model [3][4][5] to predict the output states value. The PID controller [6] is the master controller and the fuzzy control is the slave control to enhance the master one [7]. Furthermore, we cannot make sure that the forecasting step size and PID parameters.Moreover, we will apply genetic algorithms (GAs)[8] to find the appropriate parameter values for the desired system.

The proposed fitness function contains three performance measures (the integral absolute error, overshoot, and steady-state error). 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 [9][10][11].

II. THE PREDICTION POWER SYSTEM STABILIZER

The structure of the grey prediction fuzzy PID control power system stabilizer is shown in Fig.1. It is composed of five units：

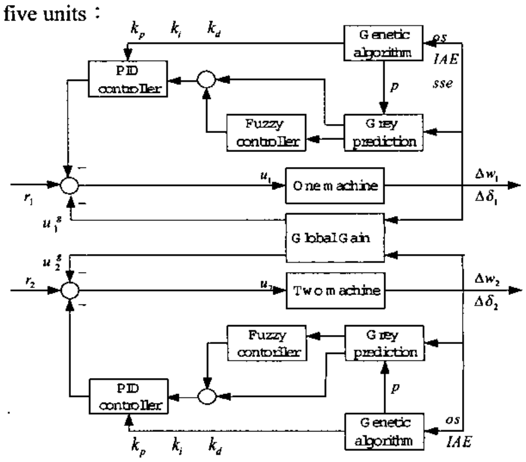

Fig.1 The structure of the optimal design for power system dynamic stabilizer by grey prediction PID control

A. Grey predictor unit：

The grey predictor is used to predict the forecasting values $\Delta\hat{\delta}$ and $\Delta\hat{\omega}$, these values provide the PID and Fuzzy controller.

B. Fuzzy controller unit：

The fuzzy system is constructed from a set of Fuzzy IF-THEN rules that describe how to choose the input of PID under certain operation conditions.

C. The PID controller unit：

The PID controller is using the simple structure in the general processes. The control signal of power system is generated from this unit.

D. The global gain unit：

The global gain is obtained from the optimal reduced order model of the whole system by using only output feedback.

E . The genetic algorithm unit：

Genetic algorithms (GAs) are derivative-free optimization methods using the concepts of natural selection and evolution for efficient glottal searches.

III. THE GREY PREDICTION FUZZY PIDCONTROLLER

A. The Grey Prediction

Prof. Deng initiated grey system theory [3][4] in 1982; Cheng Biao propped a grey prediction controller [5] in 1986. 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 [12][13].

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

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

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

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

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

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

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

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

The grey differential equation is

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

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

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

where

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

and

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

Based on the solution of the whitening (4) is

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

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

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

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

$$\hat{y}^{(0)} = IAGO \cdot \hat{y}^{(1)} \tag{11}$$

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

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

B. The Fuzzy Controller

The structure of the two-input and one-output FC is shown Fig. 2

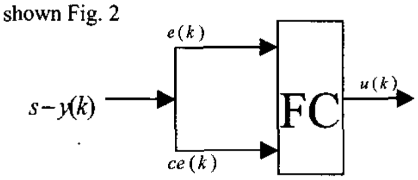

Fig.2 Schematic diagram of fuzzy controller

where

$$e(k) = [s - y(k)] \tag{13}$$

$$ce(k) = [e(k) - e(k-1)] \tag{14}$$

with

k ：the sampling instance

s ：the set-point

$y(k)$ ：the plant output

$e(k)$ ：the control error

$ce(k)$ ：the change in error (error rate)

$u(k)$ ：the fuzzy output

The basic components of a typical fuzzy controller include：(a)the fuzzification algorithm used for defining the linguistic variables in the fuzzy control rules; (b)the fuzzy control rules used for characterizing the control strategies of the expert; (c)the defuzzification algorithms used for getting crisp output from the fuzzy output set. More detailed descriptions of fuzzy sets and their operations can be found in [14]. In this paper, we use a simplified fuzzy reasoning method where triangular-shaped membership functions and the real values (singletons) are used for characterizing these linguistic values of the antecedent part and the consequent part, respectively. They are briefly described in the following.

(a). *Fuzzification algorithm*：

The fuzzification algorithm for $e(k)$ and $ce(k)$ is shown in Fig3(a), where the triangular-shaped membership functions are used, the fuzzification algorithm for $u(k)$ is shown in Fig3(b), and the real numbers are used. "NL", "NM", "NS", "Z0', "PS", "PM", and "PL" stand for "Negative-Large", "Negative-Medium", "Negative-Small", "Zero", "Positive-Small", "Positive-Medium", and "Positive-Large", respectively.

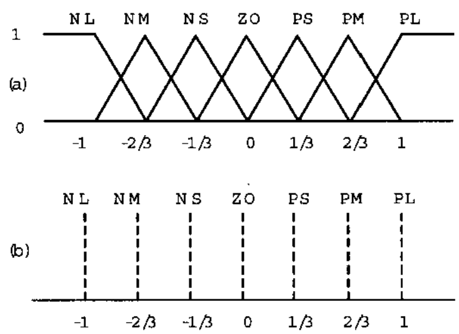

Fig.3 Membership functions of fuzzy sets used in the control rules

(b). *Fuzzy control rules* :

The fuzzy controller is constructed by a rule base of individual control rules which are conditional linguistic statements of relationship between inputs and outputs. The set of control rules can be expressed as follows :

Rule i : If e is E_i and ce is CE_i then u is U_i

Where e, ce and u are linguistic variables and E_i, CE_i and U_i are linguistic values with membership functions $E_i : Ue \rightarrow [0,1]$, $CE_i : Uce \rightarrow [0,1]$, and $U_i : Uu \rightarrow [0,1]$ corresponding to the universe discourse of Ue, Uce and Uu, respectively. The membership functions of the above fuzzy sets are depicted in Fig.3, where the universe of discourse of each input is normalized in the interval [-1,1]. It is known that the control rules have an important effect on the control performance. The rules may be determined according to the step response of the system under study [15]. In this paper, the used control rules are given in Table 1.

Table 1.Rules used in the fuzzy controller. u for different coils of e and ce

		$e(t)$						
		NL	NM	NS	ZO	PS	PM	PL
$ce(t)$	NL	NL	NL	NL	NL	NM	NS	ZO
	NM	NL	NM	NM	NM	NS	ZO	PS
	NS	NL	NM	NM	NS	ZO	PS	PM
	ZO	NL	NM	NS	ZO	PS	PM	PL
	PS	NM	NS	ZO	PS	PM	PL	PL
	PM	NS	ZO	PS	PM	PL	PL	PL
	PL	Z0	PS	PM	PL	PL	PL	PL

(c). *Defuzzification algorithm* :

If we sum all the output fuzzy sets to form the resultant output set, the defuzzification algorithm is used to convert it into a scalar output. In general, there are many methods to carry out this procedure. In this paper, the used defuzzification algorithm is the weighted average method. That is, when the input $e(k)$ and $ce(k)$ are input to the FC, the scaled control input $u(k)$ is obtained by the following equation :

$$u(k) = \frac{\sum_{i=1}^{49} w_i \cdot y_i}{\sum_{i=1}^{49} w_i} \tag{15}$$

where

$$w_i = E_i(e(k)) \cdot CE_i(ce(k)) \tag{16}$$

is the truth value of the antecedent part in the ith rule and y_i is the real value of the consequent part in the ith rule.

C. 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 :

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{17}$$

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

IV. THE GENETIC ALGORITHMS

GAs are search techniques using the mechanics of natural selection and natural genetics for efficient global searches[8]. In comparison to the conventional searching algorithms, GAs has the following characteristics : (a) GAs work directly with the discrete points coded by finite length strings (chromosomes), not the real parameters themselves; (b) GAs consider a group of points (called a population size) in the search space in every iteration, not a single point; (c) GAs use fitness function information instead of derivatives or other auxiliary knowledge; and (d) GAs use probabilistic transition rules instead of deterministic rules. Generally, a simple GA consists of the three basic genetic operators : (a) Reproduction; (b) Crossover; and (c) Mutation. They are described as follows[16].

(a). *Reproduction* :

Reproduction is a process to decide how many copies of individual strings should be produced in the mating pool according to their fitness value. The reproduction operation allows strings with higher fitness value to have larger number of copies, and the strings with lower fitness values have a relatively smaller number of copies or even none at all. This is an artificial version of natural selection (strings with higher fitness values will have more chances to survive).

(b). *Crossover* :

Crossover is a recombined operator for two high-fitness strings (parents) to produce two offsprings by matching their desirable qualities through a random process. In this paper, the uniform crossover method is adopted. The procedure is to select a pair of strings from the mating pool at random, then, a mark is selected at random. Finally, two new strings are generated by swapping all characters correspond to the position of the mark where the bit is "1". Although the crossover is done by random selection, it is not the same as a random search through the search space. Since it is based on the reproduction process, it is an effective means of exchanging information and combining portions of high-fitness solutions.

(c). *Mutation* :

Mutation is a process to provide an occasional random alteration of the value at a particular string position. In the case of binary string, this simply means changing the state of a bit from 1 to 0 and vice versa. In this paper we provide a uniform mutation method. This method is first to produce a mask and select a string randomly, then complement the selected string value correspond to the position of mask where the bit value is "1". Mutation is needed because some digits at particular position in all strings may be eliminated during the reproduction and the crossover operations. So the mutation plays the role of a safeguard in GAs. It can help GAs avoid the possibility of mistaking a local optimum for a global optimum.

The GA includes five fundamental parameters : (a) Population size, which influences amount of search points in every generation. The more population size in the GAs will increase the efficiency of searching, but it will time consuming; (b) Crossover probability, which influences the efficiency of exchanging information. In general, the crossover probability between 0.6 and 1; (c) Mutation probability, which occur with a small probability in the GAs, In general, the mutation probability under 0.1. A large mutation probability in GAs will eliminate the result of reproduction and crossover, which let GAs become a random search; (d) Chromosome length, which influences the resolution of the searching result. The GAs with longer chromosome length will have the higher resolution, but it will increase the search space; (e) Generations, which influences the searching time and searching result. The GAs with larger search space and less population size, it needs more generations for a global optimum.

V. THE OPTIMAL DESIGN

In this paper, we proposed a method to select the PID gains and forecasting step value by genetic algorithms (GAs) based on some performance measures of the system's response, so we denote $R_i = (k_p, k_i, k_d, p)$. Furthermore, we want to find the parameters to facilitate the controlled system with small integral absolute error, overshoot, and steady-state error. So we define the following fitness function[17] :

$$f(R_i) = g_1(IAE(R_i)) + g_2(OS(R_i)) + g_3(SSE(R_i)) \quad (18)$$

where $f(R_i)$, $IAE\ (R_i)$, $OS\ (R_i)$, and $SSE\ (R_i)$ are the fitness value, integral absolute error, overshoot, and steady-state error about R_i, respectively. $g_1(.), g_2(.)$, and $g_3(.)$ are three function to evaluate the system performance and defined by

$$g_1(IAE\ (R_i)) = e^{-iae} \quad (19)$$

$$g_2(OS\ (R_i)) = e^{-overshoot} \quad (20)$$

$$g_3(SSE\ (R_i)) = e^{-sse} \quad (21)$$

According to the proposed fitness function, the selected R_i with a higher fitness value will provide the controlled system with the desired performance of small integral absolute error, overshoot, and steady-state error.

VI. NUMERICL RESULTS

A. Full Order Model

The Two machine-infinite-bus power system full order model given in [8][9] is shown Fig. 4.

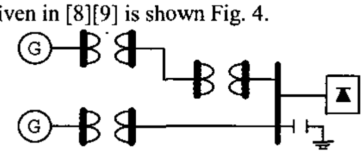

Fig.4 The two machine-infinite-bus power system

$$\dot{x} = Ax + Bu \quad (22)$$

where

$$x = [\Delta\omega_1 \quad \Delta\delta_1 \quad \Delta e'_{q1} \quad \Delta V_{F1} \quad \Delta\omega_2 \quad \Delta\delta_2 \quad \Delta e'_{q2} \quad \Delta V_{F2}]^T$$

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

$$A = \begin{bmatrix} -0.244 & -0.0747 & -0.1431 & 0 & 0 & 0.0747 & 0.0041 & 0 \\ 377 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -0.046 & -0.455 & 0.244 & 0 & 0.046 & 0.13 & 0 \\ 0 & -39856 & -194988 & -50 & 0 & 39858 & -3967 & 0 \\ 0 & 0.178 & -0.0433 & 0 & -0.2473 & -0.178 & -0.146 & 0 \\ 0 & 0 & 0 & 0 & 37699 & 0 & 0 & 0 \\ 0 & 0.056 & \begin{matrix}0\\0.1234\end{matrix} & 0 & 0 & -0.0565 & -0.3061 & 0.149 \\ 0 & -677.39 & -1023422 & 0 & 0 & 677.78 & -1336416 & -50 \end{bmatrix}$$

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

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

$$Minimize\ J = \frac{1}{2}\int_0^\infty \left\{x^T(t)Qx(t) + u^T(t)Ru(t)\right\}dt \qquad (23)$$

Where

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

R=*diagonal* (1, 1)

The eigenvalues of the power system are given in Table 2.

Table2. System eigenvalues

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

B. Grey predictor

From the (18) we getting the optimal forecasting step size p=4.9326 for each forecasting values ($\Delta\omega_1$, $\Delta\omega_2$).

C. PID controller

From the (18) we getting the optimal k_p, k_i and k_d are 194.3346, 73.9927 and 196.6789.

D. Genetic Algorithm

The following parameters of GAs are considered：

Popouation size=50

Crossover probability=0.8

Mutation probability=0.02

Chromosome length=48 (12 bit for each parameters)

Generations=100

Kp, Ki and Kd range=[0 200]

Forecast step range=[0 20]

E. Simulation results

The transient responses of the angular frequencies with a 5% change in the mechanical torque of both machines are shown in Fig. 8-9. And the torque angle responses are shown in Fig. 10-11.

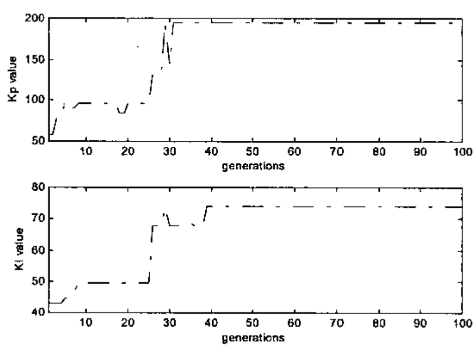

Fig .5 The Kp and Ki value convergence diagram

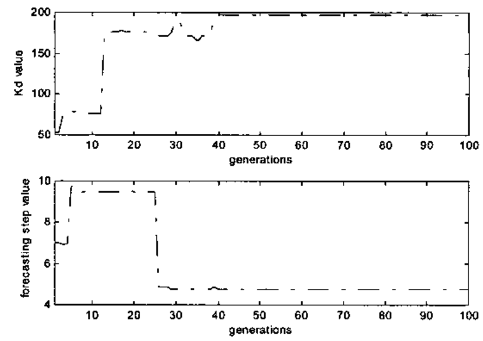

Fig.6 The Kd and forecasting step value convergence diagram

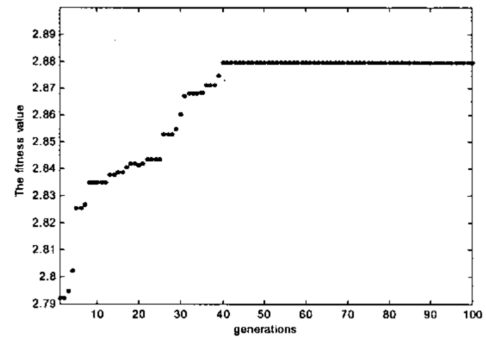

Fig.7 The fitness value convergence diagram

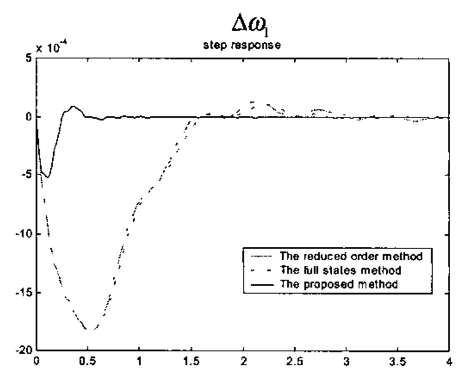

Fig.8 The angular frequency response of machine one

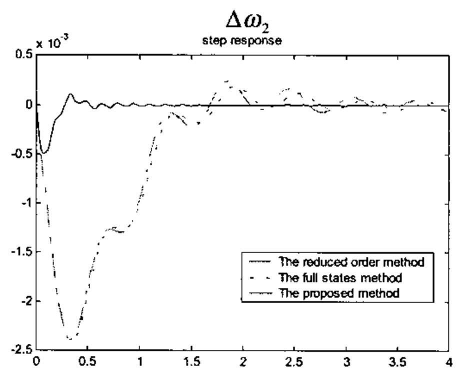

Fig.9 The angular frequency response of machine two

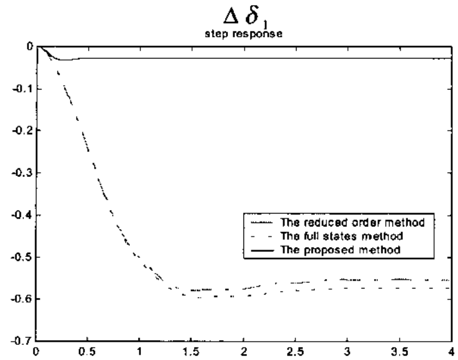

Fig.10 The torque angle response of machine one

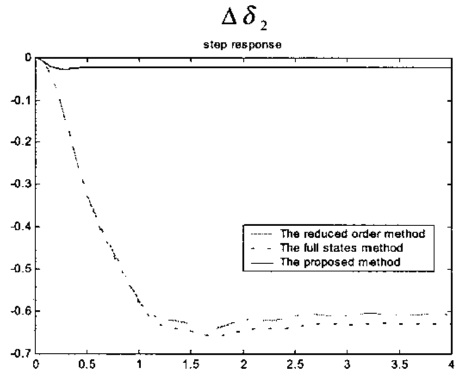

Fig.11 The torque angle response of machine two

VII. CONCLUSIONS

In this paper we suggest a new design procedure for the power system stabilizer. The proposed method combines the grey system theorem, the fuzzy theorem and the PID control to replace the traditional full order optimal control method. The GA is used to select appropriate parameters of the PID and forecasting step values. A two machine-infinite-bus power system have been considered in this paper.

Finally, comparison of the proposed method with traditional optimal control and the optimal reduced method, the effectiveness of the grey prediction PID control power system stabilizer in enhancing the dynamic performance stability is verified through the simulation results.

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