International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 07 | July - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

Design of an on-line rule tuning grey prediction fuzzy controller for Power System Control

Pratibha Shrivastava[1], D.N. Dewangan[2]

Department of Applied Mathematics, Rungta College of Engg. & Tech., Raipur, C.G

Department of Mechanical Rungta College of Engg. & Tech., Raipur, C.G.

---***---

Abstract - The grey PID type fuzzy controller (GFPIDC) designed in this paper, can predict the future output values of the system accurately. However, the forecasting step-size of the grey controller determines the forecasting value. When the step-size of the grey controller is large, it will cause over compensation, resulting in a slow system response. Conversely, a smaller step-size will make the system respond faster but cause larger overshoots. The value of the forecasting step-size is optimized according to the values of error and the derivative of the error. Moreover, the output of the grey controller is updated using the prediction error for better controller performance. An on-line rule tuning grey prediction fuzzy control system is also presented in this paper, which contains the advantage of the grey prediction, fuzzy theory and the on-line tuning algorithm. The on-line rule tuning grey prediction fuzzy control system structure is constructed so that the rise time and the overshoot of the controlled system can be maintained simultaneously.

***Key Words*:** PID Controller, Power System Stabilizer (PSS), On-line rule tuning, Grey Prediction, Grey Fuzzy PID Control

1.INTRODUCTION

During the last two decades, grey system theory has developed rapidly and caught the attention of researchers with successful real-time practical applications. It has been applied to analysis, modeling, prediction, decision making and control of various systems such as social, economic, financial, scientific and technological, agricultural, industrial, transportation, mechanical, meteorological, ecological, geological, medical, military, etc., systems. In control theory, a system can be defined with a color that represents the amount of clear information about that system. For instance, a system can be called as a black box if its internal characteristics or mathematical equations that describe its dynamics are completely unknown. On the other hand, if the description of the system is, completely known, it can be named as a white system. Similarly, a system that has both known and unknown information is defined as a grey system. In real life, every system can be considered as a grey system because there are always some uncertainties. Due to noise from both inside and outside of the system of our concern (and the limitations of our cognitive abilities!), the information we can reach about that system is always uncertain and limited in scope. There are many situations in industrial control systems that the control engineer faces the difficulty of incomplete or insufficient information. The reason for this is due to the lack of modeling information or the fact that the right observation and control variables have not been employed.

The power system stabilizers 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**.** 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. In this paper, we adopt a grey model to predict the output states value. The PID controller is the master controller and the fuzzy control is the slave control to enhance the master one. Furthermore, we cannot make sure that the forecasting step size and PID parameters.

After the grey system theory was initiated by Deng in 1982, Cheng proposed a grey prediction controller to control an industrial process without knowing the system model in 1986. From that moment, more and more applications and researches of the grey prediction control were presented.

The essential concept of this paper is that the forecasting step size in the grey predictor can be tuned according to the input state of the system during different periods of the system response. To approach this object, we propose an on-line rule tuning mechanism so that it can quickly regulate an appropriate negative or positive forecasting step size. An on-line rule tuning algorithm using the concept of reinforcement learning and supervised learning is proposed to tune the consequent parameters in the fuzzy inference system such that the controlled system has a desired output.

This paper is proposed on-line rule tuning grey prediction fuzzy control system is described an inverted pendulum control problem is considered to illustrate the effectiveness of the proposed control scheme.

Grey Fuzzy Theory

Grey System Modeling

Grey numbers, grey algebraic and differential equations, grey matrices and their operations are used to deal with grey systems. A grey number is such a number whose value is not known exactly but it takes values in a certain range. Grey numbers might have only upper limits, only lower limits or both. Grey algebraic and differential equations, grey matrices all have grey coefficients.

Generations of Grey Sequences

The main task of grey system theory is to extract realistic governing laws of the system using available data. This process is known as the generation of the grey sequence. It is argued that even though the available data of the system, which are generally white numbers, is too complex or chaotic, they always contain some governing laws. If the randomness of the data obtained from a grey system is somehow smoothed, it is easier to derive the any special characteristics of that system. For instance, the following sequence that represents the speed values of a motor might be given:

X(0) = (200, 300, 400, 500, 600)

It is obvious that the sequence does not have a clear regularity. If accumulating generation is applied to original sequence, X(1) is obtained which has a clear growing tendency.

X(1) = (200, 500, 900, 1400, 2000)

GM (n, m) Model

In grey systems theory, GM (n,m) denotes a grey model, where n is the order of the difference equation and m is the number of variables. Although various types of grey models can be mentioned, most of the previous researchers have focused their attention on GM (1,1) model in their predictions because of its computational efficiency. It should be noted that in real time applications, the computational burden is the most important parameter after the performance.

GM (1, 2. ***GM (1, 1) Model***

GM (1, 1) type of grey model is most widely used in the literature, pronounced as “Grey Model First Order One Variable”. This model is a time series forecasting model. The differential equations of the GM (1,1) model have time-varying coefficients. In other words, the model is renewed as the new data become available to the prediction model. The GM (1,1) model can only be used in positive data sequences. In this paper, a non-linear liquid level tank is considered. It is obvious that the liquid level in a tank is always positive, so that GM (1, 1) model can be used to forecast the liquid level. In order to smooth the randomness, the primitive data obtained from the system to form the GM (1, 1) is subjected to an operator, named Accumulating Generation Operation (AGO), described above. The differential equation (i.e. GM (1, 1)) thus evolved is solved to obtain the n-step ahead predicted value of the system. Finally, using the predicted value, the inverse accumulating operation (IAGO) is applied to find the predicted values of original data. Consider a single input and single output system. Assume that the time sequence $X^{(0)}$ represents the outputs of the system) x.

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), \dots \dots x^{(0)}(n)\right), n \geq 4 \qquad (1)$$

Where X(0) is a non-negative sequence and n is the sample size of the data. When this sequence is subjected to the Accumulating Generation Operation (AGO), the following sequence X(1) is obtained. It is obvious that X(1) is monotone $i^{0)}$(n)) , n ≥ 4

$$X^{(1)} = \left(\left(x^{(1)}(1), x^{(1)}(2), \dots \dots x^{(1)}n\right)\right), n \geq 4 \qquad (2)$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), k = 1,2,3, \dots . . n \qquad (3)$$

The generated mean sequence Z(1) of X(1) is defined

- $$z^{(1)} = \left(z^{(1)}(1), z^{(1)}(2), \dots \dots z^{(1)}(n)\right) \qquad (4)$$

Where z(1)(k) is the mean value of adjacent data, i.e.

$$z^{(1)}(k) = 0.5x^{(1)}(k) + 0.5x^{(1)}(k-1), k = 2,3, \dots . . n \qquad (5)$$

The least square estimate sequence of the grey difference equation of GM (1,1) is defined as follows:

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{6}$$

The whitening equation is therefore as follows:

$$\frac{dx^1(t)}{dt} + ax^1(t) = b \tag{7}$$

In above, $[a,b]^T$ is a sequence of parameters that can be found as follows:

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{8}$$

Where

$$Y = \left[x^{(0)}(2), x^{(0)}(3), \cdots\cdots\cdots, x^{(0)}(n)\right]^T \tag{9}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(2) & 1 \\ . & \\ . & \\ . & \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{10}$$

According to equation (8), the solution of x(1)(t) at time k:

$$x_p{}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}$$

To obtain the predicted value of the primitive data at time (k+1), the IAGO is used to establish the following grey model.

$$x_p{}^{(0)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1 - e^{a}) \tag{12}$$

And the predicted value of the primitive data at time (k+H):

$$x_p{}^{(0)}(k+H) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-a(k+H-1)}(1 - e^{a}) \tag{13}$$

The parameter (a) in the GM (1,1) model is called “development coefficient” which reflects the development states of X(1)p and X(0)p . The parameter b is called “grey action quantity” which reflects changes contained in the data because of being derived from the background values.

Grey Fuzzy PID Type Controller (GFPIDC)

Rule Base and Membership Functions

In a conventional fuzzy inference system, an expert, who is familiar with the system to be modeled, decides on the number of rules.

Table 1

A GENERAL FUZZY PID TYPE RULE BASE

e.$\dot{e}$	NL	NM	NS	ZR	PS	PM	PL
PL	ZR	PS	PM	PL	PL	PL	PL
PM	NS	ZR	PS	PM	PL	PL	PL
PS	NM	NS	ZR	PS	PM	PL	PL
ZR	NL	NM	NS	ZR	PS	PM	PL
NS	NL	NL	NM	NS	ZR	PS	PM
NM	NL	NL	NL	NM	NS	ZR	PS
NL	NL	NL	NL	NL	NM	NS	ZR

The fuzzy PID type control rule base employed in this paper is shown in Table 1. The membership functions of error, change rate of error and control signal, shown in Fig.2, are chosen as triangular membership functions.

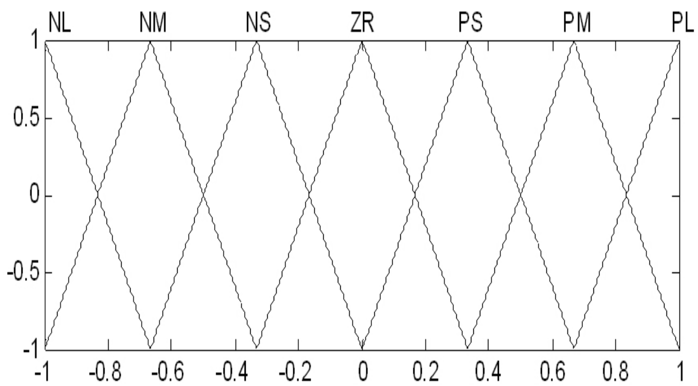

Fig.2 The membership functions of e, e˙ and u.

Design of Adaptive Grey Fuzzy PID Type Controller (GFPIDC)

In most control applications, the control signal is a function of the error present in the system at a prior time. This methodology is called as “delay control”. In grey systems theory, prediction error is used instead of current measured error. In similar lines, during the development of the grey PID type fuzzy controller, the prediction error is considered as the error of the system.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 07 | July - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

The block diagram of the grey fuzzy PID control system with the adaptive grey PID type fuzzy controller with a variable prediction step-size proposed in this paper are showed in Fig.3.

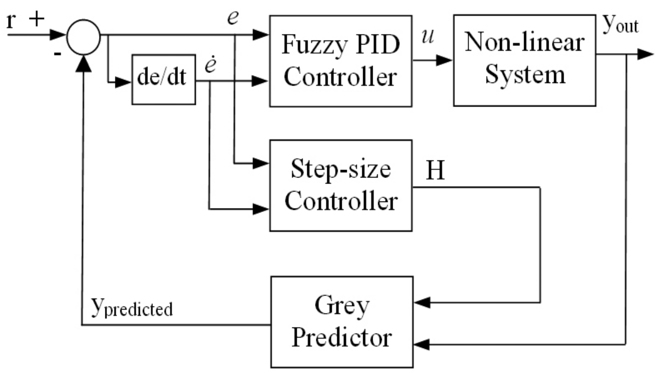

Fig.3 Block diagram of the adaptive grey fuzzy PID control (GFPIDC) system with a variable prediction step-size.

In order to adapt the forecasting step-size H to different states of the controller changing with error and the derivative of the error, another fuzzy controller is designed. The inputs of this fuzzy controller are e and

e˙. The output variable is forecasting step-size H. Triangle membership functions are used for fuzzification process.

The fuzzy variables e and e˙ are partitioned into 5 subsets (NL, NS, ZR, PS and PL) and the output variable H is partitioned into 5 subsets (VS, S, MD, B, VB). The range of e, e˙ and H is considered as [-0.5;1], [-0.06;0.06] and [0;70], respectively.

Table 2

A GENERAL RULE BASE FOR FUZZY STEP SIZE CONTROLLER

H Step-Size		E				
		PL	PS	ZR	NS	NL
$\dot{e}$	PL	VB	VB	B	MD	VS
	PS	VB	B	MD	S	S
	ZR	S	S	S	S	MD
	NS	S	S	MD	MD	VB
	NL	VS	MD	B	B	VB

On-Line Tuning Grey Fuzzy PID Controller (GFPIDC)

Essentially, the traditional grey prediction controller structure uses a fixed forecasting step size. The traditional grey prediction controller is excellent to reduce or prevent the overshoot, but it lengthens the rise time of the system response. This is because the grey prediction controller prevents errors when the system starts to work so that the rise time is lengthened and the overshoot is reduced. From the experiments, we know that the traditional grey prediction controller with a small fixed forecasting step size always emerges a small rise time and a large overshoot. On the other way, the grey prediction controller with a large fixed forecasting step causes a small overshoot and a large rises time of the system response. From the viewpoint of the system performance, we propose a on-line rule tuning mechanism to regulate a suitable forecasting step size for each control action during the system response so that the short rise time and the small overshoot can be taken about at same time. In this paper, an on-line rule tuning mechanism is built by a fuzzy inference system to produce an appropriate forecasting step size. The block diagram of the on-line rule tuning grey prediction fuzzy control system is shown in Fig.4, in which the on-line rule tuning mechanism is used to regulate the appropriate forecasting step size of the grey predictor. A fuzzy controller is employed to directly control the plant, and it is designed with some rough experiment rules. The grey predictor uses a suitable forecasting step size to forecast the output of the plant and feeds the forecasting information back to the fuzzy controller and they are described as follows:

Grey Predictor

The grey predictor uses a suitable forecasting step size to forecast the system behavior and feeds the forecasting information back to the fuzzy controller to decide an appropriate control action. In this paper, we adopt the modified GM (1,1) model for the grey prediction. The basic grey prediction method can be described as follows:

$$\hat{y}^{(0)} = LAGO.GM(1,1).AGO.y^{(0)} \qquad (16)$$

Where $y(0)$ is a non-negative original data sequence and described by

$$y^{(0)} = \{y^{(0)}(1), y^{(0)}(2), \dots \dots y^{(0)}(n)\}, n \geq 4$$
(17)

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 07 | July - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

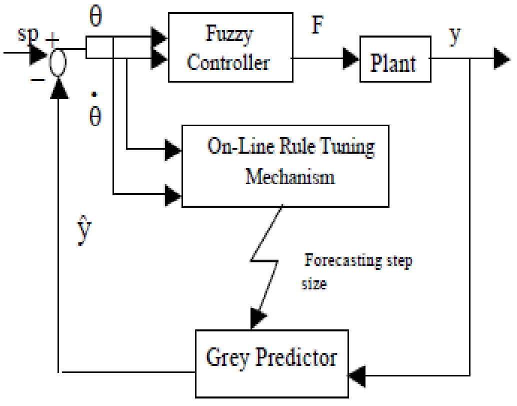

Fig.4 The On-line rule tuning grey prediction fuzzy controller structure.

The On-line rule tuning grey prediction fuzzy controller structure.

$y^{(0)}$ is a forecasting value of y, AGO takes the accumulated generating operation on *y*(0), IAGO takes the inverse accumulated generating operation on $y^{(0)}$. Hence, the forecasting value of *(n p)* can be calculated by

$$y^{(0)}(n+p)=\left(y^{(0)}(1)-\frac{u}{a}\right)(1-e^{a})e^{-a(n+p-1)} \;,n\geq 4 \qquad (18)$$

Where p is the forecasting step, a and u are the development coefficient and the grey input, respectively. According to the grey prediction process, the input data of the grey predictor must be a non-negative sequence. However, the data sequence of the system may be positive or negative values. It is necessary to map the negative data to the relative positive data by the data mapping methods. In this paper, we use two data mapping operator, one is the mapping generating operator (MGO), and the other is the inverse mapping generating operator (IMGO) which offered by Hong et al. Their definitions are as follows: Let$y^{(0)}$) be an initial sequence and ${Y_m}^{(0)}$ be a mapping sequence data of y(0), then

$${Y_m}^{(0)}=MGO.y^{(0)}=b^{\gamma y^{(0)}}b,\gamma>0 \qquad (19)$$

Where b and *1* are positive constants selected by the designer. Similarly, the IAGO can be defined as follows:

$$y^{(0)}=IMGO.{Y_m}^{(0)}=\frac{1}{\gamma}\log_b {y_m}^{(0)} \qquad (20$$

Therefore, the modified grey prediction structure can be constructed by

$$y^{(0)}=IMGO.IAG0.GM(1,1).AGO.MGO.y^{(0)}$$
(21)

On-line rule tuning mechanism

The proposed on-line rule tuning mechanism is described as below:

A fuzzy inference system is used to update the forecasting step size of the grey predictor at each sampling time. The state evaluator is used to give a judging value to lead the direction of tuning algorithm. The parameter modifier receives the evaluation value from the state evaluator and the output forecasting step value from the on-line rule tuning mechanism to update the consequent parameters of the fuzzy inference system at each sampling time. The control purpose is to control the plant such that the output of the controlled system y(t) approaches to the set-point (sp).This structure can be described by the following four parts: (1) Fuzzy inference system, (2) State evaluator, and (3) Parameter modifier. (4) An on-line evaluation tuning algorithm.

Fuzzy inference system

In this paper, a fuzzy inference system with the same premise part of fuzzy rules of the fuzzy controller is considered to construct the on-line rule tuning mechanism. The fuzzy rules of the on-line rule tuning mechanism can be described in Table 2. When the weighted average method is used, the output of the on-line rule tuning mechanism i.e. forecasting step size can be obtained by the following equation:

$$\text{Forecasting step size (FS)}=\frac{\sum_{i=1}^{5} w_i.fs_i}{\sum_{i=1}^{5} w_i} \qquad (22)$$

Where fs_i is the real value of the consequent part in the i-th rule, and w_i is the firing strength of the

premise part in the i-th rule i, describe in equation. The initial tuning rules of consequent real values are randomly selected as (fs1=5.8369405304423232; fs2=-18.51280926723867; fs3=-12.78117097008453; fs4= 14.98682383169478). The control objective is to regulate the forecasting step size such that the output of the controlled system has the desired output.

Description of Control Object (Powe System)

The Power system is shown in Fig.5 that consists of two fully symmetrical areas linked together by two 220 kV lines of 300 km length. Each area is equipped with two identical round rotor synchronous acts as thermal plant generators rated 25kV/800MVA connected to transformer (T1, T2, T3, and T4). The synchronous machines (G1, G2, G3, and G4) in all area have identical parameters, except for inertia which is *H*=7.5s for all generators in Area 1 and H=7.255s for all generators in Area 2. Thermal generating plants having identical speed regulators and fast static exciters with a 250 gain at all locations. Each generator produces 750 MW. The loads are assumed everywhere as constant impedance load. The Area 1 and Area 2 loads are 987 MW (L1) and 1765MW (L2), respectively. The load voltage profile was improved by installing 209 MVAr capacitors (C1 and C2) in each area to make closer to unity. Area 1 is exporting to Area 2 through two tie-lines and a single tie-line with power transfer level 445 MW and 335 MW, respectively.

System Dynamic Modeling

The system nonlinear dynamic model is derived by neglecting the resistances of all system components including generator, transformers and transmission lines and is given as the following.

$$\delta = \omega_0(\omega - 1)$$

$$\dot{\omega} = (P_m - P_e - D\Delta\omega)/M$$
$$\dot{E_q}' = (-E_q + E_{fd})/T_{do}' \tag{23}$$
$$\dot{E_{fd}} = [-E_{fd} + E_a(V_{ref} - V_t)]/T_a$$

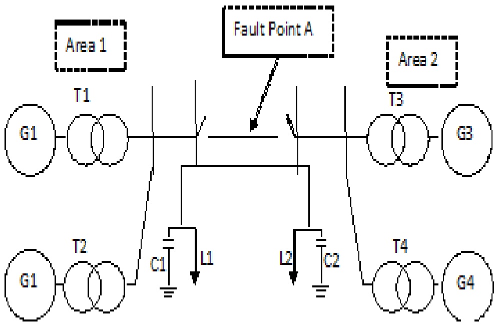

Fig. 5 Power System

After linearizing the non-linear dynamic model the system linear dynamic model is obtained. Dynamic model of the system in the state-space form is calculated as the following. The model has also some constants denoted by *Ki* is known as Heffron-Phillips mode

$$\Delta\dot{\delta} = \omega_0\Delta\omega$$
$$\Delta\dot{\omega} = (-\Delta P_e - D\Delta\omega)/M$$
$$\Delta\dot{E}_q' = (-\Delta E_q + \Delta E_{fd})/T_{do}' \tag{24}$$
$$\Delta\dot{E_{fd}} = -\left({}^{1}/_{T_a}\right)\Delta E_{fd} - \left({}^{K_a}/_{T_a}\right)\Delta V$$

$$\begin{bmatrix}\Delta\dot{\delta}\\ \Delta\dot{\omega}\\ \Delta\dot{E}_q'\\ \Delta\dot{E}_{fd}\end{bmatrix} = \begin{bmatrix} 0 & \omega_0 & 0 & 0\\ -\frac{K_1}{M} & 0 & -\frac{K_2}{M} & 0\\ -\frac{K_4}{T_{do}'} & 0 & -\frac{K_3}{T_{do}'} & \frac{1}{T_{do}'}\\ -\frac{K_aK_5}{T_a} & 0 & -\frac{K_aK_5}{T_a} & -\frac{1}{T_a}\end{bmatrix} \cdot \begin{bmatrix}\Delta\delta\\ \Delta\omega\\ \Delta E_q'\\ \Delta E_{fd}\end{bmatrix} + \begin{bmatrix} o & 0\\ \frac{1}{M} & 0\\ 0 & 0\\ 0 & \frac{K_a}{T_a}\end{bmatrix} \cdot \begin{bmatrix}\Delta T_m\\ \Delta V_{ref}\end{bmatrix} \tag{25}$$

PSS Stabilizer Based on Grey Fuzzy PID Controller

The PSS is provided to improve the power system oscillations. It provides the electrical damping torque in phase with the speed deviation to improve power system damping. The combination of pole placement and nonlinear programming techniques is considered to design the PSS with GFPIDC configuration (PSS-+GFPIDC). PID controller is used for stabilization in this system. The input of this stabilizer is the speed changing being modeling from the generator. The output of this controller is delivered to (stabilization voltage) the stimulation block to stabilizer the power system undulation. The aim is to control the angle between load and generator speed.

The PSS+GFPIDC parameters are tuned from open loop transfer function to close loop based on Nichols chart, Nyquist plane and fuzzy logic. Therefore, the open loop transfer function and maximum peak response parameter make the objective function which used to adjust PID parameters. The PSS+GFPIDC parameters are tuned in a nonlinear objective function with nonlinear constraints and solved by the nonlinear programming and fuzzy sets. On the other hand, the objective function *J* (*KP* ,*KI* ,*KD*) with the constraints *f* (*KP* ,*KI* ,*KD*) is solved considering the nonlinear programming to obtaining of the PID controller parameters (*KP* ,*KI* ,*KD*) and forming its gain

$G_{PID}(s) = \frac{K_P + K_1}{s + K_D.s}$ The PID gain is applied to the power system gain *GPS* (*s*) in equation (3) as a closed loop system to building PSS+GFPIDC controller and making angular velocity ω. The power system without PSS is unstable and the PSS+GFPIDC structure is stable which its performance done by the defined constraints over the objective function.

Conclusion

This paper proposes a grey Fuzzy PID Controller (GFPIDC) with a variable prediction horizon for power system stability control. The simulation results show that the proposed method not only reduces the overshoot and the rise time but also maintain a better disturbance rejection. In real life, there are always some uncertainties because an accurate mathematical model of a physical system cannot generally be defined. Noise that exists in various stages of the system is an additional problem. The proposed adaptive grey GFPIDC has the ability to handle these difficulties. An on-line rule tuning mechanism is constructed to provide an appropriate forecasting step size to the grey predictor. An on-line rule grey fuzzy PID control system structure with an appropriate positive or negative forecasting step size is present so that the system controlled by the proposed structure has a good overall performance. Observing the result of simulation, it is obvious that the GFPIDC controller-based PSS stabilizer (PSS-GFPIDC) can stabilize the mentioned synchronous generator. It is also observed that the system turned back to its stabilizer mode after disturbance, due to the three-phase short circuit, to compensate the bad impact of disturbance.

References

1. Anderson P. M. and Fouad A.A., “Power system control and stability’ Ames, 1owa: lowa state university press, 1977.
2. Deng J., "Control problems of grey system," Systems & Control Letters, Vol. 1, No. 5, pp. 288-294, 1982.
3. Deng J., "Grey Systems Control," Huazhong University of Science and Technology Press, Wuhan, 1985. (in Chinese)
4. Cheng B., "The Grey Control on Industrial Process," Journal of Huangshi College, Vol. 1, pp. 11-23, 1986. (in Chinese)
5. Deng J. L., “Introduction to grey system theory”, *The Journal of Grey System*, Vol. 1, pp. 1-24, 1989.
6. Berenji H. R. and Khedkar P., "Learning and tuning fuzzy logic controllers through reinforcements," IEEE Transaction on Neural Networks, Vol. 3, No. 5, pp. 724-740, 1992.
7. Lai L. Y. and Lee M. Y., “Fuzzy tuning of integrator output of PID controllers for a DC motor system,” Chung Yuan I., vol. XXIL, pp. 126-131, Dec. 1993.
8. Kundur P., “Power System Stability and Control”, McGraw-Hill, 1993.
9. Hong C.M., Chiang C.T., Lin S.C., "Design of Grey Prediction Controller Based on Fuzzy Reasoning," The 2nd National Conference on Fuzzy Theory and Applications (Fuzzy'94), pp. 66-71, 1994.
10. Lin C. J. and Lin C. T., "Reinforcement learning for an ART -based fuzzy adaptive learning control network," IEEE Transaction on Neural Networks, Vol. 7, No. 3, pp. 709-731, 1996.