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Research Article

DEVELOPMENT OF GREY FUZZY CONTROLLERS

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ABSTRACT

This paper combines the advantages of the grey prediction theory, fuzzy theory to design a rule adaptive grey Prediction fuzzy controller. These different forecasting step sizes are generated by a rule adaptive mechanism with the technology of fuzzy theory. The rule adaptive grey prediction fuzzy controller structure is proposed so that the rise time and the overshoot of the controlled system can be maintained simultaneously. Finally, the inverted pendulum control problem is used to illustrate the effectiveness of the proposed control scheme.

This paper presents a grey–fuzzy predictive controller that is based on fuzzy theory, grey prediction and on-line switching algorithms. The grey predictor is applied to extract key information and reduce the randomness of the measured non-stationary time-series signals from sensors, and send the prediction information to the fuzzy controller. The complete mathematical model is derived and the sufficient condition for convergence is given. To achieve better transient performance and steady-state responses, an on-line switching mechanism is adopted to regulate appropriately the forecasting step size of the grey predictor, according to the error feedback from different periods of the system response.

INTRODUCTION

The concept of grey system theory, which has a certain prediction capability, offers an alternative approach for various kinds of conventional control methods, such as PID control and fuzzy control. For instance, grey PID type fuzzy controller 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. In order to obtain a better controller performance, another fuzzy controller is designed for changing the step-size of the grey controller. 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. It is clear that the proposed adaptive PID type fuzzy controller is effective in controlling such a non-linear system by changing the prediction horizon adaptively for real-time working.

This paper presents a grey–fuzzy predictive controller that is based on fuzzy theory, grey prediction and on-line switching algorithms. The grey predictor is applied to extract key information and reduce the randomness of the measured non-stationary time-series signals from sensors, and send the prediction information to the fuzzy controller. The complete mathematical model is derived and the sufficient condition for convergence is given. To achieve better transient performance and steady-state responses, an on-line switching mechanism is adopted to regulate appropriately the forecasting step size of the grey predictor, according to the error feedback from different periods of the system response. Experimental results obtained from a plant show that the control accuracy and robustness are much improved when the proposed new method is applied. Traditional fuzzy control (TFC) theory and methods have been widely used in industry, and the analysis of control rules and membership function parameters has been investigated extensively. In general, the TFC strategy adopts the previously measured information, and the control signal is a function of the previous system error and its deviation, namely ‘‘delayed control’’. In many circumstances, it is feasible and practicable and guarantees the basic requirements of global stability and acceptable performance. Recently, many researchers focus on how to select a proper and dynamic

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forecasting step to control a system. Different techniques have been adopted to regulate the grey forecasting step size, including fuzzy logic, neural networks, genetic algorithms, etc. From the experiments, we know that a grey predictor with a negative and fixed forecasting step size always has a small settling time and a large overshoot. On the other hand, a grey predictor with a large positive and fixed forecasting step size has a small overshoot and a large settling time. To improve the fuzzy system's performance, we propose a novel grey fuzzy predictive control (GFPC) strategy using an on- line dynamic switching mechanism. It finds a suitable forecasting step size for each control action of three modes, namely a big positive-step forecasting mode, a small positive-step forecasting mode and a negative-step forecasting mode. When the system error is large, the negative-step forecasting mode is used to increase the upward momentum of the output curve. This is to speed-up the system response for shortening the settling time.

When the system error is small, the big positive-step forecasting mode is used to prevent the overshoot. The last condition is used when the middle error occurs. For convenience, the fuzzy controller in this paper adopts traditional two-input and one-output structure which behaves approximately like a PD controller with variable parameters. The entire input signal is obtained from the grey predictor according to the complementary behavior of the distinct modes. Then the sufficient condition for convergence is derived. From experimental results, we find this design not only can drastically reduce the system overshoot, but also can maintain the characteristic of the shorter settling time of the system compared to TFC. The rest of this paper is organized as follows. In Section 2, the structure and the mathematical model of the GFPC is presented. The sufficient condition for convergence of the proposed control algorithm is derived. In Section 3, simulation results with the proposed control scheme are obtained. Finally, conclusion remarks and future work are presented in Section 4.

Design of grey–fuzzy predictive control

Traditional grey prediction model

The grey predictive method has been successfully used to model the dynamic systems indifferent fields such as agriculture, ecology, economy, statistics, meteorology, industry, environment, and soon. It can predict poor, incomplete or uncertain messages in a system without the need of a long-term historical data. It reveals underlying regular conditions within a random time sequence via a special data processing. Different from the existing statistic methods for prediction, grey predictive method uses data generation method, such as ratio checking (RC) and accumulated generating operation (AGO) to reduce the stochastic of raw datum and obtain more regular sequence from the existing information. The general form of a grey differential model is GM (i,j), where i is the order of the ordinary differential equation and j the number of grey variables. In general, the computing time of the grey predictive model increases exponentially as i and j increase. But prediction accuracy may not improve with large i or j values. Therefore, the traditional grey prediction model GM (1,1) is used in this paper, which can be derived by the following basic steps Step 1—RC and AGO, Step 2—Build grey model GM(1,1)

Modeling of grey–fuzzy predictive control

The configuration of the proposed GFPC with a non-line dynamic switching mechanism is shown in Fig.1 in which r(t) is the reference value, y(t) is the sensor output value, y*(t)= y*p is the grey prediction value, u(t) is the output of the fuzzy controller, and e*(t) is the deviation: e*(t) = r(t)_y*(t). The whole control strategy is based on the prediction value y*(t) of the system output y(t), y*(t) and r(t) are transmitted to the fuzzy controller and a control signal u(t) is generated to control the plant. Since the forecasting step size decides the predictive value and finally affects the control performance, an on-line switching mechanism is adopted to regulate the appropriate forecasting step size of the grey predictor. In general, when the system error is large, the system response should be quick and the switching mechanism should choose the negative-step forecasting mode. Then, the grey predictor has the ability of predicting the ''previous'' behavior of the system, and the predictive value of the output will be large for a decreasing system response.

Therefore, the fuzzy controller will transmit a big control signal to speed-up the system response and result in a shorter settling time. When the system error is very small, the system response should be decreased and the switching mechanism should choose the big positive-step forecasting mode. Then, the forecasting value of the output will be small so that the fuzzy controller generates a smaller forecasting control signal to prevent the system over- shoot. Therefore, this mode leads to a slow system response so that the overshoot of the fuzzy control system with a grey predictor is smaller than that of the fuzzy control system without a grey predictor. However, this causes a long settling time. When the system error is in a special definite range, the switching mechanism should choose the small positive-step forecasting mode to overcome the drawback of the other two modes.

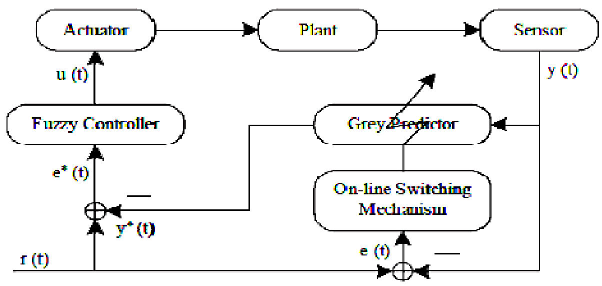

Fig 1 The structure of grey–fuzzy predictive controller

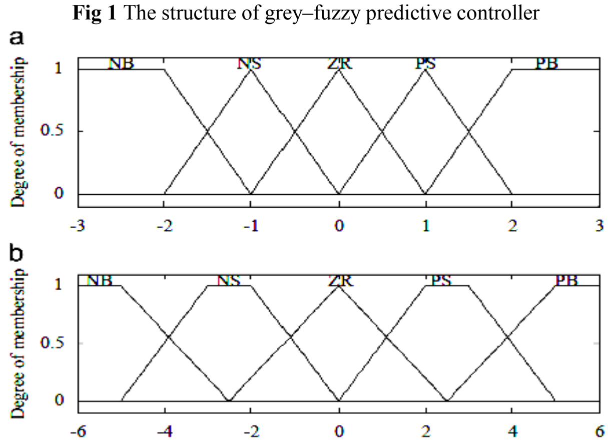

Fig 2 Membership functions of fuzzy control system: (a) membership function of input fuzzy sets (e* and De*) and (b) membership function of output fuzzy sets (Du)

The control rules are shown in Table 1. Fig.3 shows the unit step response of the system obtained in simulation by using GFPC (the dotted line), TFC (the solid line), and traditional PID control with Kp = 5, ki = 0.1, kd = 0.01 (the dashed line), respectively. The performance indices with these three different methods are shown in Table 2. As can be seen, the proposed method cannot only reduce the system overshoot efficiently but also maintain the characteristic of the shorter settling time of the system. The structure of the proposed method is shown in Fig.4. It is well-known that the network-induced delay is brought in to the control systems along with the inserted communication network, which not only prevents us from applying some conventional theorem to NCSs, but also brings many unstable factors that degrade the stability and control performance of the system.

Table 1 Fuzzy reasoning rule (U)

$\Delta E/E$	NB	NS	ZR	PS	PB
NB	PB	PB	PS	PS	ZR
NS	PB	PS	PS	ZR	ZR
ZR	PS	PS	ZR	ZR	NS
PS	PS	ZR	ZR	NS	NS
PB	ZR	ZR	NS	NS	NB

Table 2 the performance indices with three different methods

Performance	Settling time (s)	Overshoot (%)
PID	2.16	19.24
TFC	1.00	8.26
GFPC	0.90	2.90

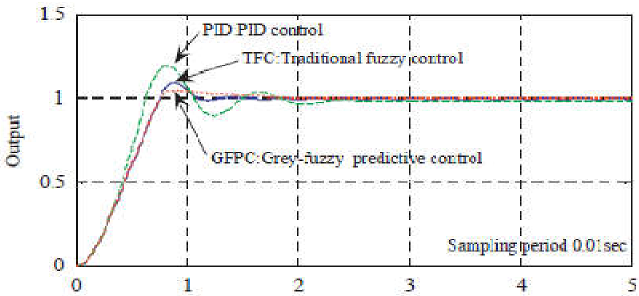

Fig 3 Simulation results of the given system

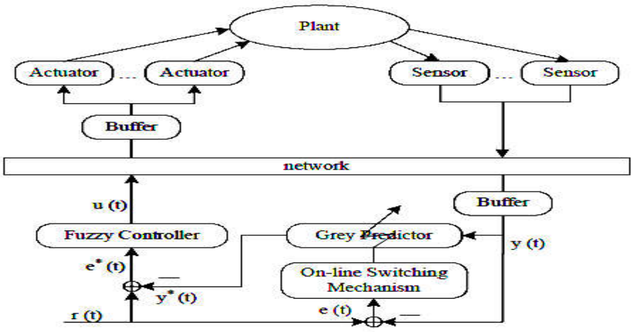

Fig 4 we use buffers to change random time delays into constant time delays

In Fig.4, we use buffers to change random time delays into constant time delays. The size of each buffer should be equal to the length of the signal data from the zero-step to the maximum- step network delay. In this way, the random network delay can be treated as a constant delay after the buffer. This implies that if the transmission delay of the data on the network is less than the maximum delay, they have to stay in the buffer until the maximum delay is reached. In Fig.5, the upper bounds of the communication time-delays in the forward and backward channels are equal to the system sampling period(i.e. k = f = T), and in Fig.6 the upper bounds of the communication time delays in the forward and backward channels are three times of system sampling period (i.e. k = f= 3T). The performance indices with these three different methods in NCSs are shown in Table 3. As can be seen from the simulation results, two experiments with different time delays in forward and backward channels were conducted to test the GFPC design. By simulating a non-linear plant, we successfully improve the system control performances and robustness. The results are better than the ones that the traditional fuzzy and PID control strategies can provide.

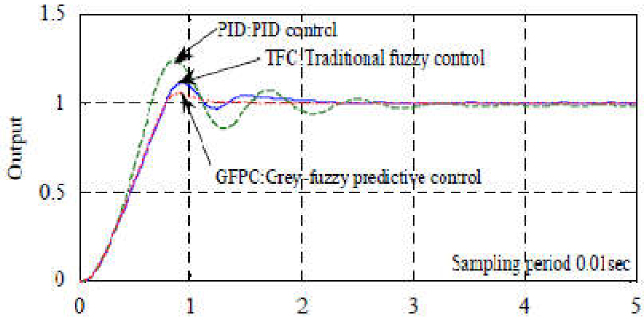

Fig 5 Simulation results with the upper bounds of forward and backward channels k = f = T in NCSs

Table 3 Performance indices with these three different methods in NCSs

Performance	Settling time (s)	Overshoot (%)
	K=f=T	
PID	2.46	23.24
TFC	1.75	10.26
GFPC	1.2	6.90
	K = f =3T	
PID	infinite	33.24
TFC	infinite	16.26
GFPC	1.34	10.90

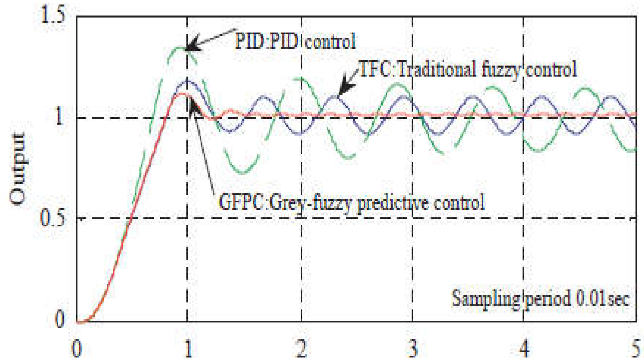

Fig 6 Simulation results with the upper bounds of forward and backward channels k = f = 3T in NCSs

Fuzzy control has been successfully applied to various industrial processes in recent years. However, its control rules and membership functions are usually obtained by trial-and-error method. In this research, we propose an associate Grey-neural model design for a compensator. A hybrid Proportional-Integral-Derivative (PID) controller which combines the Ziegler-Nichols PID controller with the Grey-neural prediction model is presented. Different characteristics of the employed controllers have been appropriately acquired. It is easy to implement and is efficient for multivariable optimization problems. The simulation result shows that the fuzzy controller can be designed to achieve good performance merely using the Grey-neural prediction. A lot of applications of fuzzy control have already received much attention and interest since the concept of the fuzzy control was introduced. The experience gained over the past few years has shown that fuzzy control may often be a preferred method of designing controllers for dynamic systems even if traditional methods can be used. The structure of fuzzy system can be classified into many types according to a variety of applications. One of the most popular types is the error feedback fuzzy controller, the first application in the world, which is called conventional fuzzy logic controller (FLC) in this paper. The control method of modeling human language has many advantages, such as simple calculation, as well as high robustness, without need to find the transfer function of the system, suitability for nonlinear systems, etc. The human-friendly controls are extensively implemented by people. In particular, fuzzy control compared with classical control or modern control has a better control effect in the case of the nonlinear, time-varying, uncertain system. Thus, we propose a new technique that can prevent the system response from exceeding the set point and can adjust the rising time using the compensator model with grey-neural prediction. The experimental result shows that the proposed fuzzy hybrid PID controller not only drastically reduces the overshoot, but also maintains a small extent of steady-state error, and will not cause a longer settling time.

A Brief of Fuzzy Controller

In recent years, fuzzy logical controllers appear to give a new technique to obtain a good response without having good models of process to be controlled. Up to the present, fuzzy theory and its application still have been developed constantly, and have been used successfully and widely in a variety of fields. There are three processes involved in the implementation of an FLC; fuzzification of inputs, a rule base or an inference engine and defuzzification to obtain a "crisp output." Fuzzification involves dividing each input variables' universe of discourse into ranges called fuzzy sets. A function applied across each range determines the membership of the variable's current value to the fuzzy sets. The value at which the membership is maximum is called the peak value. Width of a fuzzy set is the distance from the peak value to the point where the membership is zero. Linguistic rules express the relationship between input variables. Fig.7 is an example of a matrix of rules that covers all possible combinations of fuzzy sets for two input variables. The rules describe a proportional integral-derivative FLC (PIDFLC). The rule matrix is just a convenience and still represents all the rules in "English" of the form:

$$R_N: If\ error\ is\ E_i\ and\ change\ in\ error\ is\ \Delta E_j\ then\ output\ is\ U_{ij}$$

where ($1 \leq i \leq$number of sets for error), ($1 \leq j \leq$number sets for change in error) and ($1 \leq N \leq$ number of sets for error multiplied by the number of sets for change in error). Ei and ΔE_j are fuzzy sets for error and change in error, respectively and U_{ij} are the output fuzzy sets. In this case, each variable has seven fuzzy sets with the total of 49 rules. The notation PB means positive big; PM means positive medium; PS means positive small; ZO means zero; NS means negative small; NM means negative medium; and NB means negative big. The defuzzification process determines the "crisp output" by resolving the applicable rules into a single output value.

De / e / u	NB	NM	NS	ZO	PS	PM	PB
NB	NB	ZO	NM	NM	ZO	ZO	ZO
NM	NM	NM	NS	NM	ZO	ZO	ZO
NS	NM	ZO	ZO	ZO	ZO	ZO	PB
ZO	ZO	NS	ZO	ZO	ZO	PB	ZO
PS	NS	ZO	ZO	PS	ZO	PS	PM
PM	ZO	ZO	ZO	PM	PS	PM	PM
PB	ZO	ZO	ZO	PM	PM	PM	PB

Fig 7 Rule Matrix for PIDFLC

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 reason for using the grey prediction controller is that the next grey predicted output from an unknown plant based on a few past output can always provide us some important information to better control the system. The traditional control strategies adopt the previous information of the system to control the system behavior so that it is impossible to control the system before the behavior of the system moves toward the bad situation. In fact, the conventional grey prediction controller uses the forecasting information of the system output to control the system behavior so that it can reduce the overshoot strongly. Unfortunately, this way increases the rise time of the system at the same time. To improve this shortcoming, we propose an adaptive forecasting step tuning mechanism so that it can adaptively regulate an appropriate negative or positive forecasting step size by a fuzzy inference method.

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. For instance, the data collected from a motor control system always contains some grey characteristics due to the time-varying parameters of the system and the measurement difficulties. Similarly, it is difficult to forecast the electricity consumption of a region accurately because of various kinds of social and economic factors. These factors are generally random and make it difficult to obtain an accurate model. The traditional grey predictor structure uses a fixed prediction horizon. A grey predictor with a small fixed forecasting step-size will make the system respond faster but cause larger overshoots. Conversely, the bigger step-size of the grey predictor will cause over compensation, resulting in a slow system response. In order to obtain a fast system respond with a little overshoot, the step-size of the grey predictor can be changed adaptively. In the literature of the grey system theory, there are some methods that tune the step-size of the grey predictor according to the input state of the system. In order to determine the appropriate forecasting step-size, some online rule tuning algorithms using a fuzzy inference system have been proposed for the control of an inverted pendulum, fuzzy tracking method for a mobile robot and non-minimum phase systems.

Grey Theory

Grey system is a novel scientific theory and is first proposed by Professor Deng Julong in the 1982. It, mainly, works on a system analysis with poor, incomplete, or uncertain messages. Particularly the single-variable first-order differential equation is used to model the GM (1,1) that only uses a few data for modeling process. The prediction procedure is as followed:

Step 1: At least four output data are needed to approximate a system. For a non-negative time series, collect n raw data:

$$y^{(0)} = \{y^0(1), y^0(2), \ldots \ldots y^0(n)\} \quad (1)$$

Step 2: Take the accumulated generating operation (AGO) to obtain $y^{(1)}$ from $y^{(0)}$:

$$y^{(1)}(k) = \sum_{i=1}^{k} y^{(0)}(i)\,, k = 1,2,3, \ldots \ldots . . n \quad (2)$$

Step 3: Apply a consecutive neighbor generation z(1) from y(1) by the following mean generating operation (MGO): (k = 2,3,…,n)

$$z^{(1)}(k) = 0.5y^{(1)}(k) + 0.5y^{(1)}(k-1) \quad (3)$$

Step 4: Establish grey differential equation of GM (1, 1):

$$y^{(0)}(k) + a^{(1)}(k) = b \quad (4)$$

In which, parameter [a,b] can be obtained by using the least-square method as followings:

$$\hat{a} = \begin{bmatrix} a \\ b \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (5)$$

Where

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -Z^{(1)}(n) & 1 \end{bmatrix}, Y = \begin{bmatrix} y^{(0)}(2) \\ y^{(0)}(3) \\ \vdots \\ y^{(0)}(n) \end{bmatrix} \quad (6)$$

Step 5: Set up the prediction model GM (1,1) as:

$$\hat{y}^{(1)}(k+1) = \left(y^{(1)}(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \quad (7)$$

$$\hat{y}^{(0)}(k+1) = \hat{y}^{(1)}(k+1) - \hat{y}^{(1)}(k) \quad (8)$$

Step 6: Calculate the predictive output at time sequence $(n+p)^{th}$ step:

$$\hat{y}^{(1)}(n+p) = \left(y^{(1)}(1) - \frac{b}{a}\right) e^{-a(x+y-1)} + \frac{b}{a} \quad (9)$$

$$\hat{y}^{(0)}(n+p) = \hat{y}^{(1)}(n+p) - \hat{y}^{(1)}(n+p-1) \quad (10)$$

where p is the step size of the grey prediction.

Combining Fuzzy and PID Type Control

Analysis of a Fuzzy Controller

Consider a product-sum type fuzzy controller with two inputs and one crisp output (MISO). Let the inputs to the fuzzy controller be the error e and the rate of change of the error e˙, and the output of the fuzzy controller (that is the input to the controlled process) be u. If an analysis of this controller is made, it can be seen that it behaves approximately like a PD controller. We can therefore consider it as a time-varying parameter PD controller. Such a controller is named as a PD type fuzzy controller (PDFC) in the literature. It is well known that if the controlled system is type “0”, a P or PD type controller cannot eliminate the steady-state error. Although the use of an integral term in the controller (such as PI controller) can take care of the steady-state error, it can deteriorate the transient characteristics by slowing the response. However, with a PID-type fuzzy controller fast rise times and small overshoots as well as short settling times can be achieved with no steady-state error.

PID Type Fuzzy Control

In order to design a PID type fuzzy controller (PIDFC), one can design a fuzzy controller with three inputs, error, the change rate of error and the integration of the error. Handling the three variables is however, in practice, quite difficult. Besides, adding another input to the controller will increase the number of rules exponentially. This requires more computational effort, leading to larger execution time. Because of the drawbacks mentioned above, a PID type fuzzy controller consisting of only the error and the rate of change of error is used in the proposed method. This allows PD and PI type fuzzy controllers to work in parallel. An equivalent structure is shown in Fig.8, where α and β are the weights of PI and PD type controllers, respectively. Similarly, K and Kd are the scaling factors for e and e˙, respectively.

As the α/β ratio becomes larger, the effect of the derivative control increases with respect to the integral control.

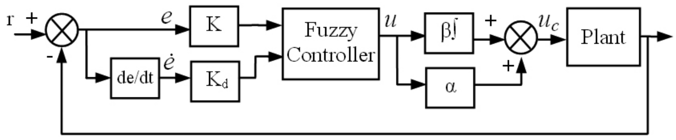

Fig 8 Block diagram of the PID type fuzzy control system

The output of the controller can be expressed as,

$$u_c = \alpha u + \beta \int u dt$$

This controller is called as PID type fuzzy controller (PIDFC).

Design of Adaptive Grey PID Type Fuzzy Controller

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. The block diagram of the grey fuzzy PID control system with a fixed prediction horizon and the adaptive grey PID type fuzzy controller with a variable prediction horizon proposed in this paper are showed in Fig.9 and Fig.10, respectively.

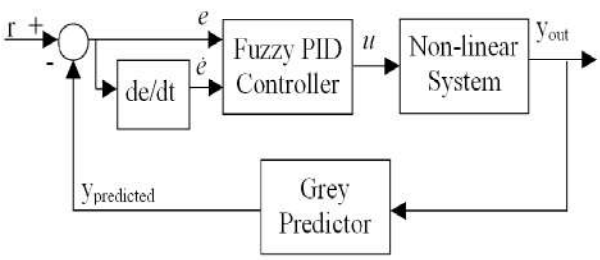

Fig 9 Block diagram of the grey fuzzy PID control system with a fixed prediction horizon

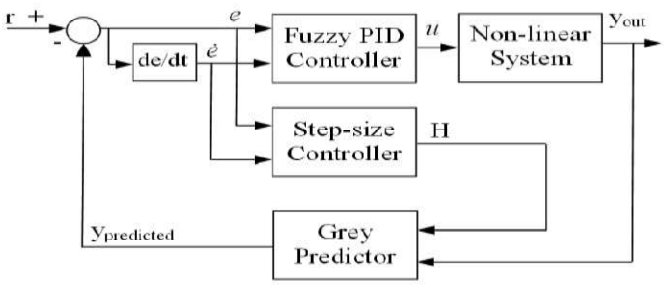

Fig 10 Block diagram of the adaptive grey fuzzy PID control system with a variable prediction horizon

Non-Linear Model Simulations

In this section, computer simulated dynamic responses are performed on the non-linear liquid level system that was modeled in the previous section. The non-linear system differential equations are simultaneously solved by using the Dormand- Prince algorithm. The numerical values used in this paper are K = 1 and Kd = 0.1. The simulation sample time T is equal to 0.4s. Fig.11 shows the response of the model to PDFC, PIFC and PIDFC. As can be seen the system response is very fast but there is a steady-state error with PDFC. With PIFC, the system does not have a steady-state error but a big overshoot and a slow response. The steady-state error of the system can be eliminated with a fast response using PIDFC.

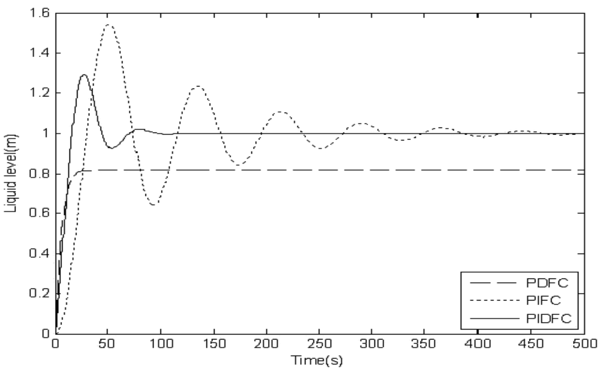

Fig 11 Step responses of the system to PDFC

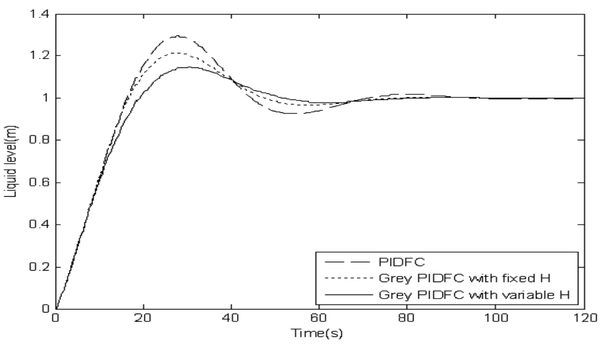

Fig 12 Step responses of the system to grey PIDFC with a fixed H=20 and grey PIDFC with variable H

Fig.12 shows the step responses of the system to PIDFC, grey PIDFC with a fixed H and grey PIDFC with variable step size. With grey PIDFC using a variable step-size, the system has a fast rise time and a reasonable overshoot. However, a switching characteristic can be seen on the response of the grey PIDFC with variable step-size. Fig.13 shows the unit step responses of the system to grey PIDFC with a fixed step-size and grey PIDFC with variable step-size with the band-limited white noise at the output measurement. The noise power, which is the height of the power spectral density of the white noise, is equal to 0.0002. The correlation time of the noise is equal to 0.4 sec. Although the response of the conventional grey controller is acceptable, the grey predictor with variable step-size is better under noisy conditions. This indicates that adaptive grey predictive controllers are more robust in real-time systems that are subject to noise from both inside and outside of the system.

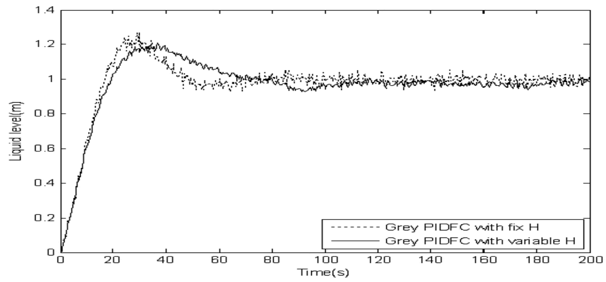

Fig 13 Step responses of the system to grey PIDFC with a fixed H=20 and grey PIDFC with variable H when the surface area of the outlet a out is reduced to its 0.2 times its normal value

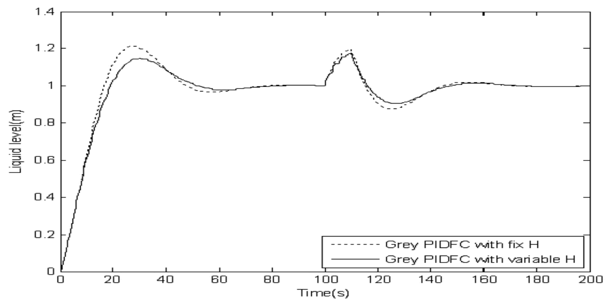

Fig 14 Step responses of the system to grey PIDFC with a fixed H=20 and grey PIDFC with variable H when there is white noise at the output measurement

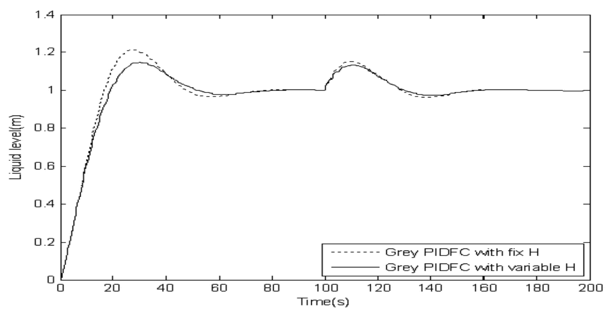

Fig 15 Step responses of the system to grey PIDFC with a fixed H=20 and grey PIDFC with variable H when the surface area of the outlet a out is reduced to zero for 10 seconds

Fig.11-12 show the unit step responses of the non-linear liquid level system to grey PIDFC with a fixed step-size and grey PIDFC with variable step-size when the surface area of the outlet aout is reduced to its 0.2 times its normal value in 100th second and reduced to zero between 100th and 110th seconds, respectively. Comprising uncertainties and lack of sufficient amount of information (like most ScNs); in which, the term ‘grey’ indicates the system information that lays between the clearly and certainly known ones (the white part) and the unknown ones which contains any knowledge of the system structure (the black part); so that grey systems include partially known and partially unknown characteristics.

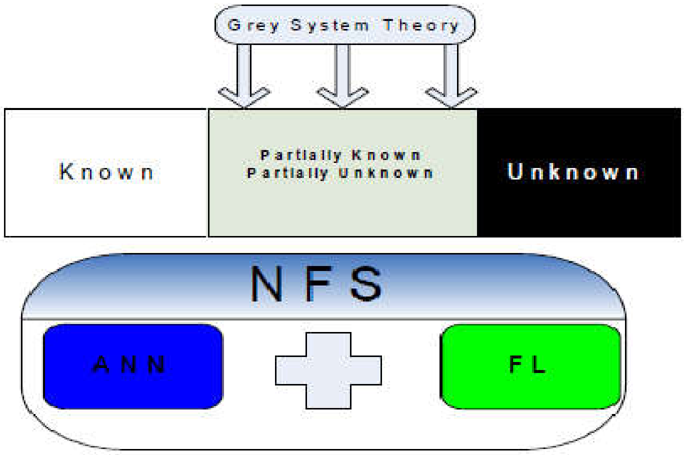

Fig 16 Grey system theory

Neuro-fuzzy systems (NFS); which also known as hybrid intelligent systems, can simply be defined as the combination of two complementary technologies: ANNs and FL. This combined system has the abilities of deducing knowledge from given rules (which come from the ability of fuzzy inference systems (FIS)), learning, generalization, adaptation and parallelism (which come from the abilities of ANN). So these hybrid systems cover the frailty of both FL (i.e., no ability of learning, difficulties in parameter selection and building appropriate membership function, etc.) and ANN (i.e., black box, difficulties in extracting knowledge, etc.) and became a robust technology using both systems powerful abilities.

The usage of hybrid NFS is rapidly increasing in many areas both civilian and military domain such as process controls, design, engineering applications, forecasting, modular integrated combat control systems, medical diagnosis, production planning and etc. This multilayer fuzzy inference integrated networks use neural networks to adjust membership functions of the fuzzy systems. This structure provides automation for designing and adjustment of membership functions improving desired output by extracting fuzzy rules from the input data with the trainable learning ability of ANNs and also overcomes the black box structure (i.e., difficulties of in understanding and explaining the way it deducts) of learning process of ANNs. Many studies have been made using different architectures of these hybrid systems, such as architectures fuzzy logic based neurons, neuro-fuzzy adaptive models and ANNs with fuzzy weights.

CONCLUSION

This paper proposes a grey PIDFC with a variable prediction horizon for a nonlinear liquid level system. 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 PIDFC has the ability to handle these difficulties. In this paper, an associate Grey-neural model design for a compensator. We propose a hybrid model which can integrate the advantages of fuzzy controller and grey-neural predictor to reduce the overshoot, and adjust rising time. The simulation results have demonstrated the availability of this new model which combines Grey-neural predictor and fuzzy controller. This paper describes the design of a novel grey–fuzzy predictive controller, which combines grey and fuzzy theory with the on-line rule switching mechanism. Three forecasting modes are obtained, namely, big positive-step forecasting mode, small positive-step forecasting mode and negative-step mode. When the system error is large, the negative-step mode is used to increase the upward momentum of the output curve for shortening the settling time. when the system error is small, the positive-step mode isused to prevent the overshooting. The control signal is obtained according to the complementary behavior of the distinct modes. Simulation results indicate that the precision and robustness of the proposed GFPC method is better than other TFC methods for both NCSs and non-NCSs. However, the proposed method is only applicable for a class of fuzzy logic controllers with symmetric and monotonic rule tables which are equivalent to a linear state feedback controller. How to choose the proper switching value, reduce conservation and make the results satisfy other fuzzy controllers is one of the most important issues to be investigated in the future.

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