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Development of Grey Fuzzy Controller for Power system Reliability Evaluation Problems and Preventive Maintenance Suggestions

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Abstract

System reliability modeling in terms of fuzzy set theory is basically utilizing the type-2 fuzzy sets, where the fuzzy membership is assumed as point-wise positive function ranging on [0,1]. Such a practice might not be practical because an interval valued membership may reflect the vagueness of system better according to human thinking patterns. The Grey fuzzy set is more capable to handle the uncertainty of system using type-2 fuzzy set.

In this paper, we explore the basics of the GM (1,1) fuzzy sets theory and illustrate its application in terms of development of reliability models for Power system reliability evaluation problems and Preventive Maintenance (PM) suggestions with example.

Keywords

Grey Fuzzy, Reliability Evaluation, Preventive Maintenance (PM)

1. Introduction

System operating and maintenance data are often imprecise and vague. Therefore fuzzy sets theory (Zadeh 1988) opened the way for facilitating the modeling fuzziness aspect of system reliability. In this piece of research work, we proposed an effective method to design the power system stabilizers (PSS). The design of a PSS based on Grey Fuzzy PID Control (PSS+GFPIDC) 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, we favor a control scheme that uses only some desired state variables, such as torque angle and speed. The grey PID type fuzzy controller (GFPIDC) designed in this paper, can predict the future out put 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 overcompensation, 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 here, 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.

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.

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 as low 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. In another paper, a Sugeno type fuzzy inference system has been proposed for large time delay systems.

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 line arregulator 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. (Woo.,Chung. and Lin.(2000).)

After the grey system theory was initiated by Deng in1982, 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 fore casting 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 a non-line rule tuning mechanism so that it can quickly regulate an appropriate negative or positive forecasting step size. A non-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 out put.

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.

2. The Structure of Power System Stabilizer

The structure of the grey prediction fuzzy PID control (GFPIDC) power system stabilizer is composed of five units:

2.1 Grey predictor unit: The grey predictor is used to predict the forecasting values Δ8 and Δ ω, these values provide the PID and Fuzzy controller.

2.2 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.

2.3 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.

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

2.5 Online-Tuning unit: 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 from this unit.

3. Grey Fuzzy Theory

3.1 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.

3.2 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)

3.3 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.

3.4 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 thesystem) x.

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

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 monotonei$^{0)}$(n)) , n ≥ 4

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

Where

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

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

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

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

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

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

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

The whitening equation is therefore as follows:

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

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

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

Where

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

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

According to equation (6.8), the solution of x(1)(t) at time k:

$$x_p{}^{(1)}(k+1) = \left[x^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a} \qquad \text{............... (11)}$$

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

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

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

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

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.

4. Probability of a Grey Fuzzy System

Grey fuzzy sets are the most widely used type-2 fuzzy sets because they are simple to use and because, at present, it is very difficult to justify the use of any other kind (e.g., there is no best choice for a type-1 fuzzy set, so to compound this non-uniqueness by leaving the choice of the secondary membership functions arbitrary is hardly justifiable). When the Grey fuzzy sets are interval type-2 fuzzy sets, all secondary grades (flags) equal 1 [e.g.$\forall f_{x_1}\left(u_l^i = 1\right)$ and),$\forall g_{x_1}\left(w_l^i = 1\right)$In this case we can treat embedded type-2 fuzzy sets as embedded type-1 fuzzy sets,so that no new concepts are needed to derive the union, intersection, and complement of such sets. After each derivation, we merely append interval secondary grades to all the results in order to obtain the final formulas for the union, intersection, and complement of interval type-2 fuzzy sets. Closed-form formulas exist for these operations, and their derivations can be found.

The key concept to extend the classical probability calculus toward the fuzzy probability calculus is the indicator function of a random event A∈ ϑ, aσ-field of Ω.

$$\vartheta_A(w) = \begin{cases} 1 & if \;\; \omega \in A \\ 0 & if \;\; \omega \neq A \end{cases}$$

$$P_r(A) = \int_{\Omega} \vartheta_A(\omega) dP \qquad (14)$$

One fundamental fact is that the right hand is an abstract Lebegue integral. Classical probability calculus requires random event *A* is a common subset, i.e., for all ω∈*A*, such a belonging relation is definite: it either belongs to *A* or it does not, there is no middle ground. Therefore classical probability calculus is short of the capability to describe fuzzy random events. Zedeh (1965) defined fuzzy set in terms of the extension to indicator function of a normal subset into membership function of a subset into membership function of a fuzzy set *A* is mapping from Ω onto [0,1]

$$\mu_{\underline{A}}: \Omega \rightarrow [0,1].$$

This mapping is called the membership function of $\tilde{A}$, whichis a Borel measurable function representing the degree of element ω belonging to fuzzy set. Thus the probability of fuzzy event is defined as

$$P_r[\underline{A}] = \int_{\Omega} \mu_{\underline{A}}(\omega)dP \quad (15)$$

Given a probability space (Ω,ϑ,P), let φbe the collection ofall the fuzzy event on Ω, then (Ω,φ,P) is called the induced fuzzy probability space from (Ω,ϑ,P). Therefore, the fuzzyprobability calculus can be established naturally as theextension to the classical probability calculus except themembership of the interception of two fuzzy events

$$\mu_{\underline{A}\cap\underline{B}} \cong \mu_{\underline{A}}, \mu_{\underline{B}}$$

for maintaining the classical formality of independence, conditional probability, law of total probability as well as Bayes formula.

5. A Grey Fuzzy Reliability Model of Repairable Systems

A Virtual Allowable Capacity Model for Repairable System

A basic idea of the reliability model proposed here is essentially taking from that of the traditional power availability-unavailability state modeling of an Electrical power system. If we treat a repairable system as a virtual electrical power system, then the system parameters, the maintenance parameters and its operational environment parameters together can form a virtual allowable capacity, denoted as C_a, which would restrain or control the system functioning state. The virtual allowable capacity plays a role similar to the power availability level in the power availability-unavailability model, which will determine a virtual allowable operating time t_a, denoted as P_{av}. On the other hand, the system functioning or operating causes system wear-out and increases its failure hazard. Therefore, the actual system functioning plays a role similar to the unavailability level, denoted as P_{un}.

The limiting state equation of the reliability of functioning power system is:

$$Z = P_{av} - P_{un} \quad (16)$$

Furthermore it is assume that the limiting state Z is normally distributed random variable. It is intuitive to say that both P_{av} and P_{un} are random and fuzzy in nature. The failure of the system is assumed to be a Grey fuzzy event with membership function

$\overline{\mu}_{\tilde{A}}(z)=\overline{FOU(\tilde{A})} = \forall z \in Z$

$\underline{\mu}_{\tilde{A}}(z)=\underline{FOU(\tilde{A})}= \quad \forall z \in Z$

6. The Power System Reliability Example

A set of operating data of power system extracted from a Power plant is used. A fuzzy analysis was performed on the same data in terms of Grey fuzzy set for obtaining the point-wise relative membership grades $\mu_{\tilde{A}}(u)$. For illustration purpose, we convert$\mu_{\tilde{A}}(u)$into Grey membership grades [$\overline{\mu}_{\hat{C}a}(t_a), \underline{\mu}_{\hat{C}a}(t_a)$] by assigning the depth of vagueness π=0.1 at$\mu_{\tilde{A}}(u)$ =0.5and π=0 at $\mu_{\tilde{A}}(u)$ =0 or 1.0. Here Grey membership grades[$\overline{\mu}_{\hat{C}a}(t_a), \underline{\mu}_{\hat{C}a}(t_a)$] are around $\mu_{\tilde{A}}(u)$ in table 1.

For a recorded failure time or Preventive Maintenance (PM) time, the corresponding the allowable time satisfies

$$\overline{\mu}_{\widetilde{Ca}}(t) = \overline{1} - \overline{t}_a/t_{max}$$

$$\underline{\mu}_{\widetilde{Ca}}(t) = \overline{1} - \underline{t}_a/t_{max}$$

that is, the allowable time $\overline{t}_a = t_{max}\left(\overline{1} - \overline{\mu}_{\widetilde{Ca}}(t)\right)$

$$\underline{t}_a = t_{max}\left(\overline{1} - \underline{\mu}_{\widetilde{Ca}}(t)\right)$$

Therefore the virtual system state: $\overline{z} = \overline{t}_a - \overline{t}$

$$\underline{z} = \underline{t}_a - \underline{t}$$

For failure times, $t_{max} = max\{t_1k_1, \dots, t_{31}k_{31}\} = 147$, while for the censoring (PM) times,$t_{max} = max\{t_1(1-k_1), \dots, t_{31}(1-k_{31})\} = 217$,Then$\left[\underline{\mu}_{\widetilde{Ca}}(t), \overline{\mu}_{\widetilde{Ca}}(t)\right]$,$[\underline{t}_a, \overline{t}_a]$,and $[\underline{z}, \overline{z}]$, interval values arecalculated and listed in Table 1.

Table 1. "Observed" $[\overline{t}_a, \underline{t}_a]$and $[\overline{z}, \underline{z}]$-valued for each PM.

t_i	k_i	$\mu_{\tilde{A}}(u)$	$[\overline{\mu}_{\hat{C}a}(t), \underline{\mu}_{\hat{C}a}(t)]$	$[\overline{t}_a, \underline{t}_a]$	$[\overline{z}, \underline{z}]$
54	0	0.5	[0.450,0.550]	[97.65,119.35]	[43.65,65.35]
133	1	0.8	[0.780,0.820]	[26.46,32.34]	[-106.35,-100.66]
147	0	0.818	[0.800,0.836]	[35.588,43.4]	[-111.41,-103.6]
72	1	0.6	[0.560,0.640]	[52.92,64.68]	[-19.08,-7.32]
105	1	0.8	[0.780,0.820]	[26.46,32.34]	[-78.35,-72.66]
115	0	0.375	[0.338,0.413]	[127.379,143.654]	[12.37,28.65]
141	0	0.538	[0.492,0.584]	[90.272,110.236]	[-50.72,-30.65]
59	1	0.667	[0.630,0.701]	[43.35,54.39]	[-15.04,-4.06]
107	0	0.125	[0.113,0.138]	[187.32,192.64]	[80.04,85.47]
59	0	0.2	[0.180,0.220]	[169.77,177.94]	[110.42,118.94]
36	1	0.4	[0.360,0.440]	[82.34,94.04]	[46.32,58.08]
210	0	0	[0.000,0.000]	[217,217]	[7,7]
45	1	0.429	[0.386,0.472]	[77.616,90.258]	[32.616,45.258]

69	0	0.6	[0.560,0.640]	[78.12,95.48]	[9.12,26.48]
55	0	0.889	[0.877,0.900]	[21.7,26.691]	[-33.3,-28.309]
74	1	0.875	[0.853,0.888]	[16.464,21.609]	[-57.536,-52.391]
124	1	0.774	[0.756,0.800]	[29.4,35.868]	[-94.6,–88.132]
147	1	0.667	[0.630,0.701]	[43.953,54.39]	[-102.9,-93.345]
171	0	0.375	[0.338,0.413]	[127.379,143.65]	[-43.621,-27.346]
40	1	0.667	[0.630,0.701]	[43.654,54.39]	[3.953,14.39]
77	1	0.778	[0.756,0.800]	[29.4,35.868]	[-47.6,-41.132]
98	1	0.6	[0.560,0.640]	[52.92,64.68]	[-45.08,-33.32]
108	1	0.6	[0.560,0.640]	[52.92,64.68]	[-45.08,-33.32]
110	0	0.667	[0.630,0.701]	[64.883,80.29]	[-45.117,-29.71]
85	1	1	[1.000,1.00]	[0,0]	[-85,-85]
100	1	0.556	[0.512,0.600]	[58.8,71.34]	[-41.2,-28.264]
115	1	0.8	[0.780,0.820]	[26.46,32.34]	[-88.54,-82.66]
217	0	0.2	[0.18,0.220]	[169.26,177.94]	[-47.74,-39.06]
25	1	0.429	[0.386,0.472]	[77.616,90.258]	[52.616,65.258]
50	1	0.429	[0.386,0.472]	[77.616,90.258]	[27.616,40.258]

From the table, it is easy to notice that most of the failure cases (κ_i=1), the $[\underline{z},\bar{z}]$–valuesobserved are **negative**, which indicates the system falls in “**failure”**and “**power unavailable”**state,while quite a few of the censoring cases, the $[\underline{z},\bar{z}]$-values observed are **positive**, whichindicates the system is still in **"reliable"** and **"power available"** state. The signs of these "observed"$[\underline{z},\bar{z}]$-values confirm that the membership degree of the allowable capacity,$\left[\underline{\mu}_{\widetilde{Ca}}(t),\overline{\mu}_{\widetilde{Ca}}(t)\right]$ makesense. The mean and standard deviation of the interval-valued normal random variable$[\underline{z},\bar{z}]$can be accordingly estimated as $[\underline{m},\overline{m}]$=[-18.744,-8.853] and $[\underline{\sigma},\bar{\sigma}]$=[65.886,66.458] respectively. The fact that $[\underline{m},\overline{m}] \leq \bar{0}$clearly indicates the system requires preventive maintenance (PM). Power System data$[\underline{t}_a,\bar{t}_a]$can be used to fit Weibull distributions for further conventional reliability analysis.

6. Conclusion

The concept of Grey fuzzy system is briefly discussed in this work and argues its necessity to use Grey fuzzy system idea for the modeling power system reliability. The method of Grey fuzzy system can be used to conduct fuzzy inference on the power system reliability directly. However, the virtual operational state of a power system gives another inside of the power system reliability status. Using Grey fuzzy system to analyze the power system reliability status and preventive maintenance suggestions seems more meaningful. As a matter of fact, it is more realistic to calculate the Grey membership grades and then use the logical function idea to have the Grey membership grades for the power system reliability status.

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