RESEARCH ON MODELING OF THE HIGH-DENSITY CURRENT ELECTRON GUN SYSTEM BASED ON T-S FUZZY MODEL

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Abstract

The stability of the electron beam is considered as an important performance of industrial electron accelerators. For the beam control system of the accelerator, it is significant to obtain the accurate model of the electron gun system. The paper presents a fuzzy modeling method based on the Takagi-Sugeno (T-S) fuzzy model. A T-S model can be obtained using the system identification algorithms from input-output data. In our approach, fuzzy c-means (FCM) clustering algorithm is applied to identify the model structure. And a hybrid method based on quantum-inspired differential evolution algorithm (QDE) and genetic algorithm (GA) is proposed to learn the parameters of T-S fuzzy model. Experiments on the Box-Jenkins gas furnace data have verified the validity of the modeling approach. The simulation results show that the T-S fuzzy model is very well to describe the electron gun system and reveal its performance.

INTRODUCTION

Particle accelerators first developed in nuclear physics research are now used for a number of practical applications. After more than 80 years of development, many thousands of accelerators are in use around the world in areas ranging from medical applications to industrial processes.

The paper presents the research on electron beam of electron accelerators for industrial radiation applications. Considering the nonlinearities, time varying characteristics and large inertia of the electron gun system, it is difficult to express its characteristics using precise mathematics model. Currently, the electron beam control methods usually rely on the experience and knowledge.

Fuzzy logic method can deal with complex control problems more preciously than traditional control techniques. Fuzzy modeling based on the fuzzy logic has the capability to model the behaviour of complex nonlinear system containing uncertainties. As one of the classical rule-based fuzzy model, Takagi-Sugeno (T-S) fuzzy model [1] can approximate complex nonlinear systems with fewer rules and higher modeling accuracy. The main purpose of fuzzy modeling is to generate a set of fuzzy rules from the given input-output data. In general, the design of T-S fuzzy model consists of two parts: structure identification and the parameter learning.

Fuzzy c-means (FCM) [2] is a method of clustering based on optimizing an objective function. In the paper, the partition of input space is realized by FCM clustering algorithm and the number of data clusters equals to the number of rules.

The paper proposes a new learning algorithm, which is based on quantum-inspired differential evolution algorithm (QDE) [3] and genetic algorithm (GA) [4]. QDE is mainly based on Q-bits and states superposition of quantum mechanics. In QDE algorithm, differential evolution (DE) is used to update the state of Q-bits. Quantum computation would gain more processing power than the classical computer technology through the ability to be in multiple states. Besides, QDE has many advantages such as quick convergence speed and good global search capability. GA is a mathematical search algorithm which mimics biological evolution. The idea of the parallel optimization algorithms is searching for a global optimum among a collection of candidate solutions. It is expected that advantages of both QDE and EA are kept so that the hybrid algorithm can improve the efficiency and accuracy of the optimization process.

The rest of the paper is organized as follows: Section 2 introduces the basic concepts of T-S fuzzy model. Section 3 illustrates the hybrid algorithm of QDE and GA. Section 4 analyzes the experimental results. The conclusions are summarized in Section 5.

DESCRIPTION OF T-S FUZZY MODEL

The T-S fuzzy model was proposed by Takagi and Sugeno in 1985 [1]. For multi-input single-output (MISO) systems, the typical T-S model consists of a set of IF-THEN rules and each rule is composed of an antecedent part and a consequent part as follows:

$$\begin{aligned} R^i &: \textit{if } x_1 \textit{ is } A_1^i \textit{ and } x_2 \textit{ is } A_2^i \textit{ and} \ldots \textit{and } x_r \textit{ is } A_r^i \\ &\textit{then } y^i = p_0^i + p_1^i x_1 + p_2^i x_2 + \ldots + p_r^i x_r \quad (1 \le i \le c) \end{aligned} \tag{1}$$

where R^i is the ith rule $(1 \le i \le c)$, $x = [x_1, x_2, \ldots, x_r]$ are input variables, $A_j^i (1 \le j \le r)$ represents fuzzy set, y^i is the output of rule R^i, $p_j^i (0 \le j \le r)$ represents the consequent parameter. The model output y is the weighted average of the individual rule outputs $y^i (1 \le i \le c)$.

The essential idea of T-S fuzzy model is to decompose the nonlinear system into a number of simple linear subsystems and treat every subsystem by applying the linear system theory.

T-S FUZZY MODELING METHOD

In this section, we describe the T-S fuzzy modeling method and present the hybrid algorithm based on QDE and GA.

Modeling Method

Generally speaking, the whole process can be summarized as follows:

- Input variables selection. The first task is to select proper input variables of the fuzzy model from the process variables. The selection is complex and usually decided by experience and expert according to the actual demand.
- Data division. The purpose of the FCM is to split data samples into several groups, which also determines the structure of the fuzzy model.
- Fuzzification of the input variables. All the selected input variables must be converted into fuzzy value via the Gaussian membership functions.
- Estimation of the premise parameters. The proposed hybrid algorithm of QDE and GA is applied to optimize the parameters in the membership functions.
- Identification of the consequent parameters. Since the premise parameters is given, the consequent parameters can be by the recursive least square algorithm.

The Hybrid Algorithm based on QDE and GA

The algorithm uses a Q-bit string as a representation and is applied to solve the optimization problems in the binary-valued space.

The hybrid Algorithm of QDE [3] and GA [4] works as follows:

Step1. Initialize the population and Set $t=0$ (t is the generation number, T is the maximum generation number.)

Step2. While (t<T) // Start the hybrid algorithm

{ // Start QDE method

Step2-1 Perform the value mutation operator according to the kind of the attributions.

Step2-2 Perform the weight mutation operator.

Step2-3 Perform the crossover operator.

Step2-4 Evaluate the fitness of each individual.

Step2-5 Perform the selection operator.

// Terminate QDE

}

{// Start GA method

Step2-6 Calculate the fitness of each chromosome in the population and apply the selection operator to the current population.

Step2-7 Create a new population with the crossover operator.

Step2-8 Use the mutation operator.

// Terminate QDE

}

Step3. If the iterative generation gets to the maximum generation number, go to step 4, else set t=t+1 and go to step2

Step4. Save the best individual and terminate the hybrid method.

EXPERIMENTS

Application to the Box-Jenkins gas Furnace Data

The Box-Jenkins gas furnace data [5], which has been widely adopted in many papers, is considered as a standard experimental data to test the validity of fuzzy modeling. In order to verify the effectiveness of our method, we conduct the proposed modeling algorithm on the Box-Jenkins gas furnace data and try to compare with other modeling approaches in [6] and [7]. We try to predict $y(t)$ based on $\{y(t-1), u(t-4)\}$ and the rules number is set to be two. The mean of square error (MSE) is adopted as a performance index of the fuzzy model, which is given by the following formula:

$$MSE = \frac{1}{N}\sum_{t=1}^{N}[y(t) - \hat{y}(t)]^2 \qquad (2)$$

where N is number of input-output data pairs, $\hat{y}(t)$ is the actual output, $y(t)$ is the model output.

The whole process is completed in MATLAB and the performance comparison of the proposed algorithm with other modeling methods is listed in Table 1.

Table 1: Comparison Results for Box-Jenkins Gas Furnace

Type	Number of Input variables	Rules Number	MSE
Sugeno and Yasukawa [6]	3	6	0.190
Wei Li and Yupu Yang [7]	2	2,2	0.1608
Our method	2	2	0.124

Compared to other modeling methods, the value of MSE in our article is lower. Thus the results illustrate the effectiveness of the proposed algorithm. Figure 1 presents a simulation of our model at MATLAB environment. The stars are the real output and the circles denote the model output predicted by our modeling algorithm. As is seen, the model output fit the experimental data well. It is demonstrated that the proposed modeling method has a good ability of accuracy and generalization.

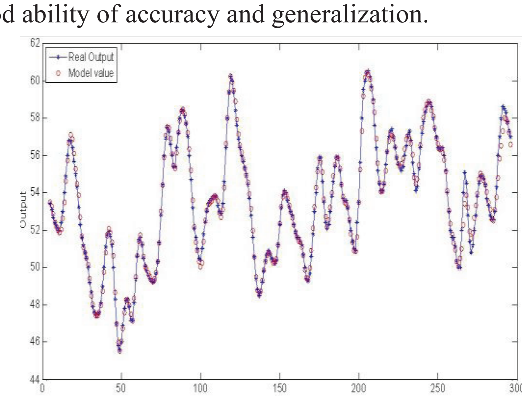

Figure 1: Simulation results of Box-Jenkins gas data.

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Modeling of the High-density Current Electron Gun System

In this section, the proposed fuzzy modeling method is applied to build the model of the high-density current electron gun system.

The LaB_6 electron gun system is used in our experiment. It mainly consists of a LaB_6 cathode electron-gun, a 40kV/500mA stabilized high voltage power supply, a high voltage isolated power supply for the LaB_6 filament, a water-cooled Faraday cup, the beam current measurement system, the beam scanning system and the vacuum system. In the experiment, all measurements are carried out under normal operating conditions. Firstly the LaB_6 cathode must be preheated for activating purpose. Then the electron beam can be adjusted by changing the filament voltage of the electron gun manually. During the test, 88 input-output data pairs (filament voltage V_f and output beam current I_e) are recorded while operating at a high DC voltage of 27.5kV.

Then

$$X = (V_f(k), V_f(k-1), V_f(k-2), I_e(k-1), I_e(k-2), I_e(k-3))$$

is defined as the input variable, I_e is defined as the output variable. The clusters number is two. After identification based on the measured data pairs, the final T-S fuzzy model is described as the following:

$$\begin{aligned} R^1 &: \textit{if } V_f(k) \textit{ is } U(167.6304, 9.7395) \textit{ and } V_f(k-1) \textit{ is } U(171.3098, 7.8544) \\ &\quad \textit{and } V_f(k-2) \textit{ is } U(173.2650, 10.0567) \textit{ and } I_e(k-1) \textit{ is } U(178.4189, 10.3739) \\ &\quad \textit{and } I_e(k-2) \textit{ is } U(159.1473, 8.7305) \textit{ and } I_e(k-3) \textit{ is } U(171.4842, 10.2915) \\ &\textit{then } y^1 = -35.2491 + 20.7265V_f(k) - 19.3770V_f(k-1) - 1.1552V_f(k-2) \\ &\qquad + 0.9061I_e(k-1) - 0.0464I_e(k-2) + 0.1552I_e(k-3) \end{aligned}$$

$$\begin{aligned} R^2 &: \textit{if } V_f(k) \textit{ is } U(172.2007, 11.4366) \textit{ and } V_f(k-1) \textit{ is } U(174.4793, 13.7267) \\ &\quad \textit{and } V_f(k-2) \textit{ is } U(169.0966, 11.8695) \textit{ and } I_e(k-1) \textit{ is } U(219.5725, 14.6949) \\ &\quad \textit{and } I_e(k-2) \textit{ is } U(182.8530, 13.0224) \textit{ and } I_e(k-3) \textit{ is } U(106.5200, 12.0994) \\ &y^2 = -7.7319 + 1.2932V_f(k) - 1.6785V_f(k-1) + 0.4316V_f(k-2) \\ &\qquad + 1.0038I_e(k-1) + 0.4563I_e(k-2) - 0.4590I_e(k-3) \end{aligned}$$

$$u(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}, \ (x \in U(c,\sigma))$$

The simulation is shown in Figure 2. We can see from the figure that the modeling error of the proposed method (MSE=0.1610) is very small and the T-S fuzzy model can approximate the electron gun systems with fewer rules and higher modeling accuracy.

CONCLUSION

In the paper, we proposed a hybrid algorithm based on QDE and GA and applied the algorithm in parameters identification. The algorithm combines the advantages of quantum computing and biological evolution. The experimental results performed on the Box-Jenkins gas furnace data show the effectiveness of the proposed approach. We successfully build the T-S fuzzy model of the LaB_6 high-density current electron gun system. The simulation shows that the final T-S fuzzy model has a good ability to approximate the electron gun system and can predict the actual output very well. Our future research aims at developing the fuzzy controller [8] based on the T-S fuzzy model of the high-density current electron gun system.

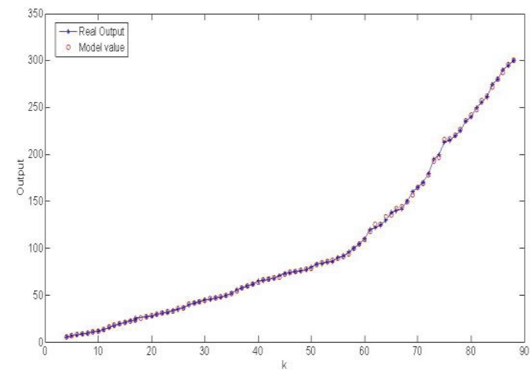

Figure 2: Simulation results of LaB_6 electron gun data.

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