A New PID-type Fuzzy Neural Network Controller based on Genetic Algorithm with improved Smith Predictor

Ruiqi Wang, Ke Li, Naxin Cui, Chenghui Zhang

Abstract—Owing to the problem of control difficulty for the complex system, which has the characteristics of the large inertia, the pure time-delay and the model uncertainty in the industrial processes, a new PID-type fuzzy neural network controller (FNNC) based on Takagi-Sugeno-Kang (TSK) inference is proposed. Real-coded Chaotic Quantum-inspired Genetic Algorithm (RCQGA) is used to optimize the membership function parameters and TSK parameter sets simultaneously with faster convergence speed and more powerful optimizing ability. The pure time-delay effect of the complex object is compensated by a Smith predictor combined with Radial Basis Function (RBF) neural network identifier. The structure and control tactics of the controller are presented and tested by simulations and experiments in the heating furnace system. The proposed algorithm, as confirmed by the results of simulation and experiment compared with the Smith-Fuzzy-PID controller, exhibits good dynamic adjustment, high steady-state accuracy, strong resistant ability to interference and good robustness.

I. INTRODUCTION

It is well known that the large inertia, the pure time-delay and the time-varying parameter are common in many industrial processes. Nevertheless, few papers are devoted to solve the problems mentioned above completely in the past. To improve the control performance, several schemes of self-tuning PID controllers are proposed in the past. Junghui Chen proposed using neural network to on-line update PID controllers for nonlinear process control [1]. But the neural network has a number of shortcomings such as determining network’s architecture with heuristic methods, existence of local minima solutions, etc. O. Cordon, F. Herrera, P. Villar, designed a PID controller by fuzzy inference [2]. The shortage of the fuzzy control is difficult to get fine control accuracy and obtain expert knowledge. Chinghung Lee proposed a PID controller by fuzzy neural network [3]. Nevertheless, the learning algorithm is not efficient.

FNNC combines the capability of fuzzy reasoning in handling uncertain information and the capability of neural network in learning from processes. It can learn to control a complex system and adapt to a wide range of variations in plant parameters. But the increasing complexity of multi-layer neural network composed by fuzzy language rules and membership functions, results in huge network structure, complex computation and control effective decline. Thereby the higher requirements of learning algorithm of control system are risen. Fuzzy neural networks are traditionally trained by using gradient-based methods, which may fall into local minimum during the learning process and has requirements on continuity or convexity of the solution space [4]-[6].

In this paper, to overcome the problems encountered by the conventional learning methods, Real-coded Chaotic Quantum-inspired Genetic Algorithm (RCQGA) algorithms are adopted to optimize the membership function parameters and TSK parameter sets of FNNC simultaneously because of their capabilities of directed random search for global optimization. In this algorithm, real chromosomes are inversely mapped to Q-bits in the solution space (The smallest unit of information stored in a two-state quantum computer is called a quantum or Q-bit). Q-bits probability guided real cross and chaos mutation are applied to real chromosome's evolution and searching [7]. Compared with the conventional Genetic Algorithm, RCQGA explores the search space with faster convergence speed and more powerful optimizing ability.

On the other hand, the useful method to overcome the effect of delay is to adopt predictive technique. The earliest predictive method is Smith predictor. However, this method is very sensitive to exact plant’s model, and its ability of disturbance-resistant is weakened. Therefore, its applications are limit because of complex uncertain industrial processes or controlled plants [8]. To overcome the mentioned problems, an improved Smith predictor combined with Radial Basis Function (RBF) neural network identifier is used to overcome the effect of delay in this paper. The RBF neural network is adopted to non-linearly approximate the plant model which is removed the effective of the time-delay.

The paper starts from the description of the control system structure. Then architecture of fuzzy neural network based on TSK inference is presented in Section III and RCQGA used...
to optimize the membership function parameters and TSK parameter sets of FNNC simultaneously is proposed in the section IV. After that the improved Smith predictor combined with RBF neural network identifier is discussed in Section V. The results of simulation and experiment are provided in sections VI and VII to demonstrate the good dynamic adjustment, high steady-state accuracy, strong resistant ability to interference and good robustness of the proposed controller. Concluding remarks are given in Section VIII.

II. THE CONTROL SYSTEM STRUCTURE

System structural drawing of control algorithm is raised in this paper, as shown in Fig.1. From the Fig.1, we see, the control system is divided into three parts: (1) an improved Smith predictor with RBF neural network identifier. (2) Based on RCOGA, FNNC is used to adjust PID controller parameters, reach the optimization of performance index and make the output neural layer correspond to three-parameter of PID control. (3) It uses increment PID control arithmetic, and the plant is close-loop controlled. And the online self-adjusting of three parameters: \( kp, ki, kd \) are realized by FNNC.

![Fig. 1. The Structure of Control System](image)

III. THE FUZZY NEURAL NETWORK BASED ON TSK INFERENCE

The new designing FNNC is illustrated in Fig.2, it is implemented by five layers feed-forward neural network.

![Fig. 2. Architecture of FNN based on TSK inference](image)

The first layer: input layer

In this layer, each neuron expresses an input variable and the number of the neuron is equal to the number of the variables in the rule base antecedent. The neuron transfers the value of the variable \( x_i \) to the next layer through the function \( F \), the outputs are represented as:

\[ o_j^{(1)} = F(x_i) = x_i, i = j \]  

(1)

Where, the layer has two neurons, which present the error \( e(t) \) and the derivative of error \( ec(t) \), respectively.

The second layer: antecedent membership function layer

In this layer, each neuron performs a membership function. The Gaussian function is adopted here as a membership function, then

\[ net_j^{(2)} = \frac{(o_j^{(1)} - m_y)}{(\sigma_y)^2} \]  

(2)

\[ o_j^{(2)} = f_j^{(2)}(net_j^{(2)}) = \exp(net_j^{(2)}) \]

Where, \( m_y \) and \( \sigma_y \) are the mean (or center) and the variance (or width) of the Gaussian function in the \( j \) th term of the \( i \) th input linguistic variable, respectively.

The third layer: rule layer

The links in the layer are used to implement the antecedent matching. The matching operation or the fuzzy AND aggregation operation is chosen as the simple PRODDUCT operation instead of the MIN operation [9]. The number of neurons is equal to the number of the fuzzy rules, then for the \( j \) th rule neuron

\[ net_j^{(3)} = \prod_i \mu_i^{(3)} o_j^{(2)} \]  

(3)

\[ o_j^{(3)} = f_j^{(3)}(net_j^{(3)}) = net_j^{(3)} \]

Where, \( \mu_i^{(3)} = 1 \), \( n \) is the number of the input variables.

The fourth layer: normalization layer

This layer has the same number of nodes as in the previous layer.

\[ net_j^{(4)} = o_j^{(3)} \]  

(4)

\[ o_j^{(4)} = \frac{net_j^{(4)}}{\sum_i net_i^{(4)}} \]

Where, \( m \) is the number of fuzzy rules.

The fifth layer: output layer

Each node in this layer has \( N + M \) number of inputs, which can be separated into two groups: \( M \) inputs from the normalization layer and \( N \) data inputs. The inputs from the normalization layer provide the firing strength of the associated fuzzy rules.

\[ net_j^{(5)} = \omega_0 x_0 + \omega_1 x_1 + \cdots + \omega_N x_N \]  

(5)

\[ o_k^{(5)} = \sum_j net_j^{(5)} o_j^{(4)}, k = 1, 2, 3 \]

Where, \( k \) is the number of outputs. \( \omega_0, \omega_1, \cdots, \omega_N \) are the weights of the \( k \) th output. \( o_1^{(5)}, o_2^{(5)}, o_3^{(5)} \) are three parameters \( kp, ki, kd \) of PID controller, respectively.
IV. FUZZY NEURAL NETWORK OPTIMIZED BY REAL-CODED
CHAOTIC QUANTUM-INSPIRED GENETIC ALGORITHM

A. The Real-coded Chaotic Quantum-inspired Genetic
Algorithm (RCQGA)

A real-coded chaotic quantum-inspired genetic algorithm
(RCQGA) is based on the chaotic and coherent characters of
Q-bits [5]. In this algorithm, real chromosomes are inversely
mapped to Q-bits in the solution space. Q-bits probability-guided real cross and chaos mutation are applied
to the evolution and searching of real chromosomes. Chromosomes consisting of the membership function
parameters \( m_y \sigma_y \) and TSK parameter sets \( \omega_{\alpha_0} \) are coded as
an adjustable vector with real number components that are
searched by the RCQGA.

B. Evolutionary process of real-coded chaotic
quantum-inspired genetic algorithm

The quantum-inspired algorithm is used in this paper to
deal with the complicated situation where a vast number of
adjustable parameters. RCQGA adopts a Multi-bit instead of
Q-bit to denote a real number. In the evolutionary process,
RCQGA Chaotic mutation and Q-bit probability crossover
was adopted to make the best of Q-bit coherence and chaos.
An initial chromosome is consisted of randomly generated
uniformity real number list

\[
P(t) = \begin{bmatrix} z_1^t & z_2^t & \cdots & z_n^t \\ \theta_1^t & \theta_2^t & \cdots & \theta_n^t \end{bmatrix}
\]

Where, \( z_i^t \) is a real number obeying uniformity, \( z_i^t \in [a_i, b_i] \). 
\( \theta_i^t \) is the \( i \)th variable phase angle of the \( t \)th Chromosome

\[
\theta_i^t = \arcsin \left( \frac{z_i^t - a_i}{b_i - a_i} \right).
\]  

So every chromosome's information can be indicated in
phase space and real number space at one time.

C. Real number crossover and chaotic mutation

Suppose some generation reserve the best individual and
phase angle denoted by \( B(t) \) and \( \theta(t) \) , this generation
population is denoted by \( P_1(t), P_2(t), \cdots, P_n(t) \) , corresponding
phase angle is denoted by \( \theta_1(t), \theta_2(t), \cdots, \theta_n(t) \) [5]. The next
generation is generated by quantum crossover

\[
\Delta \theta_i^t = \theta_i^t - \theta(t), \quad 1 \leq i \leq n
\]

\[
P(t+1) = B(t) \cos^2(\Delta \theta_i^t) + P_i(t) \sin^2(\Delta \theta_i^t).
\]  

Chaotic sequence \( C \) is adopted to limit disturb currently
generation real number chromosome. Here the chaotic
sequence is expressed by

\[
C(t+1) = 4C(t)(1 - C(t)) \\
C(t) \neq 0.5 \text{ and } 0 < C(t) < 1.
\]

Limiting amplitude of chaotic sequence is adjusted by the
global minimal fitness value function. The disturb sequence amplitude can be denoted by

\[
\lambda_i = \exp \left( \frac{b - f(Z_i)}{b} \right)
\]

\[
\Delta \theta_i = \lambda_i \cdot C(i).
\]

In this way, we can achieve all population mutation by

\[
\begin{pmatrix}
\hat{Z}_i^t \\
\hat{\theta}_i^t
\end{pmatrix} =
\begin{pmatrix}
\cos(\Delta \theta_i) & -\sin(\Delta \theta_i) \\
\sin(\Delta \theta_i) & -\cos(\Delta \theta_i)
\end{pmatrix}
\begin{pmatrix}
Z_i^t \\
\theta_i^t
\end{pmatrix}
\]

D. The detailed process of RCQGA

Step 1: initial population \( P(t) \) : confirms the size of
population \( n \), iteration generation \( G \), applies randomly
uniformity distributed function generate \( n \) real number
chromosome and all initial population in all solution subspace,
calculates every variable phase angle \( \theta_i^t \) of every
Chromosome by Eq.(7).

Step 2: evaluate all the individuals of population by fitness
function and reserve the best solution. If the fitness value is
better than the global optimization value, acquire the
individual's information as the global best solution; otherwise
go on evolution in subpopulation.

Step 3: reserve the best individual. If the stopping condition
is satisfied then reserve the individual of coincidence global
optimization value, otherwise go on to the following steps
[5].

Step 4: apply Eq.(8) to perform selection and quantum
crossover for \( P(t) \) to generate \( P(t+1) \) in the subpopulation.
Bad fitness individuals of \( P(t+1) \) apply Eqs.(10) and (11) to
perform chaotic mutation.

Step 5: let \( t = t + 1 \) and go back to step 2 until the stopping
condition is satisfied. The following flowchart illustrates in
details the process of RCQGA.

\[
\lambda_i = \exp \left( \frac{b - f(Z_i)}{b} \right) \\
\Delta \theta_i = \lambda_i \cdot C(i).
\]

E. Tuning the membership function parameters and TS
parameter sets simultaneously

The Real-coded Quantum-inspired Genetic Algorithm is
used to learn the center value \( m_y \), the width coefficient \( \sigma_y \)
and the weight value \( \omega_{\alpha_0} \) of FNNC shown in Section III.
To evolutionarily obtain the adjustable parameters, the
membership function and TSK parameter sets are coded as a
vector with real number components.

For the N pattern data \((X_k, y_k)\) \((k = 1, 2, \cdots, N)\). We consider \(\hat{y}_k\) as the actual output of the network and the target error function \(e(t) = \frac{1}{2} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2\). The performance of each chromosome is evaluated according to its fitness. After generations of evolution, it is expected that the genetic algorithm converges, and a best chromosome with largest fitness (or smallest error) representing the optimal solution to the problem is obtained. There are three aspects to measure the publicity degree of a control system, accuracy, robust, and fast. And the rise time \(t_r\) shows the fast of the system [10].

Here control quantity, error and the rise time are chosen as the constraint conditions of RCQGA optimization. Objective Function is

\[
J = \int_0^\infty \left( \alpha_1 |e(t)| + \alpha_2 \dot{\hat{y}}(t) + \alpha_3 |y(t)| \right) dt + \alpha_4 \cdot t_u.
\]

(12)

Where, \(\alpha_1, \alpha_2, \alpha_3, \alpha_4\) are constants, \(\alpha_4 >> \alpha_1, \dot{y}(t) = y(t) - y(t-1), u(t)\) is the output of controller.

Suppose the fitness function equals to the reciprocal of \(J\), we can find the optimal parameters for fuzzy neural networks by RCQGA.

V. THE IMPROVED SMITH PREDICTOR WITH RBF NEURAL NETWORK IDENTIFIER

Radial Basis Function (RBF) neural network has been used extensively in the areas of pattern recognition, system modeling and identification [11]. RBF network form a special architecture of neural network, which is characterized by several main advantages: the simplicity of its structure, faster learning algorithm, and better approximation capabilities.

In this paper, an improved Smith predictor with Radial Basis Function (RBF) neural network identifier, whose initial weights and biases are obtained by off-line training method, is adopted. It can compensate the large delay of complex uncertain industrial processes or controlled plants. The RBF neural network is adopted to non-linearly approximate the plant model which is removed the effective of the time-delay.

We can derive the delay time \(\tau\) according to the response curve. Then shift the input sample sequence with time delay \(\tau\) to remove the effective of time-delay and sample 100 sets of input and output data. After that train RBF neural network with the selected data sets to get the initial weights and bias of network. The simulation with MATLAB about RBF neural network is done. The training error is shown in Fig.4.

VI. SIMULATION RESULTS AND ANALYSIS

Owing to the large inertia, the pure time-delay and the model uncertainty in the industry control, the heating furnace is typical delegate. To verify the effectiveness of proposed algorithm, a simplified model of heating furnace is adopted to simulate with MATLAB, whose transfer function is described by

\[
G(s) = \frac{4}{1 + 472s} e^{-224s} \text{ (13)}
\]

The inputs of FNCC are the error \((e)\) and error change \((ec)\), and the outputs are three parameters of PID controller, \(kp, ki, kd\). The population size of Genetic algorithm is 50. The crossover probability \(Pc\) is 0.88 and mutation probability \(Pm\) is 0.05. After 500 iterations of learning, the curve of objective function and optimized input membership function is shown in Fig.5, Fig.6 and Fig.7, respectively. In the Figs.(6) and (7) solid lines are distribution of member function of smith-Fuzzy-PID and dotted lines are drawn after learning by RCQGA.

The set input is 100 and the same interference is composed on the model at the time of 6000s which lasts 500s. The output results of the proposed algorithm and Fuzzy-PID with conventional Smith predictor (smith-Fuzzy-PID) are shown in Fig.8.

Fig. 5. Comparison of the optimization process of Objective Function between RCQGA and QGA.
It is clearly seen that RCQGA has exciting advantages over conventional QGA of the convergence speed and optimizing ability. From the simulation results of the example, the proposed algorithm has the characteristics of good dynamic adjustment, high steady-state accuracy and strong resistant ability to interference, compared with Smith-Fuzzy-PID control algorithm.

VII. EXPERIMENTAL RESULTS AND ANALYSIS

Based on the industry principle of the big inertia, the pure time-delay and the model uncertainty, the temperature control system platform for heating furnace is built, as shown in Fig.9. It’s a set of four-zone heating device, each zone has one 800W heating rod and the first zone has one 300W heating rod used to simulate the interference. In each heating zone, according to the distance of temperature sensor from the heating rod, the different time-delay and inertia of controlled object is simulated.

We apply the proposed algorithm in the temperature control experiments. The basic characteristics of dynamic adjustment, strong resistant ability to interference and robustness are discussed, compared with those of Smith-Fuzzy-PID controller.

(a) The object is the first heating zone. The set temperature is 100 °C and interference is imposed on at the time of 6000s which lasts 500s. The output results are shown in Fig.10 and Fig.11. The vertical axis is in 0.1 °C as a unit, and the horizontal axis in seconds. The comparison between the proposed algorithm and Smith-Fuzzy-PID is shown in TABLE. I.

(b) The object is the second heating zone. The set temperature is 100 °C. The output results are shown in Fig.12 and Fig.13. The comparison between the proposed algorithm and Smith-Fuzzy-PID is shown in TABLE. II.
We can see that the conventional Smith-Fuzzy-PID controller is based on precise model of the controlled objects, so the control effect is unsatisfactory when the object is lack of precise model and has time-varying parameters or large time-delay. Furthermore, due to lack of experience of experts or inaccurate in Fuzzy controller, the PID parameters can not achieve optimal. But owing to the system mentioned above, the PID-type FNNC based on RCQGA with improved Smith Predictor has the characteristics of better dynamic adjustment, higher steady-state accuracy, stronger resistant ability to interference and good robustness.

**VIII. CONCLUSION**

A new PID-type fuzzy neural network controller (FNNC) based on TSK inference is proposed in this paper. The Real-coded Chaotic Quantum-inspired Genetic Algorithm (RCQGA) is used to optimize the membership function parameters and TSK parameter sets of FNNC simultaneously with faster convergence speed and more powerful optimizing ability. The pure time-delay effect of the controlled object is compensated by improved Smith predictor combined with Radial Basis Function (RBF) neural network identifier. It is clearly seen that the proposed algorithm has the characteristics of good dynamic adjustment, high steady-state accuracy, strong resistant ability to interference and good robustness. It solves the problems of the large inertia, the pure time-delay and the time-varying parameter simultaneously in industrial processes. The solution is applied on the production line of industrial extrusion blow molding machine. Extensive research effort has been devoted at the stability criteria in the fitness function evaluation of GA and the optimization of the FNNC design.

**ACKNOWLEDGMENT**

This work was supported by the National Nature Science Foundation of China (60874016) and the Research Fund for the Doctoral Program of Higher Education of China (200804220047).

**REFERENCES**


