第 13 卷第 6 期
1996 年 12 月

控制理论与应用
CONTROL THEORY AND APPLICATIONS

Vol. 13, No. 6
Dec., 1996

A Hybrid Intelligent Control for Industrial Rotary Kiln Plant *

WANG Yaonan

(Department of Electrical Engineering, Hunan University • Changsha, 410082, PRC)

Abstract: This paper presents a new hybrid intelligent control (HIC) that combines the techniques of expert control and fuzzy neural network. The HIC consists of knowledge base, information pre-processor, and intelligent coordinator in a hierarchical structure. The basic idea is to give an effective control strategy to complex controlled plant using a knowledge-based coordinator so as to achieve the desired performance. The results of simulation as well as temperature control for industral rotary kiln furnace were performed to demonstrate the feasibility and effectiveness of the proposed scheme.

Key words: expert system; fuzzy neural network; intelligent control; temperature control

1 Introduction

Industral rotary kiln burning process is a typical nonlinear and strongly intercoupled controlled plant. The plant can not be satisfactorily controlled by conventional control methods. Recently, a considerable number of reseraches on the intelligent control system with a human-like inference and adaptation ability have been proposed[1]. Usually, there may be two representative approaches in designing the intelligent control. One approach is the application of fuzzy expert control which can emulate human operators. The other approach is the use of neural network which has the distinct learning and adaptive capabilities.

In the fuzzy expert control, the precise mathematical model of a plant may not be required. It makes use of the theory of fuzzy set to process the linguistic form of "if-then" control rule. An existing problem is that it is not always possible to derive a good set of decision rules heuristically. For example, the shape and location of membership function for each fuzzy variable must be obtained by heuristic approach. Also an expert can not easily to construct the efficient control rule base. Use of neural networks to learn system behavior seems to be a good way to solve above mentioned problems associated with fuzzy expert control design. In the neural network, knowledge acquisition can be automatically done by learning the input-output relation. The neural network has the charateristics of

* This research is supported by sate key pattern Recognition Labortatory Foundation, Chinese academy of science.
Manuscrpt received Jun, 20, 1995, revised Jan, 10, 1996.

high parallelism, fault-tolerance, adaptive and learning ability . But there exist some problem in the neural control. Firstly it is not easy to decide the optimal number of layers and neurons. Secondly the learning algorithm of the neural network has the low convergence speeds, especially, the neural network takes a numerical computation rather than symbolic computation, the processing way makes it difficult to interpret the obtained results in the language.

In order to seek for more powerful and effective control strategy for rotary kiln plant, this paper proposes a hybrid intelligent control scheme integrating expert system techniques and fuzzy neural network learning methods. The proposed control scheme consists of the expert controller (EC), the fuzzy neural controller(FNC), and the knowledge based coordinator(KBC). The KBC, is a high-level coordinator with a hierarchical structure. The EC and FNC are low-level real-time controllers. The detailed structure parameters of the low-level controllers are not required by the KBC, thus allowing individual controller to be designed independently. This implies that the designed controllers can be coordinated to perform more sophisticated tasks than originally intended.

2 The Design of the Hybrid Intelligent Control System

2.1 The Structure of the Hybrid Intelligent Control

For industrial rotary kiln plant, the hybrid intelligent control (HIC) is proposed and shown in Fig. 1.

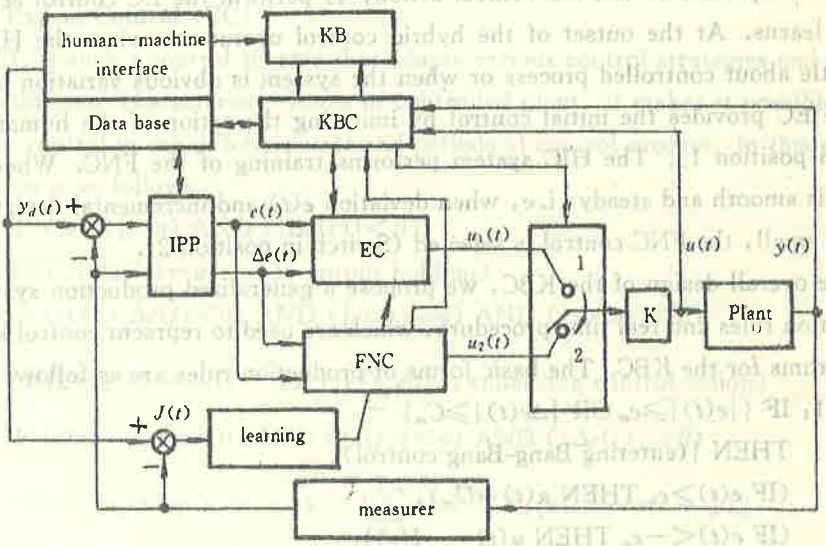

Fig. 1 The structure of the hybrid intelligent control(HIC)

The HIC consists of expert control (EC), knowledge base (KB), fuzzy neural controller (FNC), information pre-processor (IPP), and real-time knowledge based coordinator (KBC). The KBC is responsible for a goal-oriented search in its knowledge base and the overall system stability. It first determines how to achieve the desired control strategy, expert control algorithms and initial control task of the plant by searching for a goal in its knowlege base according to the characteristics of system performance. Here, the error and error increment of the plant output, and the quality of a step response are commonly used to evaluate system performance. It then teaches fuzzy neural control how to accomplish the same control of the EC. Following initial training, the FNC executes the control action. The KBC continuously evaluates the FNC performance, and the EC executes the control action when the errors duo to changes in the plant or executing environment require retraining of the FNC. Furthermore, the EC component must ensure the tasks of control completion while the FNC are relearning. The KBC does not monitor the FNC when the FNC component gradually guarantees the global asymptotic stability by itself, so that the KBC reduces many tasks of searching and reasoning, and the control performance of the overall hybrid intelligent control system is improved.

2.2 Design of the Knowledge-Based Coordinator (KBC)

The purpose of hybrid coordination control is to combine the technique of expert control (EC) and fuzzy neural control (FNC) so as to achieve the desired real-time control. The form of the KBC is a production system and used forward chainer for an inference engine. The KBC attempts to select the best control scheme in accordance with its knowledge about the process.

The main tasks of the KBC are: 1) Knowledge acquisition and learning; 2) training of the FNC; 3) optimizatin of FNC control action; 4) perform the EC control action while the FNC learns. At the outset of the hybrid control operation, when the HIC system knows little about controlled process or when the system is obvious variation of working state, the EC provides the initial control by imitating the action of the human operator (switch in position 1). The HIC system performs training of the FNC. When working condition is smooth and steady, i.e, when deviation $e(t)$ and incremental deviation $\Delta e(t)$ are rather small, the FNC control is selected (Switch in position 2).

In the overall design of the KBC, we propose a generalized production system based on production rules and real time procedure, which are used to reprsent control knowledge and algorithms for the KBC. The basic forms of production rules are as follows:

Rule 1: IF $\{|e(t)|\geqslant e_m$ OR $|\Delta e(t)|\geqslant C_m\}$
THEN {(entering Bang-Bang control),
(IF $e(t)>e_m$ THEN $u(t)=U_m$),
(IF $e(t)<-e_m$ THEN $u(t)=-U_m$)}

Rule 2: IF $\{(e_s<|e(t)|\leqslant e_m)$ OR $(C_s<|\Delta e(t)|\leqslant C_m\}$
THEN {(set the EC control action) AND (initial training weights of the FNC) AND $(u(t)=u_1(t))\}$

Rule 3: IF $\{(|e(t)|\leqslant e_s)$ AND $(|\Delta e(t)|\leqslant C_s\}$
THEN {(set the FNC control) AND (update weight of the FNC) AND (stop

the KBC the search) AND $(u(t)=u_2(t))\}$

Rule 4: IF $\{(J<\varepsilon)$ AND $(|e(t)|<e_s)\}$

THEN {(stop the KBC the search) AND (set the FNC control action) AND (stop the learning of the FNC) AND $(u(t)=u_2(t))\}$

Rule 5: IF $\{(J\geqslant\varepsilon)$ AND $(|e(t)|<e_s)\}$

THEN {(entering the FNC control) AND (modify weight of the FNC) AND $(u(t)=u_2(t))\}$

Rule 6: IF $\{(J\leqslant\varepsilon)$ AND $(|e(t)|>e_s)\}$

THEN {(set the EC control action) AND (the real-time learning of the FNC) AND $(u(t)=u_1(t))\}$

Rule 7: IF {(The learning time $>N$) AND $(|e(t)|>e_s)\}$

THEN {(stop the iterative operation) AND (choose initial weights value, $w(o)=w(t)$) AND (set the EC control) AND $(u(t)=u_1(t))\}$

where $e(t)=y_d(t)-y(t)$, $\Delta e(t)=e(t)-e(t-1)$, $J=\frac{1}{2}\sum_{i=1}^{n}(y_d-y_i)^2$, e_s and e_m donote deviation bounds, c_s and c_m indicate incremental deviation threshold valuse, ε is a small positive constant, $u(t)$ is the input to the plant, $u_1(t)$ is the EC control output, $u_2(t)$ is the FNC control output, $y(t)$ is the output value of the plant, $y_d(t)$ is the desired value.

2.3 The Expert Control (EC)

The EC is such a control scheme that adopts various control strategies and modes according to different characteristic states of controlled plant. It makes it possible to adopt appropriate control in the different state and periods at control process. In this paper, the EC algorithm is as follows

EC_1: IF $(|e(t)|<\alpha)$ AND $(|\Delta e(t)|<\beta)$

THEN $(u_1(t)=u(t-1)$, output holding)

EC_2: IF $(e(t)\cdot\Delta e(t)<0)$ AND $(|e(t)|\geqslant\alpha)$ AND $(|\Delta e(t)|<\beta)$

THEN $u_1(t)=u_1(t-1)+\lambda\sum_{i=1}^{n-1}e_i(t)$, enhancing control action)

EC_3: IF $(e(t)\cdot\Delta e(t)<0)$ AND $(|e(t)|<\alpha)$ AND $(|\Delta e(t)|\geqslant\beta)$

THEN $(u_1(t)=u_1(t-1)+\lambda\sum_{i=1}^{n-1}e_i(t)+K_d[e(t)-e(t-1)]$

EC_4: IF $(e(t)\cdot\Delta e(t)\geqslant 0)$ AND $(|e(t)|<\alpha_1)$

THEN $\{u_1(t)=u_1(t-1)+K_p[e(t)-e(t-1)]+\frac{T_s}{T_i}e(t)+\frac{T_d}{T_s}(e(t)-2e(t-1)+e(t-2))]$, PID control}

EC_5: IF $(e(t)\cdot\Delta e(t)\geqslant 0)$ AND $(|e(t)|>\alpha_1)$

THEN $\{u_1(t)=u_1(t-1)+K_d[e(t)-e(t-1)]\}$

In above rules, λ indicates forgetting factor, K_p is the proportional amplification coefficient; K_d is the differential coefficient, α, α_1 and β are threshold values.

3 Design of the FNC

3.1 Fuzzy Neural Controller (FNC)

In the Figure 2 shows the basic structure of the fuzzy neural control. The fuzzy neural network controller is a three-layered Gaussian base function neural with two inputs variables (x_1, x_2) and one output control increment $u(x_1, x_2)$. Let's assumed each of the input variables has seven membership function. The term set of each fuzzy variable is NB, NM, NS, ZO, PS, PM, PB, where NB, NM, … are abbreviations for the commonly used names "Negative Big", "Negative Medium", and so on.

The Layers (Ⅰ)~(Ⅱ) in Fig. 2 correspond to the antecedent part of the fuzzy control rules, and the layers (Ⅲ)~(Ⅳ) correspond to the conclusion part. The input-output relationships of the FNC units are defined as

Ⅰ) output units $O_l^{(1)} = x_l,\ l = 1, 2$ (1)

Ⅱ) output units $O_{lk}^{(2)} = \exp[-(\frac{x_l - a_{lk}}{b_{lk}})^2],\ k = 1, \cdots\cdots, 7$ (2)

Ⅲ) output units $O_{ij}^{(3)} = O_i^{(2)}(x_1) \times O_j^{(2)}(x_2)$

$$= \exp\{-[(\frac{x_1 - a_i}{b_i})^2 + (\frac{x_2 - a_j}{b_j})^2]\},\ i \in I, j \in J = I \quad (3)$$

Ⅳ) output units $O^{(4)} = u(x_1, x_2) = \sum_{i \in I} \sum_{j \in J} W_{ij} \times O_{ij}^{(3)}(x_1, x_2)$ (4)

where x_l is the input pattern $(e(t), \Delta e(t))$, $u(x_1, x_2)$ is the output of the network, W_{ij} is the connective weights, a_i and b_i are the center and shape factor of the Gaussian function.

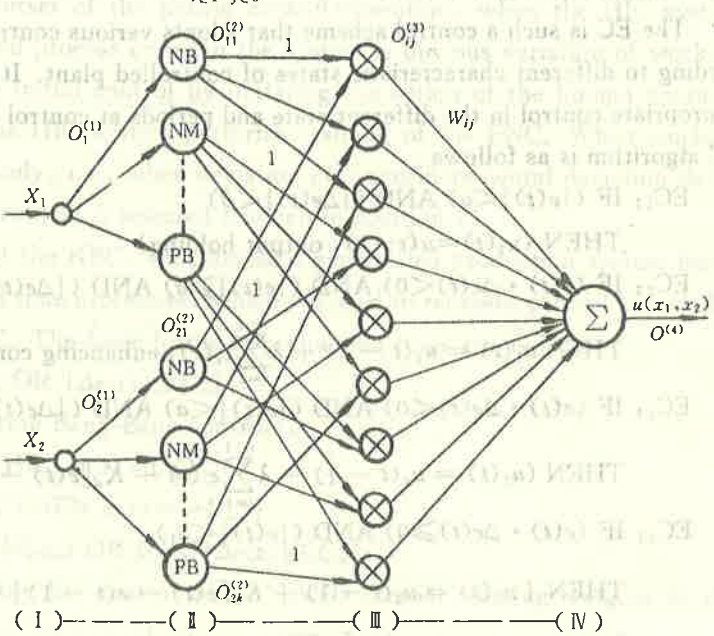

Fig. 2 The structure of the fuzzy neural control (FNC).

3.2 Leaning algorithm

After construction the antecedent part and conclusion part of fuzzy rule by the FNC, next step is to train the connection weights (W_{ij}) of the FNC and turn the membership function parameters (a_i, b_i) to the anteceedent part. In order to obtain desired control in the FNC, the algorithm[2] based on Davidon's minimization approach is used for learning to minimize difference between the desired output and the actual output of the plant. An error function to be minimized is defined as follows:

$$J_e = \frac{1}{2}\sum_{i=1}^{m} E_i^2(t) = \frac{1}{2}\sum_{i=1}^{m}(y_d(t) - y(t))^2 \tag{5}$$

then, the weights W_{ij} and parameters (a_i, b_j) in the FNC are updated as follows.

$$W_{ij}(t+1) = W_{ij}(t) - H_{ij}E(t)\cdot\nabla E(W_{ij})/\beta_{ij}(t), \tag{6}$$

$$a_i(t+1) = a_i(t) - H_iE(t)\cdot\nabla E(a_i)/\beta_i(t), \tag{7}$$

$$b_j(t+1) = b_j(t) - H_jE(t)\cdot\nabla E(b_j)/\beta_j(t), \tag{8}$$

where

$$H(t+1) = \lambda^{-1}[H(t) - H(t)\nabla E\nabla E^T H(t)/\beta(t)], \tag{9}$$

$$\beta(t+1) = \lambda + \nabla E^T H(t)\cdot\nabla E. \tag{10}$$

$E(t) = y_d(t) - y(t)$, $H(t)$ is the Hessian matrix, the recursive updates of $H(t)$ is of rank 1. $\nabla E(W_{ij})$, $\nabla E(a_i)$, $\nabla E(b_j)$ are the first derivatives of $E(t)$ with respect to W_{ij}, a_j and b_j, respecvely. They can be drived as follows

$$\nabla E(W_{ij}) = \frac{\partial E}{\partial W_{ij}} = -[y_d(t) - y(t)]\cdot\left(\frac{\partial y(t)}{\partial u(t)}\right)\cdot O_{ij}^{(3)} = \delta_j\cdot O_{ij}^{(3)} \tag{11}$$

where

$$\delta_j = -[y_d(t) - y(t)]\frac{\partial y(t)}{\partial u(t)}, \tag{12}$$

$$\nabla E(a_i) = \frac{\partial E}{\partial y(t)}\cdot\frac{\partial y(t)}{\partial u(t)}\cdot\frac{\partial u(t)}{\partial a_i} = -2\delta_j\cdot W_{ij}(x_i - a_i)\cdot O_{ij}^{(3)}/b_j^2 \tag{13}$$

$$\nabla E(b_j) = \frac{\partial E}{\partial y(t)}\cdot\frac{\partial y(t)}{\partial u(t)}\cdot\frac{\partial u(t)}{\partial b_j} = -2\delta_j\cdot W_{ij}(x_i - a_j)^2\cdot O_{ij}^{(3)}/b_j^3 \tag{14}$$

Note that we evaluate the Jacbian $\frac{\partial y(t)}{\partial u(t)}$ in equation (12)as

$$\frac{\partial y(t)}{\partial u(t)} \approx \frac{y[u(t+1)] - y[u(t)]}{u(t+1) - u(t)}. \tag{15}$$

4 System Simulation and Temperature Control for Rotary Kiln

4.1 Examples of Simulation

In system simulation, the FNC is constructed by the 2-14-49-1 neuron. We used the 49 fuzzy control rules[4]. The constant of the control rules are set as the initial connection weights $W_{ij}(0)$ for the FNC. The center points of the fuzzy sets NB, NM, NS, ZO, PS, PM, PB, $a_i(0)$ $(i=1,2\cdots7)$ are $-6, -4, -2, 0, 2, 4, 6$, respectively. The width values of the membership function, $b_j(0)$ are all unity so as to equally allocalte seven fuzzy set on the range $[-6, 6]$, here, $b_j(0) = 2.5^2$.

Example 1 The controlled plant is a nonlinear system with a stochastic disturbance acting on it. The plant is in the form:

$$y(t) = \frac{y(t-1)e^{-y(t-1)} + u(t-1)}{1 + u(t-1)e^{-y(t-1)}} + \omega(t)$$

where $\omega(t)$ is a white noise with 0.15 standard variance. The parameters are selected as KBC: $e_m = 15$, $e_s = 1.2$, $\varepsilon = 0.02$, $\alpha = 4$, $\alpha_1 = 1.5$, $\beta = 0.2$, $\lambda = 0.45$.

The response of the plant is illustrated in Fig. 3.

Example 2 The plant is a nonlinear system with time delay, i. e.

$$y(t)=\frac{y(t-1)y(t-2)y(t-3)y(t-4)u(t-4)-y(t-1)y(t-2)y(t-3)u(t-4)+u(t-5)}{1+y^3(t-3)+y^2(t-4)}$$

where time delay $d=4$, Fig. 4 illustrates the step response curves of the HIC control.

4. 2 Temperature control of the rotary kiln furance

After system simulations procedure, the proposed the HIC control scheme is applied to the temperature control of industrial rotary kiln. The temperature control system can be divide into five main components: the rotary kiln furance, the temperature sensor module, the programmable input-output interface board, the microcomputer(80386) and the actuator. The interface circuit board consists of an analogue-to-digital (A/D)convertor, a digital-to-analogue (D/A) convertor and a programmable peripheral interface device. In the experiment, the sampling time is 30 seconds, and the setpoint are 500℃, 1000℃, respectively. Fig 5 illustrates the temperature response of the kiln furnace. The HIC system can give co-ordination control of the EC and the FNC. When the system knows little about controlled process, the expert controller provides the initial control by imitating the actions of the human expert operator. The weights of the fuzzy network are convergent, a good control result can be obtained by the FNC.

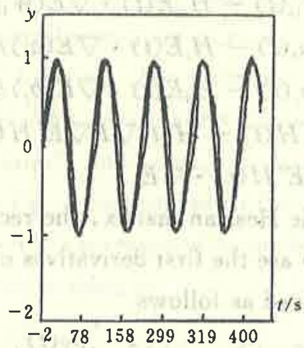

Fig. 3 Output of the plant for Example 1

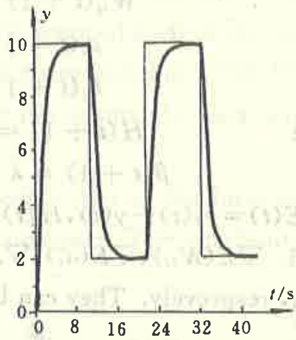

Fig. 4 Output of the plant for Example 2

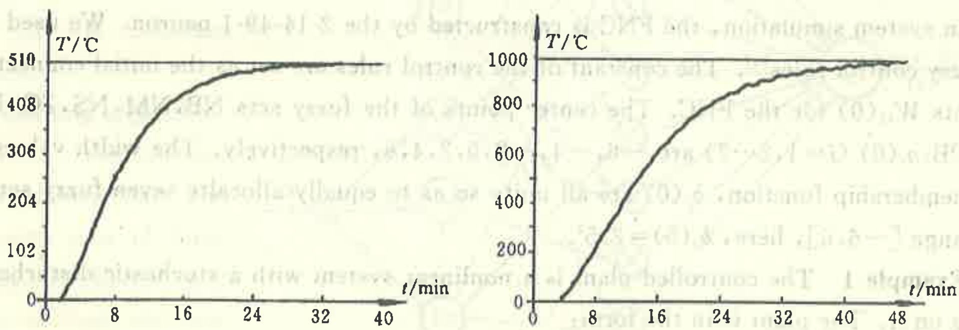

Fig. 5 The temperature response of the kiln furnace

5 Conclusion

A new hybrid intelligent control system based on the expert control and the fuzzy neural networks has been proposed in this paper. The simulation results and the practical application of the industral rotary kiln furnace show that the proposed HIC system has two important characteristics of adaptation and learning. From the results of the experiments, it can handle some nonlinear, slow time-varying, and stochastic disturbed process control problems, and can obtain good control performance. The proposed control scheme can be also used in complex process control.

References

[1] Lee Chungchien. A self-Learning Rule-Based Controller Employing Approximate Reasoning and Neural Net Concepts. Int. J. Intelligent Systems, 1991, 6: 71—93

[2] Davidon, W. C.. New Least-Square Algorithms. Optimization Theory and Application, 1976, 18(2): 187—197

[3] WANG Yaonan. Intelligent Control Integrating Expert System and Neural Networks. Int. J. Advances in Modelling & Analysis AMSE Press, 1994, 43(4): 23—28

[4] WANG Yaonan. An Adaptive Control Using Fuzzy Logic Neural Network and its Appicantions, Control Theory and Application, 1995, 12(4): 437—444

一种工业回转窑炉的混合智能控制

王耀南

(湖南大学电气工程系·长沙,410082)

摘要: 本文提出一种专家控制与模糊神经网络控制相结合的新型混合智能控制(HIC). 这种 HIC 控制系统由知识库、信息预处理器、智能协调控制器组成. 计算机仿真和实际的工业回转窑炉温控实验结果表明, HIC 具有良好的控制性能.

关键词: 专家系统; 模糊神经网络; 智能控制; 温度控制

本文作者简介

王耀南 1958 年生. 现湖南大学电气工程系教授, 博士生导师. 主要从事计算机应用、工业自动化、人工智能、智能控制理论与应用、计算机视觉与图像处理的研究.