FUZZY NEURON HYBRID CONTROL FOR CONTINUOUS STEEL CASTING

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Abstract: The fuzzy neuron hybrid control method is proposed for mold level control of the continuous steel casting in this paper. The dynamic characteristics of the continuous steel casting process is described. To the plant with big uncertainties and grave nonlinearities, the fuzzy neuron hybrid control system is set up and the new model-free controller is designed. In this control system, the fuzzy neuron hybrid controller is constructed by the fuzzy PI controller and the neuron controller, the gain of the neuron controller is tuned by using a fuzzy algorithm. The simulation tests of mold level control are made under various conditions with different casting speeds, new gate valve and old gate valve, changing in the valve position loop gain. The results demonstrate that the new controller has good performance, very strong robustness and adaptability.

Keywords: continuous casting, mold level control, fuzzy neuron hybrid control, model-free control

1. INTRODUCTION

Today the mold level control of the continuous casting has attracted much attention from iron and steel producers, because the performance of mold level control and the surface quality of the final product are highly correlated (Barron, *et al.* 1998). However, to obtain an accurate level control of the mold level is not an easy task for the control system design since there exist grave nonlinearities and big uncertainties in this process.

To deal with the problem of mold level control, conventional control approaches have been investigated for improving performance of mold level controller. Kiupel, *et al.* (1994) proposed a parallel control structure with a complementary fuzzy logic controller to improve the performance of conventional PI mold-level control. Graebe, *et al.* (1995) discussed the careful modeling of a continuous steel casting process, implemented and evaluated three control strategies that consist of a PI controller with high frequency dither, a linear and a nonlinear cascade controller. Barron, *et al.* (1998) developed a discrete feedback control laws under model uncertainties. Kong, *et al.* (1992) dealt with the adaptation of the gain of a PID controller according to casting parameters such as slab width or extraction speed. The main drawbacks of these controllers are that they work only for one particular type of static nonlinearity and rely on the exactly mathematical modeling of the plant. The common feature of those control methods is to compensate a particular characteristic of the continuous casting process such as time variations, nonlinearities, disturbances, *etc*. Therefore, they are difficult to obtain satisfactory performance.

In addition to conventional control methods, many researchers have paid attention to using fuzzy system technique and neural networks to tackle the problem of mold level control. Being simple to design and implement, the former is more practical than the latter. Dussnd, *et al*. (1998) designed a fuzzy controller using the expert knowledge for controlling the process during disturbed phases. Joo, *et al*. (2002) developed a fuzzy control scheme to regulate the molten steel level in the strip casting process where the parameters of the fuzzy control were stably adapted by using the Lyapunov-stability theory. Bedi, *et al.* (1999) presented a method to the fuzzy sliding mode control for mold level, in which fuzzy rules were used to change the slope of a sliding hyperplane to obtain faster reaching time of the system trajectory. Having the parallel processing and learning capabilities, neural networks may be a better way to design control systems for nonlinear processes. However, the weaknesses of neural networks, such as complex training algorithm, slow convergence and local minima, limit their applications in mold level control. Hence, Wang, *et al.* (1991) proposed the adaptive neuron model and its learning strategy for control. The neuron model-free control method is very simple and can give good performance. Being used in hydraulic turbine generators and some industrial processes (Wang, *et al.* 1993; Wang, *et al.* 1994), the neuron control has reached its success. By combining a fuzzy controller with the neuron controller, the fuzzy neuron hybrid control method is proposed for mold level control of the continuous steel casting process in this paper.

This paper is organized as follows. Section 2 describes the continuous steel casting process and modeling. Section 3 designs the fuzzy neuron hybrid control system for mold level control, the hybrid controller is constructed by the fuzzy PI controller and the neuron controller, and the gain of the neuron controller is tuned by a fuzzy algorithm. The simulation test results are given in section 4. The conclusions are summary at section 5.

2. THE PROCESS DESCRIPTION AND MODELING

The continuous steel casting is the process of molding molten metal into solid blooms. A schematic diagram of the process is shown in Fig.1 (Graebe, *et al.*, 1995), where the ladle [a] is acting as a reservoir for the molten metal and the valve [c] regulating its flow into the mold [d]. The tundish [b] acts as an intermediate reservoir that retains a constant supply to mold when an emptied ladle is being replaced by a full one. The cast metal undergoes two cooling processes. Primary cooling occurs in the mold and produces a supporting shell around the still liquid center [e]. This semi-elastic strand is then continuously withdrawn from the mold through a series of supporting rolls containing the secondary cooling stage [f, g], after which the newly strand is cut into blooms by torch cutters. [i] is the mold level, it can be measured by a mold level sensor.

Being complex, with big uncertainties, nonlinearities and running under a high temperature condition, it is hard to model the continuous steel casting process. This caster mainly consists of hydraulic actuators, a slide gate valve and a mold.

The hydraulic actuators are prone to nonsmooth nonlinearities such as slip-stick friction and backlash.

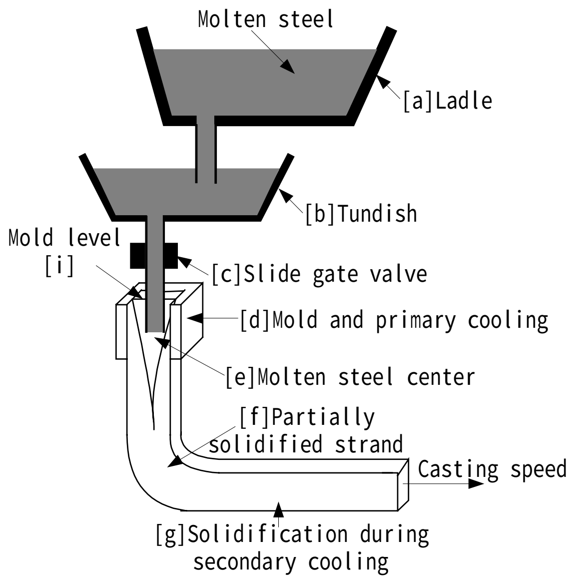

Fig.1 Simplified continuous steel caster

The nonsmooth nonlinearities can be compensated by a high bandwidth controller (Graebe, *et al*., 1995). Thus, the approximate transfer function of the valve position loop is $k_v/(\beta s+1)$, where k_v, β are the parameters of the loop.

The slide gate valve consists of three identical plates, with the outer two fixed and the center one sliding in between (in Fig.2). All plates contain an orifice of radius R, so that the effective flow area of matter into the mold is determined by the overlapping orifice areas. When the center plate is at position x_v, elementary trigonometric considerations show that the effective flow area is given by

$$A_v = R^2(\alpha - \sin(\alpha)) \quad (1)$$

$$\alpha = 2\cos^{-1}(1-\frac{x_v}{2R}), \quad 0 \le x_v \le 2R \quad (2)$$

The process also has smooth nonlinearities due to the flow dynamics and valve geometry. The nonlinear model is given by (Graebe, *et al*., 1995)

$$\frac{dy(t)}{dt} = \frac{A_v}{A_m} c_v c_c \sqrt{2gh} - u_1 \quad (3)$$

where A_m is the casting cross sectional area, c_v is a velocity coefficient dependent on the viscosity of the steel grade being cast, c_c is a coefficient of contraction with value 0.6 for a new valve with sharp edges and 0.95 for worn valve with rounded edges, and h the height of matter in the tundish. Therefore, this plant has time variations.

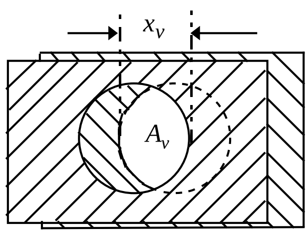

Fig. 2. Slide gate valve

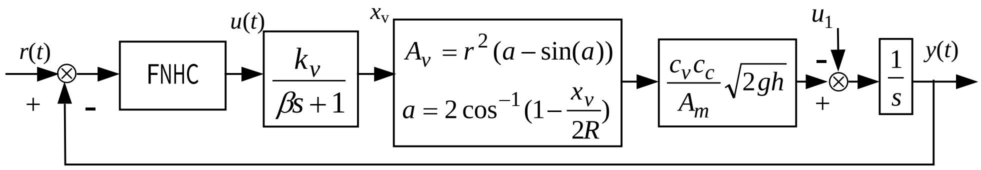

Fig.3. Mold level control system for the continuous steel casting

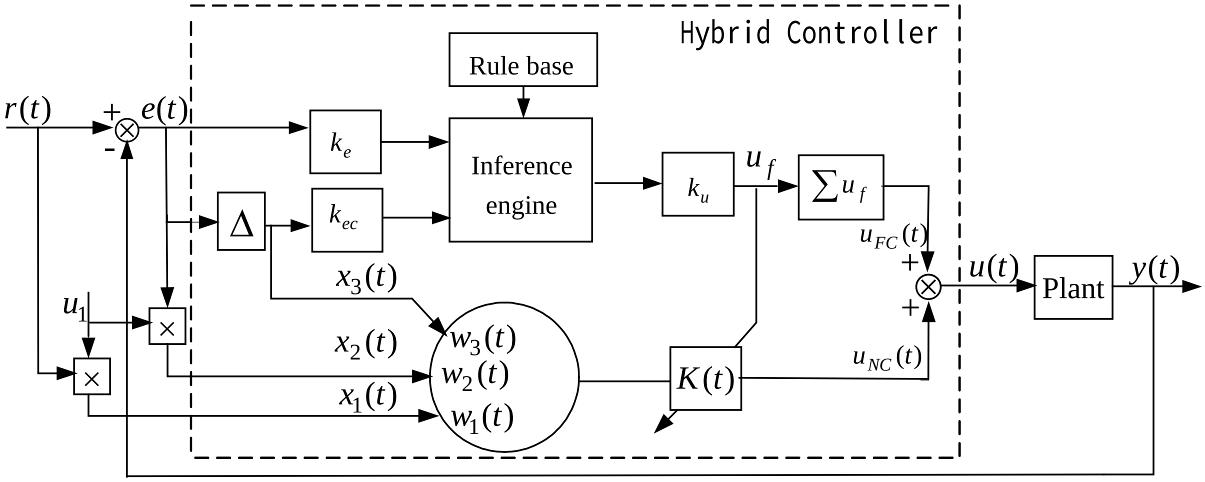

Fig.4 fuzzy neuron hybrid control system for continuous steel casting

By analysising the continuous steel casting, the approximate model is given (Graebe, *et al.*, 1995) and the mold level control system is shown in Fig.3, where, $r(t)$ is the setpoint, $y(t)$ is the mold level, $u(t)$ is the control signal, FNHC is the fuzzy neuron hybrid controller, u_1 is the casting speed.

3. FUZZY NEURON HYBRID CONTROL

Control of the mold level is a challenging problem by using conventional control or fuzzy control method, because of the grave nonlinearities and big uncertainties of the continuous steel casting process. If the neuron model-free control method is directly used to control this process, it is also difficult to have satisfactory performance. Considering the dynamic characteristics of the continuous steel casting process in Fig.3, the fuzzy neuron hybrid control system for this process is set up in Fig.4.

In Fig.4, the controller is designed based on the hybrid structure consisting of the fuzzy PI controller and the neuron controller. In the hybrid structure, the gain of the neuron controller is tuned by the fuzzy algorithm, the sum of the outputs of the fuzzy PI controller and neuron controller is the output of the hybrid controller. $u(t)$ is the control signal produced by the hybrid controller. $y(t)$ is the system output. $r(t)$ is the setpoint. $x_i(t)$ is the inputs of the neuron. $u_{NC}(t)$ is the control action produced by the neuron. $u_f(t)$ is the output of the fuzzy PD controller, which is used to update the neuron gain $K(t)$. $u_{FC}(t)$ is the control action of the fuzzy PI controller.

3.1 Fuzzy PI Control

When a basic fuzzy system is designed, the following three problems should be solved.
(1) fuzzify the input variables
(2) design a fuzzy rule base for the inference engine
(3) defuzzify the output U of the inference engine

The key to have good performance of a fuzzy control system is the regulation of the fuzzy rule base according to the plant. A method for regulating fuzzy control rule base is presented by Long and Wang (1982), which can express the fuzzy control inference process by a simple formula as follows

$$U = <\lambda E + (1-\lambda)EC> \quad (4)$$

where E, EC are supposed to be the fuzzy input variables of a control system error $e(t)$ and its change $\Delta e(t)$ respectively, λ is the factor regulating the fuzzy rule base. $<x>$ denotes the inference engine to have the nearest whole number of x. By changing the factor λ, the control rule base can be regulated, therefore, the fuzzy control system performance can be changed conveniently. U is the output of the inference engine. It has been proved that formula (4) has the same functions as a conventional fuzzy rule base.

Thus, the fuzzy system can be written as

Fuzzifier: $E = <k_e e(t)>$, $EC = <k_{ec}\Delta e(t)>$ (5)

Fuzzy inference: $U = <\lambda E + (1-\lambda)EC>$ (6)

Defuzzifier: $u_f(t) = k_u U$ (7)

where k_e, k_{ec} are fuzzification factors of inputs $e(t)$ and $\Delta e(t)$ respectively, $\lambda \in (0,1)$. k_u is the

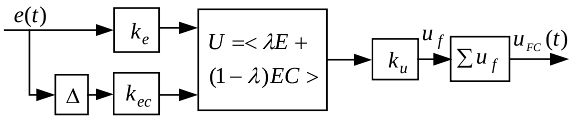

Fig.5 Fuzzy-PI controller

defuzzification factor of the fuzzy inference engine output, $u_f(t)$ is the fuzzy system output. Obviously, the fuzzy controller given above is a PD type controller according to Eqs. (5), (6) and (7). According to the description as above, the fuzzy PI controller is constructed shown in Fig.5. In Fig.5, the output of fuzzy PI controller is

$$u_{FC}(t) = \sum_{i=0}^{t} u_f(i) \tag{8}$$

Substituting Eqs. (5) (6) and (7) into Eq. (8) leads to

$$u_{FC}(t) = k_u \sum_{i=0}^{t} < \lambda < k_e e(i) > +(1-\lambda) < k_{ec} \Delta e(i) >> \tag{9}$$

Hence the simple fuzzy controller becomes a fuzzy PI type controller.

3.2 The Neuron Model, the Learning Strategy For Control and Neuron Control

The adaptive neuron model (in Fig.6) for model-free control is proposed by Wang (the author), *et al*. (1991). In Fig.6, *E* is the surroundings of the neuron. The neuron output $u(t)$ can be written as

$$u(t) = K \sum_{i=1}^{n} w_i(t) x_i(t) \tag{10}$$

where, K>0 is the neuron proportional coefficient; $x_i(t)$ (i=1, 2, ⋯, n) denote the neuron inputs; $w_i(t)$ are the connection weights of $x_i(t)$ and they are determined by some learning rule. It is widely believed that a neuron self organizes by modifying its synaptic weights. According to the wellknown hypothesis proposed by D. O. Hebb, the learning rule of a neuron is hence formulated as

$$w_i(t+1) = w_i(t) + dp_i(t) \tag{11}$$

where, d>0 is the learning rate; $p_i(t)$ denote learning strategy.

There are two simple learning strategies as follows
(1) Hebbian learning, i.e.

$$p_i(t) = u(t) x_i(t) \tag{12}$$

It expresses that an adaptive neuron depending on its adaptability makes actions and reflections to the unknown surroundings.
(2) Supervised learning, i.e.

$$p_i(t) = z(t) x_i(t) \tag{13}$$

It expresses that an adaptive neuron, which does forced learning under supervising of the teacher's signal $z(t)$, makes actions and reflections to the unknown surroundings.

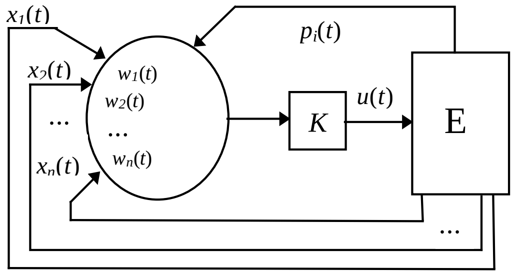

Fig. 6. The neuron model for control

The associative learning strategy is suggested for control purposes as follows by Wang, *et al*. (1991).
(3) Associative learning, i.e.

$$p_i(t) = z(t) u(t) x_i(t) \tag{14}$$

It expresses that an adaptive neuron, which uses the learning way integrating Hebbian learning and Supervised learning, makes actions and reflections to the unknown outsides with the associative search. It means that the neuron self-organizes the surrounding information under supervising of the teacher's signal $z(t)$ and gives the control signal. It also implies a critic on the neuron actions.

According to the neuron model and its learning strategy described as above, the neuron model-free control method is proposed as follows (Wang, *et al*., 1991)

$$\begin{cases} u(t) = \dfrac{K \sum_{i=1}^{n} w_i(t) x_i(t)}{\sum_{i=1}^{n} w_i(t)} \\ w_i(t+1) = w_i(t) + de(t) u(t) x_i(t) \end{cases} \tag{15}$$

$$e(t) = r(t) - y(t) \tag{16}$$

where $u(t)$, $y(t)$ are the input and output of the plant respectively, and $u(t)$ is the control signal produced by the neuron. $r(t)$ is the setpoint, and the neuron inputs $x_i(t)$ can be selected by the demands for the control system designs. Used in hydraulic turbine generators and some industrial processes, the neuron model-free controller has reached its success (Wang, *et al*., 1993; Wang, *et al*., 1994).

3.3 The Fuzzy Neuron Hybrid Control Method

According to the section 3.1 to 3.2 and Fig.4, the fuzzy neuron hybrid control method is proposed as following formula.

$$u(t) = u_{NC}(t) + u_{FC}(t) \tag{17}$$

where $u_{NC}(t)$ is the output of the neuron model-free controller.

$$\begin{cases} u_{NC}(t) = [K(t) \sum_{i=1}^{3} w_i(t) x_i(t)] \Big/ [\sum_{i=1}^{3} |w_i(t)|] \\ w_i(t+1) = w_i(t) + d_i e(t) u_{NC}(t) x_i(t) \end{cases} \tag{18}$$

$K(t)$ is the gain of the neuron model-free controller, which is regulated by

$$K(t) = K(t-1) + u_f(t) \tag{19}$$

where $u_f(t)$ is obtained by Eq.(7). $K(t) \geq k_1 e^{-u_1}$, where k_1 is a constant to be chosen. Considering the demands of different casting speeds, the neuron inputs are chosen as follows

$$x_1(t) = u_1 r(t),\ x_2(t) = u_1 e(t),\ x_3(t) = \Delta e(t) \tag{20}$$

where the casting speed u_1 is included in the formula.

In Eq.(17), $u_{FC}(t)$ is the output of the Fuzzy PI controller, it is given by

$$u_{FC}(t) = k_u \sum_{i=0}^{t} < \lambda < k_e e(i) > + (1-\lambda) < k_{ec} \Delta e(i) >> \tag{21}$$

Hence, the fuzzy neuron hybrid control method for mold level control is proposed as

$$\begin{cases} u_{NC}(t) = [K(t)\sum_{i=1}^{3} w_i(t) x_i(t)] \Big/ [\sum_{i=1}^{3} |w_i(t)|] \\ u_{FC}(t) = \sum_{j=0}^{t} u_f(j) \\ u(t) = u_{NC}(t) + u_{FC}(t) \\ E = < k_e e(t) >, EC = < k_{ec} \Delta e(t) > \\ u_f(t) = k_u < \lambda E + (1-\lambda) EC > \\ K(t) = K(t-1) + k_u U, K(0) = k_1 e^{-u_1} \\ w_i(t+1) = w_i(t) + d_i (r(t) - y(t)) u_{NC}(t) x_i(t) \\ x_1(t) = u_1 r(t),\ x_2(t) = u_1 e(t),\ x_3(t) = \Delta e(t) \end{cases} \tag{22}$$

where k_e, k_{ec}, k_u, k_1 are the parameters of the hybrid controller.

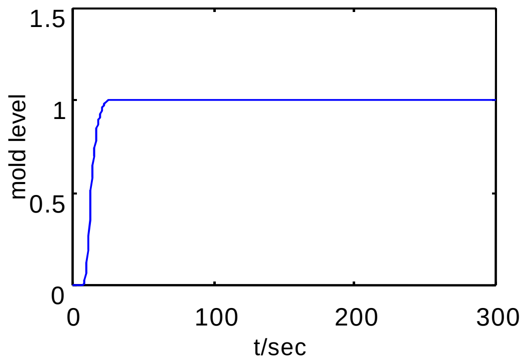

Fig.8 Tracking setpoint under the standard case

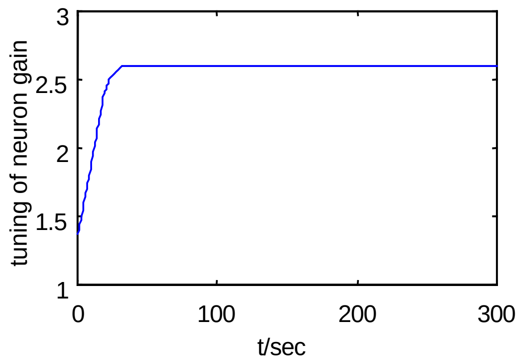

Fig.9 Tuning the neuron gain $K(t)$ under the standard case

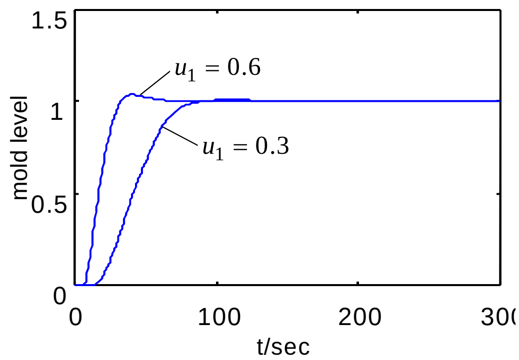

Fig.10 Tracking setpoint when $u_1 = 0.6$ or 0.3

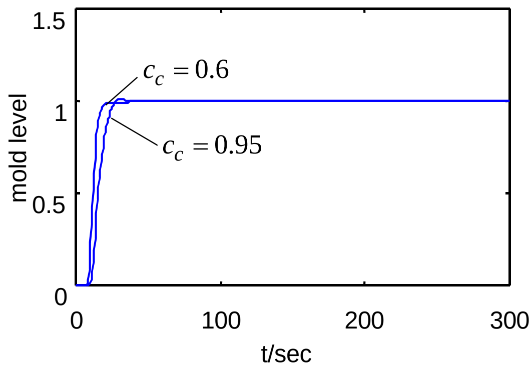

Fig.11 Tracking setpoint when c_c =0.6 or 0.95.

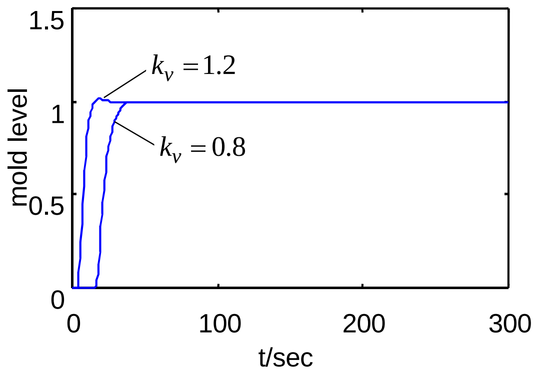

Fig. 12 Tracking setpoint when the valve position loop gain k_v =1.2 or 0.8

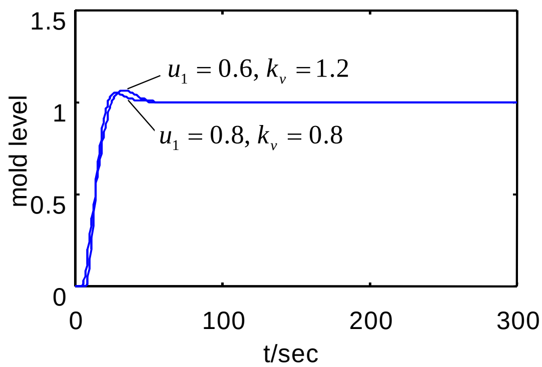

Fig.13 Tracking setpoit when u_1=0.6, k_v =1.2 or u_1=0.8, k_v =0.8

4. SIMULATION TESTS AND RESULTS

To verify the effectiveness of the proposed control method Eq.(22). The simulation tests of mold level control for the continuous steel casting process are made. The parameters of the plant are supposed as: $g = 9.8$, $h = 0.9$, $A_m = 1$, $c_v = 0.24$, $c_c = 0.74$, $R = 0.8$, $\beta = 1$, $k_v = 1$. All experiments are carried out to track the setpoint using the same controller parameters which are fetched roughly under the case of $u_1 = 1$, c_c =0.74, k_v =1. The parameters of the fuzzy hybrid controller are selected as: $k_e = 8$, $k_{ec} = 8$, $k_u = 0.006$, $\lambda = 0.8$, $d_1 = 100$, $d_2 = 25$, $d_3 = 100$, $k_1 = 3$. The sample period is chosen as $T = 0.6$sec. In order to examine the performance of the proposed model-free control method, the robust tests are also made under the conditions of different casting speeds, both new slide gate valve and old gate valve, and the changing of the valve position loop gain. The simulation results are shown as from Fig.8 to Fig.13. Fig.8 shows the control result of tracking setpoint under the standard case. Fig.9 is the result of fuzzy tuning the neuron gain $K(t)$ under the same case as Fig.8. Figs 10 to 13 are the robust tests using the proposed controller. Fig.10 illustrates the control results of tracking setpoint under the case of $u_1 = 0.6$ or 0.3. Fig.11 demonstrates the control results of tracking setpoint under the case of c_c =0.6 (for new valve) or c_c = 0.95 (for old valve). Fig.12 is the control results of k_v =1.2 or 0.8. Fig.13 displays the control results of u_1=0.6, k_v =1.2 or u_1=0.8, k_v =0.8.

The simulation results illustrate that good performance is obtained in all test cases and high precision mold level control is reached. The control system responds quickly, smoothly and almost without overshoot. Even if the dynamic characteristics of the nonlinear plant changes greatly, the proposed model-free controller still has very strong robustness and adaptability.

5. CONCLUSIONS

In this paper, the fuzzy neuron hybrid control method is proposed to mold level control of the continuous steel caster. In this control system, the hybrid controller is constructed by the fuzzy PI controller and the neuron controller, the gain of the neuron controller is tuned online by a fuzzy algorithm. The simulation tests under various conditions are made. The results illustrate high precision mold level control is reached and the proposed control method can efficiently control mold level for the plant with big uncertainties and grave nonlinearities. This model-free controller has good performance, very strong robustness and adaptability. The controller is very simple and of great value in practice.

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