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AGC-ASC Synthetic Neural Net Control System in Rolling Process

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Abstract: Automation Gauge Control(AGC) and Automatic Shape Control(ASC) are coupling each other. The coupling models of AGC-ASC synthetic system for the thickness-crown have been established and two artificial neural networks controllers are given. The simulation of computer shows that the AGC-ASC synthetic system can obtain the expected thickness and shape precision with both schemes.
Key words: neural network, neural net controller, AGC-ASC synthetic system

The thickness and the shape (crown and flatness) of strip are the important quality index for the product of the Hot Strip Mill and Cold Tandem Mill. The control function for gauge (AGC) and control function (ASC) are also the important functions in the Distributed Computer Control System.

Due to these functions will all affect the parameters of the deformation zone between the rolls and the strip, then affect on the Rolling Force. There are strong coupling between the functions of AGC and ASC.

In the rolling process, when the parameter which will effect on the rolling force are changed, it will effect on the elastical deformation of the components of the stand and finally effect on the roll gap and Thickness of the strip, it also effect on the elastic bending deformation of rolls and finally effect on the crown and the flatness of the strip.

The Set-Up Models for thickness and for crown will make them distributed as like the curves of Fig. 1.

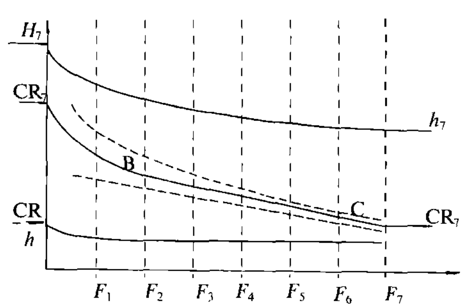

Fig.1 Crown and thickness distributed curves
CR_0, H—crown and thickness of strip exiting from rougher
CR_7/H_7—exit crown and thickness of F_7

To keep the ratio of crown and thickness constant in the F_2 to F_7 is the basic condition to keep good flatness of strip. When the thickness deviation is existing, the AGC will control the roll gap to tune the exit thickness, it will change the rolling force, then change the exit crown of this stand, it will destroy the constant of the ratio of crown and thickness.

When the bending system control the roll bending force to eliminate the deviation of crown, the effect will on the contrary.

This paper would like to probe into the possibility of the application of Neural Net Controller to control the AGC-ASC synthetic system.

1 Models of Thichness – crown Synthetical System

In the rolling process, some relations are as fellow

$$S = h - \frac{P - P_0}{C_P} - \frac{F}{C_F} \tag{1}$$

Equation (1) is called the equation of elastic deformation of stand. where S – roll gap after zeroing; P_0 – zeroing force; P – rolling force; C_P – mill modulu under rolling force; C_F – mill modulu under roll bending force; h – stand exit thickness; F–roll bending force.

$$\mathrm{CR} = \frac{P}{K_P} + \frac{F}{K_F} + E_\Sigma(\omega_\mathrm{H} + \omega_\mathrm{W}) + E_\mathrm{C}\omega_\mathrm{C} \tag{2}$$

where CR – crown of exit strip; ω_H – heat roll crown;

ω_W – wear and tear roll crown; ω_C – crown controlled by CVC; K_P – bending modulu under rolling force; K_F – bending modulu under rolling bending force ; E_Σ, E_C – coefficients.

$$P = P(R, H, h, B, T, w) \tag{3}$$

Equation (3) is called rolling force equation, where R – radius of working roll; B – strip width; H – stand entrance thickness; T – strip temperature on this stand; w – strip chemical composition (mass fraction, %).

By using Talor series develop formula to equation (3), neglecting the items which are constant in the process of AGC-ASC, only hold back the first order items, we have

$$\delta P = \frac{\partial P}{\partial H}\delta H + \frac{\partial P}{\partial h}\delta h \tag{4}$$

taking differential with equations (1) and (2)

$$\delta S = \delta h - \frac{\delta P}{C_P} - \frac{\delta F}{C_F} \tag{5}$$

$$\delta \mathrm{CR} = \frac{\delta P}{K_P} + \frac{\delta F}{K_F} \tag{6}$$

from equations (5), (6), we get

$$\delta h = \frac{1}{C_P - \frac{\partial P}{\partial h}}\left[C_P \cdot \delta S + \frac{\partial P}{\partial H}\delta H + \frac{C_P}{C_F}\delta F\right] \tag{7}$$

let $\frac{\partial P}{\partial H} = Q$, then $\frac{\partial P}{\partial h} \cong -Q$.

Q is called the elastical rigidity coefficients.

then $$\delta h = \frac{1}{C_P + Q}\left[C_P\delta S + Q\delta H + \frac{C_P}{C_F}\delta F\right] \tag{8}$$

noticing eqations (8) from (4), we see

$$\delta P = \frac{C_P Q}{C_P + Q}\left[\delta H - \delta S - \frac{\delta F}{C_F}\right] \tag{9}$$

Substituting (9) into (6), obtains

$$\delta \mathrm{CR} = \frac{1}{K_P}\left[\frac{C_P Q}{C_P + Q}(\delta H - \delta S - \frac{\delta F}{C_F}\right] + \frac{\delta F}{K_F} \tag{10}$$

Consequently, the AGC-ASC model is formed of equations (8) ~ (10).

However, equations (8) and (10) is a static model only. Every single system (screw down position system and roll bending force control system) needs all response time to arrive the expected value. Due to the fast speed properties, hydraulic roll bending force system and hydraulic gap position system can be regarded as inertia system.

Let it is respectively

$$G_1(S) = \frac{K_1}{1 + T_1 S} \text{ and } G_2(S)\frac{K_2}{1 + T_2 S}.$$

The measurement of exit thickness and crown is considered to be a delay unit ($e^{-\tau s}$), so the thickness-crown synthetical system can be written as

$$\begin{bmatrix}\delta h \\ \delta \mathrm{CR}\end{bmatrix} = \begin{bmatrix}G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s)\end{bmatrix}\begin{bmatrix}\Delta\mu_1 \\ \Delta\mu_2\end{bmatrix} + \begin{bmatrix}\eta_1 \\ \eta_2\end{bmatrix} \tag{11}$$

where:

$$G_{11}(s) = \frac{C_P}{C_P + Q}\cdot\frac{K_2}{1 + T_2 S}e^{-\tau s};$$

$$G_{22}(s) = (\frac{1}{K_F} - \frac{1}{K_P}\cdot\frac{C_P Q}{C_P + Q}\cdot\frac{1}{C_F})\cdot\frac{K_1}{1 + T_1 S}e^{-\tau s};$$

$$G_{12}(s) = \frac{C_P}{C_P + Q}\cdot\frac{1}{C_F}\cdot\frac{K_1}{1 + T_1 S}e^{-\tau s};$$

$$G_{21}(s) = -\frac{1}{K_P}\cdot\frac{C_P Q}{C_P + Q}\cdot\frac{K_2}{1 + T_2 S}e^{-\tau s};$$

$$\eta_1 = \frac{Q}{C_P + Q}\delta H;\ \eta_2 = \frac{1}{K_P}\cdot\frac{C_P Q}{C_P + Q}\delta H.$$

The classical PID control method is sample and can be used easily, but it is used for single input/output system major. Due to the coupling, the AGC-ASC control system must be decoupling each other. In the fellow we study the probability of designing neural net controller for the AGC-ASC synthetic system.

2 AGC-ASC Neural Net Controller

2.1 Double adaptive neural-like networks controller

The networks controller takes the double adaptive neural-like form, every neural is made of associate searching element (ASE) and self-adaptive commenting element (ACE). By using output of the controlled plant, the AEC gives information and makes effect on the ASE, the ASE produces the control law. The structure of control system shown in Fig. 2.

The activation functions are given by

$$\left.\begin{aligned} S_i(t) &= k_i f_i[w_{ij}(t), x_{ij}(t)] \\ P_i(t) &= g_i[v_{ij}(t), z_{ij}(t)] \end{aligned}\right\} \tag{12}$$

where w_{ij}, v_{ij} – net weight; k_i – output coefficients; g_i, f_i – activation function; x_{ij}, z_{ij} – net input.

The activation function may be linear or nonlinear function, for ordinary systems the linear function can satisfy requirement. In order to guarantee the convergence of the algorithm, a norm form is present ed as follow:

ASE:

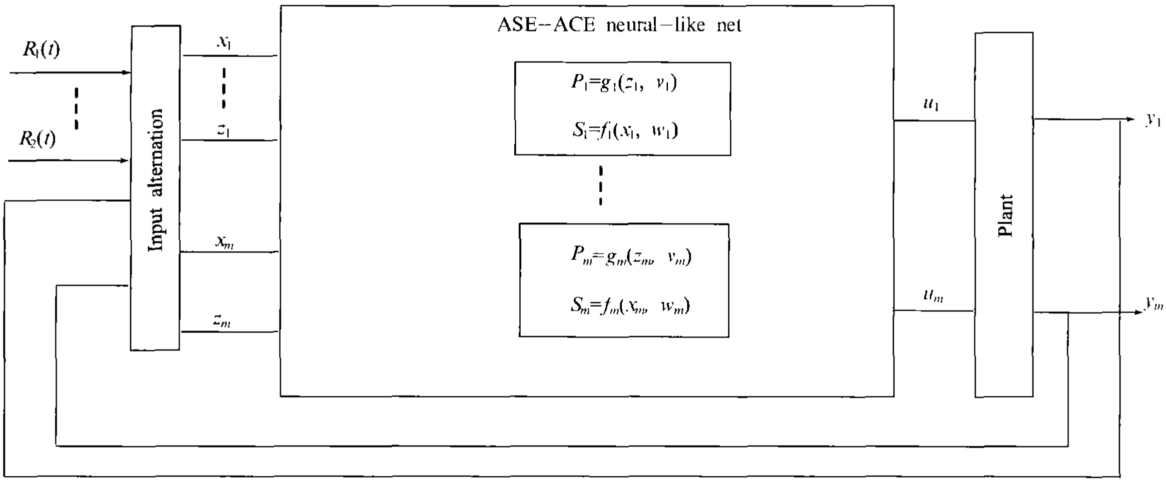

Fig.2 Double adaptive neural-like net control system

$$S_i(t) = k_i \sum_j w_{ij}(t) x_{ij}(t) \,/\, \sum_j w_{ij}(t) \tag{13}$$

$$w_{ij}(t) = w_{ij}(t-1) + \eta(t) E_i(t) S_i(t-1) x_{ij}(t-1) \tag{14}$$

$\eta_i(t)$ is leaning ratio, taking the form

$$\eta_i(t) = \begin{cases} \eta_i(t) \cdot \varepsilon & E(t) \le E(t-1) \\ \eta_i(t-1) \,/\, \varepsilon & E(t) > E(t-1) \end{cases} \tag{15}$$

where $\varepsilon > 1$, $\eta(0)$ is a random value, $\eta(0) \in (0,1]$, $E_i(t)$ is error function and given by

$$E_i(t) = \frac{1}{2}\sum_{k=1}^{n} d_k [y_k(t) - P(k)]^2 \tag{16}$$

$P_k(k)$ come from ACE as fellow.

$$\begin{cases} P_i(t) = g_i[v_{ij}(t),\ z_{ij}(t-d)] \\ \Delta v_{ij}(t) = \eta_i(t) E_i'(t) P_i(t) z_{ij}(t) \end{cases} \tag{17}$$

$g_i(x)$ take the same form as $f(x)$, when $d \ne 0$, $P_i(t)$ is the predictive value of $z_i(t)$, $P_i(t) = y_i\,|t-d$; when $d=0$, the ACE act as output filter, $P_i(t) = y_i(t|t)$.

Error function is of the form

$$E_i'(t) = \frac{1}{2}\sum_{k=1}^{n} [R_k(t) - y_k(t)]^2 \tag{18}$$

networks input alternation is given by the following

$$\begin{cases} x_{i1}(t) = P_i(t) - P_i(t-1) \\ x_{i2}(t) = x_{i1(t)} - x_{i1}(t-1) \\ x_{i3}(t) = x_{i2}(t) - x_{i2}(t-1) \end{cases} \tag{19a}$$

$$\begin{cases} z_{i1}(t) = R_i(t) - y_i(t) \\ z_{i2}(t) = z_{i1}(t) - x_{i1}(t-1) \\ z_{i3}(t) = z_{i2}(t) - z_{i2}(t-1) \end{cases} \tag{19b}$$

Equations (13)~(19) construct the double adaptive neural-like controller together.

2.2 The integral model algorithm controller based on Hopfield neural networks

Model algorithm control is one kind of predictive control, it is made of internal model, feedback tuning, rolling optimality, reference track and adopting pulse model. The algorithm can predicts the output states of future with input-output information of future and previously. By rolling optimality with quadratic index, it calculate the control law of current time. This algorithm predict the output state of system first and then determine the control action at present, so it has the properties of predictive. It is better obviously than the classical control method which get the feedback first and determine the control latter.

The plant is represented by the pulse response model

$$y(k+1) = g_1 u(k) + g_2 u(k-1) + \cdots + g_N u(k-N+1) + \xi(k+1) \,/\, \Delta$$

The model algorithm control law are given by[3]

$$\Delta U(k) = (G^{\mathrm{T}} Q G + \lambda)^{-1} G^{-1} Q \times [Y_r(k+1) - F_0 U(k-1) - he(k)] \tag{20}$$

where $\Delta U(k)$ – control increment vector;

$\Delta U(k) = [\Delta u(k), \Delta u(k+1), \cdots, \Delta u(k+M-1)]^{\mathrm{T}}$;

M – the control region; $h = [h_1, h_2, \cdots, h_p]^{\mathrm{T}}$;

$e(k) = y(k) - y_m(k)$; $y_m(k)$ – the output of model at present;

$U(k-1) = [u(k-N+1),\ u(k-N+2), \cdots, u(k-1)]^{\mathrm{T}}$;

$$F_0 = \begin{bmatrix} g_N g_{N-1} g_{N-2} \cdots g_3 & g_1 + g_2 \\ g_N \quad g_{N-1} \cdots g_4 & g_1 + g_2 + g_3 \\ \ddots \quad \vdots & \vdots \\ 0 \quad g_N \quad \cdots g_{P+2} & \sum_{i=1}^{P+1} g_i \end{bmatrix}$$

$Y_r(k+1)$ – reference input vector;

$Y_r(k+1) = [y_r(k+1), y_r(k+2), \cdots, y_r(k+P)]^{\mathrm{T}}$;

$y_r(k+i)$ – reference input value;

$Q = \mathrm{diag}[q_1, q_2, \cdots, q_P],\ q > 0,\ i = 1, \cdots, P;$

$\lambda = \mathrm{diag}[\lambda_1, \lambda_2, \cdots, \lambda_M],\ \lambda_i > 0,\ i = 1, \cdots, M;$

$$G = \begin{bmatrix} g_1 & & 0 \\ g_2 + g_1 & g_1 & \\ \vdots & \vdots & \\ \sum_{i=1}^{P} g_i & \sum_{i=1}^{P-1} g_i \cdots & \sum_{i=1}^{P-M+1} g_i \end{bmatrix}$$

Equation (20) gives the control law increment $\Delta u(k)$, $\Delta u(k+1), \Delta u(k+M-1)$, the closed loop control scheme is adopted in general, which only use the control increment $\Delta u(k)$, k+1 and latter the control law to calculate again.

It is obvious that solving for $\Delta U(k)$ from equation (20) involves computation of inverse matrix, however, $\Delta U(k)$ computation need a longer time when M is a large value. So it is difficult to satisfy the fast speed preporty of system in this case. A method which use Hopfield networks to solve the $\Delta U(k)$ is given[13].

The Hopfield neural networks[1] (see Fig. 3), the output of any neuron can potentially be connected to the input of any neuron.

T_{ij} is connection matrix elements, I_i is input bias currents, the state equation of the networks are of the form

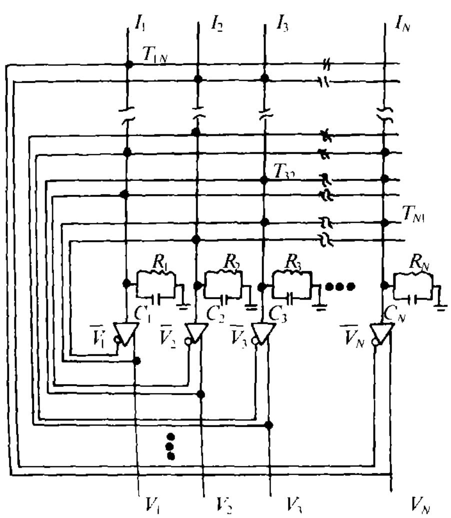

Fig.3 Hopfield neural networks

$$\begin{cases} C_i \dfrac{\mathrm{d}U_i(t)}{\mathrm{d}t} = \sum_{j=1}^{M} T_{ij} V_j(t) - \dfrac{U_i(t)}{R_i} + I_i \\ V_i(t) = g_i(U_i(t)),\ i = 1, 2, \cdots, M \end{cases} \tag{21}$$

where $U_i(t)$ and $V_i(t)$ is input and output voltages respectively, define the values of the connectivities (T_{ij}) and input bias currents (I_i) as fellow

$$T = (G^{\mathrm{T}} Q G + \lambda)$$

$$I = G^{\mathrm{T}} Q [Y_r(k+1) - F_0 U(k-1) - he(k)]$$

and let $g(u) = k_1 u$, $k_1 > 0$, then the Hopfield networks is stable and the stable points voltages approach the solution of equation(20), that is the solution of the model algorithm control.

3 Computer Simulation of the AGC-AFC Synthetic Neural Net Control System

(1) Consider the disturbance of thickness as the form

$$\Delta H = 0.02|\sin\omega t| + v(t)\ \text{(mm)}$$

where $v(t)$ is the white noise with zero-mean and the covariance is taken to be 0.01, the other parameters list in table 1. The simulation results of AGC-ASC system using double adaptive neural-like controller are shown in Fig. 4. It shows from Fig. 4 that the influence of thickness is reduced and the expected AGC-ASC control precision is obtained with not need decoupling system. However, if we do not use control action, the exit thickness and crown is belong

Table 1 Simulation parameters

τ/s	0.04
$C_P/(\mathrm{N \cdot m^{-1}})$	5.70×10^9
$C_F/(\mathrm{N \cdot m^{-1}})$	1.50×10^{10}
$K_P/(\mathrm{N \cdot m^{-1}})$	5.26×10^{10}
$K_F/(\mathrm{N \cdot m^{-1}})$	1.00×10^{10}
T_1/s	0.01
T_2/s	0.05
K_1	1
K_2	1
$Q/(\mathrm{N \cdot m^{-1}})$	1.24×10^{10}

to [-80 μm, 80 μm] majority.

(2) In order to apply the model algorithm control based on Hopfield neural networks to AGC-ASC system, we need dynamic decoupling with equation (11). The block diagrams of decoupling system is shown in Fig. 5.

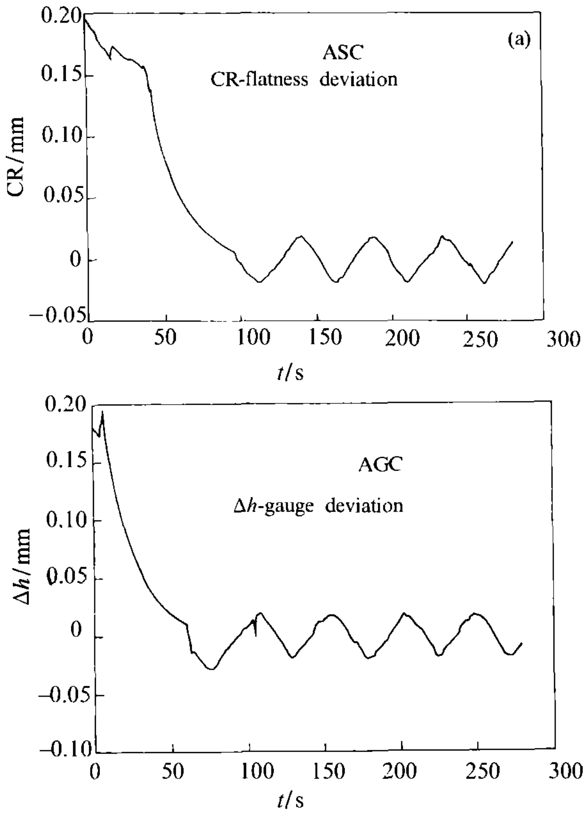

Fig.4 Simulation curve of result output using double adaptive neural-like controlled

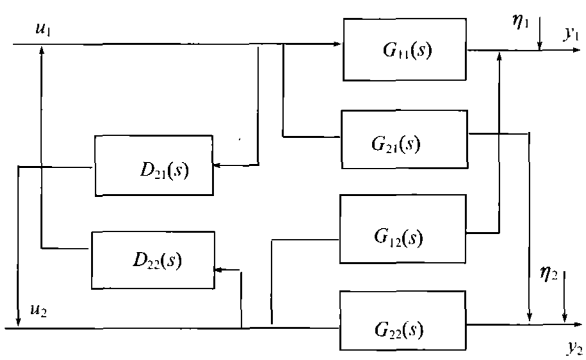

Fig.5 Block diagram of decoupling system

let
$$D_{21} = -\frac{G_{21}(s)}{G_{22}(s)}, \quad D_{12}(s) = -\frac{G_{12}(s)}{G_{11}(s)},$$
then the open loop system transfer matrix is
$$\begin{bmatrix} G_{11}(s) & 0 \\ 0 & G_{22}(s) \end{bmatrix}.$$

Consider the same disturbance of thickness and related parameters, the simulation of AGC-ASC system using model algorithm control based Hopfield networks shows the satisfactory behavior, see Fig. 6, not only the control precision arrived, but also the system response speed is more quickly.

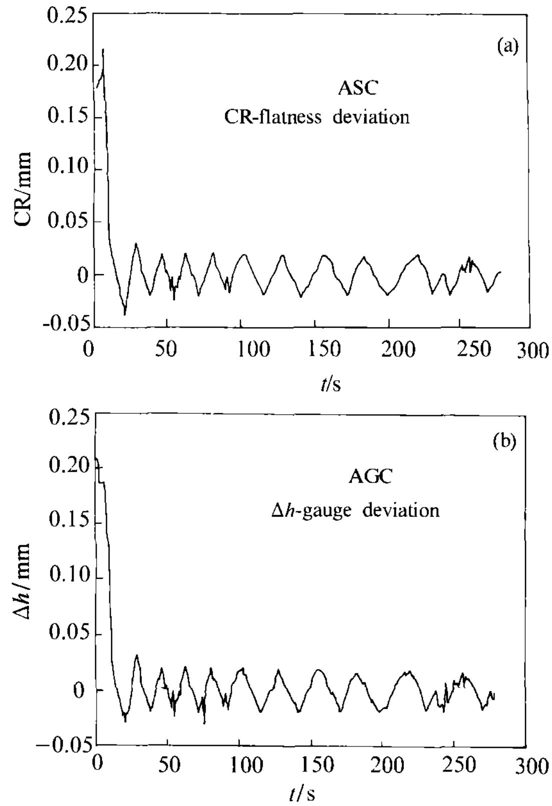

Fig.6 Simualtion curve of result output using model algorithm control

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