Optimizing Cooperative Control based on Genetic Algorithm for ElectroSlag Remelting Process

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Abstract—The cooperative control of both electrode remelting rate and position was applied in order to obtain optimal electroslag remelting metallurgy effect and improve melting production efficiency. The electroslag remelting process model was analyzed. Cooperative controller parameters were optimized by improved genetic algorithm based on ITAE criterion. The dynamic performance was analyzed to electroslag remelting control system. Study results show that optimizing cooperative control comes true stable control both electrode melting rate and electrode position. The control system has faster dynamic response and not overshoot.

***Key words*—Electroslag remelting model, genetic algorithm (GA), Multi-loop optimizing control, Dynamic analysis**

I. INTRODUCTION

Electroslag remelting control should be made remelting ingot obtain to perfect metallurgy effect and improve melting production efficiency. Both constant current control and constant voltage control may result in melting pool depth increase owing to heat condition and ingot configuration change. Melting rate was increased and can not assure steady melting rate in melting process, because electrode shorten, resistance loss reduce and induction loss based on induction loop close also reduce. Constant melting rate was come true by melting rate control loop and slag resistance control loop [1-3]. However, various variables are coupling in electroslag remelting control process.

Electroslag remelting process and model was analyzed. Cooperative control was adopted between electrode melting rate and position. Controller parameters were optimized by improved genetic algorithm with ITAE rule. Dynamic performance of both electroslag remelting control system was studied.

II. ELECTROLSLAG REMELTING PROCESS MODEL ANALYSIS

A. Electrolslag Remelting Process Model

The model for electroslag remelting process including heat transfer model of the slag pool, model of the melting dynamics of the electrode, model of input electric power in slag pool and model of electrode immersion depth was established and verified by Seokyoung Ahn [4].

The model of the melting dynamics of the electrode can be written as:

$$\dot{\Delta} = \frac{\alpha_r C_{\Delta\Delta}}{\Delta} - \frac{C_{\Delta p}}{h_m} P_{\dot{m}} \tag{1}$$

$$\dot{S}_e = -\frac{\alpha_r C_{s\Delta}}{\Delta} + \frac{C_{sp}}{h_m} P_{\dot{m}} \tag{2}$$

Where, Δ is boundary layer thickness (cm), α_r is room temperature thermal diffusion coefficient (cm^2/s), h_m is volume specific enthalpy at melt temperature (J/cm^3) and dimensionless constants are material specific and derived as

$$C_{\Delta\Delta} = \frac{224(\Lambda^* + 1)}{3\Lambda^* + 11}\left(\frac{1}{2} + \frac{\beta h_m}{3}\right)$$

$$C_{\Delta p} = \frac{32\Lambda^*}{3\Lambda^* + 11}$$

$$C_{s\Delta} = \frac{56\Lambda^*}{3\Lambda^* + 11}\left(\frac{1}{2} + \frac{\beta h_m}{3}\right)$$

$$C_{sp} = \frac{11\Lambda^*}{3\Lambda^* + 11}$$

Where, Λ^* is the Stefan number, β is a diffusivity parameter

$$\Lambda^* = \frac{h_m}{h_{\sup} - h_m}$$

$$\beta = \frac{\alpha_m - \alpha_r}{\alpha_r}$$

Where, h_{sup} is superheat temperature specific enthalpy of the electrode (J/cm^3), α_m is thermal diffusion coefficient at melt temperature (cm^2/s).

The heat model of slag pool transfer to electrode remelting surface can be written as:

$$P_m = (1 + \mu_r) H_e (T_s - T_m) \tag{3}$$

Where, P_m is melt power (W),H_e is equivalent thermal coefficient of electrode (W/cm^{2}K),μ_r relative melt efficiency, T_s

is temperature of the slag (K), and T_m melts temperature of the electrode (K).

The model of the slag pool temperature can be written as:

$$\dot{T}_s = \frac{1}{\rho_s V_s C_s}\begin{bmatrix} P_{in} - H_e(1+\mu_r)(T_s - T_m) \\ - H_s 2\pi r_m h_s (T_s - T_{ss}) \\ - \sigma\varepsilon(2\pi r_m^2 - 2\pi r_e^2)(T_s^4 - T_\infty^4) \end{bmatrix} \quad (4)$$

Where, ρ_s is density of the slag (g/cm3), V_s is volume of the slag (cm^3), C_s is specific heat of the slag (J/gK), T_{ss} *is* solidus temperature of the slag (K), H_s is equivalent thermal coefficient of the slag (W/cm^{2}K), r_e is radius of the electrode (cm), r_m is radius of the crucible (cm), h_s is height of the slag (cm), σ is Stefan–Boltzmann constant (W/m^{2}K^4), ε is emissivity of the slag, T_∞ is room temperature (K).

P_{in} is determined by both the input current I and slag resistance R_s, and can be written as:

$$P_{in} = VI = R_s(d)I^2. \quad (5)$$

Slag resistance vs. immersion depth of electrode relationship can be determined by fig.2 [4].

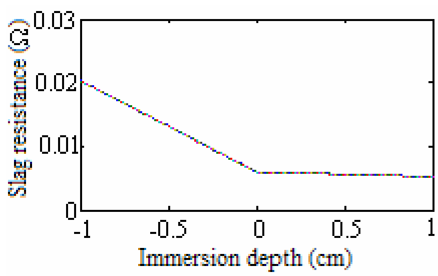


Figure 1. The relation of electrode depth vs. slag resistance

The volume of the slag is changed very slowly so it is assumed the volume of the slag remains relatively constant. The immersion depth of electrode d can be written as:

$$\dot{d} = -\dot{S}_e + \frac{1}{1 - \frac{A_e}{A_s}} v_{ram}. \quad (6)$$

Where, V_{ram} is the ram velocity, A_e is area of cross section of the electrode (cm^2), A_s is the area of cross section of slag pool (cm^2).

The model of electrode remelting rate can be written as :

$$m_e = \rho_e A_e \dot{S}_e \quad (7)$$

B. *The Linearization of Model*

In order to study the system characteristic and design controller, the model was linearized at operation point of steady state. The operation point is as follows [4]: Moving boundary layer thickness is 14.8 cm, the temperature of slag pool is at 2200K, the electric current is 5121A, the electrode moving speed is 0.0074 cm/s, the electrode immersion depth in the slag pool is 0 cm opposite position of shallow layer area and the electrode melting speed is 50.2 g/s. Current and ram velocity act as input variables. Electrode melting rate and position act as output variables. it can be written as:

$$U^0 = [5121 \quad 0.0074]^{\mathrm{T}}$$
$$X^0 = [14.8 \quad 2200]^{\mathrm{T}}$$
$$Y^0 = [50.2 \quad 0]^{\mathrm{T}}$$

The linearization method was written as:

$$\begin{cases} \dot{X} = AX + BU \\ Y = CX + DU \end{cases}$$

The opening loop transfer function of system after linearization can be written as:

$$G(s) = \begin{bmatrix} \dot{m}e \\ d \end{bmatrix} = \begin{bmatrix} G_{11}(s) & G_{12}(s) \\ G_{21}(s) & G_{22}(s) \end{bmatrix} \cdot \begin{bmatrix} I \\ V \end{bmatrix} =$$

$$\begin{bmatrix} \frac{0.00010(s+0.004148)}{(s+0.00958)(s+0.004023)} & \frac{-4.2089\times10^{-8}(s+0.004148)}{s(s+0.004023)(s+0.00958)} \\ \frac{2.5783\times10^{-14}(s+0.004148)}{s(s+0.00958)(s+0.004023)} & \frac{2.7778}{s} \end{bmatrix} \cdot \begin{bmatrix} I \\ V \end{bmatrix}$$

III. OPTIMIZING CONTROL BASED ON GENETIC ALGORITHM

A. *Multi-loop PID Control*

Electroslag remelting process is multi-variable control system having coupling relationship. In order to obtain to electroslag remelting process precision control, multi-loop PID controller was designed as a whole object of multi-variable electroslag remelting system. Control frame of remelting process can be seen Fig.2.

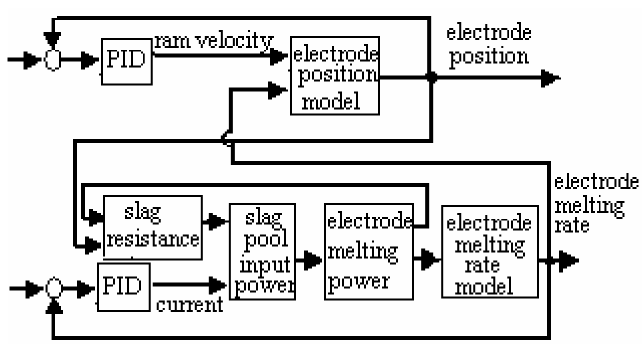


Figure 2. PID control frame of Electroslag remelting process

B. *Genetic Algorithm'S Realization*

It is different between multi-loop PID parameters setting and single loop PID parameter setting [5]. Optimal control parameters contribute to improve control system performance. Simple genetic algorithm has shortages of early mature and slow velocity of convergence. Therefore, improved genetic algorithm was applied to optimize controller parameter in electroslag remelting process.

Improved genetic algorithm adopted real-encoding. Compared with binary code, real-encoding straightly describes continuous parameters of optimized problem. It is easy to analysis and comprehending because it need not coding and decode. Real encoding contributes to improve precision and speed of operation.

The population was initialized by random number in range of controller parameter value. Fitness function was defined by reciprocal of optimizing target. Dynamic constraints was treated through penalty factor was added to fitness function. So that fitness function with penalty factor guided genetic operation.

Selection operator adopted deterministic sampling selection in order to avoid that high fitness value individuals rapidly hold on population at early stage [6]. Then the population evolution stops as nearly identical fitness value of individuals in population. Some individuals with biggest fitness value in deterministic sampling selection can be reserved to next generation population so that individual competition ability is embodied.

Arithmetic crossover operator can be written as [6]:

$$\begin{aligned} A' &= \alpha A + (1-\alpha)B \\ B' &= \alpha B + (1-\alpha)A \end{aligned} \tag{8}$$

Uniformity mutation strategy of mutation operator can be written as [6]:

$$x_k^{'} = U_{mean}^k + r(U_{\max}^k - U_{\min}^k) \tag{9}$$

$[U_{\min}^k, U_{\max}^k]$ is the scope of mutation individual. U_{mean}^k is the mean value, r is random number with uniform probability in [0, 1].

Dynamic self-adjusting crossover probability Pc was adopted in crossover operator. During crossover operator process, high fitness value individual was crossed at much higher probability so that possibility of high quality gene existing in next generation is much higher. It accords with nature evolutional law. When mutation operator was running, mutation probability was self-adjusting in order to avoid damaging dominant gene and produce new gene. It avoids trapping in locally optimal solution. Adjusting formulas of Pc and Pm can be written as [7]:

$$P_c = \begin{cases} 0.90 - \dfrac{0.3\times\left(\bar{f} - f'\right)}{(f_{\max} - \bar{f})}; & f' \le \bar{f} \\ 0.90, & f' > \bar{f} \end{cases} \tag{10}$$

$$P_m = \begin{cases} \dfrac{0.5\times(f_{\max} - f)}{(f_{\max} - \bar{f})}; & f > \bar{f} \\ 0.5 & f \le \bar{f} \end{cases} \tag{11}$$

f' is the bigger sufficiency value of two individuals. $\bar{f}$ is average value sufficiency. $f_{\max}$ is the maximum sufficiency value in population.

C. *Electroslag Remelting Controller Parameter Optimizing*

Genetic algorithm optimizes multi-loop PID controller parameters of electroslag remelting process with the ITAE rule [8], see figure 3. A generation population includes in 30 individuals. The structure of individual can be written as:

$$\underbrace{kp_1 \;\; ki_1 \;\; kd_1}_{\text{PID}} \; \underbrace{kp_2 \;\; ki_2 \;\; kd_2}_{\text{PID}}$$

When improved genetic algorithm was applied to optimize controller parameters of electroslag remelting process, the dynamic restriction must deal with. Penalty factor method was adopted when overshoot was produced. Objective function can be written as:

$$J = \sum_{i=1,j=1}^{n,n} \left(t * \left|e_{ij}(t)\right| + \omega * \left|e_{ij}(t)\right|\right), \omega = 100 \tag{11}$$

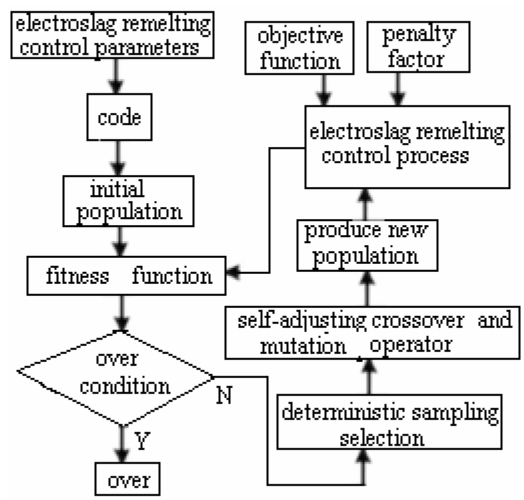


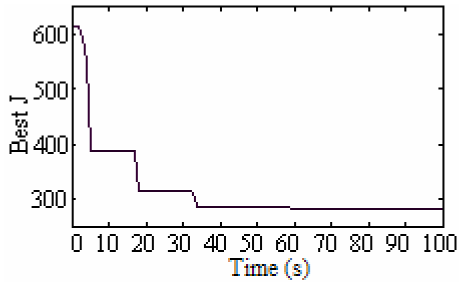
Figure 3. Gram of GA optimization control

IV. ANALYSIS DYNAMIC PERFORMANCE OF ELECTROSLAG REMELTING CONTROL PROCESS

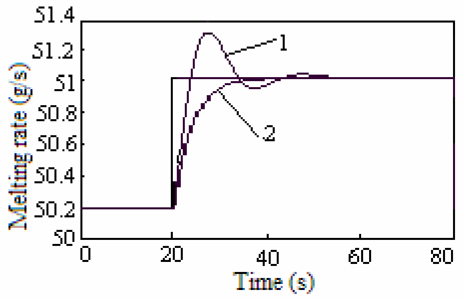
Dynamic performance of electroslag remelting control system was studied when electrode melting rate step changed from 50.2g/s to 51g/s. Simulation result can be seen in fig.4.

Under the function of multi-loop PID optimizing control parameter based on optimizing target(see fig4 (a)), electrode melting rate took 20s to attain new steady value and electrode position in slag pool was nearly invariable (see fig.4 (b), (c)). Compared with attenuating curve tuning PID, optimizing control results based on GA improved are much better. During control process, current was adjusted during electrode melting rate attained new steady value (see fig.4 (d)). At the same time, ram velocity was adjusted to assure electrode position in the slag invariable (see fig.4 (e)).

Electrode position in the slag pool was come true stable control to contribute to improve metal effect because its distance between electrode and melting pool was maximum. The metal melting drop had the longest effective travel and slag washing effect was sufficiency. It made electric energy maximum translate into heat energy, so improved melting production efficiency [3].

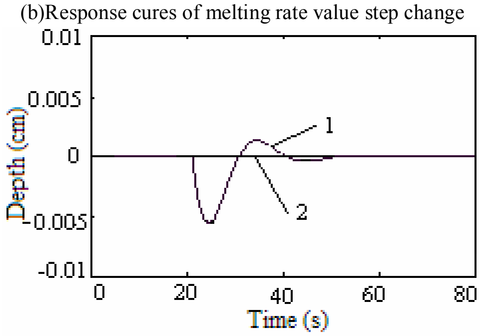


(a)Optimizing target change process



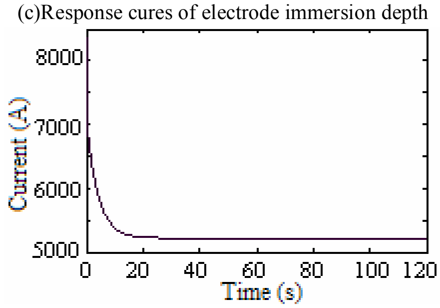
1- Attenuating curve -PID 2-GA-PID

(b)Response cures of melting rate value step change

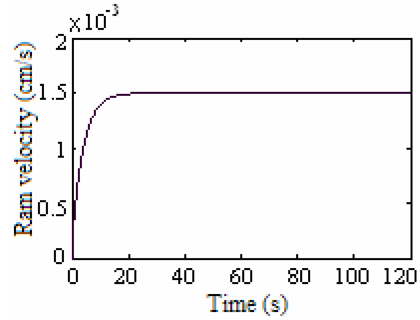


1- Attenuating curve -PID 2-GA-PID

(c)Response cures of electrode immersion depth



(d)Cures of current change based on GA



(e)Cures of electrode velocity change based on GA

Figure 4. Multi-loop PID control step response

V. CONCLUSION

(1) Improved genetic algorithm and self-adjusting strategy assurances convergence of algorithm and improves search performance in electroslag remelting optimize control process. It makes PID controller using lesser control energy to achieve optimal control effect.

(2) Cooperative optimizing control come true steady control between electrode melting rate and position. Dynamic responses of electroslag remelting process are rapid and do not have overshoot.

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