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Adaptive neural network controller for the molten steel level control of strip casting processes †

Hung-Yi Chen[1,*] and Shiuh-Jer Huang[2]

[1]Department of Mechanical Engineering, Mingchi University of Technology, Taishan, Taipei, Taiwan
[2]Department of Mechanical Engineering, National Taiwan University of Science and Technology, Taipei, Taiwan

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Abstract

The twin-roll strip casting process is a steel-strip production method which combines continuous casting and hot rolling processes. The production line from molten liquid steel to the final steel-strip is shortened and the production cost is reduced significantly as compared to conventional continuous casting. The quality of strip casting process depends on many process parameters, such as molten steel level in the pool, solidification position, and roll gap. Their relationships are complex and the strip casting process has the properties of nonlinear uncertainty and time-varying characteristics. It is difficult to establish an accurate process model for designing a model-based controller to monitor the strip quality. In this paper, a model-free adaptive neural network controller is developed to overcome this problem. The proposed control strategy is based on a neural network structure combined with a sliding-mode control scheme. An adaptive rule is employed to on-line adjust the weights of radial basis functions by using the reaching condition of a specified sliding surface. This surface has the on-line learning ability to respond to the system's nonlinear and time-varying behaviors. Since this model-free controller has a simple control structure and small number of control parameters, it is easy to implement. Simulation results, based on a semi-experimental system dynamic model and parameters, are executed to show the control performance of the proposed intelligent controller. In addition, the control performance is compared with that of a traditional PID controller.

Keywords: Molten steel level control; Strip casting processes; Adaptive neural network controller; Radial basis functions; On-line learning

1. Introduction

It is well known that the strip casting process integrates casting and rolling into a single production step to produce thin steel strips directly from molten metal. The twin-roll strip casting process can produce 1-5 mm thin steel strips directly from the molten steel. The production line from molten liquid steel to the final steel-strip is shortened and the production cost is reduced significantly as compared to conventional continuous casting. Furthermore, since the strip casting process has a high cooling rate, it can increase the mechanical properties of steel [1, 2]. However, strip casting process dynamics have the properties of nonlinear uncertainty and coupled behaviors, and the molten steel level control problem is still an important topic for investigation to guarantee steel strip quality. Graebe et al. [3] demonstrated the model and various nonlinearities appearing in the continuous casting process and proposed different issues that needed to be solved in the controller design. Hesketh et al. [4] applied an adaptive control strategy for the mould level control of a continuous steel slab casting. Hong et al. [5] investigated the modeling and control of a twin-roll strip caster. They analyzed different critical dynamics, including molten steel pool leveling, and developed a two-level control strategy to achieve a constant strip thickness and to maintain a constant roll separating force.

Since the dynamic characteristic of this strip casting process is very complicated, it is difficult to establish an appropriate dynamic model for a model-based controller design. Hence, a model-free fuzzy control strategy is considered to solve this problem [6-8]. However, the design of a traditional fuzzy controller fully depends on an expert, or the experience of an operator, to establish the fuzzy rule bank. Generally, this knowledge is difficult to obtain. A time-consuming adjustment process is required to achieve the specified control performance. Thus, these factors hinder its application and implementation.

In this work, an adaptive neural network controller without process dynamic model requirements is proposed to control the molten steel level of the strip casting process. The proposed control strategy is based on a radial basis function (RBF) structure combined with a sliding-mode control scheme.

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*Corresponding author. Tel.: +886-2-29089899, Fax.: +886-2-29063269
E-mail address: hychen@mail.mcut.edu.tw

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An adaptive rule is employed to on-line adjust the weights of radial basis functions, which is derived from the reaching condition of a specified sliding surface. Since the proposed structure has the capability of adjusting the weights of the RBF continuously, the initial weights can be start from zero. Here, the adaptive neural network controller is designed for regulating the height of the stopper controlled by an electric servomotor to achieve the desired molten steel level during the strip casting process. The control performance is evaluated based on numerical simulation results. In addition, the performance of this proposed controller is compared with that of a traditional PID technique to show the performance improvement.

This paper is organized as follows. Section 2 describes the twin-roll strip casting process dynamics and system model for simulation purpose. Section 3 presents the model-free adaptive neural network control strategy. Section 4 describes the numerical results of the proposed controller. Finally, conclusions are presented in Section 5.

2. System model for simulation purpose

A process mathematical model, which describes the relationship between the command inputs and the measured outputs, is required for the dynamic simulation to evaluate the numerical dynamic performance of a model-free controller. The mathematical model for the molten steel leveling dynamics developed in [7] is described in this section. Fig. 1 shows a diagram of the strip casting process. For developing the mathematical model, it is assumed that the molten steel is incompressible, and the two rollers are identical. The continuity equation of the liquid steel can be described as:

$$\frac{dV}{dt} = Q_{in} - Q_{out} \tag{1}$$

where V is the volume of the molten steel stored between the twin-roll cylinders, Q_{in} is the control input flow into the space between roll cylinders, and Q_{out} is the output flow from the roll cylinders. The volume V can be calculated as:

$$V = AL_r \tag{2}$$

where L_r is the length of the roll cylinders and A is the area of the oblique, calculated as follows:

$$A = 2\int_0^y \left[\frac{x_g(t)}{2} + R - \sqrt{R^2 - y^2} \right] dy \tag{3}$$

where $x_g(t)$ is the roll gap, R is the radius of the roll cylinder, and $y(t)$ is the height of molten metal above the axis of the rollers. By substituting Eqs. (2) and (3) into Eq. (1), we obtain:

$$\frac{dV}{dt} = L_r \frac{dA}{dt} = L_r \left[y\frac{dx_g}{dt} + \left(x_g + 2R - 2\sqrt{R^2 - y^2} \right) \frac{dy}{dt} \right] \tag{4}$$

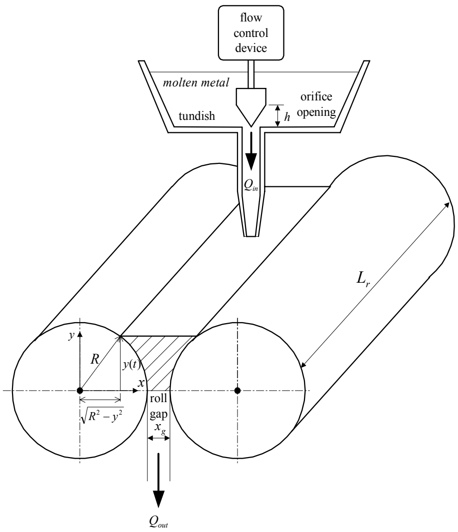

Fig. 1. Diagram of the strip casting process.

If $\left(x_g + 2R - 2\sqrt{R^2 - y^2} \right)$ is defined as $B_r(x_g, y)$, the following form can be derived from Eq. (1):

$$\frac{dy}{dt} = \frac{1}{B_r(x_g, y)L_r} \left(Q_{in} - Q_{out} - L_r y \frac{dx_g}{dt} \right) \tag{5}$$

Here, the input flow Q_{in} can be derived from the stopper opening height $h(t)$ and a nonlinear time-varying input flow rate parameter $a(t)$, depending on the shape of the nozzle and the stopper, clogging/unclogging dynamics, and the height and viscosity of the molten metal in the tundish.

$$Q_{in} = a(t) \cdot h(t) \tag{6}$$

where the orifice opening, $h(t)$, which is equal to the height of the stopper, is controlled by an electric servomotor. Due to the fast response of the electric servomotor, the stopper motion dynamics are assumed to be negligible. In addition, if the response of the stopper actuator is fast enough, the orifice opening can be derived as:

$$h(t) = ku(t) \tag{7}$$

where $u(t)$ denotes the control input and k is the servo gain.

The output flow Q_{out} can be derived from the product of roll surface tangential velocity v_r, roll gap x_g, and the length of the roll cylinder L_r:

$$Q_{out} = L_r x_g v_r \tag{8}$$

The dynamic model will only be used in the numerical simulations for evaluating the dynamic performance of the proposed adaptive neural network controller. The designing process of the proposed controller does not need this dynamic model and the strategy is described in the next section.

3. Adaptive neural network controller

The sliding mode control theory was proposed by Utkin [9] in 1977. Thereafter, Slotine [10], and Edwards and Spurgeon [11] developed the theoretical works of the sliding mode controller well and expanded its applications. The sliding mode control can be used to handle the nonlinear behavior of a system, model uncertainty, and external disturbance. Here, the sliding surface variable, s, is selected as the controlled variable for designing a neural network (NN) controller.

Consider a second-order system with e and $\dot{e}$ as the phase plane variables. The sliding surface on the phase plane for this nonlinear system can be defined as:

$$s = \left(\frac{d}{dt} + \lambda\right) e = \dot{e} + \lambda e \tag{9}$$

where s is the sliding variable, e is the tracking error, and λ is a strictly positive constant. This sliding variable, s, will be used as the input signal for establishing a NN model to approximate the control law. The sliding-mode controller can be derived based on the instantaneous approximating model at each sampling instant.

Since the back propagation NN has the disadvantages of slower learning speed and local minimal convergence, the RBF neural network (RBFNN) was proposed to solve these problems [12-14]. The semi-affine nonlinear functions were employed as the activation function in a hidden layer instead of sigmoid functions. Hence, it will simplify the NN structure and increase the learning speed. Here, a RBFNN is employed to model the mapping between the sliding surface variable, s, and the system control law, u. The Gaussian function is used as the activation function of each neuron in the hidden layer. The excitation values of these Gaussian functions are the distances between the input values of sliding variables and the central positions of Gaussian functions.

$$\theta_j = (s - c_j)^2 = \left\| s - c_j \right\| \tag{10}$$

where s is the input sliding variable and c_j is the central position of neuron j. The weighting, w_j, between input layer neurons and hidden layer neurons are specified as constant 1. The weights, w_k, between hidden layer neurons and output layer neurons are adjusted based on an adaptive rule. Then, the output of a RBFNN is:

$$g(s) = \sum_{j=1}^{n} w_j \phi_j \left(\left\| s - c_j \right\| \right) \tag{11}$$

where $\phi_j(s) = \exp(-(\left\| s - c_j \right\|^2)/\sigma_j^2)$ is a Gaussian function, j is the j th neuron of the hidden layer, σ_j and c_j are the spread factor and central position of the Gaussian function, respectively, n is the number of neurons, and s is the input value of the RBFNN.

A RBFNN-based controller is proposed here by combining an adaptive rule and the technique of sliding mode control. For a single-input and single-output case, the control input of the RBFNN controller is defined as:

$$u = \sum_{j=1}^{n} w_j \exp\left(-\frac{\left\| s - c_j \right\|^2}{\sigma_j^2} \right) \tag{12}$$

where n is the number of hidden layer neurons. In order to combine the advantages of the sliding mode and adaptive control schemes into the RBFNN, a sliding surface variable, s, is chosen as the input value of the RBFNN, and an adaptive rule is introduced to adjust the weights between hidden and output-layer neurons.

Based on the Lyapunov Theorem, the sliding surface reaching condition is $s\dot{s} < 0$. Here, a RBFNN is employed to approximate the nonlinear mapping between the sliding input variable and the control law. The weights of the RBFNN should be regulated based on the reaching condition, $s\dot{s} < 0$. An adaptive rule is designed to adjust the weights for searching the optimal weighting values and obtaining the stable convergence property. The adaptive rule is derived from the steep descent rule to minimize the value of $s\dot{s}$ with respect to w_i. The updated equation of the weighting parameters is:

$$\dot{w}_j = -\Gamma \frac{\partial s(t)\dot{s}(t)}{\partial w_j(t)} \tag{13}$$

where Γ is the adaptive rate parameter. Based on the chain rule, the above equation can be rewritten as:

$$\begin{aligned} \dot{w}_j &= -\Gamma \frac{\partial s(t)\dot{s}(t)}{\partial u(t)} \frac{\partial u(t)}{\partial w_j(t)} \\ &\cong \gamma s(t) \exp\left(-\frac{\left\| s - c_j \right\|^2}{\sigma_j^2} \right) = \gamma s(t) \phi_j(s) \end{aligned} \tag{14}$$

where Γ is the adaptive rate parameter and γ is the chosen overall learning rate parameter. Then, the weights between hidden and output layer neurons can be on-line adjusted to achieve the learning ability of RBFNN. Those weight values are the most important parameters in this control strategy because they determine the ratio of each radial basis function in the control law. The control block diagram of this adaptive neural network controller is shown in Fig. 2.

During the strip casting operation process, the molten metal level controller is designed for regulating the height of the molten metal in the tundish at an appropriate value to guarantee steel strip casting quality. However, the molten steel level is influenced by the various process parameters and disturbance. In addition, it has nonlinear and coupling dynamics as shown in Eq. (5). For example, the molten pool level $y(t)$ is significantly affected by process parameters, such as roll gap,

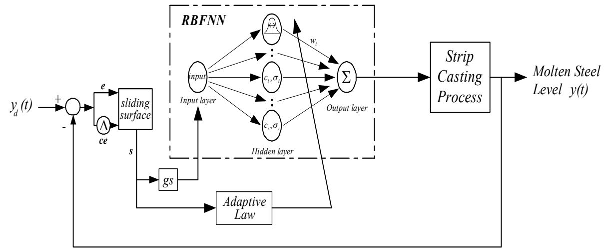

Fig. 2. The adaptive neural network control block diagram.

speed, and in/out flow rates. It is difficult to establish an accurate dynamic model for model-based control design. Here, the model-free adaptive neural network controller is employed to monitor the molten steel level.

4. Numerical results

During the roll casting process, once the molten metal comes into contact with the rotating rollers, a thin solidification shell is formed on the surface of each roller. The shells gradually grow in thickness from each roller surface, finally coming into contact with each other and welding together at a position around the roller exit, called the solidification final point. If the molten metal level is higher than the desirable value, the solidification final point will occur above the roller exit. This frequently results in heat cracking and damage to the cooling roller surface, in addition to material structural abnormalities in the steel strip. The control process may become ultimately unstable. If the molten metal level is lower than the desirable value, the solidification final point will occur below the roller exit. The steel strip surface will have inferior quality due to the breakout and oxidation. Hence, the molten metal leveling control is the important process control parameter that guarantees the solidification final point and rolling strip quality. The molten steel level must be maintained within the endurable bounded range during the full casting process, except in the initial startup operating mode, by filling the molten steel into the twin roll cylinders from the tundish.

In order to verify the effectiveness of the proposed intelligent controller, the following numerical simulations are performed. The system parameters used in the simulation study are selected as: $R = 650$ (mm), and $L_r = 1350$ (mm). These values were chosen from previous researches [7, 8]. The variation of the input flow rate, $a(t)$, used to describe the slow nozzle clogging and sudden unclogging is shown in Fig. 3 from reference [7]. The initial molten steel level and desired molten steel level were set to be 200 and 210 mm, respectively. The sampling frequency was selected as 100 Hz. The parameter λ in the sliding surface was set as 150. This value will influence the slope of sliding surface and the system response speed. In order to adjust the covering range of Gaussian functions, the parameter $gs = 1000$ was selected to regulate the sliding surface input variable. The learning rate parameter γ was set to 0.28. The central positions of the five radial basis functions were set at -2, -1, 0, $+1$, and $+2$.

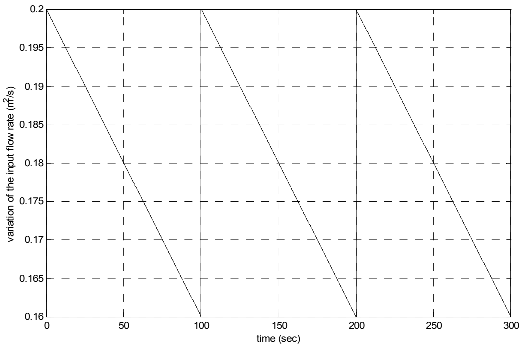

Fig. 3. Variation of the input flow rate.

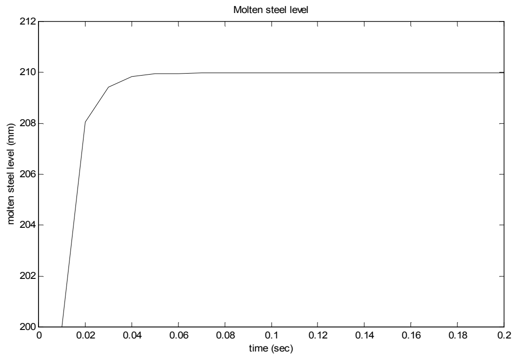

Fig. 4. Case A: Molten steel level (transient response).

The spread factor of these Gaussian functions was specified as the constant 1.

Case A: The parameters x_g and v_r are constant.

The system parameters roller gap x_g and roller speed v_r used in this simulation are set as constant, $v_r = 13$ mpm and $x_g = 2$ mm. In practice, it is important for these parameters to reach the desired molten steel level y_d in a short period of time without overshooting, and to guarantee the molten steel level within a bounded endurable region during the casting process. The dynamic responses of the proposed controller based on numerical results are shown in Fig. 4 (transient response) and Fig. 5 (steady-state response). The variations of the orifice opening are shown in Fig. 6. The dynamic responses and the variations of orifice opening of the traditional PID controller are shown in Figs. 7 and 8, respectively. Since the variation of the input flow rate had a sudden change from 0.16 to 0.2 m^2/s at the moments of 100, 200, and 300 s, the small change in time (200 s) in Fig. 5 is due to the sudden variation of the input flow. It takes about six steps (60 ms) for the height of molten steel, y, to converge to the desired molten steel level, y_d, using the proposed controller. The converging time of the molten steel level is faster than the result, 0.4 s from reference [8] and that of the PID controller. In addition, it can be observed that the steady-state error can be kept within 0.02 mm to the end of the control process even in instances where the input flow rate varies due to the sudden unclogging.

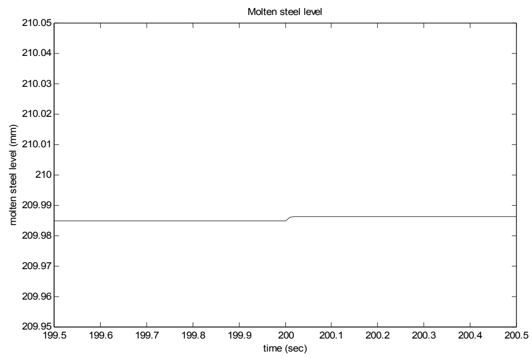

Fig. 5. Case A: Molten steel level (steady-state response).

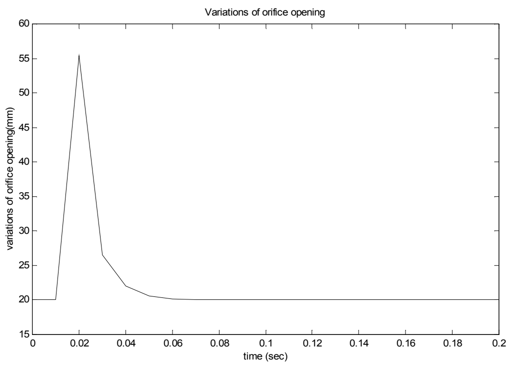

Fig. 6. Case A: Variations in orifice opening.

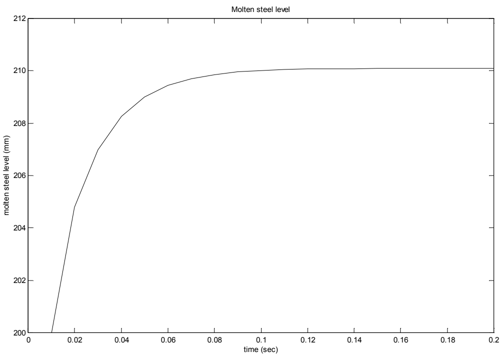

Fig. 7. Case A: Molten steel level (PID controller: $k_p = 20$, $k_i = 0.1$, and $k_d = 1$).

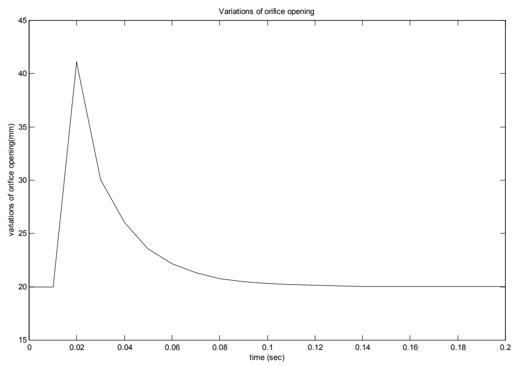

Fig. 8. Case A: Variations of orifice opening (PID controller: $k_p = 20$, $k_i = 0.1$, and $k_d = 1$).

Case B: The parameters x_g and v_r are not constant.

Since the system roller gap x_g and roller speed v_r parameters may have some perturbations in the real strip casting process, the values of x_g and v_r with certain variations instead of as constants are chosen in this simulation. These parameter perturbations are set as random variations with a maximum amplitude that is 20% of the system nominal parameter values. The disturbances are added for the entire control process to represent the parameter perturbations. The dynamic responses of the proposed controller based on its numerical results are shown in Fig. 9 (transient response) and Fig. 10 (steady-state response). The variations in orifice opening are shown in Fig. 11. It takes about eight steps (80 ms) for the height of molten steel, y , to converge to the desired molten steel level, y_d , with ± 0.2 mm steady-state error using

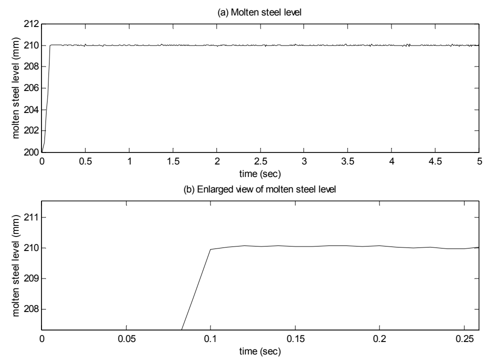

Fig. 9. Case B: Molten steel level (transient response).

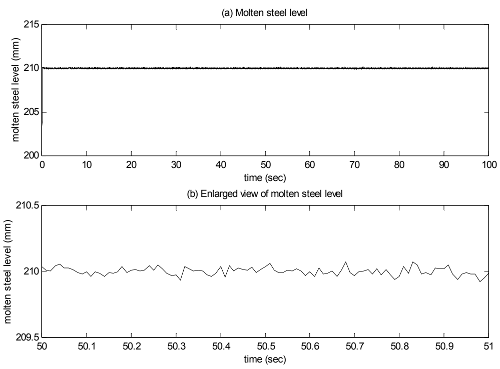

Fig. 10. Case B: Molten steel level (steady-state response).

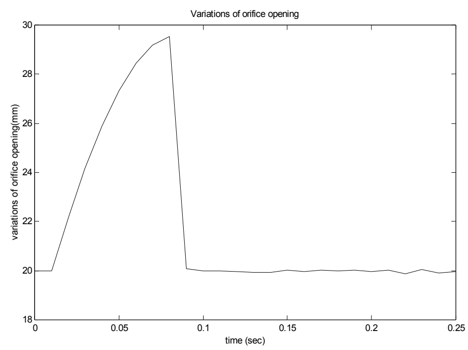

Fig. 11. Case B: Variations in orifice opening.

the proposed controller. The converging time of the molten steel level is faster than the result of [8] and the steady-state error is smaller than the result, ± 1 mm of [7].

Based on the simulation results, it can be observed that the proposed controller can effectively regulate the molten steel level at the preset desired level without overshooting.

5. Conclusions

Strip casting process dynamics have the properties of nonlinear uncertainty and time-varying characteristics. It is difficult to establish an accurate process model for designing a model-based controller to monitor the strip quality. A model-free adaptive neural network controller is employed to control the molten steel level of the strip casting process. The proposed control strategy has online learning ability for responding to the system's nonlinear and time-varying behaviors during the molten steel level control. From the simulation results, it can be observed that the converging time of the molten steel level is less than 80 ms for both simulation cases. In addition, the proposed control strategy can effectively monitor the molten steel at the preset desired level without overshooting to guarantee steel strip casting quality. Furthermore, from the control results, it can be concluded that the performance of the proposed controller is better than that of a traditional PID controller. This has significantly reduced the trial-and-error efforts of implementing a PID control strategy.

References

[1] X. Liang, F. Pan, S. Zhou, P. Ding and X. Xu, Edge containment of a twin-roll caster for near-net-shape strip casting, *Journal of Materials Processing Technology*, 63 (1997) 788-791.

[2] R. Cook, P. G. Grocock, P. M. Thomas, D. V. Edmonds and J. D. Hunt, Development of the twin-roll casting process, *Journal of Materials Processing Technology*, 55 (1995) 76-84.

[3] S. F. Graebe, G. C. Goodwin and G. Elsley, Control design and implementation in continuous steel casting, *IEEE Control Systems Magazine*, 15 (4) (1995) 64-71.

[4] T. Hesketh, D. J. Clements and R. Williams, Adaptive mould level control for continuous steel slab casting, *Automatica*, 29 (4) (1993) 851-864.

[5] K. S. Hong, J. G. Kim and M. Tomizuka, Control of strip casting process: decentralization and optimal roll force control, *Control Engineering Practice*, 9 (2001) 933-945.

[6] M. Dussud, S. Galichet and L. P. Foulloy, Application of fuzzy logic control for continuous casting mold level control, *IEEE Transactions on Control System Technology*, 6 (2) (1998) 246-256.

[7] M. G. Joo, Y. H. Kim and T. Kang, Stable adaptive fuzzy control of the molten steel level in the strip casting process, Control Theory and Applications, IEE Proceedings D, 149 (5) (2002) 357-364.

[8] Y. Park and H. Cho, A fuzzy logic controller for the molten steel level control of strip casting process, *Control Engineering Practice*, 13 (2005) 821-834.

[9] V. I. Utkin, Variable structure systems with sliding modes. *IEEE Transactions on Automatic Control*, AC-22 (1977) 212-222.

[10] J.-J. E Slotine and W. Li, Applied Nonlinear Control, Prentice-Hall, Englewood Cliffs, NJ, (1991).

[11] C. Edwards and S. K. Spurgeon, Sliding Mode Control-Theory and Applications, Taylor & Francis, London, UK, (1998).

[12] R. M. Sanner and J.-J. E. Slotine, Gaussian network for direct adaptive control. IEEE Trans. Neural Networks, 1992, 3, 837-863.

[13] S. J. Huang, K. S. Huang and K. C. Chiou, Development and application of a novel radial basis function sliding mode controller, *Mechatronics*, 13 (2003) 313-329.

[14] H. Y. Chen and S. J. Huang, Ti6Al4V laser alloying process monitoring by using adaptive neural network controller, *Journal of Materials Processing Technology*, 201 (2008) 297-302.

Hung-Yi Chen received his M.S. degree from Auburn University, AL., USA and his Ph.D. degree from National Taiwan University of Science and Technology, Taiwan, R.O.C., in 1991 and 2006, respectively, both in Mechanical Engineering. Since 1997, he has been with Mingchi University of Technology, where he is currently an associate professor. His research interests include intelligent control applications, mechatronics, automation, and machine tool control.

Shiuh-Jer Huang received his B.Sc. degree from National Cheng-Kung University, Tainan, Taiwan, in 1978, his M.Sc. Degree from National Taiwan University, Taipei, Taiwan, in 1980, and his Ph.D. degree from the University of California, Los Angeles, USA, in 1986, all in Mechanical Engineering. In 1986, he joined the faculty of the Department of Mechanical Engineering, National Taiwan University of Science and Technology in Taipei, Taiwan, where he is currently a professor. His research interests are in vehicle active suspension systems, robotic system analysis and application control, factory automation, and machine tool control.