A Neural Network Approach to the Control of the Plate Width in Hot Plate Mills

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Abstract

Deviation of a slab width from the desired value in hot plate mills has caused significant yield loss by trimming and demanded tighter width tolerances of rolled plates. This necessitates vertical rolling with considerable width accuracy. In this paper, a slab width control system is proposed in order to meet the stringent requirement on the plate dimensional tolerance. The control system adopts a multi-layer perception neural network to account for the complicated process dynamics characterized by nonlinear, time-varying and uncertain properties. A series of simulation works were conducted to evaluate the performance of the proposed control system for various operating conditions and networks design parameters. The control performance is analyzed in detail in terms of the system response accuracy and robustness to rolling temperature variation.

1. Introduction

The process of rolling the slab in hot plate mills can be divided into two principal stages called edging and gap rolling, as shown in Fig.1. These two sub process are directly coupled in the sense that the slab dimension modified by the edger motion affects the subsequent motion of the horizontal roll which in turn produces the slab dimension needed to be modified by the edger during multipass reversible rolling. Therefore, precise control of the slab width is ultimately required in order to provide the gap roll with accurate slab width dimension so as to produce slabs of desired thickness and width at the exit of the roll. Another important objective of this edging is to reduce the yield loss caused by trimming when irregular width is formed at the plate edge[1].

The irregular width spread occurs as a result of plastic deformation[2,3]. This phenomenon is very much complex and influenced by thickness reduction process. This leads the rolling control problem to be very complicated and made it intricate to achieve the desirable specification in the plate dimension. Due to this reason the width allowances have been considered as a function of the target width which takes into account the minimum side trim needed and risk of rolling under width[4].

These are several causes that result in rather unsatisfactory width control performance[5]. The inaccurate edger set-up model, degradation of various mill equipment, variation of operation conditions and environments may be responsible for that. One important factor responsible for the cause is the inherent characteristics of the edging process that are expressed by uncertainty, high nonlinearity and time varying property arising from the material deformation process and the dynamics of the hydraulic servo systems. In addition to this complexity, temperature variation during rolling and the variation of the dimension of incoming cast slabs come into the process in a form of disturbance. This situation necessitates a new approach in designing the edging process controller other than the conventional one.

There is abundance in research efforts in thickness rolling control. Also, some previous works[6~8] on automatic width control for hot strip mills have been reported. However, there are few research works on automatic width control of hot slab in roughing mill[9]. In this paper, a neural network approach is attempted in an effort to solve the difficulty involved with the process control. The neural network-based control system adopts an error feedback learning method to learn the inverse model of the edging process. This controller is combined with a conventional PD controller to ensure stability that might be impaired in transient learning period. This controller is designed at a steady state to produce a command signal in such a way that the actual output tracks the desired value of the plate width. Since performance of the proposed controller is affected by the structure and learning parameter of neural network, their effects are investigated in detail. A series of simulation works are carried out for various operating conditions to evaluate the effectiveness of the proposed controllers.

The evaluation of the NN-based control system shows that the desired value of the slab width can be obtained with a very good accuracy regardless of the variations in slab dimension and temperature.

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2. The width control system

The control system of an edge rolling mill called edger is partitioned into three sub systems as shown in Fig.2. It consists of a hydraulic positioning system, a rolling stand consisting of two rolls and a steel plate to be rolled and a width sensor which measures instantaneous width of the slab.

The control action begins as the plate is entering the mill. According to the command signal a servo value of the hydraulic servo system is operated in such a way that the piston generates the required rolling force. This force, in turn, produces a width dimension of the plate to be controlled. A sensor then measures the instantaneous width of the plate and this signal is feedback to the controller for comparison with the reference signal. Utilizing the error between the actual and reference signals, the controller generates appropriate command signal for the next time step to actuate the servo value. This action is repeated until the actual width value reaches steady state. In this control system, the hydraulic system has to be robust to handle the high edging force of slabing to meet the demand of edging and also should respond quickly to command signal coming out from the servo controller.

It is noted here that the control system shown in the figure differs slightly from those installed in the actual production lines in view of sensor location. Here, we consider the edging process independently from the thickness control process in order to confine ourselves to the design problem of width control only. There are several factors to be considered for accurate measurement of the width; location of width sensor, width sensing technology and accuracy of length tracking. One thing to be most carefully treated here is the sensor location, since it critically affects the control performance. It should be located as close to edgers as possible to minimize the effect of time-delay of the feedback signal and length tracking error. If this can not be achieved, then desirable control performance many not be guaranteed.

The edging process model

Edging accomplished by rolling introduces plastic deformation of the hot slab, resulting in width reduction. There are two major phenomena associated with the process that follow the reduction; elongation of the rolled slab and increase on thickness. The thickness increases greater near the edger, which causes the material to bulge at edge in a shape of dog's bone as shown in Fig.1. It also causes head and end of tail extrusion that can result in under-width tapes at the ends. The amount of thickness rolling also affects the width of the plate through lateral plastic flow of material, which increases width. For the development of the width control system, we will consider only edging process model without consideration of the horizontal roll.

The process model involves characterizing the relationship between the given dimension of the plate and the roll force. Let F denote the rolling force required to develope the plastic deformation of the plate. According to Okado[10], the F is calculated by

$$F = \sigma \cdot H_o \cdot L \cdot Q \tag{1}$$

where σ is the stress of the plate, H_o is the initial thickness of the plate entering the edger, L the contact length of the roll width of the plate during rolling, and Q is the shape factor to be adjusted when the contact area is represented by H_o multiplied by L. In the above, the σ is given by

$$\sigma = 0.40\, exp(\frac{4000}{T}) \cdot \varepsilon^{0.41} \cdot \dot{\varepsilon}^{(\frac{0.126T}{1000}+0.075C-0.050)} . \tag{2}$$

And the L is expressed by

$$L = \sqrt{R(B_o - B_D)} \tag{3}$$

where R is the radius of the edger roll, B_o is the initial width of the plate, and B_D is the width of the dog's bone. The shape factor Q can be expressed in terms of the mean plate width B_m, the contact length L and the initial thickness H_o as follows:

$$Q = 1.59 - 666\frac{H_o}{B_o} + 0.11\frac{B_m}{L} + 1.08\frac{H_o}{B_o} \cdot \frac{B_m}{L} \tag{4}$$

where the B_m is given by

$$B_m = B_o - \frac{2}{3}(B_o - B_D) . \tag{5}$$

The above equations reveal that the actual width of the dogbone B_D is determined by the rolling force applied to the material and that their relationship is highly nonlinear. In conclusion, the dogbone width B_D is primarily affected by the rolling force, the temperature of the rolled plate, the roll radius and the initial dimension of the incoming plate.

The hydraulic servo system

As shown in Fig.2 the servo system consists of a servo value that adjusts the flow rate of oil entering a cylinder and a hydraulic cylinder that provides appropriate rolling force through a piston motion. The piston motion is largely governed by the servo value motion, which controls the instantaneous pressure built within each side of the chamber. As it will be seen later, the dynamics of the hydraulic servo system is highly nonlinear and time-varying due to oil flow phenomena and uncertain due to leakage of oil and variation of working oil temperature.

If the servo value used is assumed to be of a three-land-four-way spool value then the dynamics of the value can be expressed by [11]

$$\dot{x}_v + a\, x_v = b\, u \tag{5}$$

where x_v denotes the spool position, u the control voltage, $(\dot{\cdot})$ the time derivative of the quantity $(\cdot)$, and a and b are assumed to be constant.

The flow equation governing the oil flow through the orifice of the spool is given by

$$Q_L = C_s w x_v \sqrt{\frac{1}{\rho}(p_s - \frac{x_v}{|x_v|} p_L)} \tag{6}$$

In the above, the variables are given by

Q_L = oil flow
C_s = leakage coefficient of the servo value
ρ = density of the working oil
w = area gradient of the value
p_s = supply oil pressure
p_L = load press of the cylinder

The continuity equation governing oil flow through the cylinder can be derived as follows, if phenomena of cavitation and saturation do not occur within the cylinder.

$$Q_L = A_p \dot{x} + C_t p_L + \frac{V_t}{4\beta} \cdot \frac{dp_L}{dt} \tag{7}$$

where $\dot{x}$ is the piston velocity, A_P is the piston area, V_t is the total cylinder volume, β is the effective bulk modulus of the oil and C_t is the total leakage coefficient of the cylinder.

Due to this oil flow motion the dynamics of the piston that produces the rolling force against the plate is governed by

$$M\, \ddot{x} + c\dot{x} + F = p_L A_p \tag{8}$$

where M is the effective mass of combining the roll and the piston, c is the viscous damping coefficient, and F is the rolling force. Since the piston position x, that is the roll position is equal to the plate width, B_D, the above equation determines the instantaneous width of the plate according to the rolling force F.

It is noted that the rolling force and resulting plate deformation in Eq. 1 is derived based upon empherical approach. Therefore, the relationship may not be accurate in the sense that the model may be often affected by some other conditions and parameter variation that are not considered in the assumptions made for derivation of the model. Also, the roll motion governed by the hydraulic actuator given in Eq.(5). through (8) is subject to be highly nonlinear, uncertain and time varying due to its inherent characteristics.

The above discussions imply that the conventional approach may not be a good solution to design the plate width control system, since the approach requires obtaining a precise dynamic model although it may contain some degree of uncertainty in its parameters. This design difficulty leads us to consider a neural-network based control system design that can work well even in the situations mentioned in the above.

3. A neural network-based control system

The hydraulic width control system needs to have following characteristics :

(1) work very well with wide range of the plate width variation,
(2) show robustness to texternal disturbance coming into the process.

There may be several configurations of the control system to achieve these performances. The configuration considered herein is a feedback error learning neural network controller[12] which basically learns an inverse dynamic model of the control system which otherwise is not exactly known a priori. The learning is accomplished by a multi-layer perceptron as shown in Fig. 3. It is noted in this figure that a PD controller is combined with the neural network model to provide stability of the control system especially at initial learning stage.

In the system block diagram the objective of the neural network controller is to learn the inverse model of the rolling process from the learning signal provided by the PD controller. If this is fulfilled, the network output produces the desired plate width at steady state. In other words, this implies that the network is so trained as to make the PD controller output u_{PD} zero at steady state.

As shown in Fig. 4, network adopted here is a two hidden layers perceptron. The input variables entering into the input layer of the network include the desired dogbone width, the error between the desired and actual width, the rate of error change and the rolling force. Upon receiving these input values, the network starts to generate the output u_{NN} based upon learning signal. This u_{NN} is added to the u_{PD} and the resulting control input drives the hydraulic servo unit which in turn actuates the edge roll against the incoming slab. The procedure to train the network begins with defining the system error function which in this case can be formulated as

$$E = \frac{1}{2}(u_T - u_{NN})^2 \cdot \tag{9}$$

The objective of training the neural network is to minimize the error E. This is equivalent to say that the weight parameter of the network are required to be adjusted so as to make the u_{PD} vanish at steady state. Let us consider first the weight adaptation for the output layer. The update rule adopting the gradient descent method can be expressed by

$$w_{kl}(m+1) = w_{kl}(m) - \eta \frac{\partial E(m)}{\partial w_{kl}(m)} \tag{10}$$

where w_{kl} denotes the weight connecting the kth neuron at the output layer and l th neuron at the lth hidden layer, as shown in the figure, η is the learning rate and m is the time step. The second term in the right hand side of the Eq.(10) is written by

$$-\eta \frac{\partial E(m)}{\partial w_{lk}(m)} = \eta \ \{u_T(m) - u_N(m)\} \ \frac{\partial u_N(m)}{\partial w_{lk}(m)}. \tag{11}$$

The first and second terms in the right hand-side of Eq.(11) are expressed by

$$u_T(m) - u_N(m) = u_{PD}(m) \tag{12}$$

$$\frac{\partial u_N(m)}{\partial w_{lk}(m)} = \frac{\partial u_N(m)}{\partial net_l(m)} \cdot \frac{\partial net_l(m)}{\partial w_{lk}(m)} \ .$$

If Eq.(12) is substituted into Eq.(11) and the resulting equation is again substituted into Eq.(10), the updating equation for w_{kl} of the output layer is rewritten by

$$w_{lk}(m+1) = w_{lk}(m) + \eta \, o(m) \cdot f(net_l(m)) \ u_{PD}(m) . \tag{13}$$

In terms of δ_l (m) defined by $\partial E(m) / \ \partial net_i(m)$ the above equation is expressed by

$$w_{lk}(m+1) = w_{lk}(m) + \eta \ \delta_l(m) \cdot o_l(m) \tag{14}$$

The learning rule for w_{kj} of the kth hidden layers can be derived by using the back propagation algorithm [5]. The resulting updating equation is

$$\begin{aligned} \delta_k(m) &= \dot{f}(net_k(m)) \sum_{l=1}^{L} \delta_l w_{kj} \\ w_{kj}(m+1) &= w_{kj}(m) + \eta \delta_k(m) o_j(m) \end{aligned} \tag{15}$$

where $\delta_k(m)$ is the delta function of the kth neuron of the hidden layer, $o_j(m)$ is the output of the jth neuron of the jth hidden layer, L is the number of neuron in the output layer.

Now, the feedback error learning can be made by utilizing Eqs. (14) and (15). The training procedure can be described. with the aid of the control system block diagram shown in Fig.3. The training begins with initialization of the weights. With this initialized weights the neural network produces output which, then, is added to the PD controller output. This combined signal actuates servo value of the hydraulic system which in turn drives the rolling mill. The resulting width value is compared with the desired width, B_d and the error is fed to the PD controller. Then, the controller generates a new output which is used for a signal of training the neural network at this time step. This procedure is repeated until the control system reaches a steady state at some time step.

4. Simulation Results and Discussions

The designed control system is evaluated in terms of the accuracy of the control and robustness to the system parameter variation. The effects of the network structure and learning rate on the control performance are also investigated.

For this purpose it is assumed that there occur decrease of slab temperature during rolling and change in the desired width. Fig. 5 shows the response of the slab width control for various network structures for η = 0.1. In this simulation the desired slab width is assume to be 2010mm, and initial width of the incoming slab is 2020mm. The variation of the network structure does not significantly affect the transient response of the plate control. In terms of the integral of absolute error criterion (IEA) and the setting time, the structure 4×10×10×1 with η = 0.1 is found to yield better performance than the other two structures.

The effect of a disturbance is investigated by using the temperature variation of the slab. The temperature variation is assumed to occur and decrease from 1000°C to 900°C, as shown in Fig 6(a). Due to this variation, the rolling force required for control varies according to Eq. (1). The performance of rejecting this disturbance is illustrated in Fig. 6(b). The disturbance persists until around 1.5 sec and thereafter the plat width reaches the desired value. The effect of the network structure in this case shows similarity to the case of Fig 5. In Fig 7 the result obtained from variation of operating point is shown for two different desired plate widths, 2015mm and 2005mm. The initial rise of the response for the case of 2005mm appears rather slow because of the saturation phenomenon of the actuator. The saturation causes slow response and rather large overshoot near 0.5 sec.

Fig.8 shows of the integral of the absolute error (IEA) for two different controllers, the proposed MLP controller and the PID controller when the desired width value is set to B_o* = 2020 + 10 sin 0.5t. The figure shows that the tracking error caused by proposed NN controller decreases as time increases. On the other hand, the conventional controller can not decrease the IAE with time. This is because the IAE value remains constant if this type of the controller reaches the steady state.

5. Conclusions

The process reducing the slab width in hot Plate mill has been considered to produce rolled products with a desired dimension which otherwise increases the yield loss caused by trimming. Since the edging process is characterized by nonlinear, time-varying and uncertain properties, a neural network-based control system has been adopted to take into account these characteristics. The performance of the proposed controller was simulated for various operating points, rolling temperatures, and network structures. The results of the width control obtained from the simulations show satisfactory accuracy in achieving the desired width and robustness to the temperature variation. The performance is found to show no significant difference with variation of the network structure and learning parameter.

In width control at actual rolling mills the plate width is varied due to thickness rolling action. Therefore the proposed control system needs to take into account the plate width deviation from the desired value to be made after the horizontal rolling.

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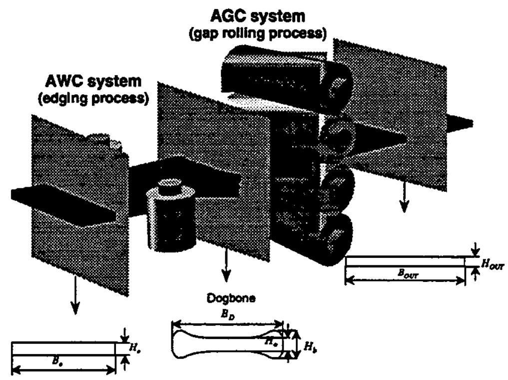


Figure 1. The edging process

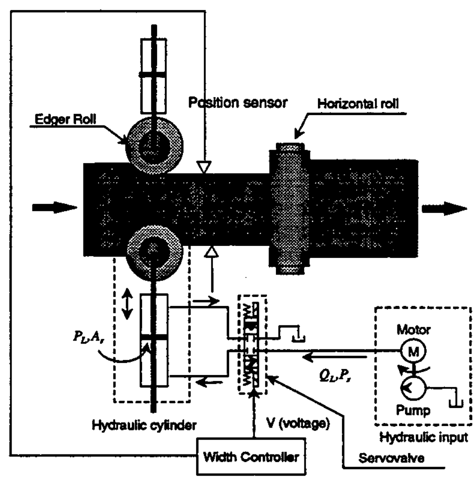


Figure 2. The structure of the automtic width control system

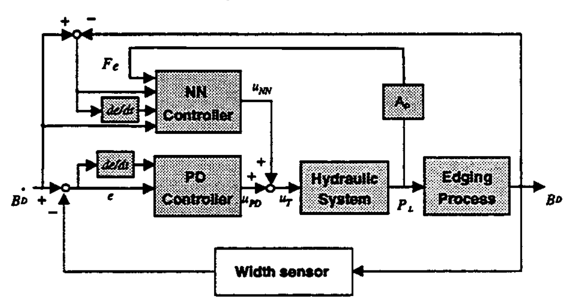


Figure 3. The neural network controller

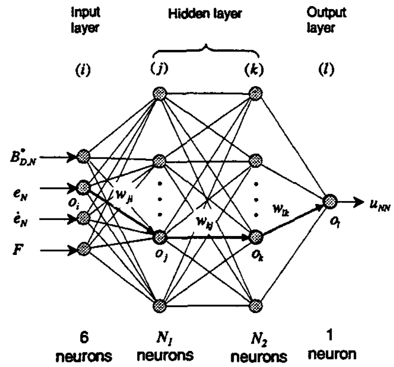


Figure 4. The structure of the multilayer perceptron

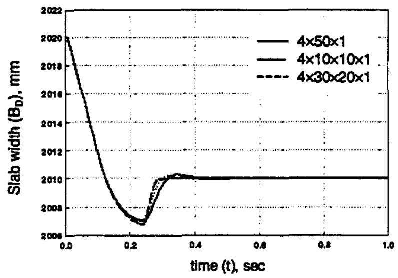
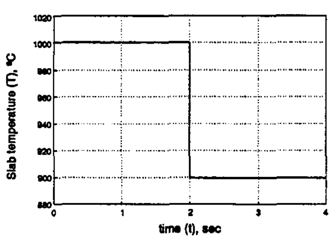
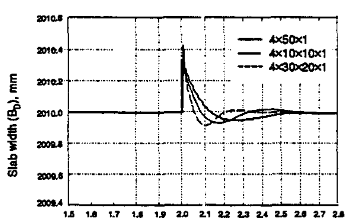


Figure 5. The transient response of neural network controller



(a) The change of plate temperature



(b) output width of the plate

Figure 6. The transient response due to temperature variation

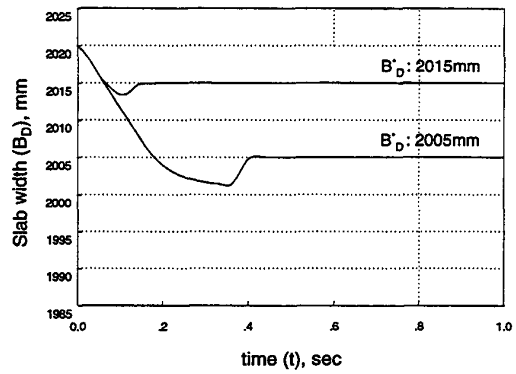


Figure 7. The width of response variation due to the operating condition change

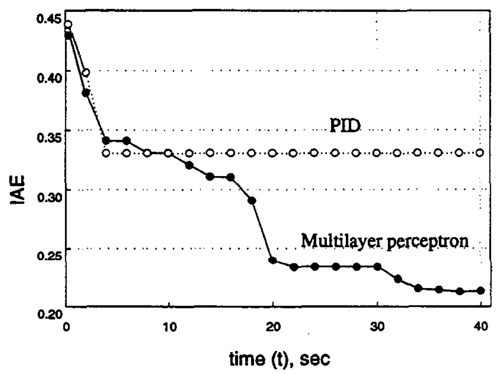


Figure 8. The integral absolute errors