INPUT SELECTION TECHNOLOGY OF NEURAL NETWORK AND ITS APPLICATION FOR HOT STRIP MILL

†Cheol Jae Park and †Duk Man Lee

†Rolling Technology and Process Control Research Group, Technical Research Laboratories, POSCO, Pohang, 790-785, Republic of Korea

Abstract: In this paper, the control system is proposed to obtain the desirable width margin of a strip in a rolling process. The neural network model is also suggested to improve the prediction performance of the width spread. The selection method of input parameter for the network using the hypothesis testing is proposed in this paper. The developed network model is based on the measured data such as the entry, delivery width margin of finishing mill and process setup data such as unit tension between stands, roll force, temperature, etc. Moreover, an edger control scheme is proposed to guarantee the desired strip width of finishing mill. It is shown through the field test of Pohang No.1 hot strip mill of POSCO that the width margin is greatly improved by the network model and the control scheme proposed in this paper.

Keywords: Hot strip mill, Neural network, Statistical testing, Width control, Roughing mill, Finishing mill, Width model

1. INTRODUCTION

Normally the width of strip in hot rolling mill is controlled at roughing mill. The width spread model and AWC, having the function of short stroke to compensate the width shortage at finishing mill, have been popular. What the width control is adopted only at roughing mill is that the width spread is ignored at finishing mill because of the difficulties of experiment at high temperature and analysis by the complexity of process parameters, etc. At the finishing mill, the width control is not performed and only the tension control using the looper system is applied to reduce the width fluctuation.

The tension of hot strip is mainly controlled by looper system which is located between rolling stands at finishing mill. Price (Price, 1973) proposed a static/dynamic model for looper including its drive. Clark et al. (Clark *et al.*, 1997) developed a hydraulic looper system in order to get high response time. Conventional looper control generally adopts PID scheme for the looper angle and tension regulation. Since interaction between angle and tension is existed, Okada et al. (Okada *et al.*, 1998) and Seki et al. (Seki *et al.*, 1991) proposed decoupling model and applied an optimal multivariable controller to prevent the interaction, where the tension is controlled by changing the torque of looper motor and mill motor speed. The tension is greatly fluctuated at finishing mill because of a temperature hunting and operating condition of operators. Imanari (Imanari *et al.*, 1997) developed H_∞ controller instead of looper PID in order to reduce the tension fluctuation and simulated the algorithm to verify the effect. Hesketh et al. (Hesketh *et al.*, 1998) designed the tension controller based on the output feedback. The algorithm is used recursive nonlinear technique and induced by backstepping logic. Moreover Asano et al. (Asano *et al.*, 2000) proposed a decentralized and impedance controller based on two degree of freedom IMC(Internal Mode Control) structure.

However, these previous results have usually focused on design of tension controller to reduce the width fluctuation. The controller has two critical issues. One is the various model uncertainties of looper system, which are operator's inexperience, unknown dynamic parameters to difficult to measure. The other is not easy to apply the real plant because of the complexity of the controller structure, etc.

Thus the width control at finishing mill is required in reality because the width spreads at finishing as well as roughing process. Moreover, width prediction model as well as tension controller in order to control the width at finishing mill is needed. Neural network model is proposed to predict the width spread. At the design of the neural network model, the input selection method of network is important. In this paper, a statistical approach to select the input of the network is presented. Many researchers have studied to select properly the network input. (Yu *et al.*, 2000; Wu and Massart, 1996; Back and Trappenberg, 2001) The conventional methods are weight pruning (Ledoux and Grandin, 1994) and data pretreatment, etc. The weight pruning technique is the reduction method of the input dimension, which selects the effective variables, synaptic weights by using measure of the saliency.(Reed, 1993) PCA(Principal of Component Analysis)(Luo *et al.*, 1999; Kambhatla and Leen, 1997)is the one of the most popular data pretreatment methods, but it is not easy to apply the rolling process, which is the nonlinear physical system including many process parameters. Therefore, the systematically selecting technology of neural network input related to width change is needed.

The paper is organized as follows: Section 2 gives a brief description of the plant. In Section 3, the neural network learning model to raise the precision of the width prediction is proposed. The statistical method to select network input is proposed. Section 4 describes the application results of the Pohang No.1 hot strip mill(P1H) of POSCO. Conclusions and further work are discussed in Section 5.

2. PLANT DESCRIPTION AND CONTROL PROBLEM

Figure 1 shows a layout of Pohang No.1 hot strip mill of POSCO. The slab produced from the continuous casting plant is reheated in the furnace and the slab of furnace exit is edged at sizing press. The roughing mill is the process which the thickness and width of the slab are roughly rolled. The width of the hot rolled strip is nearly determined at this stage.

Next, the strip at the exit of roughing is edged once more at the edger of F0 stand and moves to finishing mill area. The finishing mill has 6 stands with the inter-stand looper control system. Loopers absorb the mass flow unbalance due to the inter-stand strip speed difference.

Normally, the roll gap and force are set up and controlled using 2 dimensional rolling model on the assumption that the width at the finishing mill is constant. That is the reason that 3 dimensional rolling model varying the width is very complicated to apply. But the width at the horizontal rolling of the F0 and finishing mill spreads to the width direction which is not constraint.

Conventional width control at the roughing mill is called AWC which controls the gap of the E1,E2 using the width measurement system(RW). Moreover, the F0 edger gap by the empirical prediction of the width spread quantity is set up in advance. But the performance of the width control is diminished because the exact width model has not been developed at the finishing process. Therefore, the width model and controller at the process are needed.

AWC, conventional width controller, has the two main control issues. One is FB(Feed Back) AWC which controls the gap of the edger(E2) to decrease the difference between the target width and the measured width from the RW sensor. The other is RF(Roll Force) AWC which is the control method to consider the width spread after horizontal rolling.

3. NEURAL NETWORK MODEL OF WIDTH PREDICTION

The field test result has the prediction error 2.23mm as described. The error is caused by the uncertain rolling condition, for example operator manual intervention, lack of the temperature uniformity, setup error, etc. Since the error is not small, in this paper, the neural network learning model which compensates the model error is proposed. In particular, a statistical approach to select the input of the network is presented. The proposed algorithm can simplify the procedure and effort of the input selection.

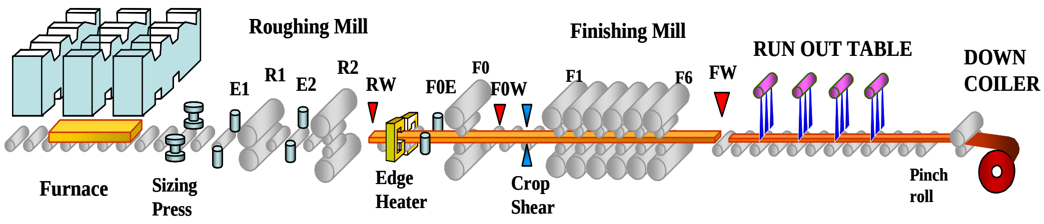

Fig. 1. Configuration of hot strip rolling mill

3.1 *Hypothesis Testing*

A statistical hypothesis is usually a statement about a set of parameters of a population distribution (Ross, 2000). It is called a hypothesis because it is not known whether or not it is true. Suppose that $X_1, \cdots, X_n$ is a sample of size n from a normal distribution having an unknown mean μ and a known variance σ^2 and null hypothesis(H_0), alternative hypothesis(H_1) in testing are defined as equation (1).

$$\begin{aligned} &H_0 : \mu = \mu_0 \; and \\ &H_1 : \mu \neq \mu_0, \end{aligned} \tag{1}$$

where μ_0 is some specified constant.

Since $\overline{X} = \sum X_i/n$ is a natural point estimator of μ, it seeds reasonable to accept H_0 if $\overline{X}$ is not too far from μ_0. That is, the critical region of the test would be the form

$$C \;=\; \{X_1, \cdots, X_n \,:\, |\overline{X} - \mu_0| > c\}. \tag{2}$$

for some suitably chosen value c.

If the test has significance level α, then it must be determined the critical value c in equation (2). That is, c must be such that

$$P_{\mu_0}\{|\overline{X} \,-\, \mu_0| > c\} \;=\; \alpha, \tag{3}$$

where P_{μ_0} is the probability at $\mu = \mu_0$.

However, when $\mu = \mu_0$, $\overline{X}$ will be normally distributed with mean μ_0 and variance σ^2/n and random variable Z, defined by equation (4), will have a standard normal distribution.

$$Z \;\equiv\; \frac{\overline{X} - \mu_0}{\sigma/\sqrt{n}}. \tag{4}$$

Equation (3) is equivalent to

$$P\left\{|Z| > \frac{c\sqrt{n}}{\sigma}\right\} \;=\; \alpha.$$

or, equivalently,

$$2P\left\{Z > \frac{c\sqrt{n}}{\sigma}\right\} \;=\; \alpha,$$

where Z is a standard normal random variable.

However, it is known that

$$P\{Z > z_{\alpha/2}\} \;=\; \alpha/2.$$

and so

$$\frac{c\sqrt{n}}{\sigma} \;=\; z_{\alpha/2}.$$

or,

$$c \;=\; \frac{z_{\alpha/2}\sigma}{\sqrt{n}}.$$

Thus, the significance level α test is to reject H_0 if $\frac{\sqrt{n}}{\sigma}|\overline{X} - \mu_0| > z_{\alpha/2}$ and accept otherwise; or, equivalently, to

$$\begin{aligned} &reject \;\; H_0 \;\; if \;\; \frac{\sqrt{n}}{\sigma}|\overline{X} - \mu_0| > z_{\alpha/2} \\ &accept \;\; H_0 \;\; if \;\; \frac{\sqrt{n}}{\sigma}|\overline{X} - \mu_0| \leq z_{\alpha/2} \end{aligned} \tag{5}$$

From equation (5), it is determined whether or not to accept the null hypothesis by computing, first, the value of the test statistic and, second, the probability that a unit normal would exceed that quantity. This probability-called the p-value of the test-gives the critical significance level in the sense that H_0 will be rejected if the p-value is less than the significance level α and accept of it is greater than or equal. The parameter α is a constant and set to 0.05 in this paper.

3.2 *Input Selection Process*

The factors related to the width deviation at finishing mill are selected from the experimental knowledge before deciding the network inputs. The factors are as follows, namely, thickness and width set value, components(C, Si, Mn), average width deviation, steel grade, threading speed set value, thickness calculation value and unit tension set and roll force set at each stand, entry temperature value, width set at the delivery of finishing, roughing width, width margin value at F0 stand, etc. The correlation between the delivery width margin and the factors is analyzed by commercial MINITAB software. Pearson method is used to solve the correlation coefficient(r), defined as equation (6).

Table 1. Correlation of F6 width and related factors

Factor	Correlation coefficient(r)	p-value
RM width	0.605	0
F0 width	0.469	0
Unit tension	-0.37	0
⋮	⋮	⋮
Component Mn	-0.017	0.385
F4 roll force	-0.003	0.884

$$r = \frac{S_{xy}}{\sqrt{S_{xx} \cdot S_{yy}}} = \frac{\sum(x_i - \overline{X})(Y_i - \overline{Y})}{\sqrt{\sum(x_i - \overline{X})^2 \cdot \sum(Y_i - \overline{Y})^2}} \quad (6)$$

where x is an input, Y is an output variable, $\overline{X}$,$\overline{Y}$ are a mean of input, output, respectively.

From Table 1, 25 factors having the large correlation are selected. The correlations between F0 width and 25 factors are similarly analyzed. If the calculation result of the p-value is less than α, then H_0 is rejected, namely the factor is statistically signified. The factors which the p-value is less than α are selected 10 variables from the analysis.

The regression is executed to explain the appropriateness of the 10 variables using the Least Square Method(LSM). R^2 between the F0 width and 10 variables is 71% and it is the satisfied results. R^2 is called coefficient of determination, defined as equation (7).

$$R^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST}, \quad (7)$$

where SST is the total variation, SSR is the variation which can be explained by the regression, SSE is the variation which can't be explained by the regression. The relation of these variations is $SST = SSE + SSR$. Finally the selected input parameters are product thickness, width, components(C, Si), no.1 and no.2 unit tension, F1 reduction, F1 roll force, F5 entry temperature, F6 delivery width.

The structure of the network has 1 hidden layer, tangential sigmoid nonlinear function. Levenberg-Marquardt back propagation method is used for the learning. The parameters of the network are displayed in Table 2.

Table 2. Design parameters of network

	Network input	Norm. input	Output
Max	25,1300,250,80,110, 120,1,2500,1200,20	0.8	20
Min	1.2,650,0.5,0,20, 30,0,500,800,0	-0.8	0

4. FIELD TEST RESULTS AND DISCUSSION

In this section, the width control performance is checked using the developed algorithm and the control system. Figure 2 is the layout of the control system at Pohang No.1 hot strip mill, where the width measurement system(F0W) measures the entry width of the finishing mill and the width spread model estimates the delivery width at last stand. Neural network supplements the width model deficiency.

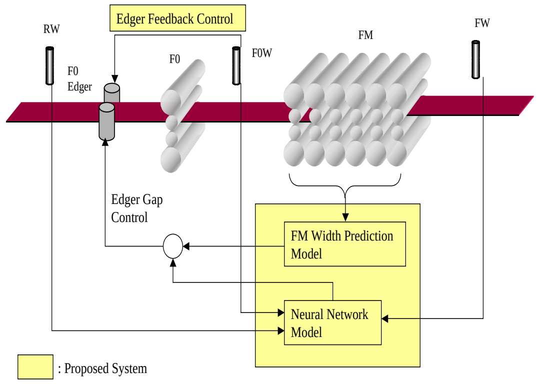

Fig. 2. Layout of width control system

4.1 *Precision Test of Developed Width Model*

The inputs of the network are the delivery width margin set value of the finishing mill, thickness, C, Si, etc, and the output is the entry width margin set value of the finishing mill(F0 delivery). Normally the set value of delivery width margin is 7mm. It is important to estimate the set value of the finishing entry width, because it is the reference width of the roughing mill and F0 edger.

The test coil is 1258 coils gathered at Sep. 2003 to analyze the precision of the developed model. Figure 3 shows the test results about performance of the width model including the learning model. The estimated width and measured width which is measured from the width measurement system(F0W) installed at this project are compared. Table 3 shows clearly the performance. The precision of the estimation is about 85(%) within 2(mm) in case of the stainless, 77.3(%) in case

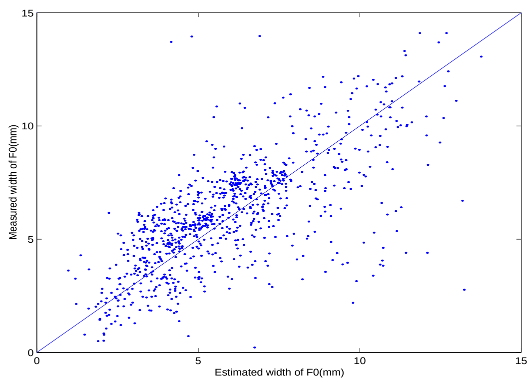

Fig. 3. Comparision of estimated and measured width

of the all coils. Moreover, the standard deviation between estimated and measured width is about 1.69(mm).

Table 3. Performance of the model

	All coils			Stainless coils		
	< 1	< 1.5	< 2	< 1	< 1.5	< 2
Perform.(%)	42.3	62	77.3	45	60	85

4.2 *Test Results of F0 Edger Control*

Until now, feedback control of F0 edger is not possible because of the absence of the reference width at the entry of the finishing. However, the newly developed width spread model and supporting neural network now make it possible to use F0 edger feedback control. Thus, the error between the predicted and measured width is calculated and the gap control quantity of F0 edger from the error is calculated.

Figure 4 shows the test result. From the figure, F6 measured width margin in this coil is 10(mm). Moreover F0 width margin predicted by neural network is 11(mm). At about 9(sec), since the measured F0 width is less than the predicted width, F0 edger feedback control is applied at about 17(sec) and the F0 actual width is recovered at that point.

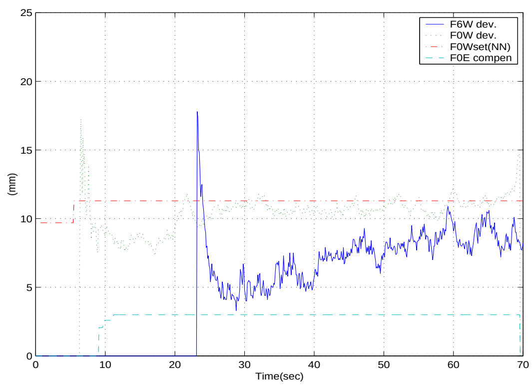

Fig. 4. Test result of edger control

Table 4 shows the effect of the control. From the test of 2 weeks, the mean and standard deviation of the F6 width have improved about 6.1(%) and 12.5(%), respectively.

Table 4. Final test results(unit:mm)

Conventional		Proposed	
width mean	deviation	width mean	deviation
8.2	1.6	7.7	1.4

5. CONCLUSION

The width prediction model which includes the flat, tension model and learning model using neural network for finishing process is developed and applied to a real plant to reduce the width margin. The effective network inputs out of the many process parameters are systematically selected by the statistical method which proposed in this paper. The method is shown to be an efficient approach to the determination of the input parameters. The hypothesis testing method is applied to select the network input and saved the time, effort. Moreover, the setup and feedback control of F0 edger are executed to control the width. The results of on line field test have shown that the mean and standard deviation of the margin have improved about 6.1(%) and 12.5(%), respectively by the proposed method. This confirms that the proposed model and control are very effective in improving the performance of the width control.

6. REFERENCES

Asano, K., K. Yamamoto, T. Kawase and N. Nomura (2000). Hot strip mill tension-looper control based on decentralization and coordination. *Control Engineering Practice* **8**, 337–344.

Back, A.D. and T.P. Trappenberg (2001). Selecting inputs for modeling using normalized higher order statistics and independent component analysis. *IEEE Transactions on Neural Networks* **12**(3), 612–617.

Clark, M.T., H. Versteeg and W. Konijn (1997). Development of new high performance loopers for hot strip mills. *Iron and Steel Engineer* pp. 64–70.

Hesketh, T., Y.A. Jiang, D.J. Clements, D.H. Butler and R. Laan (1998). Controller design for hot strip finishing mills. *IEEE Transactions on Control Systems Technology* **6**(2), 208–219.

Imanari, H., Y. Morimatsu, K. Sekiguchi, H. Ezure, R. Matuoka, A. Tokuda and H. Otobe (1997). Looper h-infinity control for hot-strip mills. *IEEE Transactions on Industry Applications* **33**(3), 790–796.

Kambhatla, N. and T.K. Leen (1997). Dimension reduction by local princiipal component analysis. *Neural Comput.* **9**(7), 1493–1516.

Ledoux, C. and J.F. Grandin (1994). Two original weight pruning methods based on statistical tests and rounding techniques. *IEE Proc. Vision, Image Signal Process* **141**(4), 230–236.

Luo, J., B. Hu, X.T. Ling and R.W. Liu (1999). Principal independent component analysis. *IEEE Transactions on Neural Networks* **10**(4), 912–917.

Okada, M., K. Murayama, A. Urano, Y. Iwasaki, A. Kawano and H. shiomi (1998). Optimal control system for hot strip finishing mill. *Control Engineering Practice* **6**, 1029–1034.

Price, J.C. (1973). The hot strip mill looper system. *IEEE Transactions on Industry Applications* **IA-9**(5), 556–562.

Reed, R. (1993). Pruning algorithms: a survey. *IEEE Trans. Neural Netw.* **4**(5), 740–747.

Ross, S.M. (2000). *Introduction to probability and statistics for engineers and scientists.* Academic Press.

Seki, Y., K. Sekiguchi, Y. Anbe, K. Fukushima, Y. Tsuji and S. Ueno (1991). Optimal multivariable looper control for hot strip finishing mill. *IEEE Transactions on Industry Applications* **27**(1), 124–130.

Wu, W. and D.L. Massart (1996). Artificial neural networks in classification of nir spectral data:selection of the input. *Chemometrics and Intelligent Laboratory Systems* **35**, 127–135.

Yu, D.L., J.B. Gomm and D. Williams (2000). Neural model input selection for a mimo chemical process. *Engineering Applications of Artificial Intelligence* **13**, 15–23.