Direct Width Control Systems Based on Width Prediction Models in Hot Strip Mill

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In this paper, a width control system is proposed to obtain the desirable width margin of a strip in the rolling process of the hot strip mill. A simplified FEM (Finite Element Method) based width prediction model (WPM) is developed to compute the width spread at each stand. A neural network based error correction model (ECM) is also introduced to compensate for modelling errors from the simplified FEM based WPM. Input variables for the neural network model are chosen by using the hypothesis testing. In addition, the width control scheme using the simplified FEM based WPM and the neural network based ECM is proposed to achieve the desired width margin in the finishing mill. It is shown through the field test of the Pohang no. 1 hot strip mill of POSCO that the performance with respect to the width margin is greatly improved by the proposed width control scheme based on two models.

KEY WORDS: hot strip mill; neural network; statistical testing; width control; roughing mill; finishing mill; width model.

1. Introduction

Recently, the customers’ demands of the quality of final products in a hot strip mill become strict and increasingly important. The major elements of the quality of the product in a hot strip mill are thickness, width, shape of the strip, etc. Specially, the width plays an important role in determining the quality of the strip. The difference between the actual width value and the reference width value, called the width margin, has often been used as a criterion of the quality. It is important to achieve a uniform width margin.

Normally the width margin of the strip in the hot strip mill is controlled in a roughing mill, where a width prediction model (WPM) and an automatic width control (AWC) have been used in order to achieve the desirable width margin. Direct controls of the width margin are conducted only in the roughing mill. However, even if they try only to prevent the width variation, some width fluctuation due to the tension between stands may happen in the finishing mill, which is located next to the roughing mill. To alleviate the width fluctuation, the indirect tension control by the looper system between rolling stands has been applied in the finishing mill. There have been some works on the tension control systems by the looper. The dynamic and hydraulic looper model is proposed by Price1) and Clark.2) Since the interaction between the looper angle and the tension exists in the conventional looper control system, Okada3) and Seki4) proposed a decoupling model, to which an optimal multivariable controller is applied. Imanari5) and Hesketh6) proposed the $H_\infty$ control and the backstepping scheme, respectively. Moreover decentralized and impedance controllers based on the internal mode control (IMC) structure were introduced by Asano.7)

The aforementioned works have focused on the tension control with looper systems in the finishing mill to reduce the width fluctuation. However, the tension control is not enough to obtain the desirable width margin in the finishing mill since it is difficult to measure the tension between stands and there exists the mass flow unbalance such as the operator intervention for the speed, roll gap, strip shape, and so on. Thus, it would be desirable to conduct direct width controls together with tension controls in the finishing mill. In this paper, the direct width control in the finishing mill will be done by prediction and correction steps. The first is to predict the width variation through the finishing mill and the second to determine the width margin at the entry of the finishing mill. The key idea is that the more accurate width margin can be achieved in consideration of the width variation through the finishing mill.

In order to predict the width variation through the finishing mill, a mathematical model with proper complexity should be developed. Isi8) proposed the three dimensional finite element method (FEM) based WPM in order to analyze the width deviation at the roll bite. This WPM is too complex to be used for the control design. In this paper, a new WPM is proposed by simplifying this FEM based WPM, which is called a simplified FEM based WPM. We need a supplementary model to compensate for modelling errors from the simplified FEM based WPM. The neural network based error correction model (ECM) is also pro-
The conventional methods are based on the weight pruning technique, which selects the effective variables and the synaptic weighting by measuring the saliency, demands too computational tasks. The PCA (Principal Component Analysis) is not easy to be applied to the rolling process because this is the nonlinear physical system including many process parameters. In this paper, a statistical approach to selecting the input variables of the network is proposed. Input variables highly correlated with the width margin are chosen by the $p$-value and the correlation coefficient. To the authors’ knowledge, it would be the first trial in the rolling mill to employ a neural network model using the statistical approach. The width control scheme using the simplified FEM based WPM and the neural network based ECM will be proposed in this paper.

The paper is organized as follows: Section 2 gives a brief description of the hot strip mill and its width control problem. In Sec. 3, the simplified FEM based WPM in the finishing mill is proposed. In Sec. 4, the neural network based ECM is proposed to raise the prediction accuracy of the physical system including many process parameters. In this paper, a statistical approach to selecting the input variables of the network is proposed. Input variables highly correlated with the width margin are chosen by the $p$-value and the correlation coefficient. To the authors’ knowledge, it would be the first trial in the rolling mill to employ a neural network model using the statistical approach. The width control scheme using the simplified FEM based WPM and the neural network based ECM will be proposed in this paper.

The width variation through the finishing mill can be written as

$$dw = f(H, h, W, R, V, \mu, \sigma_m, T_{\text{front}}, T_{\text{back}}, C, Mn, T, P) \ldots \ldots (1)$$

where $f_i$ is implicitly obtained from the analytic FEM based WPM, $dw$ total width variation through the finishing mill, $H$ entry thickness, $h$ delivery thickness, $W$ entry width, $R$ work roll radius, $V$ mill speed, $\mu$ friction coefficient, $\sigma_m$ average deformation resistance of the strip, $T_{\text{front}}$ front total tension, $T_{\text{back}}$ back total tension, $C$ carbon quantity, $Mn$ manganese quantity, $T$ strip temperature, $P$ roll force, respectively. Since the FEM model in Eq. (1) is complicated, the simple model is demanded.

The analytic FEM based WPM can be linearly approximated with respect to four sub-models, i.e., the model without tension ($f_{\text{without tension}}$), the model with tension between stands ($f_{\text{with tension}}$), the roll crown model ($f_{\text{roll crown}}$), the strip crown model ($f_{\text{strip crown}}$), and so on. The approximated width variation through the finishing mill can be written as

$$dw = dw_0 + (dw - dw_0)_{\text{with tension}} + (dw - dw_0)_{\text{roll crown}} + (dw - dw_0)_{\text{strip crown}} \ldots \ldots (2)$$

where $dw_0$ is the total width variation through the finishing mill, $dw_{\text{with tension}}$, $dw_{\text{roll crown}}$, and $dw_{\text{strip crown}}$ are the width variations induced by tension, roll crown, and strip crown, respectively.
where \( dw_0 \) is the width spread quantity in case that tension is not applied. Since the roll and the strip crown have negligible effects on the width spread, only first two terms in Eq. (2) will be considered in this paper.

### 3.1. Model without Tension

In case that the tension is not applied, the predicted width variation through the finishing mill is analytically computed from the FEM and can be expressed as follows:

\[
dw_0 = f(H, h, W, R, V, \mu, \sigma_m)
\] ..................(3)

It has been a general rule of thumb that the predicted width variation Eq. (3) can be simply represented by

\[
dw_0/W = f(\mu, r, ld/W)
\] ..................(4)

where \( r \) is the reduction rate and \( ld \), defined the contact arc length, is expressed by

\[
ld = \sqrt{ReH}
\] .................................(5)

In order to obtain a more simple model, the Eq. (4) will be more approximated. To begin with, we check how strongly four input parameters in Eq. (4) is dependent on the function. The friction coefficient \( \mu \) of the Eqs. (3) and (4) is the main factor of the total width spread as well as the process performance. Even though the value \( \mu \) is slightly varied with material, it is set to 0.3 which has been known to be a reasonable value by experience. It follows that we have only to check the effects of three remaining parameters in Eq. (4) such as \( r, ld/W, W/H \). For the parameters shown in Table 1, the width variation is computed by the analytic FEM based WPM.

The width under the various parameters to form the proper model is represented at Figs. 2–4. As shown in Fig. 2, if the ratio of \( W/H \) is increased, then the width spread is exponentially decreased. There is little width spread at the whole ratio of \( W/H \). Figure 3 shows that the width spread is proportional to the contact arc length \( (ld) \). From Fig. 4, the width spread is increased at the constant ratio \( (W/H) \) as growing the reduction rate. Thus it is known that two parameters \((r, ld/W)\) in Eq. (4) have the main effect with the width spread.

If all relations are considered, the model without tension is approximated as follows:

\[
dw_0/W = f(r, ld/W) = Ar^B ld/W^C
\] ..................(6)

where \( A, B, C \) are chosen to achieve the good approximated model from the analytic FEM based WPM and used the

Levenberg–Marquardt algorithm\(^7\) to provide a numerical solution to the mathematical problem of minimizing a sum of squares of the errors. Since two parameters \((r, ld/W)\)

### Table 1. Simulation conditions of the model without tension.

| Condition | Set value |
|-----------|-----------|
| \( W/H \) | 20, 40, 60, 80, 100, 120, 140, 160, 200, 240, 290, 320, 400, 480, 560, 640, 720, 800, 880, 1000 |
| Constraint | \( H \) 1–50mm |
| Constant | \( W \) 700–1500mm |

\( R=300\text{mm}, \ C=0.1\%, \ V=240\text{rpm}, \ \mu=0.3 \)
have the similar magnitude for the ratio \((dw/W)\) as shown in Figs. 3, 4, the parameters \(B, C\) have the similar range of 1.2–2.3. The selected parameters are \(A=1.311, B=1.431, C=2.023\), respectively.

The comparison between the proposed model without tension and the analytic FEM based WPM is shown in Fig. 5 and Table 2. The standard deviation of the model error is 0.07 mm. Thus it can be seen that the proposed model is well approximated to the analytic FEM based WPM.

### 3.2. Model with Tension

The model in consideration of the tension between stands is represented as

\[
dw - dw_0 = f(H, h, W, r, V, \mu, \sigma_m, T_{\text{front}}, T_{\text{back}}) \quad \ldots \ldots \ldots \ldots (7)
\]

It has been a general rule of thumb that Eq. (7) can be simply represented as previously stated.

\[
\frac{dw - dw_0}{W} = f \left( \mu, r, \frac{ld}{w}, \frac{W}{H}, ft, bt \right) \quad \ldots \ldots \ldots \ldots (8)
\]

where \(ft\) front unit tension, \(bt\) back unit tension are defined as follows.

\[
ft = \frac{T_{\text{front}}}{\sigma_m}, \quad bt = \frac{T_{\text{back}}}{\sigma_m} \quad \ldots \ldots \ldots \ldots (9)
\]

Since the deviation of the deformation resistance is expressed by the ratio of the tension, the resistance effects about various steel are included in the equation.

Table 3 shows the simulation conditions for the model with tension. The width deviation is also increased as the tension between stands is increased. Isii introduced that the back tension and the front tension increase the width shrinkage at the entry and the delivery of the roll bite. But the back tension has a larger effect on the width deviation rather than the front tension. Therefore the following model with tension similar to the model without tension is proposed.

\[
\frac{dw - dw_0}{W} = f \left( r, \frac{ld}{W}, bt \right) \equiv Ar^a \left( \frac{ld}{W} \right)^b bt^c \quad \ldots \ldots \ldots \ldots (10)
\]

where \(A, B, C\), and \(D\) are chosen to obtain a good approximated model from the analytic FEM based WPM. The selected parameters are \(A=-0.973, B=1.219, C=1.746, D=0.975\), respectively.

The standard deviation between the developed model with tension (Eq. (8)) and the analytic FEM based WPM is 0.036 mm as shown in Table 4. The proposed model is very close to the analytic FEM based WPM as seen in Fig. 6.

| Table 4. Comparison between model with tension and analytic FEM based WPM. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Average error (mm) | Max error (mm) | Standard dev. (%) | <0.10 (%) | <0.25 (%) | <0.5 (%) |
| 0.016 | 0.243 | 0.036 | 93.96 | 96 | 100 |

Table 3. Simulation conditions of model with tension.

| Condition | 20, 40, 60, 80, 100, 120, 140, 160, 200, 240, 290, 320, 400, 480, 560, 640, 720, 800, 880, 1000 |
| Constraint | H, W | 1~50mm, 700~1500mm |
| Constant | R=300mm, C=0.1%, V=24rpm, \(\mu=0.3\) \(bt=3, 4, 5, 6\) of flow stress, \(ft=0.9, 1, 0.1, 0.2\) of bt |

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3.3. Total WPM

The total WPM is represented by integrating above models.
- F1 stand:
  \[ W_i - W_0 \equiv f \left( r, \frac{ld}{W_0} \right) W_0 \]
  \[ = 1.311 r^{1.431} \left( \frac{ld}{W_i} \right)^{2.023} W_0 \]
- F2–last stand:
  \[ W_i - W_j \equiv \left[ f \left( r, \frac{ld}{W_j} \right) + f \left( r, \frac{ld}{W_i}, bt \right) \right] \]
  \[ = 1.311 r^{1.431} \left( \frac{ld}{W_i} \right)^{2.023} - 0.973 r^{1.219} \left( \frac{ld}{W_j} \right)^{1.746} \]
\[ \left( \frac{ld}{W_i} \right)^{0.975} \]

where \( i \) is stand number \((i=1, 2, \ldots, 5)\).

3.4. Test of Total WPM

How well the proposed model works in the field is shown in Table 5. From the table, the standard deviation of the error between the width prediction of the total WPM and the measured data of the works is 2.23 mm. It can be seen that the proposed model describes the real system well.

4. Neural Network Based ECM

The developed simplified FEM based WPM has the prediction error 2.23 mm as mentioned in the previous section. The prediction error is due to the uncertain rolling condition such as operator manual intervention, nonuniform temperature, setup error, and so on. Since the prediction error is not small enough to ignore, the neural network based ECM is proposed in this section to compensate the error of the simplified FEM based WPM. Since there are many factors related to the width margin in the finishing mill, it is important to select the significant input factors. In particular, the statistical approach is introduced to make it more systematic to select the input variables of the network.

4.1. Selection of Input Variables

The factors related to the width margin in the finishing mill are determined from the experimental knowledge as candidates of the neural network input variables. We choose 25 factors correlated with the entry width margin of the finishing mill. The factors are shown in Table 6. The reference width margin at the entry of the finishing mill is predicted from the neural network based ECM in order that the reference width margin at the delivery of the finishing mill is 7 mm. So we will focus on the entry width margin. The correlation with the entry width margin of the finishing mill is analyzed to choose the input variables by the commercial MINITAB software.

The test samples are taken from May 10 to Jul. 20, 2003 (2595 coils). The correlation coefficient \((\rho)\) can be computed empirically by

\[ \rho = \frac{\sum (x_i - \bar{X})(y_i - \bar{Y})}{\sqrt{\sum (x_i - \bar{X})^2 \cdot \sum (y_i - \bar{Y})^2}} \]

where \(x_i, y_i\) are each value of the samples, \(\bar{X}, \bar{Y}\) are the sample means, respectively.

The correlation between F0 width margin (the entry width margin of the finishing mill) and 25 factors are shown in Table 6. The statistical appropriateness of the selected factors is estimated by the \(p\)-value. The test static should be calculated in order to get the \(p\)-value. The \(t\)-distribution test is adopted in case of unknown population variance between two samples. It assesses whether the normalized-means of two groups are statistically different from each other. It is applied in this paper to analyze the statistical significance between F0 width margin and other factors. The \(T\) test static is calculated by

\[ T = \sqrt{n-2} \cdot \frac{\rho}{\sqrt{1 - \rho^2}} \]

where \(n, n-2\) are the number of samples, the degree of freedom, respectively. The \(p\)-value is converted by the \(t\)-distribution table. For example, the \(T\) test static is 1.426 in case of the F6 roll force \((\rho=0.028, n=2595)\). The \(p\)-value can be converted easily to 0.154 in case of the two-tailed test from the \(t\)-distribution table. The significance level for the \(t\)-test is set to 0.05 which is commonly adopted for a hypothesis testing. This means that we would find a statistically significant difference between the means with the probability 0.05. The \(p\)-values of other factors can be converted similarly as seen in Table 6.

The null hypothesis \((H_0)\), alternative hypothesis \((H_1)\) in the hypothesis testing are defined as follows:
It is determined whether or not to accept the null hypothesis by computing the $p$-value. If the $p$-value is less than significance level $\alpha$, then $H_0$ is rejected, namely the factor is statistically signified. The $p$-value gives the critical significance level in the sense that:

- reject $H_0$ if $p$-value $< \alpha$
- accept $H_0$ if $p$-value $\geq \alpha$

From the analysis, the 10 variables with $p$-values below $\alpha$ are selected, where $\alpha$ is set to 5%. The selected 10 input variables for the model are the product thickness, product width, components (C, Si), no. 1 and no. 2 unit tension, F1 reduction, F1 roll force, F5 entry temperature, F6 delivery width margin, and the output of the network is F0 width margin. The selected variables are above 0.17 for the correlation coefficient and 0.0 for the $p$-value. The component C and the product thickness are also selected because the steel grade and its size are important factors, even if the correlation coefficient is below 0.17.

The designed network has the 1 hidden layer and the tan-sigmoid nonlinear function. The Levenberg–Marquardt back propagation method is employed for the learning. The data is gathered from May 18 to Jun. 11, 2003 to construct and verify the network (2,513 data sets). The parameters of the network appear in Table 7.

**Table 7. Design parameters of the network.**

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

**4.2. Test of Neural Network Based ECM**

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

1,258 test coils are gathered to analyze the precision of the developed model. Figure 10 shows the performance test results of the model. The width margin which is predicted by the neural network based ECM for the entry of the finishing mill and the width margin which is measured from F0W established at this research are compared. Table 8 shows the performance. The precision of the estimation is about 85% within the estimation error 2 (mm) in case of...
the stainless steel. Moreover, the standard deviation between the predicted and the measured width margin is about 1.69 (mm). The standard deviation is smaller than 1.8 (mm) of the present, which shows that prediction performance is improved. Since the standard deviation is larger than that of the present in case of the selection of other variables, it can be seen that 10 variables are optimally selected.

5. Width Control System

In this section, the width control system in the finishing mill is described. The width estimation is divided into two models and controlled by the width control system. **Figure 11** shows the layout of two models and the width control system installed in the Pohang no. 1 hot strip mill, where the width measurement system (F0W) measures the entry width of the finishing mill. So far, since the width measurement system was not installed at the entry of the finishing mill, there was no way that the operator could know input width and width spread quantity through the finishing mill. The CCD2030 (F0W) stereo width measurement system is designed to measure the width of the strip being produced on a continuous basis in a hostile environment. It works on a real time basis to measure the width of the hot strip. The measurement system as stated is established at the entry of the finishing mill, the control cubicle and the controller of the system are established at the works.

The output of the simplified FEM based WPM is the width spread through the finishing mill. Since the width margin at delivery of the finishing mill is demanded 7 [mm], the width margin at entry of the finishing mill, called $\Delta W_{\text{ent,FEM}}$, can be calculated. Moreover the output of the neural network based ECM ($\Delta W_{\text{ent,NN}}$) is the width margin at the entry of the finishing mill in order to compensate the output of the simplified FEM based WPM. Finally the reference width margin at the entry of the finishing mill is expressed by using the appropriate weighting factor as the following equation:

$$\Delta W_{\text{ent,ref}} = \beta \Delta W_{\text{ent,FEM}} + (1 - \beta) \Delta W_{\text{ent,NN}} \text{........(17)}$$

where $\beta$ is a weighting factor of the models.

The algorithm of the edger gap initialization in Fig. 11 is expressed as the following logic:

1) The entry (absolute) width set value of the finishing mill ($W_{\text{ent,ref}}$)

$$W_{\text{ent,ref}} = W_{\text{H,ref}} + \Delta W_{\text{ent,ref}},$$

$$W_{\text{H,ref}} = W_{\text{ref}} \times (1 + \eta T)$$

where $W_{\text{ref}}, \eta$ and $T$ are the delivery width (absolute) set value of the finishing mill, the line expansion coefficient and the coil temperature, respectively. The $\eta T$ is a compensation factor for the width difference between cold strip width and hot strip width.

2) The width spread at the F0 stand: $W_{\text{F0}}$

3) The width set value between F0E (F0 edger) and F0: $W_{\text{F0E}}$

$$W_{\text{F0E}} = W_{\text{ent,ref}} - W_{\text{F0}}$$

4) The F0E gap set value ($S_{\text{ref}}$)

$$S_{\text{ref}} = W_{\text{F0E}} - \frac{P}{M} \text{.............(18)}$$

where $P$ is the roll force setup, $M$ is the mill constant. $P/M$ is the gap difference and it is generated since the roll is not the rigid body.

Also, the width control block is similarly expressed. The input and output of its block are $\Delta W_{\text{ent}}, \Delta S_{\text{ref}}$, respectively. The width control output and the control input of the F0E gap are expressed as follows:

$$\Delta S_{\text{ref}} = \Delta W_{\text{ent}} - \frac{\Delta P}{M} \text{.............(19)}$$

$$\Delta W_{\text{ent}} = W_{\text{ent,act}} - W_{\text{ent,ref}} \text{.............(20)}$$

where $W_{\text{ent,act}}$ is the absolute width measured by the F0W. The target of the width control is to reduce the width margin deviation of the product.

6. Field Test Results

In this section, it is shown that the performance of the width control is improved by two developed models and the width control system. **Figure 12** shows the width measurement system (F0W) established at the works.

The developed simplified FEM based WPM and the neural network based ECM with the width measurement sys-
tem make it possible to control the width margin in the finishing mill. Actually the error between the predicted and measured width margin is calculated and the gap control quantity of F0 edger from the error is calculated.

Figure 13 shows the test result. It can be seen that the average width margin (F0W dev.) measured at the entry of the finishing mill in this coil is 10 (mm). Moreover the average F0 width margin (F0W set) predicted by two models is 11 (mm). At about 9 (s), since the measured F0 width margin is less than the predicted width margin, the width control (F0E compen) is applied along the direction of the edger gap open at about 17 (s) and the F0 actual width margin is recovered at that point. The time difference between the edger gap reference and the feedback value is caused by the distance (F0 edger/H11011 F0W: 7 m) and the delay time (1.5 s) of the edger system.

Figure 14 shows another test result. From the figure, both the middle part and the head of the strip are also controlled by edger gap feedback in order to prevent the width deviation.

Table 9 shows the effect of the control. From the on-line test of 2 800 coils for 3 months, the mean and standard deviation for the width margin of the product are improved by 6.1(%) and 12.5(%), respectively. Statistically, the sigma level is improved from 2.6σ to 3.1σ (upper specification limit (USL): 10 (mm)). Defects Per Million Opportunities (DPMO) is also improved by 59.6(%) from 135 000 to 54 800. The mean of the width margin represents the quantity of the side trimming. The side trimming of the strip is decreased by the reduction of the mean value. Furthermore, it is shown through the field test that the width variation is diminished by the decrease of the standard deviation.

7. Conclusions

The width control system with the simplified FEM based WPM and the neural network based ECM is developed and applied to the Pohang no. 1 hot strip mill of POSCO in order to reduce the width margin deviation.

A simplified FEM based WPM was proposed to predict the width spread through the finishing mill. The effects of several process parameters computed by the FEM were investigated and then an approximated simple model was obtained. The proposed simplified FEM based WPM was constructed for two cases: one is for the case that the tension is not applied and the other takes account of the tension.

A neural network based ECM was proposed to compensate for modelling errors from the FEM based WPM. The significant neural network input variables are systematically chosen by the statistical method where the correlation coefficients and the $p$-value are used.

The width control system consisting of the vertical rolling mill, the width measurement system and two models was proposed to control the width margin. The results of the field test of the Pohang no. 1 hot strip mill of POSCO have shown that the mean and standard deviation of the width margin have improved by 6.1(%) and 12.5(%), respectively. It is believed that the proposed models and the control scheme are very effective in improving the performance of the width control.

REFERENCES

1) J. C. Price: IEEE Trans. Ind. Appl., IA-9 (1973), No. 5, 556.
2) M. T. Clark, H. Versteeg and W. Konijn: Iron Steel Eng., 74 (1997), No. 6, 64.
3) M. Okada, K. Murayama, A. Urano, Y. Iwasaki, A. Kawano and H. Shioimi: Control Eng. Pract., 6 (1998), 1029.
4) Y. Seki, K. Sekiguchi, Y. Anbe, K. Fukushima, Y. Tsuji and S. Ueno:
5) H. Imanari, Y. Morimatsu, K. Sekiguchi, H. Ezure, R. Matsuoka, A. Tokuda and H. Otobe: *IEEE Trans. Ind. Appl.*, 33 (1997), No. 3, 790.

6) T. Hesketh, Y. A. Jiang, D. J. Clements, D. H. Butler and R. Laan: *IEEE Trans. Control Syst. Technol.*, 6 (1998), No. 2, 208.

7) K. Asano, K. Yamamoto, T. Kawase and N. Nomura: *Control Eng. Pract.*, 8 (2000), 337.

8) A. Isii, G. Yamada, S. Ogawa, T. Yoshida and M. Ataka: 43rd Japan Society for Technology of Plasticity, (1992), 219.

9) D. L. Yu, J. B. Gomm and D. Williams: *Eng. Appl. Artif. Intell.*, 13 (2000), 15.

10) W. Wu and D. L. Massart: *Chemometrics Intell. Lab. Syst.*, 35 (1996), 127.

11) A. D. Back and T. P. Trappenberg: *IEEE Trans. Neural Netw.*, 12 (2001), No. 3, 612.

12) C. Ledoux and J. F. Grandin: *IEE Proc. Vision, Image Signal Process.*, 141 (1994), No. 4, 230.

13) R. Reed: *IEEE Trans. Neural Netw.*, 4 (1993), No. 5, 740.

14) J. Luo, B. Hu, X. T. Ling and R. W. Liu: *IEEE Trans. Neural Netw.*, 10 (1999), No. 4, 912.

15) N. Kambhatla and T. K. Leen: *Neural Comput.*, 9 (1997), No. 7, 1493.

16) S. M. Ross: *Introduction to Probability and Statistics for Engineers and Scientists*, Academic Press, London, (2000), 271.

17) W. H. Press and S. A. Teukolsky: *Numerical Recipes in Fortran*, 2nd ed., Cambridge University Press, USA, (1992), 678.