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A Method to Determinate the Thickness Control Parameters in Cold Rolling Process through Predictive Model via Neural Networks

The single stand rolling mill governing equation is a non-linear function on several parameters (input thickness, front and back tensions, yield stress and friction coefficient among others). Any alteration in one of them will cause alterations on the rolling load and, consequently, on the outgoing thickness. This paper presents a method to determinate the appropriate adjustment for thickness control considering three possible control parameters: roll gap, front and back tensions. The method uses a predictive model based in the sensitivity equation of the process, where the sensitivity factors are obtained by differentiating a neural network previously trained. The method considers as the best control action the one that demands the smallest adjustment. One of the capital issues in the controller design for rolling systems is the difficulty to measure the final thickness without time delays. The time delay is a consequence of the location of the outgoing thickness sensor that is always placed to some distance to the front of the roll gap. The proposed control system calculates the necessary adjustment based on a predictive model for the output thickness. This model permits to overcome the time delay that exists in such processes and can eliminate the thickness sensor, usually based on X-ray. Simulation results show the viability of the proposed technique.

Keywords: Steel industry, rolling process, neural networks, controllers

Introduction

The single stand rolling mill governing equation is a non-linear function on several parameters Eq. (1). Any alterations on either of them: input thickness (h_i), front (t_f) or back (t_b) tensions, average

yield stress (\bar{y}) or friction coefficient (μ) will cause alterations on the rolling load (P) and, consequently, on the outgoing thickness (h_o).

$$h_o = f(P, h_i, t_b, t_f, \mu, \bar{y}, E, R, W, M) \quad (1)$$

where: E: Roll radius; R: Roll radius; W: Strip width; and M: Stiffness Rolling Mill modulus (kgf/mm)

When such alterations in the rolling process occur, three control parameters are mainly used to restore the outgoing thickness and, therefore, ensuring the $\Delta h_o = 0$ condition: the roll gap, the front and back tensions. The best control parameter will restore the output thickness for its nominal value with the smallest possible adjustment. In this paper, a method to determinate the appropriate adjustment, considering the three control parameters, will be presented. The method uses the sensitivity equation of the process obtained by differentiating a neural network (Zárate 1998). The sensitivity equation corresponds to the predictive model for the cold rolling process, that allows to calculate the output thickness.

To verify the proposed method, a new Automatic Gage Control (AGC) system for output thickness control is proposed. Basically, an AGC system (Wallace, 1964; Hisikawa, 1990) is a feedback control system applied to rolling mills to ensure that output strip thickness will be as constant as possible. To measure the thickness deviations two techniques have been extensively used in the steel industry:

- The first one includes a sensor (X-ray) located after the roll gap, what causes a time delay in the feedback system and produces a significant deterioration in the control performance.
- The second technique indirectly calculates the output thickness from the measurement of the roll load. This technique presents problems for thin strips, because variations in the strip thickness have little effect on the measured roll load (Zeltkals and Ricciatti, 1977; Chicharo and Tung, 1990; Zárate, 1998).

The proposed technique in this paper does not follow any of the classical approaches. It uses direct gap measurements to implement the controller. The method uses a neural network and sensitivity factors to obtain the predictive model as proposed in Zárate (1998), Zárate et al (1998 b) and Zárate and Helman (1999). By using a predictive model, it is possible to eliminate the time delay in the feedback loop. Also, since it is based on direct gap measurements, it is possible to achieve the required accuracy for control proposals and elimination of the X-ray sensor.

On the other hand, Artificial Neural Network (ANN) has been receiving a great attention during the last decade, due to the capacity in solving non-linear problems by learning (Hunt, et. al. 1992; Tai et al. (1992), Yamada and Yabuta (1993); Sbarbaro-Hofer, 1993 and Guez et.al. 1998). Nowadays, ANN are receiving great attention in metallurgical processes, as it can be seen in Andersen, et. al. (1992); Smart, (1992); Zárate et. al. (1998 a, b); Gunasekera et. al., 1998; Zárate (1998); Zárate and Bittencout (2001); Schlang (2001); Zárate and Bittencout (2002); Kim (2002); Gálvez and Zárate (2003); Yang (2004) and Son (2004).

This paper is organized in five sections: In the first section, the representation of the rolling process, by means of ANN, is presented. In the second section, the expressions to calculate the sensitivity equations, through the differentiation of a neural network, are revised. In the third section, a method to calculate the adjustment parameters, when alterations on the rolling process occur, is presented. In the fourth section, the kernel of the algorithm to obtain the adequate control parameter and the predictive model will be presented. Finally, simulation results will be discussed.

Nomenclature

\bar{y} = Average yield tensile stress (N/mm²)
g = Gap (mm)
h_i = Strip input thickness (mm)
h_o = Strip output thickness (mm)
M = Stiffness Rolling Mill modulus (N/mm)
P = Rolling load (N/mm)
P_B = Rolling load x Strip width (N)
Tq = Rolling Torque (N-mm/mm)
R = Roll radius (mm)
t_f = Front tension stress (N/mm²)
t_b = Back tension stress (N/mm²)
W or *B* = Strip width (mm.)
E = Young modulus of the strip material
U_i, *i* = 0, ..., *N* are the net entries and *U₀* = 1 is a polarization input
f_i^a(.) *i* = 0, ..., *N* are the normalization entry functions and *f₀^a(.)* = 1
X_i, *i* = 0, ..., *N* are the normalized inputs *X₀* = *U₀*
W_{ij}^h *i* = 1, ..., *L* e *j* = 0, ..., *N* is the weight corresponding to the neuron *i* and entry *j*
net_j^h = ∑_{*i*=0}^{*N*} *W_{ji}^h* *X_i* *j* = 1, ..., *L* product of weights times inputs
f_j^h(net_j^h) *j* = 0, ..., *L* with *f₀^h(net₀^h)* = 1 is the sigmoid function of the hidden layer.
I_j, *j* = 0, ..., *L* are the corresponding values of the sigmoid function *I₀* = 1
W_{ij}^o *i* = 1, ..., *M* e *j* = 0, ..., *L* is the weight of the neuron *i* and entry *j* for the hidden layer.
net_j^o = ∑_{*i*=0}^{*L*} *W_{ji}^o* *I_i* *j* = 1, ..., *M* product of the weights times inputs for the hidden layer.
f_j^o(net_j^o) *j* = 1, ..., *M* is the value of the sigmoid function for the exit layer
Y_j, *j* = 1, ..., *M* are the normalized outputs of the net, obtained from the sigmoid function
f_i^b(.) *i* = 1, ..., *M* are the an-normalization functions of the outputs
Z_i, *i* = 1, ..., *M* net outputs values
e max_k, *e min_k* *k* = 1, ..., *N* higher and lower value of the inputs
s max_k, *s min_k* *k* = 1, ..., *M* higher and lower value of the outputs
LimiteInf and *LimiteSup* are the minimum and maximum values of the original data sets respectively.

Greek Symbol

μ = Friction coefficient

Representation of the Rolling Mill Operation through ANN

To represent the cold rolling process operation, Eq. (2), a multi-layer neural network, with six entries (N=6), two exits (M=2) and one hidden layer with 13 neurons (2N+1, Kovács 1996) was used. In expression (2), the neurons have as activation function (*f*) the non-linear sigmoid function, chosen in this work as the axon transfer

function being the most consistent with the biophysics of the biological neuron.

$$(h_i, g, \mu, t_b, t_f, \bar{y}) \xrightarrow{ANN} (h_o, P_B) \tag{2}$$

with \bar{y} : average yield stress; *P_B* rolling load.

Generally, the largest care to get a trained neural network lies on collecting and pre-processing neural network input data. The pre-processing operation consists in the data normalization in such a way that the inputs and outputs values will be within the range of 0 to 1.

The following procedure was adopted to normalize the input data before using it in the ANN structure:

- a) In order to improve convergence of the ANN training process, the normalization interval [0, 1] was reduced to [0.2, 0.8], because in the sigmod function the values [0, 1] aren't reached: *f* → 0 for *net* → -∞ and *f* → 1 for *net* → +∞.
- b) The data was normalized through the following formula:

$$f^a(Lo) = Ln = (Lo - Lmín) / (Lmax - Lmin) \tag{3a}$$

$$f^b(Ln) = Lo = Ln * Lmax + (1 - Ln) * Lmín \tag{3b}$$

where *Ln* is the normalized value, *Lo* is the value to normalize, *Lmin* and *Lmax* are minimum and maximum variable values, respectively.

- c) *Lmin* and *Lmax* were computed as follows:

$$Lmín = (4 \times LimiteInf - LimiteSup) / 3 \tag{4a}$$

$$Lmáx = (LimiteInf - 0.8 \times Lmín) / 0.2 \tag{4b}$$

The Eqs. (4a) and (4b) are obtained substituting in the Eq. (3a) *Ln* = 0.2 and *Lo* = *LimiteInf*; and *Ln* = 0.8 and *Lo* = *LimiteSup*. Where *LimiteInf* and *LimiteSup* are the minimum and maximum values of the original data sets respectively.

Obtaining the Sensitivity Factors

The expression to calculate sensitivity factors was proposed in Zárate (1998). In this work, an ANN multi-layer with a hidden layer is used. The ANN has N: entries, M: exits and L: neurons in the hidden layer. The differentiation of the neural network is generic and it only depends on N, M, L and on the weights of the hidden and exit layers, obtained during the training process.

$$\frac{\partial Z_k}{\partial U_i} = \begin{bmatrix} R_1 W_{11}^o & R_1 W_{12}^o & \dots & R_1 W_{1L}^o \\ R_2 W_{21}^o & R_2 W_{22}^o & \dots & R_2 W_{2L}^o \\ \vdots & \vdots & \vdots & \vdots \\ R_M W_{M1}^o & R_M W_{M2}^o & \dots & R_M W_{ML}^o \end{bmatrix} \begin{bmatrix} \frac{Q_1 W_{11}^h}{e_{max1} - e_{min1}} & \frac{Q_1 W_{12}^h}{e_{max2} - e_{min2}} & \dots & \frac{Q_1 W_{1N}^h}{e_{maxN} - e_{minN}} \\ \frac{Q_2 W_{21}^h}{e_{max1} - e_{min1}} & \frac{Q_2 W_{22}^h}{e_{max2} - e_{min2}} & \dots & \frac{Q_2 W_{2N}^h}{e_{maxN} - e_{minN}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{Q_L W_{L1}^h}{e_{max1} - e_{min1}} & \frac{Q_L W_{L2}^h}{e_{max2} - e_{min2}} & \dots & \frac{Q_L W_{LN}^h}{e_{maxN} - e_{minN}} \end{bmatrix} \tag{5}$$

with:

$$Q_k = \frac{\exp\left(-\sum_{i=0}^N W_{ki}^h X_i\right)}{\left(1 + \exp\left(-\sum_{i=0}^N W_{ki}^h X_i\right)\right)^2} \quad k = 1, \dots, L$$

$$R_k = \left(\text{smax}_k - \text{smin}_k\right) \frac{\exp\left(-\frac{V_k}{(1 + \exp(-V_k))^2}\right)}{\left(1 + \exp(-V_k)\right)^2} \quad k = 1, \dots, M$$

$$V_k = \sum_{j=0}^L W_{kj}^o f_j^h \left(\sum_{i=0}^N W_{ji}^h f_i^a(U_i)\right) \quad \text{para } k = 1, \dots, M$$

Note that Eq. (5) is valid for little variations in the process parameters and provides the linearization of the process for an operation point (Ui) (Zárate et. al. 1998c).

Determination of the Adjustment in the Control Parameters

The steps to determine the adjustments corresponding to the control of the rolling process are described as below:

I. The nominal inputs and outputs are contained in the vectors:

$$\bar{X}^* = (h_i^*, g^*, \mu^*, t_b^*, t_f^*, y^*) \quad \text{and} \quad \bar{Y}^* = (h_o^*, P^*) \quad \text{respectively.}$$

II. Through Eq. (5), it is possible to calculate the sensitivity factors for the selected nominal point. After calculating the factors, is possible to obtain the linear equation of the process, Eq. (6), neighboring the nominal operation point:

$$\Delta h_o = \Delta h_i \frac{\partial h_o}{\partial h_i} + \Delta g \frac{\partial h_o}{\partial g} + \Delta \mu \frac{\partial h_o}{\partial \mu} + \Delta t_b \frac{\partial h_o}{\partial t_b} + \Delta t_f \frac{\partial h_o}{\partial t_f} + \Delta y \frac{\partial h_o}{\partial y} \quad (6)$$

where: $\Delta X = X^* - X$

If variation takes place either in one or all the operational parameters h_i, g, μ, t_b, t_f, y , a variation will occur in the h_o value.

There is a factor K such that $\Delta h_o = 0$. Eq. (7):

$$0 = \Delta h_i \frac{\partial h_o}{\partial h_i} + \Delta g \frac{\partial h_o}{\partial g} + \Delta \mu \frac{\partial h_o}{\partial \mu} + \Delta t_b \frac{\partial h_o}{\partial t_b} + \Delta t_f \frac{\partial h_o}{\partial t_f} + \Delta y \frac{\partial h_o}{\partial y} + K \quad (7)$$

Equating Eq. (6) and Eq. (7), it is obtained:

$$K = -\Delta h_f \quad (8)$$

The value of K depends on the selected control parameter: roll gap, front or back tensions and may be defined as:

$$K = \Delta g \frac{\partial h_o}{\partial g} \quad \text{or} \quad K = \Delta t_b \frac{\partial h_o}{\partial t_b} \quad \text{or} \quad K = \Delta t_f \frac{\partial h_o}{\partial t_f} \quad (9)$$

If control action by means of the roll gap is considered, the equations to calculate the K value are:

$$K = \Delta g \frac{\partial h_o}{\partial g} = -\Delta h_o \quad \Delta g = -\frac{\Delta h_o}{\frac{\partial h_o}{\partial g}} \quad g = g^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial g}} \quad (10)$$

Similarly, choosing the front and back tensions:

$$t_b = t_b^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial t_b}} \quad (11)$$

$$t_f = t_f^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial t_f}} \quad (12)$$

Observe that expressions (10), (11) and (12) don't depend on the measurement of the rolling load, although it is necessary to know the variation in the exit thickness, which will be obtained indirectly by the predictive model.

Kernel of the Algorithm to Obtain the Control Parameters

In the previous section three possible control parameters were calculated to restore the variations in the output thickness. A strategy to select the appropriate adjustment can be to choose the parameter with the smallest adjustment. The kernel of the proposed algorithm is shown as follows:

Begin

calculate :

$$g = g^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial g}} \quad \text{control action on gap}$$

$$t_b = t_b^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial t_b}} \quad \text{control action on back tension}$$

$$t_f = t_f^* + \frac{\Delta h_o}{\frac{\partial h_o}{\partial t_f}} \quad \text{control action on front tension}$$

calculate :

$$\text{Var}_g = |g^* - g| * 100 / g^* \quad \text{adjustment of the gap}$$

$$\text{Var}_{t_b} = |t_b^* - t_b| * 100 / t_b^* \quad \text{adjustment of the back tension}$$

$$\text{Var}_{t_f} = |t_f^* - t_f| * 100 / t_f^* \quad \text{adjustment of the front tension}$$

If $\text{Var}_g < \text{Var}_{t_b}$ e $\text{Var}_g < \text{Var}_{t_f}$

Then

If $|g^* - g| < 0.001$ *Then* $g = 0.001$

If $P \uparrow$ *Then* $g \downarrow$ (control action)

If $P \downarrow$ *Then* $g \uparrow$ (control action)

else

If $\text{Var}_{t_b} \leq \text{Var}_{t_f}$

Then

If $t_b > 0.85 * S_i$ *Then* $t_b = 0.85 * S_i$

If $P \uparrow$ *Then* $t_b \uparrow$ (control action)

If $P \downarrow$ *Then* $t_b \downarrow$ (control action)

else

If $\text{Var}_{t_f} < \text{Var}_{t_b}$

Then

If $t_f > 0.85 * S_o$ *Then* $t_f = 0.85 * S_o$

If $P \uparrow$ *Then* $t_f \uparrow$ (control action)

If $P \downarrow$ *Then* $t_f \downarrow$ (control action)

End.

The proposed algorithm considers that gap values, smaller than the sensitivity of the measurement instrument, should be saturated in

the value of the sensitivity of the instrument (by example, 0.001). For back and front tensions the saturation is established in 85% of the yield stress in plane-strain deformation, in the entry (S_i) and in the exit (S_o) respectively.

Predictive Model for Output Thickness

There are several theoretical models to calculate rolling load and rolling torque. The mathematical modeling of the rolling process involves several parameters that may lead to non-linear equations of difficult analytical solution. Such is the case of Alexander's model (Alexander 1972), considered one of the most complete in the rolling theory. This model requires significant computational effort, which prevents its application in on-line control and supervision systems. On the other hand, the theoretical models allow to calculate the rolling load, where the output thickness (h_o) is an input parameter of the model. In Zárate (1998), a new representation (predictive model) to determinate the output thickness (Eq. 13), based on sensitivity factors, was presented.

$$\Delta h_o = \frac{W}{M-W} \frac{\partial P}{\partial h_o} \left(\frac{M}{W} \Delta g + \frac{\partial P}{\partial h_i} \Delta h_i + \frac{\partial P}{\partial t_b} \Delta t_b + \frac{\partial P}{\partial t_f} \Delta t_f + \frac{\partial P}{\partial \mu} \Delta \mu + \frac{\partial P}{\partial y} \Delta y \right) \quad (13)$$

Those factors are obtained through the differentiation of a neural network previously trained. For this purpose the considered neural network is represented by expression (14):

$$(h_i, h_o, \mu, t_b, t_f, y) \xrightarrow{ANN} (P, Tq) \quad (14)$$

The neural network (Eq. 14) was trained with data of the rolling process during the deformation of the material. The new representation (Eq. 13) possesses predictive characteristics, eliminating time delay and the X-ray sensor of the rolling mill system.

The predictive model can be expressed as:

$$\Delta h_o = D[S[\Delta u]] = h_o^* - h_o \quad (15)$$

or

$$h_o = h_o^* - D[S[\Delta u]] \quad (16)$$

where

$$D = \left[\frac{W}{M-W} \frac{\partial P}{\partial h_o} \right] \quad (17)$$

with

$$[S] = \left[\frac{M}{W} \quad \frac{\partial P}{\partial h_i} \quad \frac{\partial P}{\partial t_b} \quad \frac{\partial P}{\partial t_f} \quad \frac{\partial P}{\partial \mu} \quad \frac{\partial P}{\partial y} \right] \quad (18)$$

and

$$\Delta u = \begin{bmatrix} \Delta g \\ \Delta h_i \\ \Delta t_r \\ \Delta t_f \\ \Delta \mu \\ \Delta y \end{bmatrix} = \begin{bmatrix} g^* \\ h_i^* \\ t_r^* \\ t_f^* \\ \mu^* \\ y^* \end{bmatrix} - \begin{bmatrix} g \\ h_i \\ t_r \\ t_f \\ \mu \\ y \end{bmatrix} \quad (19)$$

Usually the entries of $[S]$ are calculated from equations that demand a difficult analytical solution from complex models, such as Alexander's model. In this work, $[S]$ is obtained through the differentiation of a neural network, using Eq. (5).

Control System Proposed

The controllers' classic development requests the knowledge of the dynamics of the plant besides a linear model for a specific operation point. In rolling systems there are time delays that difficult the development of control systems and that normally present a low performance (Zárate 1998). In addition to this, a characteristic of those systems is the existence of significant time delays of the order of 30 s. This can happen for low rolling speeds, that normally occur in the first stand of a tandem mill.

This work introduces a new control structure, that uses the predictive model, Eq. (16), to estimate the output thickness and the measurement of the gap, Eq. (10). Usually, an AGC measures the rolling load to determinate, through Eq. (20), the necessary adjustment for the gap and to assure the condition $\Delta h_o = 0$.

$$\Delta g = \Delta h_o \frac{\Delta P \cdot B}{M} \quad (20)$$

To calculate the adjustment of the gap, the proposed controller structure uses the sensitivity factor $\partial h_o / \partial g$ in Eq. (10). Observe that $\Delta h_o = h_o^* - h_o$ uses the predicted value of the output thickness $h_o = h_o^p$.

Figure 2 shows the controller's structure proposed. Note that the predictive model is being implemented as a virtual sensor whose exit is the output thickness h_o^p .

The Controller PD was projected to adjust the gap calculated by means of the method of the sensitivity, Eq. (10). The controller PI was introduced to eliminate possible errors in the predictive model and to guarantee the condition: $h_s^* - h_s^p = 0$.

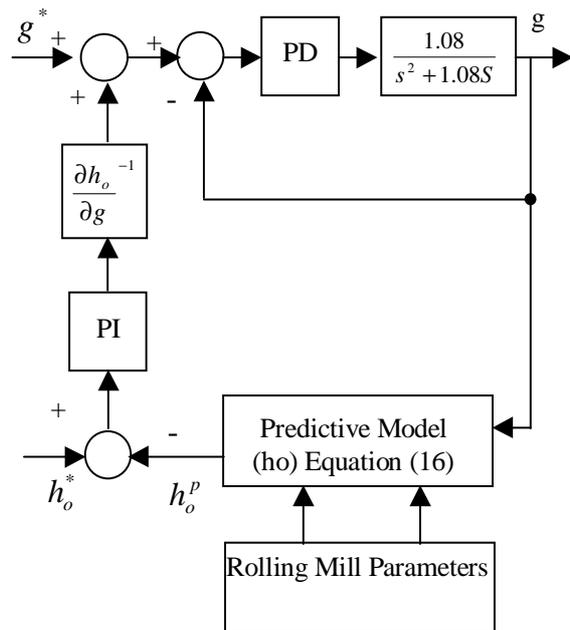


Figure 1. The proposed Control System.

Application and Results

As an example of the possibilities of the method, a numerical application to a rolling process will be presented. The operation point was chosen as: $h_i=5.0$ mm; $h_o = 3.6$ mm; $g=1.846$ mm.; $\mu =0.12$; $t_f=89.22$ N/mm²; $t_b=4.325$ N/mm²; $\bar{y}=460.106$ N/mm²; $B = 500$ mm; $E = 200054.64$ N/mm²; $R=292.1$ mm; $M=4903,300$ N/mm and $P=875310$ N/mm. With: $S_i = 250.556$ N/mm² and $S_o = 534.900$ N/mm².

To obtain the data sets for training of the neural networks, Eq. (2) and Eq. (14), the parameters were varied as shown in Table 1:

Table 1. Variation of the operational parameters.

h_i	h_o	μ	t_f	t_b	\bar{y}
$\pm 8\%$	$\pm 3\%$	$\pm 20\%$	$\pm 30\%$	$\pm 30\%$	$\pm 10\%$

Three different values were chosen for each parameter, resulting in 729 training sets. The rolling load was obtained through Alexander's model and the roll gap by the elastic equations of the rolling mill, Eq. (21).

$$g = h_o - \frac{PB}{M} \tag{21}$$

For the neural network represented by Eq. (2) (to calculate the control parameters) the final weights for the hidden and output layers with its polarization weights are:

$$W^h = \begin{bmatrix} 6.2010 & 9.4161 & -1.7278 & -0.2642 & 1.8475 & 1.3078 \\ -1.5239 & -9.2425 & -2.4238 & 0.0734 & 0.7813 & -6.0229 \\ -11.4365 & -1.7129 & 1.2562 & -0.2171 & -0.6941 & 3.3125 \\ -0.2767 & -8.3214 & -5.5920 & -0.2737 & -3.3595 & -0.8293 \\ 3.3504 & 5.2707 & 3.4006 & 0.0343 & -0.5938 & 4.7363 \\ 8.9832 & 3.9726 & 0.7990 & 9.7730 & 0.9096 & 5.5016 \\ -6.1621 & 3.4810 & 7.4542 & 0.5558 & -7.0447 & -0.9006 \\ -4.8199 & -3.2388 & 6.5208 & -3.4559 & -0.6086 & 8.9722 \\ 0.8914 & -8.2071 & -7.6049 & -0.1518 & -2.2323 & -1.5593 \\ -1.2378 & -10.6099 & -0.0338 & 0.0399 & 0.4850 & -2.1458 \\ 8.3913 & 2.3521 & 5.9967 & -8.1868 & -4.0553 & 1.8826 \\ -1.4947 & -11.9576 & -1.6808 & 0.0733 & 0.7387 & -4.2602 \\ 2.9411 & 4.8319 & -11.5151 & -1.5484 & -4.0985 & -4.2330 \end{bmatrix}$$

$$W_{bias}^h = \begin{bmatrix} -11.4784 \\ 8.9265 \\ 2.5654 \\ 10.9804 \\ -10.4911 \\ -15.1094 \\ 5.3887 \\ -4.5520 \\ 7.1306 \\ 8.8376 \\ -0.4583 \\ 8.7774 \\ 2.5081 \end{bmatrix}$$

$$W^o = \begin{bmatrix} 0.5503 & 0.4083 \\ -1.7551 & -2.1593 \\ -0.9245 & -0.1960 \\ -0.2976 & 0.2163 \\ 4.2976 & 0.9087 \\ 0.0021 & 0.0045 \\ 0.1479 & 0.1406 \\ 0.1378 & 0.0480 \\ -1.1542 & -0.0074 \\ -6.4508 & 1.0470 \\ -0.0276 & -0.0106 \\ -3.9372 & 2.4463 \\ 0.1814 & 0.0746 \end{bmatrix}$$

$$W_{bias}^o = \begin{bmatrix} 6.4599 \\ -1.4106 \end{bmatrix}$$

The weights were obtained after 330,000 iterations with an average quadratic error of 0.040 (Pentium IV 3.0 GHz).

For the neural network represented by Eq. (14) (to determine the predictive model) the final weights for the hidden and output layers with its polarization weights are:

$$W^h = \begin{bmatrix} -2.3472 & 0.7327 & -1.6876 & -0.0036 & 0.6561 & -2.6032 \\ 3.9055 & 3.0808 & -5.1249 & -2.8544 & -5.3232 & -5.6772 \\ -8.4711 & 5.1593 & 6.1539 & -1.5899 & -4.3587 & 3.4279 \\ -11.7598 & 0.2278 & -0.9994 & -0.3439 & 0.1404 & 6.6674 \\ -8.4249 & -9.2360 & -5.5525 & 1.1392 & 2.4098 & -5.1437 \\ -1.3988 & 1.6645 & 9.0436 & 0.0068 & 5.0951 & -7.2585 \\ 3.4416 & 0.4525 & 8.6002 & -6.6928 & 5.2036 & 1.8066 \\ -2.0861 & 0.6307 & -0.6206 & 0.0006 & 0.8530 & -1.8555 \\ -4.1920 & 0.5245 & -4.9311 & 7.3975 & 1.3536 & 6.6874 \\ 10.5998 & 3.1857 & -4.8274 & 1.8625 & -3.3112 & -2.8462 \\ 3.8174 & 13.3982 & -3.9206 & -1.5036 & -1.7811 & 0.6947 \\ 3.9012 & -2.6002 & 0.5488 & 2.1261 & -5.7294 & -5.7072 \\ 8.5121 & -6.7925 & -2.3503 & 2.8321 & 4.0080 & -3.0901 \end{bmatrix}$$

$$W_{bias}^h = \begin{bmatrix} 5.2510 \\ 6.0337 \\ -3.8967 \\ 5.1585 \\ 5.4216 \\ -1.0687 \\ -7.2570 \\ 0.2414 \\ -3.2777 \\ -0.9663 \\ -5.8385 \\ 3.7317 \\ -3.0088 \end{bmatrix}$$

$$W^o = \begin{bmatrix} -3.1772 & -2.9064 \\ -0.0878 & 0.0705 \\ -0.0626 & -0.0884 \\ 0.1237 & 0.0306 \\ 0.0126 & 0.0401 \\ 0.0767 & -0.0340 \\ 0.0418 & -0.0196 \\ -2.4975 & -2.2320 \\ 0.0412 & -0.0437 \\ -0.0568 & 0.0361 \\ 0.0205 & 0.0008 \\ -0.1528 & 0.1381 \\ -0.0468 & 0.0634 \end{bmatrix}$$

$$W_{bias}^o = \begin{bmatrix} 3.2107 \\ 2.8861 \end{bmatrix}$$

The weights were obtained after 540,000 iterations with an average quadratic error of 0.033 (Pentium IV 3.0 GHz).

The events sequence to determine the control operation adjustments are described as follows:

1) Define the nominal inputs: $[h_i^*, g^*, \mu^*, t_b^*, t_f^*, \bar{y}] = [5.00; 1.846; 0.12; 4.324; 89.22; 460.106]$ and provide the nominal outputs: $[h_o^*, P^*] = [3.6; 8583.81]$;

2) Calculate through Eq. (5) the sensitivity factors for the selected nominal point: $[\frac{\partial h_o}{\partial h_i}, \frac{\partial h_o}{\partial g}, \frac{\partial h_o}{\partial \mu}, \frac{\partial h_o}{\partial t_b}, \frac{\partial h_o}{\partial t_f}, \frac{\partial h_o}{\partial \bar{y}}] = [0.3566; 0.6436; 4.7345; -0.0163; -0.011; 0.0327]$;

3) Considering, for example disturbances of -2% in the input thickness, in the friction coefficient and in the back tension, define the current entries as: $[h_i, g, \mu, t_b, t_f, \bar{y}] = [4.9; 1.846; 0.118; 1.157; 89.22; 460.918]$;

4) Use an ANN, Eq. (2) previously trained to determine the current outputs: $[h_s, P_B] = [3.552; 8389.81]$;

5) Determine the three control parameters using Eqs. (10), (11) and (12): $[\bar{g}, \bar{t}_b, \bar{t}_f] = [1.920; -4.94; 46.42]$. That corresponds to corrections of: +3.8%, -639.9% and -54% respectively.

6) Apply proposed algorithm to select the control parameter. The smallest correction indicates the best control action. Notice that the calculated value for \bar{t}_b is negative and this should be saturated in $\bar{t}_b = 0$. Thus the adjustment for the output thickness should be made through gap.

To verify the control action, the three possible corrections were simulated through an iterative process using Alexander's model and Eq. (21). For the action on the gap ($\bar{g} = 1.920$) the output thickness was 3.585 mm with error of 0.42%. For the control action on the back tension ($\bar{t}_b = 0$) the output thickness was 3.555 mm with error of 1.25%. For the control action on the front tension ($\bar{t}_f = 46.42$) the

value of the output thickness was 3.584 mm with error of 0.44%. The smallest error confirms the action on the gap to restore the deviations in the output thickness.

Table 2 shows the sensitivity factors for the nominal operation point obtained by differentiation of the neural network, Eq. (14).

Table 2. Sensitivity Factors (for the Predictive Model).

$\frac{\delta P}{\delta h_i}$	$\frac{\delta P}{\delta h_o}$	$\frac{\delta P}{\delta \mu}$	$\frac{\delta P}{\delta t_b}$	$\frac{\delta P}{\delta t_f}$	$\frac{\delta P}{\delta y}$
498.66	-631.16	7909.25	-86.56	-5.83	56.75

The sensitivity factor for the adjustment of the gap is obtained in step 2: $\frac{\delta h_o}{\delta g} = 0.6436$. The transfer function of the plant considered in this work is given for:

$$G(s) = \frac{1.08}{s(s+1.08)} \tag{22}$$

The controllers' parameters PD and PI were adjusted by simulation and they were chosen as: $K_P = 5$ and $K_D = 1.5$ for the PD controller and as: $K_P = 3$ and $K_I = 1.0$ for the PI controller.

To analyze the proposed controller, two simulations were accomplished applying disturbance on the rolling parameters (Table 3).

Table 3. Disturbances in parameters.

Parameter	t (star) s.	t (final) s.	Sequence 1 (%)	Sequence 2 (%)
h_i	15	30	+ 3.0	+ 8.0
t_b	45	60	+ 10.0	+ 30.0
t_f	75	90	+10.0	+ 30.0
μ	105	120	+ 5.0	+ 20.0
y	135	150	+ 3.0	+ 10.0

Figure 2 shows the response of the output thickness for the sequence 1. In this case, the controller has an error below 1.4% and the stationary-state was reached in less than 4 s.

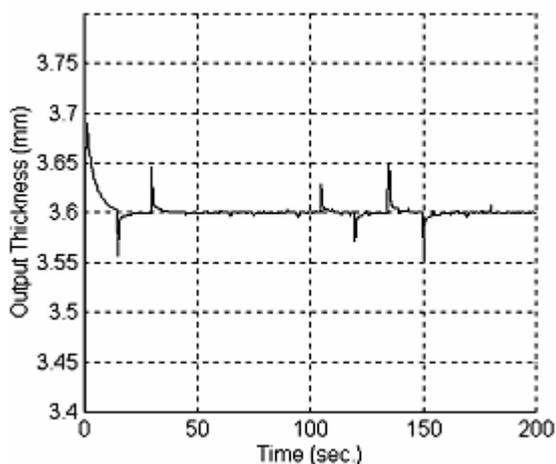


Figure 2. Output thickness response for sequence 1.

Notice that the alterations in the back and front tensions are not relevant. For sequence 1, the significant variations are due to disturbances in the average yield stress, in the input thickness and in the friction coefficient. Figure 3 shows the behavior of the gap for the same simulation.

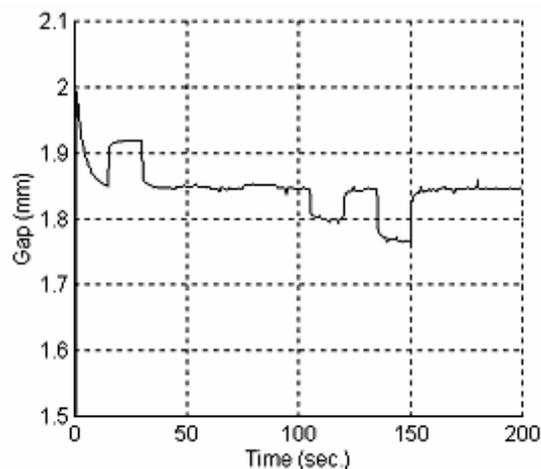


Figure 3. Gap responses for sequence 1.

The last simulation was to verify the proposed controller's robustness. Figure 5 shows the response of the output thickness for sequence 2. This sequence considers typical values of maximum deviations in the rolling processes (Bryant et. al. 1973). Observe that the output thickness of the predictive model uses sensitivity factors obtained for small disturbances in the operation point. In this case, the controller maintained the error in the output thickness below 4.1%, and the response reached the stationary state in 12 s. The Figure 6 shows the response of the gap for this situation.

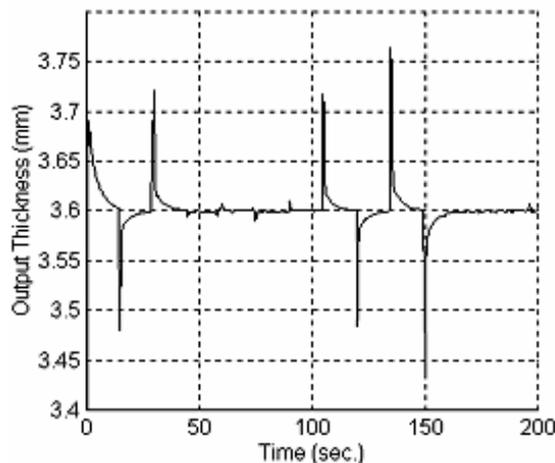


Figure 4. Output thickness response for sequence 2.

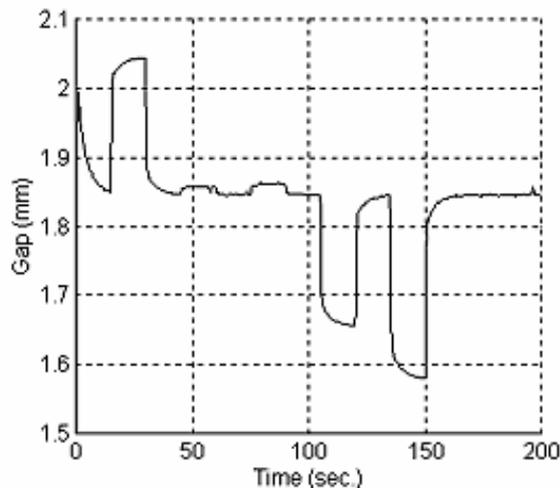


Figure 5. Gap responses for sequence 2.

Conclusion

In this paper, it was presented a method to determinate the appropriate adjustment for thickness control, considering three possible control parameters: gap, front tension and back tension. This method, a new technique AGC, uses the sensitivity factors to choose the best control parameter.

The proposed control structure uses a predictive model for the output thickness based on neural networks and sensitivity factors. The structure allows to eliminate the time delay presented in the dynamics of the system and to eliminate the thickness sensor, usually X-ray. This control system implements a virtual sensor for output thickness, allowing to estimate "on-line" outgoing thickness.

The analysis and simulation results show that the proposed structure has results that are acceptable for rolling processes. The predictive model uses sensitivity factors calculated in the neighborhood of an operation point and it was observed that the control system had a satisfactory behavior for great deviations in the nominal operation point.

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