

A MODEL-BASED PREDICTIVE CONTROL SCHEME FOR STEEL ROLLING MILLS USING NEURAL NETWORKS

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ABSTRACT. *A capital issue in roll-gap control for rolling mill plants is the difficulty to measure the output thickness without including time delays in the control loop. Time delays are a consequence of the possible locations for the output thickness sensor which is usually located some distance away from the roll gap. In this work, a new model-based predictive control law is proposed. The new scheme is a neural network based predictive control structure which is applied to roll-gap control with outstanding results. It is shown that the neural network based predictive control permits to overcome the existing time delays in the system dynamics. The proposed scheme implements a virtual thickness sensor which releases an accurate estimate of the actual output thickness. It is shown that the dynamic response of the rolling mill system can be substantially improved by using the proposed controller. Simulation results are presented to illustrate the controller performance.*

Keywords: Model-Based Predictive Control, Neural Networks, AGC Systems, Steel Industry.

1. INTRODUCTION

The development of new Automatic Gage Control (AGC) systems represents an important research field in the metallurgic industry. AGC systems vary as much in form as in complexity as do rolling mill configurations. Basically, AGC are non predictive feedback control schemes applied to rolling mill systems to achieve output strip thickness specifications.

In most cases an output thickness measurement is used as the feedback variable. Two techniques have been extensively used to evaluate output thickness deviations from its set point:

- The first one includes a sensor located after the roll gap. This approach causes a time delay in the feedback system and produces a significant deterioration in the control performance.
- The second technique consists in calculating the output thickness from measurements of the roll load. This has a problem when working with thin strips, because variation in the strip thickness has little effect on the measured roll load.

The technique proposed here does not follow any of the classical approaches, but instead of that it uses direct gap measurements and a neural network based predictive model to implement the control law (Smith, 1957).

Also, since the proposed technique is based on direct gap measurements, it permits to achieve the required control accuracy and performance. The implementation of a neural network based predictive model as a virtual output thickness sensor comes to fulfill the need for computational speed required for any on-line closed loop control.

Some relevant contributions in the area of control application of neural networks are the papers from Andersen et al (1992), Guez et al (1988), Hunt et al (1992), Khalid and Omatu (1992), Sbarbaro et al (1993), Smartt (1992), Tai et al (1992), and Yamada and Yabuta (1993).

Predictive control algorithms were initially developed in the industrial environment as computer-based control systems. Important reviews on predictive control have been published by Garcia et al (1989), Ricker (1991), Morari et al (1991), Muske et al (1993) and Rawlings et al (1994). Although, the predictive control area still lacks of a solid theoretical foundation, some important theoretical contributions can be found in the works from Lee et al (1994) and Mayne (1996).

In Section 2, a review of a neural network based model as proposed in [11] is presented. In Section 3 the proposed control scheme is introduced and discussed. In Section 4, simulation results for a rolling mill stand are presented. In Section 5 conclusions are established. And finally, in Sections 6 and 7, the paper references and notation are respectively presented.

2. A NEURAL NETWORK BASED MODEL

Predictive control algorithms are currently applied to many industrial processes. Originally, they were applied to power plants and oil refineries. Currently predictive control applications have been spread out to a large variety of industrial cases such as metallurgic industries, chemical plants, and food processing. In the industrial control environment the term "predictive control" refers to a wide diversity of control topologies. Nevertheless, a common strategy in this case is to use an accurate plant model to estimate future values of the plant output and use these estimates to perform the suitable corrections of the plant set point. In general, these schemes work in open loop.

Analytic models are usually developed having accuracy as the main objective and in general they are not appropriated for on-line closed loop control implementation. Such is the case of the well accepted Alexander's model for rolling mill plants. Alexander's model has proved to be an accurate model for simulation purposes but it requires too much computational effort and so it is inadequate for closed loop control.

In the case of rolling mill processes, a regular approach is to calibrate the system using a quite large and complete data base such as a lookup table and then run the process in open loop. Usually, the results are just good enough to meet steady state performance specifications.

In order to implement a roll-gap closed loop predictive control a numerically fast model has to be used, however, none of the existing analytical models are able to keep accuracy and be fast enough for closed loop control purposes.

An automatic gauge control (AGC) system for rolling mills utilizes the output thickness as the feedback variable. Usually the thickness sensor is placed too far from the roll-gap, and this causes a time delay in the feedback control loop which also depends on the strip speed.

Several rolling models have been proposed in the literature which in general are non linear functions of several variables of the following form:

$$P = f(y_i, h_i, h_o, t_r, t_o, \mu, E, D) \quad (1)$$

A linear form for Equation 1 can be written as

$$\Delta P = \frac{\delta P}{\delta h_i} \Delta h_i + \frac{\delta P}{\delta h_o} \Delta h_o + \frac{\delta P}{\delta t_r} \Delta t_r + \frac{\delta P}{\delta t_f} \Delta t_f + \frac{\delta P}{\delta \mu} \Delta \mu + \frac{\delta P}{\delta y} \Delta y \quad (2)$$

The strip output thickness can be computed from the elasticity equation as

$$h_o = g + \frac{P W}{M} \quad (3)$$

or

$$\Delta h_o = \Delta g + \frac{\Delta P W}{M} \quad (4)$$

From Equation 2 and 4

$$\Delta h_o = h_o^* - h_o = \frac{W}{M - W} \frac{\delta P}{\delta h_o} \left(\frac{M}{W} \Delta g + \frac{\delta P}{\delta h_i} \Delta h_i + \frac{\delta P}{\delta t_r} \Delta t_r + \frac{\delta P}{\delta t_f} \Delta t_f + \frac{\delta P}{\delta \mu} \Delta \mu + \frac{\delta P}{\delta y} \Delta y \right) \quad (5)$$

The partial derivatives in Equations 2 and 5 are known as sensitivity coefficients. It can be observed that they correspond to the linear terms of the multivariable Taylor's series expansion of the function.

Equation 5 can be written as:

$$\Delta h_o = h_o^* - h_o = K[S][\Delta u] = K[S][u^*] - K[S][u] \quad (6)$$

then

$$h_o = h_o^* - K[S][\Delta u] = h_o^* - K[S][u^*] + K[S][u] \quad (7)$$

where

$$K = \frac{W}{M - W \frac{\delta P}{\delta h_o}} \quad (8)$$

and

$$[S] = \begin{bmatrix} M & \delta P \\ W & \delta h_i & \delta t_r & \delta t_f & \delta \mu & \delta \bar{y} \end{bmatrix} \quad (9)$$

and also

$$[\Delta u] = \begin{bmatrix} \Delta g \\ \Delta h_i \\ \Delta t_r \\ \Delta t_f \\ \Delta \mu \\ \Delta \bar{y} \end{bmatrix} = \begin{bmatrix} g^* \\ h_i^* \\ t_r^* \\ t_f^* \\ \mu^* \\ \bar{y}^* \end{bmatrix} - \begin{bmatrix} g \\ h_i \\ t_r \\ t_f \\ \mu \\ \bar{y} \end{bmatrix} \quad (10)$$

It should be noticed that Equations 5, 6 and 7 can be used to determine an estimate value, \hat{h}_o , for the output thickness, h_o , given the gap variation, rolling parameters and sensitivity coefficients. Traditionally, the sensitivity coefficients in matrix $[S]$ (Equation 9) are usually determined by solving a system of nonlinear equations, such is the case of the Alexander's model for rolling processes (Alexander, 1972). Alternatively, Zárate et al (1998) proposed a new representation for the cold rolling process based on a neural network structure in which the sensitivity coefficients are obtained directly from the neural network weights. One important feature of this approach is that it permits to eliminate the effects of the time delays on the controller performance.

In this case, the network is trained with the rolling load, P , and the torque, T , chosen as the desired outputs. Also, the neural network input training vector was built such that the data sets include present and future values of the rolling mill parameter. Equation 11 shows the input training vector.

$$t.v. = [g(k) \quad h_i(k) \quad t_r(k) \quad t_f(k) \quad \mu(k) \quad \bar{y}(k) \quad h_o(k + \tau)] \quad (11)$$

where τ is the time delay which depends on the thickness sensor placement.

It should be noticed that each data set includes the present values of the rolling variables at the moment of the roll gap deformation and the corresponding future value of the thickness output. Thus, the new neural network based model is actually mapping set points at present time with the resulting output thickness in the future. This mapping gives the neural model the required predictive characteristics to implement the model predictive control law.

Figure 1 shows the block diagram used to obtain the sensitivity coefficients. Notice that, in this case, the sensitivity coefficients are calculated directly from the network inputs and the network weights (Zárate et al, 1998).

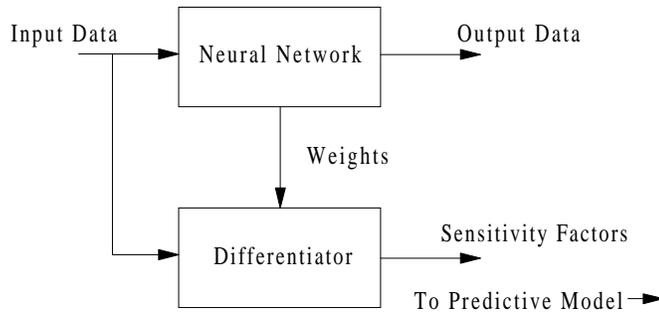


Figure 1. The Neural Network Training Scheme to obtain the Sensitivity Coefficients.

3. THE PROPOSED PREDICTIVE CONTROL SCHEME

The performance of classical techniques for control systems design usually depends on the existence of a good linear model of the plant dynamics in order to achieve an acceptable design. The lack of a good model is still more compelling in the case of predictive control in which a plant model is used to estimate, at the sampling instants, the process variables not yet available.

In the case of rolling mill systems, the performance of classical model predictive control is usually poor due to the complexity of the existing nonlinear models. Also a challenging characteristic of those systems is the existence of usually large time delays in the control loop, in rolling processes this happens especially at low strip speed.

A modern alternative to overcome these problems is the use of artificial intelligence to face model uncertainty, time delays, and nonlinear plants. Neural networks have been recently proposed as a solution for the control problem of some ill-conditioned processes [3-5]. They have been successfully applied to those cases in which the plant dynamics causes a poor performance of traditional control techniques.

This paper introduces a new control scheme that uses a predictive model proposed in Zárate et al (1998) whose parameters are obtained directly from the weights of a trained neural network as shown in Figure 1. To implement the control law, a predicted value of the output thickness \hat{h}_o is used instead of the current value of h_o which can not be measured without the interference of a substantial time delay. This value is calculated from the corresponding parameter values for each operating point.

It should be observed that a main feature of the proposed control scheme is the fact that its predictive characteristic actually improves the plant stability. This can be seen by realizing that at time $t = 0$ one can expect the error to be small, since using the predictor:

$$e(0) = h_r(0) - \hat{h}_o(0) \approx \text{small}; \quad \hat{h}_o(0) \approx h_r(0) \quad (12)$$

on the other hand, without the predictor:

$$e(0) = h_r(0) - h_o(0) \approx \text{large}; \quad h_o(0) \neq h_r(0) \quad (13)$$

Thus, the heuristic argument is that with the inclusion, in the control loop, of the proposed predictive scheme, the plant response would be smoother than without it.

The basic idea of using predictive control properties to compensate for closed loop time delays has been previously presented in the technical literature (12). However, most of the results have been for linear systems. In this work, the proposed neural network based model predictive control is a general approach applicable to any linear and nonlinear system if exits a good data base for the neural network training.

Figures 2 shows the proposed controller scheme. It should be noticed that, in this case, the predictive model is being implemented as a virtual sensor whose output is the predicted output thickness.

Finally, in cases in which some drift from the operation point (not considered in the network training) is expected, an adaptive configuration may be used in order to allow the on-line fine tuning of the predictor model as it is shown in Figure 3. In this case the neural network will be kept learning and updating the sensitivity factors as the rolling process is carry on.

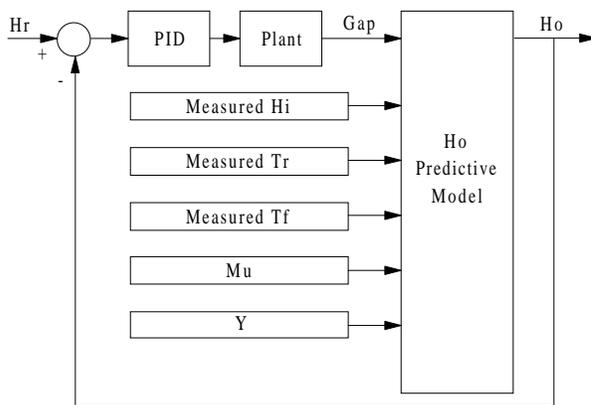


Figure 2. The Proposed Predictive Controller.

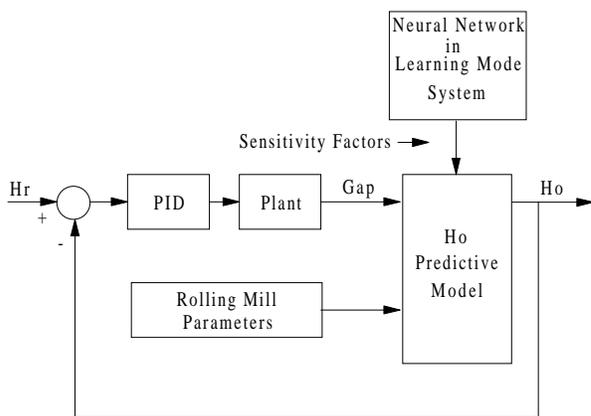


Figure 3. An Adaptive Version for the Proposed Predictive Controller.

4. SIMULATION RESULTS

To verify the performance of the proposed scheme, the Alexander's model (Alexander, 1972) was used to generate a data base for the cold rolling mill process. The neural network has been trained using an average parameter variation of 15% around the equilibrium point. The strip width was chosen as $W = 900$ mm, the absolute mill modulus as $M = 400.000$ and nominal roll gap as $g = 0.348$ mm. For simulation purposes it was assumed the strip speed to be constant and equal to 120 m/min. Also, it was assumed that the physical gap was always positive and kept in the $[0, 5]$ mm range. And finally, the actual output thickness sensor was assumed to be located 2 meters ahead from the roll gap. Table 1 presents the values for the operation point used in the neural network training. Table 2 shows the nominal values for the sensitivity factors (Equation 4) at the operation point.

Table 1.

h_i	h_o	μ	t_r	t_f	\bar{y}
5.0	3.6	0.12	0.441	9.098	46.918

Table 2.

$\frac{\delta P}{\delta h_i}$	$\frac{\delta P}{\delta h_o}$	$\frac{\delta P}{\delta \mu}$	$\frac{\delta P}{\delta t_r}$	$\frac{\delta P}{\delta t_f}$	$\frac{\delta P}{\delta \bar{y}}$
306.35	-1634.99	1423.66	-23.87	-0.14	26.79

In this case, the plant and PD controller transfer functions are given by:

$$G(s) = \frac{1.08 e^{-s}}{s(s+1.08)} \quad (14)$$

$$C(s) = \frac{3 + 8s}{\tau s + 1} \quad (15)$$

Figure 4 shows the open loop Bode diagrams of the plant. Notice that the gain and phase margins are too small to achieve good performance with classical PID controllers. Finally, Figure 5 presents the Bode of the plant with the PD controller given by Equation (6).

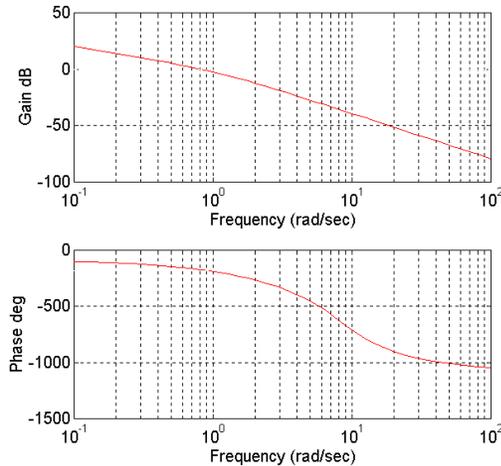


Figure 4. The Plant Bode Diagram.

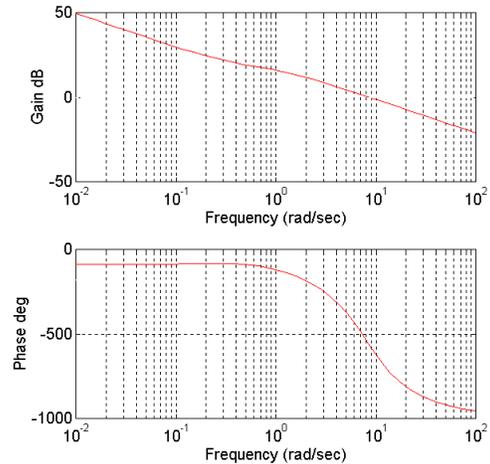


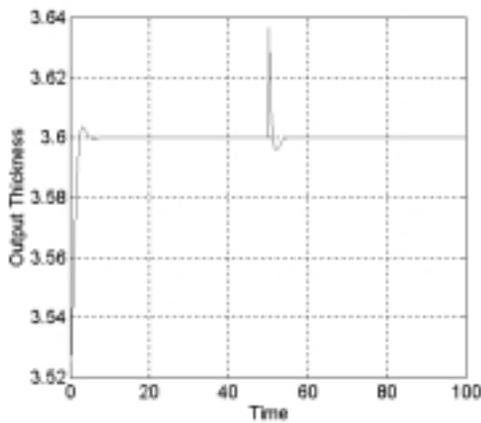
Figure 5. The Controlled Plant B.D.

It should be notice that in this case the phase margin is negative (less than -22 degrees at approximately 9 rad/s) and hence the closed loop system, without the predictor, would be unstable.

To verify the controller performance, a roll gap step input at time $t = 0$ sec. and then a perturbation step at time $t = 50$ sec. were applied. The perturbation signals were created by modifying only one of the rolling parameters (Table 1) and keeping the remaining constant.

Figure 6 shows the output thickness response for a 5% increase in the input thickness at time 50 s. It should be observed that the predictive controller kept the output thickness error less than 1% and was able to reach steady state in less than 4 sec. Figure 7. Shows the gap response for the same experiment.

Figure 8 shows the output thickness response for a 5% increase in the friction at time 50 s. In this case, the predictive controller kept the output thickness error less than 0.1% and was able to reach steady state in less than 4 s. Figure 9 shows the gap response.



Figures 6. Output Thickness for 5% Input Thickness Perturbation

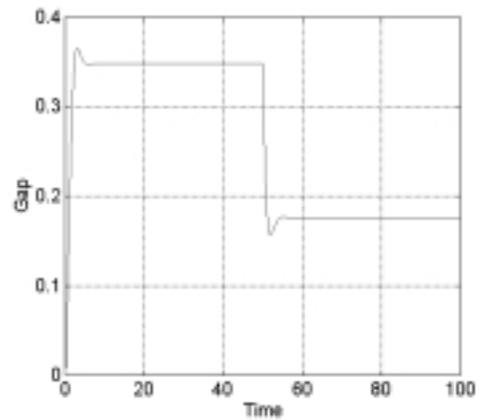
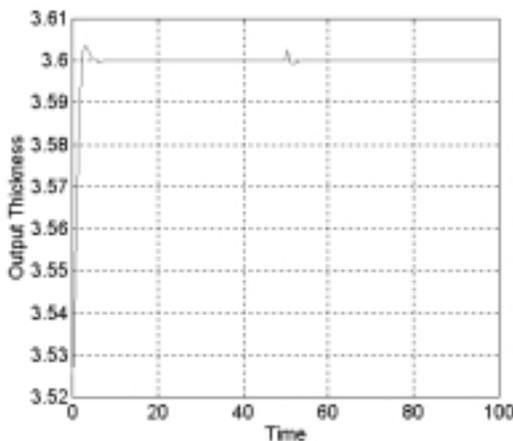
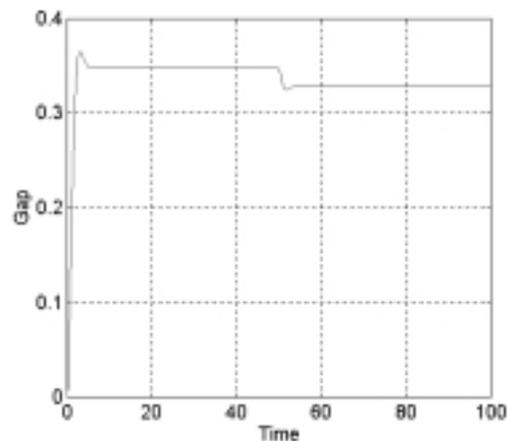


Figure 7. Gap Response for 5 % Input Thickness Perturbation.



Figures 8. Output Thickness Response for 5% Friction Perturbation



Figures 9. Gap Response for 5% Friction Perturbation

5. CONCLUSIONS

This paper presented a technique based on a neural network based predictive modeling control structure that permitted to overcome the existing time delays in dynamic systems. The technique was successfully applied to a rolling process. It was verified through numerical simulation that the dynamic response of such a system can be substantially improved by using the proposed predictive controller.

The proposed scheme implements, virtually, the thickness sensor which delivers an estimation for the output thickness. Even though the predictive model uses sensitivity factors calculated for some neighborhood of the operating point, it was observed that, the control system also performed well even for large deviations from that operating point. The analysis and simulation showed that the obtained results are good enough for rolling process.

Finally, it was showed that including the predictor in the closed loop actually stabilizes the system. The heuristic argument is that the dynamic behavior of the predictor system is similar to that of lead controllers since it makes output information available in advance for the control algorithm. The practical results is that the control signal is smother with the predictor than without it.

6. REFERENCES

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7. NOTATION

μ	=	<i>Friction coefficient</i>
\bar{y}	=	<i>Mean yielded tensile stress (kgf/mm²)</i>
g	=	<i>Gap (mm)</i>
h_i	=	<i>Strip input thickness (mm)</i>
h_o	=	<i>Strip output thickness (mm)</i>
M	=	<i>Mill modulus (kgf/mm)</i>
P	=	<i>Rolling load (kgf/mm)</i>
R	=	<i>Cylinder radio (mm)</i>
T	=	<i>Torque (kgf-mm/mm)</i>
t_f	=	<i>Front tension stress (kgf/mm²)</i>
t_r	=	<i>Back tension stress (kgf/mm²)</i>
W	=	<i>Strip width (mm.)</i>