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Cold rolling mill thickness control using the cascade-correlation neural network

by

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Abstract: The improvements in thickness accuracy of a steel strip produced by a tandem cold-rolling mill are of substantial interest to the steel industry. In this paper, we designed a direct model-reference adaptive control (MRAC) scheme that exploits the natural level of excitation existing in the closed-loop with a dynamically constructed cascade-correlation neural network (CCNN) as a controller for cold rolling mill thickness control. Simulation results show that the combination of a such a direct MRAC scheme and the dynamically constructed CCNN significantly improves the thickness accuracy in the presence of disturbances and noise in comparison with to the conventional PID controllers.

Keywords: direct MRAC, cascade-correlation neural network, dynamic neural network construction, cold rolling mill thickness control

1. Introduction

A tandem cold-rolling mill (Fig. 1) is designed to reduce the thickness of the incoming strip, supplied in a coil at room temperature, by a factor of 2 to 10, so the outgoing strip has a uniform thickness with certain dimensions, typically 20-50 *inches* in width and 0.007-0.012 *inches* in thickness. The product is vital

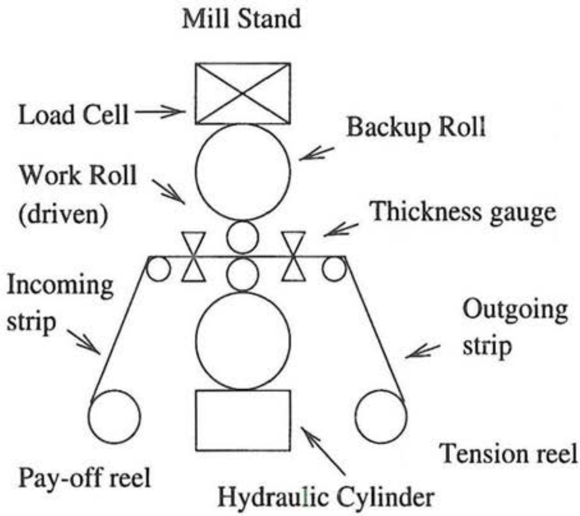


Figure 1. A single-stand reversing strip mill.

As the steel industry strives to improve product quality and reduce production costs, a viable scheme to achieve accurate thickness is of substantial interest to the industry. Considerable industrial research effort (Dutton and Groves, 1996; Grimble, 1995; Postlethwaite and Geddes, 1994) has been devoted to finding the best possible solution. Conventional thickness control systems are mainly based on the standard PID controllers, which are simple to implement but have limited accuracy. The rolling process, however, is a complex system with strong mutual interactions between the strip thickness, the roll gap position, the rolling force, and the strip hardness. Consequently, improvements in the design strategy are necessary to overcome the problem of mutual interactions.

Neural networks is a promising new technology which is becoming popular for control applications. However, most of the existing research in neural control has been concentrating on indirect control schemes, where the neural network is used to identify the process, and a controller is subsequently synthesized from this model (Brown and Harris, 1994; Harris et al., 1993; Hunt et al., 1992; Lin and Lin, 1996; Narendra and Pathasarathy, 1990; Narendra and Mukhopadhyay, 1994).

Such an approach is very prominent in applications of neural networks to steel manufacturing, where the main research efforts are concentrated on using neural network models to predict the process parameters such as the rolling force (for example, Hwu and Lenard, 1996; Pichler and Pffaffermayr, 1996).

The indirect control schemes mentioned above are following the traditional guarantee that even a very good model will lead to good control. The inherent conflict between identification and control is well-recognized (see, for example, Koussoulass and Dimitriadis, 1989). The objective of the control is to minimize (make zero) the error between the actual process outputs and the desired outputs (set-points).

However, when the error is zero, or a constant, one has no influence on the outputs and thus cannot identify process parameters (Guez et al., 1992). This refers to the lack of the persistency of excitation (Anderson, 1985). Tsakalis (1997) pointed out that the typical control law attempts to minimize the approximation error by driving the parameter estimations towards the manifold where the error becomes zero, thus allowing for the bursting phenomena. In the worst case, an appropriate arbitrarily small disturbance can be found to induce a parameter drift on this manifold, thereby causing persistent bursting.

Guez et al. (1992) argue that successful control requires the whole environment that acts systematically towards the goal of accumulating the knowledge and using it. In this paper, an attempt is made of designing such environment that includes not only the learning in the controller but also the overall control scheme that permits such learning to occur.

Consequently, the control should imply both the learning (identification) and the tracking (control in its traditional form). The authors argue that if one tries to optimize both objectives (the control and the identification), the identification solution alone would indeed play the role of the persistent excitation.

On the other hand, there are many types of neural networks which can be used as a controller (Haykin, 1999), among which the most popular one is the multilayer perceptron (MLP). However, with the MLP, there are no simple ways to determine in advance the minimal structure of the network (number of hidden layers and the minimal size of each hidden layer) necessary to achieve a desired performance. It is not uncommon to test many architectures to find the appropriate one by trial-and-error, although there are some algorithms for constructing an MLP during learning (Kavzoglu, 1999; Kwok and Yeung, 1997). In this paper, we use the cascade-correlation neural network (CCNN) (Fahlman and Lebiere, 1990) for the simplicity of its implementation.

This paper is organized as follows. Section 2 describes the control scheme and briefly reviews the CCNN. Section 3 describes the simulation model. Computer simulations using the CCNN and comparisons with the standard PID controller are shown in Section 4. Section 5 summarizes the results of this paper.

2. The control scheme and the cascade correlation neural network

A general multi-input multi-output (MIMO) nonlinear dynamical process can be represented by the following state-space representation:

$$\vec{y}(t) = \vec{g}[\vec{x}(t), \vec{\nu}(t)], \tag{2}$$

where $\vec{x} \equiv (x_1, x_2, \ldots, x_n)$ are the process inputs, $\vec{u} \equiv (u_1, u_2, \ldots, u_m)$ are the control signals (the manipulated variables), $\vec{d} \equiv (d_1, d_2, \ldots, d_p)$ are disturbance inputs, $\vec{y} \equiv (y_1, y_2, \ldots, y_m)$ are the process outputs, $\vec{\nu} \equiv (j_1, j_2, \ldots, j_m)$ are the measurement noises, and t is the sampling time. Here n, m, and p are the dimensions of corresponding vectors.

In this paper we are using a direct model reference adaptive control (MRAC) (Åström and Wittenmark, 1990) where a neural network is the controller and no models of the process are required. The overall control scheme exploits the natural level of excitation in the process under control by applying the same noisy inputs (states) signals to both the controller and the reference model.

The persistency of excitation (or the signals rich in frequency) is required for exponential stability of an adaptive algorithm. Failure to satisfy this requirement may result in bursting phenomena, also known as parameter drift (Anderson, 1985). This means that in the absence of such excitation the parameters of the controller would grow extremely large thus resulting in bursting. Consequently, the input and the output signals need to be rich in frequencies for learning to be successful.

As pointed out by Tsakalis (1997), the parameter drift can be interpreted as a non-robustness of an ill-posed optimization problem. The error bursts in this framework are the immediate consequence of a Lipschitz continuity of the parameter approximation (finite adaptation gains). The estimation/approximation of the time-varying parameters in the absence of the sufficient excitation poses a challenging theoretical problem. In such a case achieving a *limsup* performance is as hard as achieving a L_∞ performance from the initial conditions that are zero in the output errors but arbitrary in the parameters. Consequently, burst suppression in a general case requires the controllers with infinite adaptation gains or injection of excitation.

However, it is impractical/dangerous to inject artificial excitation signals into a closed-loop system, as such injection could result not only in excitation of high-order dynamic modes of the process, but also product/equipment losses. It would be more practical to exploit the noise/disturbances already existing in the process to provide such persistent excitation. While the noise/disturbances are unmeasurable, their effects on the measurable variables can be to measured.

A fundamental obstacle in overcoming the persistency of excitation problem is that the designer has limited or no control over the external inputs and, consequently, the level of excitation. This means that a high level of excitation (frequency rich and large amplitude signals) are required in order to obtain accurate parameters of the controller. However, a low-level excitation is required by a typical control objective, for example, regulation, disturbance rejection, and tracking of the low-frequency reference signals (Tsakalis, 1996).

One may look at inference canceling in adaptive signal processing for an is not well suited as it introduces some inevitable phase distortion. A better solution is to introduce an additional reference input $x_n r$ containing the noise, which is correlated with the original corrupting noise x_n. The network filters the reference noise $x_n r$ to produce an estimate of the actual noise $x*_n$. Then, the network subtracts the noise from the primary input $s + x_n$, which acts as the desired response to produce the estimate of the signal $s*$ (Zaknich and Attikiouzel, 1995).

Now in the context of the adaptive control, one may try to exploit a natural level of excitation that exists in the process under control and apply the same noisy inputs (states) signals to both the controller and the reference model. If a reference model were in the form of a filter (for example, a Butterworth filter), the output of a reference model would be a desired signal with the acceptable level of noise in it. Using the error between the actual response of the process and the desired one from a reference model, it should be possible to find a needed auxiliary function (controller) f_c. This auxiliary function would transfer the original process function f_p into a desired one between the noisy inputs (states) and the desired outputs of the reference model. In such a case a reference model represents our desired process (the controller plus the original process) f_d.

In view of the above discussion, the squared difference between the desired output set-point $\vec{y}^{sp}$ and the process output $\vec{y}$ cannot be used as the objective function to be minimized for the learning in a neural control:

$$\varepsilon_l(t) = \frac{1}{2}(y_l^{sp}(t) - y_l(t))^2. \tag{3}$$

Here $l = 1, 2, \ldots, m$. With such an objective function, the neural controller learning may proceed to a physically unrealizable situation, since the set-points obviously are not persistently exciting (Anderson, 1985). In order to overcome the lack of persistency of excitation, one may obtain the desired output response $\vec{y}_d$ from the output of a reference model with the state variables $\vec{x}$ being inputs to the model. In this case excitation is due to the actual process signals (states) affected by the disturbance signals $\vec{d}$ and the noise $\vec{n}$. See also Tsakalis (1996) for discussions on injection of the persistently excited signals in closed-loop systems.

The objective function in such a case becomes the squared difference between the outputs of the process $\vec{y}$ and the reference model $\vec{y}_d$,

$$\varepsilon_l = \frac{1}{2}(y_l - y_{dl})^2. \tag{4}$$

In addition, a reference model in the form of a filter with a desired transfer function may be used to ensure a variance in the desired dynamic characteristics of the process. The frequency response of the closed-loop may be adapted in line with the changes in the frequency responses of the filter. Such reference models may be used when the required performance of the time-varying process is an optimization-based design method using a Modulus Optimum, also called the loop-shaping method (Hågglund and Åström, 1996).

One may use a linear stable reference model, for example, a Butterworth filter (Åström and Wittenmark, 1990), since the general well-behaved nonlinear models are not yet available. The coefficients of a Butterworth filter are thus selected to correspond to the Modulus Optimum criteria for a desired performance in terms of the standard control objectives such as the overshoot, the settling time, and the steady-state error. While the use of such a general reference model would not permit us to achieve an ideal control, this should guarantee the adequate control performance for a wide range of the processes in which it is to be used. The controller (CCNN in our case) is designed to transfer the original process transfer function to a desired one.

The learning algorithm is designed to obtain the correct control signals (manipulated variables) $u_l (l = 1, 2, \ldots, m)$ corresponding to the desired process outputs y_{dl} by minimizing the learning error ε_l, defined as the difference between the desired process responses y_{dl} and the measured process outputs y_l

$$\varepsilon_l = \frac{1}{2}(y_l - y_{dl})^2. \tag{5}$$

A block diagram of the overall control system is presented in Fig. 2.

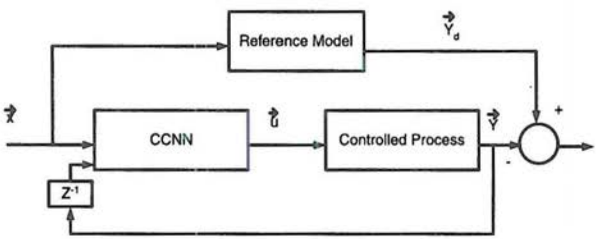


Figure 2. A block diagram of the overall control system.

Fig. 3 shows the architecture of the CCNN (Fahlman and Lebiere, 1990), used as a controller in the the above control scheme, whose construction and learning algorithms can be summarized as follows:

1. Start with a minimal network consisting of only an input layer and an output layer. Both layers are fully connected with adjustable weights. There is also a bias unit, set permanently to +1. Linear output units are used.
2. Train all connections to the output layer using the quickpropagation learning algorithm (Fahlman, 1988) until the overall error of the network no

3. If the network performance satisfies a prescribed accuracy target, the algorithm stops. In such case, as there is no hidden layer, the problem at hand is linear.
   We note that CC can thus be used to test if the problem at hand is *really* nonlinear. There is no benefit in applying neural controller to a linear or linearizable plant, as this will result in degradation of performance in terms of computation time and controller performance: the solution should not be more complex than the problem at hand (Mars et al., 1996).
4. If the network performance is not satisfactory (and therefore the problem is really nonlinear), generate candidate nodes. Every candidate node receives trainable connections from all inputs nodes and from all pre-existing hidden nodes. There are no connections between the candidate nodes and the output nodes.
5. Maximize the correlation between the activation of the candidate nodes and the residual error of the network by training all connections leading to a candidate node. The training stops when the correlation no longer improves.
6. Choose the candidate node with the maximum correlation and add it to the network. To change the candidate node into a hidden node, connect it to all output units. Return to step 2.

The algorithm is repeated until the overall error of the network falls below a pre-specified threshold.

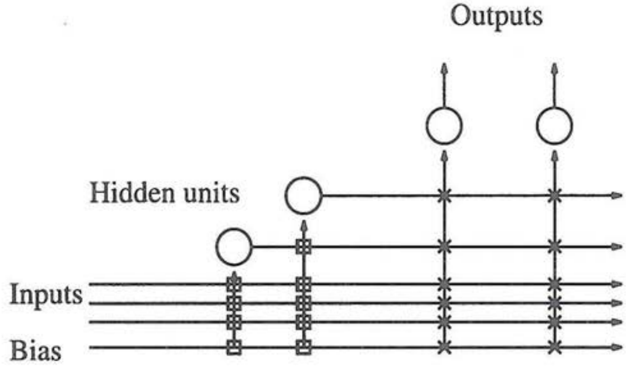


Figure 3. The structure of the cascade-correlation neural network (CCNN).

3. Simulation model of a cold rolling mill

As shown in Fig. 1, in a single-stand reversing strip mill, the incoming strip is supplied from a pay-off reel at one side of the mill, reduced in thickness as it is passed between the mill work rolls, and recoiled by a tension reel at the other the reverse direction. The process continues until the outgoing strip is of the desired final thickness. The thickness of the rolled strip is predominantly determined by the gap between the work rolls, although there are other contributing parameters, such as the tension in the strip, hardness variations in incoming materials, and hardening of the material during rolling. The roll gap is initially set by electrical screw-down drives. Once the strip is threaded, changes to the roll gap are carried out by extending/contracting hydraulic cylinders. Automatic gauge control (AGC) for cylinder control is used in two modes, pressure (load) control or position control. Fig. 4 (Dutton and Groves, 1996) shows a typical arrangement of a control loop for cylinder position. For pressure control, position transducers are replaced by pressure transducers.

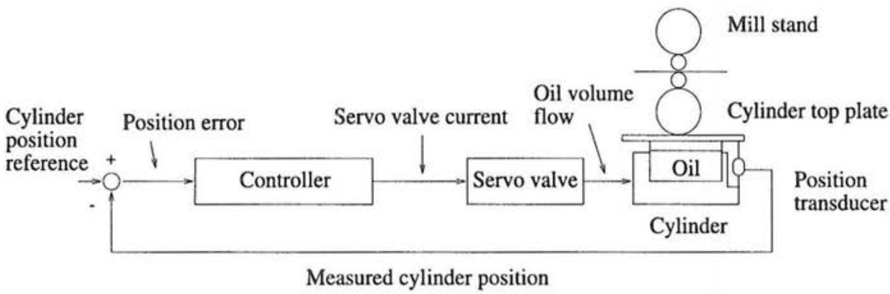


Figure 4. Automatic gauge control (AGC) gap position loop.

In practice, the cylinder position reference signal will have contributions from several other control loops not shown in Fig. 4. For example, the outgoing strip thickness will be measured and any deviation from the desired value requires reduction of the reference signal for cylinder position. However, for physical reasons, it is impossible to measure the outgoing thickness at less than some definite distance downstream of the roll gap. This introduces a transport lag, which severely degrades the gauge performance when compensating for short-duration errors. In high performance mills, the incoming thickness at the roll gap is also measured and used in a feedforward control loop, so that the cylinders are adjusted in line with variations in the roll gap. Another common disturbance to the operation of the position control loop is the roll eccentricity, arising from imperfect roll grinding and roll wear.

In our simulation studies presented in the next section, we have used an AGC position control servo valve and capsule model (Fig. 5) developed from the physical insight of the process (Dutton and Groves, 1996) to replace the servo valve and capsule in Fig. 4 (the position transducer is assumed to have

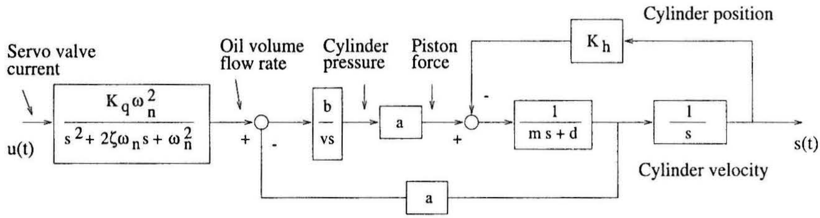


Figure 5. Servo valve and cylinder model of a position loop. Here $s = dx/dt$, $\omega_n = 120 rad/s$ is the servo valve natural frequency, $\zeta = 1.1$ is the valve damping ratio, $K_q = 25m^3/(sA)$ is the flow gain, $b = 1.4 \times 10^9 N/m^2$ is the oil compressibility, $a = 0.58m^2$ is the capsule cross-sectional area, $v = 0.0232m^3$ is the capsule volume, $m = 1 \times 10^5 kg$ is the mass of the mill, $K_h = 4.5 \times 10^9 N/m$ is the mill housing stiffness, and $d = 5 \times 10^6$ is a damping term.

Although the main emphasis is on the gap position control, the other parts of the mill need to be taken into account (such as the force control loop), as their disturbances and noise affect the performance of the position control. This results in a complete model representation of the combined mill position control, disturbances and noise (Fig. 6) (Grimble, 1995).

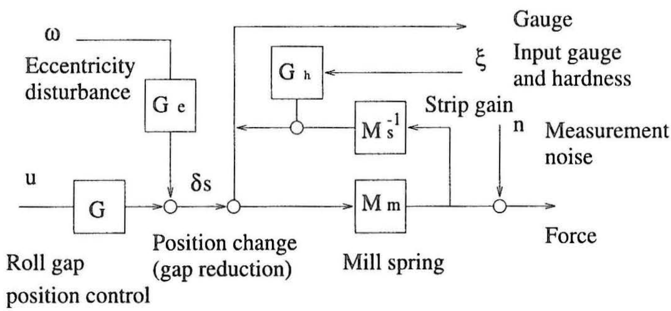


Figure 6. An overall single-stand model for the cold rolling mill.

The parameter values were selected based on the experimental and the physical property data (Grimble, 1995). The frequencies and the gain values of the model were scaled appropriately to match the experimental data.

In Fig. 6, G represents a hydraulic roll-gap model for closed-loop position control of Fig. 5. G_e is an eccentricity disturbance model:

$$G_e = 852.224/((s^2 + 0.0314s + 985.96) \times (s^2 + 0.0294s + 864.36)), \qquad (6)$$

and G_h is an input thickness and hardness disturbance model:

Here $s = \partial x/\partial t$.

Grimble (1995) experimentally verified the use of an eccentricity model comprising two lightly damped oscillators driven by zero-mean white noise with covariance $E\{\omega(t)\omega(\tau)\} = x_1^2$, where $x_1 = 0.00012$.

Since it is difficult to obtain data for hardness variation in cold rolled strip mills, we used a first order lag driven by zero-mean white noise (Grimble, 1995) with covariance $E\{\xi(t)\xi(\tau)\} = x_2^2\delta(t-\tau)$, where $x_1 = 0.00007$ and δ is the Kronecker delta function. The disturbances and noise were applied concurrently to represent a real situation when the disturbances and noise in the rolling mill are present at the same time.

A combination of these models results in a complete model representation of the combined mill and the disturbance system.

A small change model is used (Grimble, 1995) to generate roll force and gauge variations, with gauge $h(t)$ satisfying:

$$h(t) = \frac{M_m M_s^{-1}}{1 + M_m M_s^{-1}} \delta s(t) + \frac{1}{1 + M_m M_s^{-1}} \delta H(t), \tag{8}$$

where $M_m = 1.039 \times 10^9 N/m$ and $M_s = 9.81 \times 10^8 N/m$ are the mill and the strip moduli, respectively, and $s(t)$ is the roll gap setting. Thus the measured roll force $z(t)$ is:

$$\delta z(t) = M_m(\delta h(t) - \delta s(t)) + n(t), \tag{9}$$

where $n(t)$ represents measurement noise with covariance $E\{n(t)n(\tau)\} = x_3^2\delta(t-\tau)$, where $x_3 = 1000$.

Thickness control in a cold rolling mill requires the output gauge to be regulated in the presence of disturbances using the measured roll gap position and the roll force. Here we have an inferential control problem where it is not the measured variables that are controlled, but the measured variables are used to achieve control of another system variable - the strip gauge (thickness).

4. Simulation results

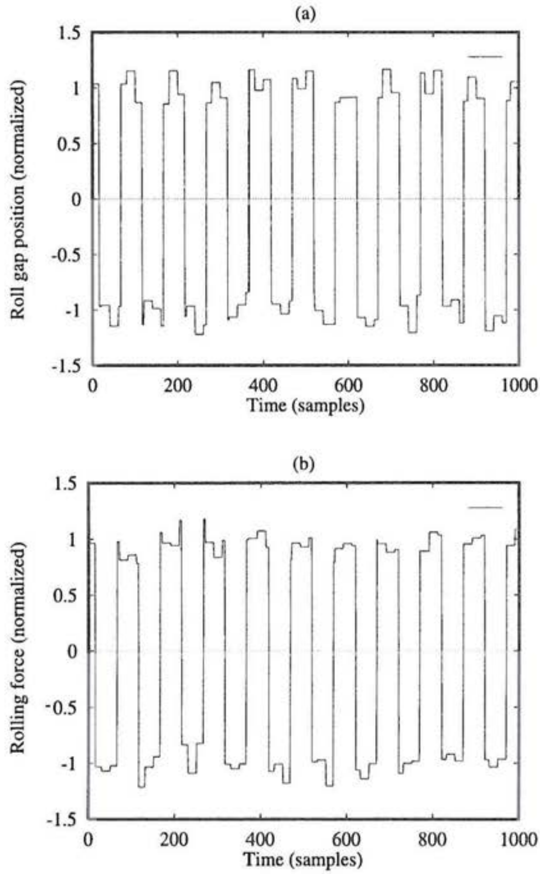
We used Butterworth's (Åström and Wittenmark, 1990) characteristic equation for the 5th order system as a reference model

$$F(s) = s^5 + 3.24\omega_n s^4 + 5.24\omega_n^2 s^3 + 5.24\omega_n^3 s^2 + 3.24\omega_n^4 s + \omega_n^5, \tag{10}$$

where ω_n is the natural frequency of the system $\omega_n = 200\ rad/s$. This form of characteristic equation gives us a damping ratio $\xi = 0.71$, and the settling time can be determined through approximate relationship $t_s \approx 4/\xi\omega_n$. The delay time t_d can also be approximated from the following relationship $t_d \approx (1 + 0.7\xi)/\omega_n$. Consequently, the number of delays in eq. (5) $c = 2$. A 4 Hz

Groves (1996) and is applied to cylinder position reference, was used as a test signal.

We used the input-output data generated using above reference model for training and testing of the CCNN. We have generated 1000 input-output data pairs using the fifth order Runge–Kutta integrator (Åström and Wittenmark, 1990) with the sampling time $t = 0.005$s, normalized to the range $[-1, 1]$. The states of the process (inputs to the CCNN controller) are the strip gauge, the rolling force, the eccentricity disturbance, and the roll gap position. We used first 500 samples for training, the other 500 for validation of controller's ability to generalize, and the whole data set for final testing of the resulting controller.



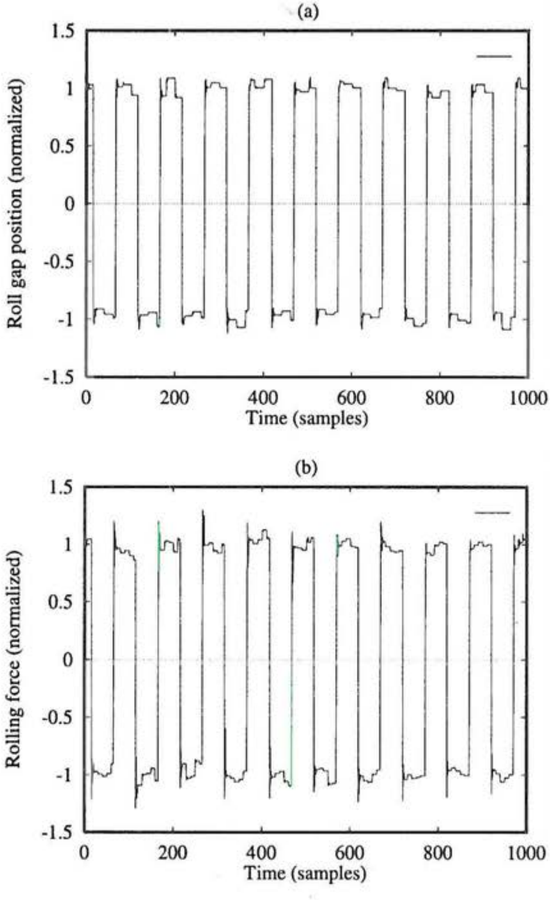


Figure 8. The performance of the PID controllers for (a) the roll gap position and (b) the rolling force.

The choice of this particular evaluation approach was based on the following reasoning:

1. Both the CCNN and the PID controllers were trained/tuned based on the first 500 samples of the input-output data.
2. For both controllers used the next 500 samples of the input-output data were used to test the controllers' ability to perform under the changing process conditions.
3. The final run of both controllers over the whole set of input-output data was used to test that the controllers are able to perform well both for the known data and the unknown data. While the performance of the

this prevents the comparison of any degradation of the performance when the controller is used on unseen data in comparison to its performance on the known (training) data. The controller's ability to generalize is at its best where there is a minimal difference between its performance on known data and its performance on unseen data. While this is well known, it is, for some reasons, rarely evaluated.

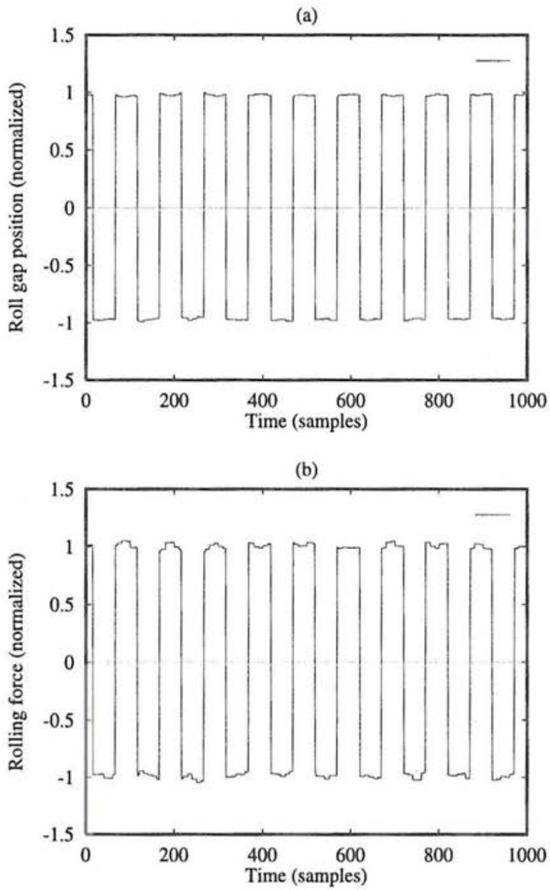


Figure 9. The performance of the cascade-correlation neural network (CCNN) controller for (a) the roll gap position and (b) the rolling force.

We selected, as a CCNN parameters, the learning rate $\eta = 0.005$, maximum growth parameter $\mu = 1.75$, weight decay term $\nu = 0.0001$, maximum tolerated of the CCNN were selected based on preliminary tests, using as a measure the minimum RMSE between the cylinder position reference signal and the ones obtained using the CCNN controller for both the position and the rolling force. For comparison, two PID controllers were used for the same simulated process (one for the position loop, another for the force loop). The parameters of PID controllers, i.e., gain $K_c = 15.5$, integral time constant $\tau_I = 1.6$, and derivative time constant $\tau_D = 2$, were selected according to the industry standard Ziegler-Nichols' method (Åström and Wittenmark, 1990). The design bandwidths for both the CCNN and the PID controllers were the same as they only depend on a natural frequency of the process and a damping ratio. As there is a well known difficulty in optimizing the PID controller to control such complex process as a rolling mill, additional fine tuning of the controller gains was utilized to obtain the best possible performance of the PID controllers.

We present the simulation results in Figs. 7–9 and Table 1. Fig. 7 shows the uncontrolled time response (root mean squared error RMSE = 0.1724 for the position and 0.1232 for the rolling force). While reducing the deviations due to disturbances and noise of the position of roll gap and the rolling force to some extent, the PID controller showed rather poor performance (RMSE = 0.0897 for the position and 0.0787 for the rolling force, as in Fig. 8). The reasons for the poor performance of the conventional "optimal" PID controller may be attributed to non-linearity and/or the coupling in the rolling process. Fixed PID controllers are thus not able to capture the underlying process behavior well.

Table 1. A comparison of the root mean squared errors (RMSE) of an uncontrolled system, a system controlled by a PID controller, and a system controlled by a cascade-correlation neural network (CCNN) controller.

	Uncontrolled	PID	CCNN
Roll gap position	0.1724	0.0897	0.0312
Rolling force	0.1232	0.0787	0.0518

In contrast, the performance of the CCNN is much better (RMSE = 0.0312 for the position and 0.0518 for the rolling force, see Fig. 9). The CCNN generated 37 hidden nodes, which signifies that the process is indeed a non-linear one. Moreover, the CCNN produced practically identical results in regards to both RMSE and the network size for different runs. The Figs. 7–9 show a typical result of the application of the CCNN controller, as it is our belief that averaging the results of a controller's application is inappropriate.

5. Conclusion

In this work we designed a direct model-reference adaptive control scheme which namically constructed cascade-correlation neural network as a controller for cold rolling mill thickness control. We have demonstrated that such a direct MRAC scheme with a CCNN as a controller significantly increased the control precision and robustness compared to the linear PID controllers in this important real-world problem. We argue that a direct MRAC scheme designed in this paper with a CCNN controller using both structure and parameter learning can provide a computationally efficient solution to control of many real-world nonlinear processes in the presence of process disturbances and measurement noise.

References

ANDERSON, B.D.O. (1985) Adaptive systems, lack of persistency of excitation and bursting phenomena. *Automatica*, **21** (3), 247–258.

ÅSTRÖM, K. and WITTENMARK, B. (1990) *Computer controlled systems, theory and design.* 2nd ed. Prentice-Hall.

BROWN, M. and HARRIS, C. (1994) *Neurofuzzy Adaptive Modelling and Control.* Prentice-Hall.

DUTTON, K. and GROVES, C.N. (1996) Self-tuning control of a cold mill automatic gauge control system. *International Journal of Control*, **65**, 573–588.

FAHLMAN, S. (1988) Faster-learning variations on back-propagation: An empirical study. *1988 Connectionist Models Summer School*, 38–51.

FAHLMAN, S. and LEBIERE, C. (1990) The cascade-correlation learning architecture. *Advances in Neural Information Processing Systems*, **2**, 524–532.

GRIMBLE, M.J. (1995) Polynomial Solution of the Standard H_∞ Control Problem for Strip Mill Gauge Control. *IEE Proceedengs, part D - Control Theory and Applications*, **142**, 515–525.

GUEZ, A., RUSNAK, I. and BAR-KANA, I. (1992) Multiple objective optimization approach to adaptive and learning control. *International Journal of Control*, **56** (2), 469–482.

HÅGGLUND, T. and ÅSTRÖM, K. (1996) Automatic tuning of PID controllers. *The Control Handbook*, CRC Press, 817–826.

HARRIS, C., MOORE, C. and BROWN, M. (1993) *Intelligent Control: Aspects of Fuzzy Logic and Neural Nets.* World Scientific.

HAYKIN, S. (1999) *Neural Networks: A Comprehensive Foundation.* Prentice Hall, 2nd ed.

HUNT, K., SBARBARO, D., ZBIKOWSKI, R. and GAWTHROP, P. (1992) Neural networks for control systems - a survey. *Automatica*, **28**, 1083–1112.

HWU, Y.J. and LENARD, J.G. (1996) Application of Neural Networks in the Prediction of Roll Force in Hot Rolling. *Proceedings of the 37th Mechanical Working and Steel Processing Conference*, 549–554.

KAVZOGLU, T. (1999) Determining Optimum Structure for Artificial Neural Networks. *Proceedings of the 24th Annual Technical Conference and Exhibition of the Remote Sensing Society (Earth Observation: From Data to*

KOUSSOULASS, N.T. and DIMITRIADIS, E.K. (1989) Computational techniques for multi-criteria stochastic optimization and control. *Control and dynamic systems, advances in theory and applications*, **30** (3), 1–17.

KWOK, T.Y. and YEUNG, D.Y. (1997) Constructive algorithms for structure learning in feedforward neural networks for regression problems. *IEEE Transactions on Neural Networks*, **8** (3), 630–645.

LIN, C.-J. and LIN, C.T. (1996) Reinforcement learning for an ART-based adaptive learning control network. *IEEE Transactions on Neural Networks*, **7**, 709–731.

MARS, P., CHEN J.R. and NAMBIAR R. (1996) *Learning algorithms: theory and applications in signal processing, control and communications.* CRC Press, Boca Raton, FL.

NARENDRA, K. and PATHASARATHY, K. (1990) Identification and control of dynamical systems using neural networks. *IEEE Transactions on Neural Networks*, **1**, 4–27.

NARENDRA, K. and MUKHOPADHYAY, S. (1994) Adaptive control of nonlinear multivariable systems using neural networks. *Neural Networks*, **7**, 737–752.

PICHLER, R. and PFFAFFERMAYR, M. (1996) Neural Networks for On-Line Optimisation of the Rolling Process. *Iron and Steel Review*, August, 45–56.

POSTLETHWAITE, I. and GEDDES, J. (1994) Gauge Control in Tandem Cold Rolling Mills: A Multivariable Case Study Using H^∞ Optimization. *Proceedings 3rd IEEE Conference on Control Applications*, **3**, 1551–1556.

TSAKALIS, K.S. (1996) Performance limitations of adaptive parameter estimation and system identification algorithms in the absence of excitation. *Automatica*, **32** (4), 549–560.

TSAKALIS, K.S. (1997) Bursting scenario and performance limitations of adaptive algorithms in the absence of excitation. *Kybernetika*, **33** (1), 17–40.

ZAKNICH, A. and ATTIKIOUZEL, Y. (1995) Application of artificial neural networks to nonlinear signal processing. *Computational intelligence, a dynamic system perspective.* IEEE Press, New York, 292–311.