Neural Network Control for Rolling Mills

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Abstract Worldwide, steel and aluminum production and manufacturing is still one of the major basic industries with a huge amount of material and energy consumption. Hence, optimization of the various process control schemes which are involved can lead to significant savings. Artificial Neural Networks are a new information processing technique which provides a novel approach to process control problems and promises major improvements. Therefore, Siemens together with FORWISS has been studying and developing neural control schemes for a number of different process control problems which occur at hot line rolling mills (Lindhoff et al., 1994). In this paper we give a brief survey of the different control aspects which were tackled with this new approach and comment on their current status.

1 Introduction

Production costs at a hot strip rolling mill could be reduced significantly by reducing the amount of material which is wasted because the produced strip does not meet the quality requirements posed by the customers. The wasted material has to be brought back into the production process by re-melting, which requires a tremendous amount of handling and energy costs.

The most important quality requirements which have to be met concern the shape of the strip. First of all, the customer requires that across the whole strip of about 1km length the desired final thickness is achieved within a tolerance of the order of 0.05 millimeters. In principal, the rolling force control loop is able to achieve this precision. However, after sending the strip into the mill, it takes a certain amount of time until the control loop has changed the preset rolling force to the force which actually yields the right thickness. This amount of time determines the length of the strip head where the thickness is not within the specified tolerance and, hence, determines the amount of material which has to be cut at the head of the strip and is wasted. To reduce this time span, process optimization systems for hot strip mills try to preset the rolling forces such that they lead to the desired thickness from the beginning and the control loop has to make as few adjustments as possible. We will describe how Neural Networks can significantly improve this presetting of the rolling force.

[1]FORWISS is the German acronym for "Bavarian Research Center for Knowledge-Based Systems".

Secondly, the customer requires that across the whole strip the width does not fall below the desired value, which would ruin the strip. To assure this requirement, the strip is currently rolled to a width which is about 12mm above the desired value. After the rolling process, the borders are cut such that the strip exactly obtains the desired width, which is usually between 800mm and 1600mm. An increase in the accuracy of the width control would allow to reduce the margin of 12mm and, hence, would significantly reduce the amount of material which is cut at the borders. To this problem, Neural Networks have also been successfully applied, which is described in Section 3.

In addition to the closest possible thickness and width tolerances, it is becoming increasingly important to be able to exercise an influence on the strip profile as well. Today hot strip mills are required to produce minimum profiles, defined in its simplest form as thickness differences between the middle and the edges of a strip, and to maintain defined profile values within close tolerances during the milling process. This is especially important because the relative strip profile cannot be modified during subsequent cold rolling. Section 4 describes how Neural Networks can be used to improve the existing models and strategies for profile control.

There are a number of other quality requirements which concern the inner structure of the material. In this difficult problem domain, Neural Network approaches have also been applied successfully (Poppe and Martinetz, 1993). In this short paper, however, we concentrate only onto the control schemes which determine the geometry of the strip.

2 Rolling Force Control

Figure 1 shows a sketch of a hot strip rolling mill consisting of four stands. At each stand n a certain relative thickness reduction $\epsilon_n = (d_{n-1} - d_n)/d_{n-1}$ has to be achieved. For this purpose at each stand a rolling force is preset before the slab runs into the mill. To achieve the right thickness reduction within a tolerance of about 0.05 millimeters, the relation between the rolling force F_n and the resulting relative thickness reduction ϵ_n has to be known very accurately to be able to preset the right rolling force; however, this relation depends on many quantities and is difficult to describe. Up to now, physical models of the underlying processes with different parameter settings for different steel qualities have been employed. The achieved accuracy, however, can still be improved significantly. Further, this approach requires tedious bookkeeping of the parameter settings for many hundred different steel qualities, and for each new steel quality the model parameters have to be adapted from scratch, which is expensive since it requires to first roll a number of strips with wrong rolling force pre-settings.

The goal of developing a Neural Network approach was not only to improve the estimation accuracy, but also to overcome the weakness of the conventional method of applying different models to different steel qualities, which does not allow to generalize to new materials. With a Neural Network which distinguishes between steel qualities by taking into account the material's chemical composition, it becomes possible to have a single model for different steel qualities. Different materials have different input vectors for the Neural Network, which allows "generalization to new materials and even to get rid completely of the rather artificial category "steel or aluminum quality".

At each stand n, the rolling mill in this case consisted of seven stands with $n = 1, ..., 7$, a Neural Network $N_n(\mathbf{x}_n|\mathbf{w}_n)$ is employed to estimate the rolling force F_n which has

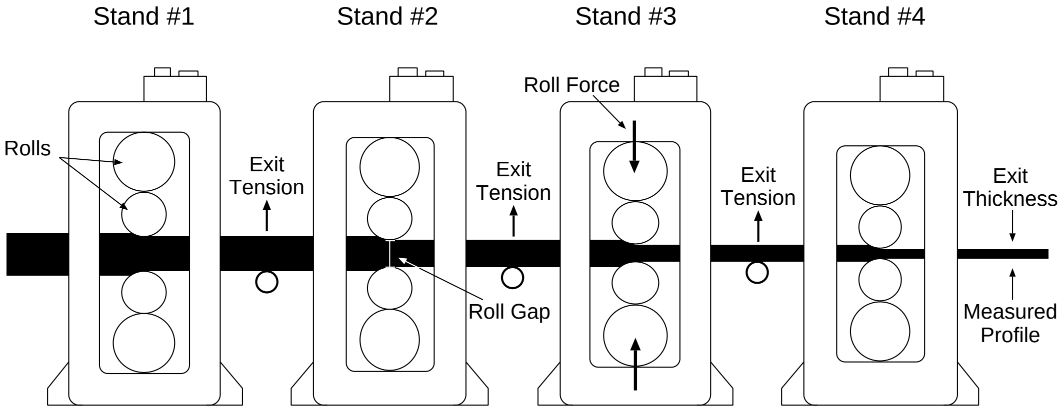

Fig. 1: Sketch of a hot wide strip rolling mill consisting of four stands. At each stand a predetermined thickness reduction of the strip takes place. The final thickness, width, and profile of the strip is measured after the last stand.

to applied at stand n. The input $\mathbf{x}_n$ for the Neural Network, a 25-dimensional vector, contains the concentration of the sixteen most important chemical elements of the material of the strip plus the physical quantities describing the strip when it has reached the stand n, e.g. the strip's width, thickness, temperature, etc. at the respective stand.

The Neural Networks are adaptive through their weights $\mathbf{w}_n$. For achieving good performance it turns out that it is necessary to adapt the networks on-line with each strip which is rolled. The adaptation of the network weights $\mathbf{w}_n$ is performed through gradient descent on the quadratic error $(F_n - N_n(\mathbf{x}_n|\mathbf{w}_n))^2$, which yields

$$\Delta \mathbf{w}_n = \eta (F_n - N_n(\mathbf{x}_n|\mathbf{w}_n)) \frac{\partial N_n(\mathbf{x}_n|\mathbf{w}_n)}{\partial \mathbf{w}_n} \tag{1}$$

as the adaptation rule.

The data from 10000 strips, which corresponds roughly to the production of one month, were available for pretraining the seven networks, i.e. each of the seven networks was pretrained with 10000 data pairs $(F_n^{(i)}, \mathbf{x}_n^{(i)})$. After this pretraining, which might be performed in a batch mode, the networks were tested in an on-line mode with 53812 strips. During this simulated on-line test, with each strip the estimation errors of the seven networks were determined and for each network an adaptation step was performed. The on-line test simulates the real application at the mill and yields exactly the rolling force error which would have been achieved if the neural network had been deployed during the five month when the 53812 strips were rolled. At the end of the on-line test the seven RMS errors over the 53812 strips were determined and could then be compared with the errors of the conventional method. The result is shown in Table 1. Averaged over the seven stands the Neural Network approach was able to achieve a reduction of the RMS error of the rolling force of 21%, which counts as a very significant improvement. The neural network approach has now successfully been tested on-line at Krupp Hoesch Stahl AG, Westfalenhütte Dortmund, and has become a major component of a commercially available process optimization system.

Stand	1	2	3	4	5	6	7
Conv. method	1005	802	772	763	769	849	859
Neural Net	767	636	557	549	619	736	754
Improvement	**+24%**	**+21%**	**+28%**	**+28%**	**+20%**	**+13%**	**+12%**

Table 1: The RMS error of the rolling force with the conventional method and the Neural Network approach (in kN). The Neural Network approach is able to reduce the RMS error up to 28%.

3 Width Control

Figure 1 shows the so-called finishing mill. At the finishing mill with its horizontal rolls only the thickness of the strip can be controlled, not its width. The width is determined in a rolling process with vertical rolls, which is performed before the strip runs into the finishing mill. The problem, however, is that during the horizontal rolling the width of the strip does change. To obtain the desired width at the end of the rolling process, it is necessary to estimate the widening of the strip by the horizontal rolling. A good estimate for this widening then enables one to reduce the width of the strip by this amount with the vertical rolling, which then leads to the required final width of the strip after the whole rolling process.

So far, the estimation of this widening has not been satisfying. It is still necessary to add a margin of about 12mm to the desired width to make sure that at the end of the rolling processes the width does not fall below the required value along the whole strip. To increase the accuracy of this widening estimation, a neural network approach has been developed. The input $\mathbf{x}$ of the neural network, a 24-dimensional vector, contains all the quantities which might influence the widening of the strip during the horizontal rolling. These are, e.g., the temperature of the strip, its thickness, the thickness reduction at each stand, the strip's width, the rolling velocity, the backward and forward tension at each stand etc. The output $N(\mathbf{x}|\mathbf{w})$ of the network is then an estimation for the widening Δb of the strip.

To achieve a good performance for the widening estimation, it is again necessary to adapt the network on-line with each strip which is rolled. The adaptation of the network weights $\mathbf{w}$ is again performed through gradient descent on the quadratic error $(\Delta b - N(\mathbf{x}|\mathbf{w}))^2$ with an adaptation step according to (1).

For pretraining the network, data pairs $(\Delta b^{(i)}, \mathbf{x}^{(i)})$ from roughly one month production were used. After this pretraining, the network was again tested in an on-line mode, this time with 70306 strips. On these 70306 strips, the Neural Network approach achieved an RMS estimation error of 2.7mm, compared to 3.7mm of the conventional method. This means that compared to the conventional method the Neural Network achieved a reduction of the estimation error of 27%. Reducing the margin of 12mm by just one millimeter translates into savings of about a million dollars per year for a modern hot wide strip rolling mill. The Neural Network approach has now successfully been deployed on-line at Thyssen Stahl AG/Beeckerwehrt for about a year.

4 Profile Control

Figure 2 illustrates the definition of the term “profile” and shows an exaggerated “bending effect” due to the roll separating forces. There are a number of additional effects that influence the strip profile, such as roll bending or roll thermal crown when the roller expands due to the heat transferred from the hot strip. All these effects overlap to produce a very complex overall profile that depends on current settings of the rolling forces and the geometry of the current strip as well as on the recent process history, because the thermal crown is influenced, e.g., by the width of previous strips and the pause time between strips. Thus, it is very difficult to obtain a mathematical model that describes this highly nonlinear and instationary process up to the desired degree of accuracy.

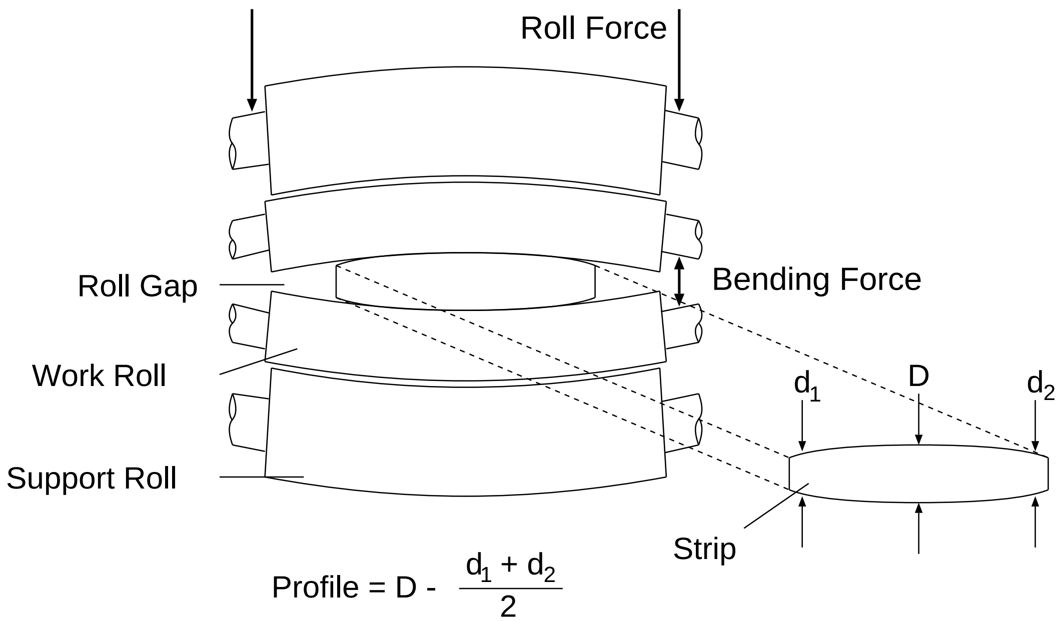

Fig. 2: Definition of the profile as the average thickness difference between the middle and the edges of a strip.

The main difficulty in the context of profile prediction is that an actual measurement of the profile can be conducted only after the last stand. This means, there are no measured values available for the intermediate profiles that could be used to verify or adapt a mathematical profile model for each individual stand. Thus, the current use of mathematical models requires delicate and repeated fine-tuning of various model parameters by hand which is obviously very expensive due to the time and the material wasted.

Figure 3 shows one possible approach how Neural Networks can be used in combination with existing mathematical models to improve the prediction capability for the final profile. The roll-gap profile at each stand is predicted by complex mathematical models (MM), which include a model of the roll bending and of the thermal crown of the roll, thus taking the process history into account. The Neural Network is used to combine the information of the MMs with other process parameters and is pretrained and then adapted on-line to provide the functional relationship that predicts the resulting profile.

This combination of Neural Networks and mathematical models allows to preserve the basic knowledge about physical dependencies as expressed by the mathematical models, while gaining an automated fine-tuning capability through the adaptive Neural Network.

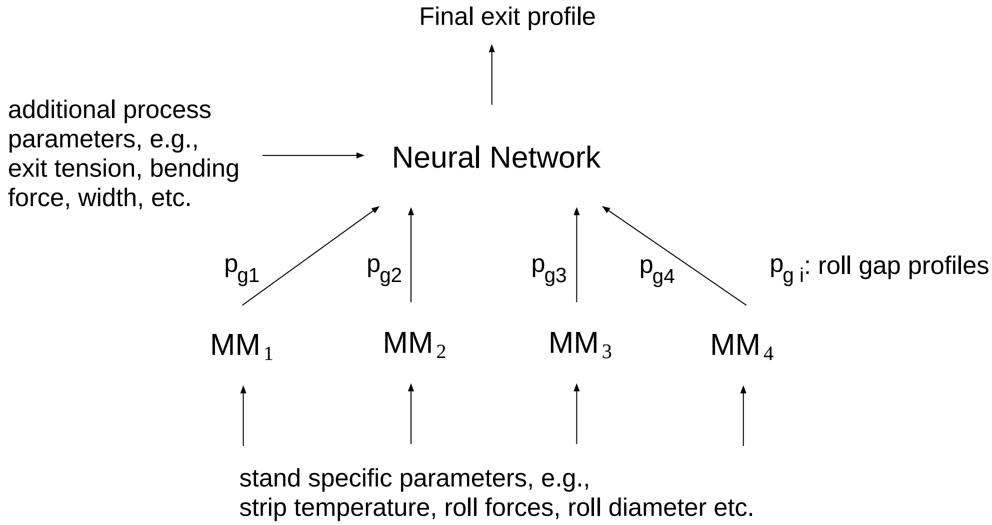

Fig. 3: One possible combination of a Neural Network with different mathematical models (MM) to predict the final profile after the rolling process.

Preliminary simulation results with actual data obtained during a 3 month period from a 4-stand hot rolling mill aluminum plant indicate that the overall prediction performance can be improved by about 20% compared to the mathematical model alone with hand-tuned parameters. On-line experiments at the mill with the combined MM/NN model are underway to validate our current simulation results.

5 Summary and Outlook

With a number of real-world applications we have shown that neural networks are able to improve the conventional control and optimization schemes for hot line rolling mills. Some of these Neural Network approaches are now major components of commercial process optimization system for rolling mills, others are still tested but already show promising results. Still only the first steps have been made. Many further control, optimization and diagnosis problems in the application domain of steel and aluminum production and manufacturing are still open to be tackled with Neural Network approaches. After the potential of Neural Networks has now been clearly demonstrated, the effort will be further increased with the goal to make Neural Networks a standard technique in process automation for steel and aluminum production and manufacturing.

References

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