NEURAL COMPUTATION IN STEEL INDUSTRY*

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Abstract

A rolling mill process control system calculates the setup for the mill's actuators based on models of the technological process. Neural networks are applied as components of hybrid neuro/analytical process models. They are the key to fit the general physical models to the needs of the automation of a specific mill.
Present applications include the calculation of the rolling force and strip temperature (hot and cold rolling); prediction of width-spread in the finishing mill; control of strip width shape; and control of the coiling temperature in a cooling train (hot rolling). The authors outline how significant benefits are achieved in rolling mill technology by using neural networks.
The work presented here is the result of a close cooperation between Siemens Corporate Technology in Munich and the Industrial Projects and Technical Services Group in Erlangen.

1. Introduction

Today's rolling mill process models are fairly mature. Typically, the adaptation of these mathematical models to the individual conditions of the plant is done using a fragmented, look-up table based approach with short- and long-term inheritance. This approach has drawbacks due to the required size for the look-up tables for large product ranges and the lack of interpolation capability. The application of neural networks within a new control strategy has reduced these problems significantly. The application strategy for neural networks within hybrid systems, their role in various rolling mill applications (rolling force, stock temperature, width) and the benefits achieved by implementations of this technology are described in this paper.

In Siemens rolling mill process control automation, neural networks always complement (but never replace) physical/analytical models. Neural networks improve the overall model accuracy around setpoints where process data is available. They are the key to fit the general physical models to the needs of the automation of a specific mill. Knowledge gathered by process engineers doing analytical modeling has not become obsolete, but plays an important role in the hybrid system as the source of the analytical system component. The analytical model structure is the basis of the complete model. Only the analytical model allows for operation in novel process setpoints and for interpretation of results.

2. Application environment

The technical process to be automated is, for example, the multiple stand finishing mill of a wide-strip hot rolling mill. From strip to strip, this is a cyclic process. On a first level a basic automation system serves sensors and actuators and performs feedback control. The next level is the process control level.
Fig. 1 depicts the hierarchical structure of a generalised process automation system. The task of the process control level is the pre-calculation, i.e. the accurate determination of the mill settings needed for the incoming strip before it actually enters the mill. The pre-calculation is based on a pool of relevant model equations. The models describe the technical process adequately, though, of course, never exactly. Because of this, a post-calculation is performed, which compensates for the error by continuously adapting the models to the living technical process.

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An on-line adaptation is carried out. At this instance, neural networks are applied. They favourably contribute to both tasks, modelling and adaptation.

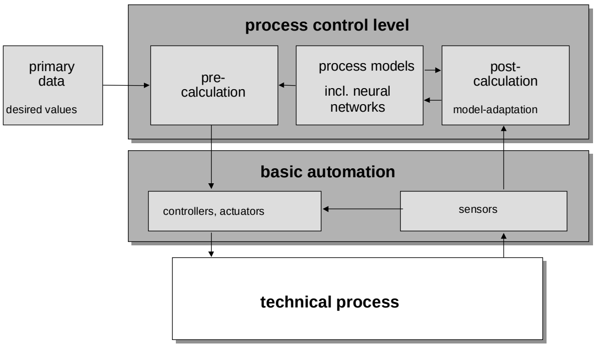

Fig. 1: Organisation of a typical process control system

3. The application strategy

The authors do not promote a replacement of the analytical models by neural networks. Combinations of neural network and classical analytical models are preferred. Such a combination of a mathematical model and a neural network can take various forms, the neural network can be employed at various stages (Portmann, *et al.*, 1995).

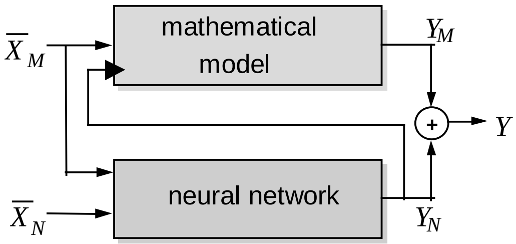

Fig. 2: Parallel configuration of an analytical model and a neural network

Fig. 2 shows one possible way: A parallel configuration of mathematical model and neural network. The mathematical model calculates an approximate value for the target value as accurately as possible, while the neural network produces an estimate of the inherent error in the mathematical model's approximation. The sum of both results should yield an accurate target value y.
Of course, the parallel combination of the two model components can also be done by multiplication.
For all kinds of neuro-analytical combinations applied in the Siemens steel mill automation, the following statements can be made:

- Within the combined system, on-line adaptation is the neural network's task.
- All knowledge that was gathered by engineers in the past doing analytical modelling has not become obsolete, but is still fully integrated into the system in form of the analytical system component.
- A model that is based only on neural networks appears as a "black box" to technologists. In contrast, the combination of neural network and mathematical model highlights the analytical relationships within the technical process.
- The neural networks adapt the general analytical models to the specific environment of the plant.

4. Novel methods

Complex applications using artificial intelligence in process automation would not have been possible without further development of existing methods. First application attempts in steel manufacturing with standard neural network methods, such as static mappings with MLP or RBF networks, failed due to process drift, the high dimension and strongly clustered nature of the relevant process data. New developments for robust on-line adaptation and "Initialisation Learning" are discussed in the following sections.
Know-how is also required concerning pre- and post-processing of the neural network input and output data. The proper choice and application of methods for e.g. data scaling, selection of relevant inputs and elimination of invariances is crucial.

Selection of relevant inputs

In many industrial applications it is not known a priori, which input variables have a significant influence on the process. In practice there are a couple of measurements which "might" be important. As well known from theoretical considerations (curse of dimensionality) the number of irrelevant and less relevant inputs should be as small as possible.
That's why we developed a method for semi-automatic detection of relevant inputs. Based on a subspace of the input parameters a neural model is trained with measured data. Then the model can be tested with a ten-fold cross-validation. This process is repeated for different input subsets. The comparison of the validation errors leads to the best subsets. The number of different input selections grows exponentially with the number of input dimensions. The computational effort can be reduced, if an intelligent search strategy is applied: in the cooling section application (see below) a combination of forward subset selection and backward subset elimination reduced the computing power compared to an exhaustive search by the factor of 100.

On-line Adaptation

For a good accuracy of the neural controller, the rolling mill's "form of the day" must be taken into account.

(Schlang, *et al.*, 1997). Undetermined or hidden influence parameters, such as wear, have an essential influence on the rolling mill process. Online adaptation accounts for this “form of the day” as well as for novel control situations (new products). Target values for the models are derived in various ways from measurements during processing (see examples). The neural models are adapted according to the error between the neural estimate for the model output and the target value derived in post-calculation. Online adaptation must be very robust to maintain stability under the rough conditions in rolling mill control and measurement systems.

Based on the theory of stable, adaptive systems and nonlinear control, Siemens has developed new neural network architectures, training and adaptation techniques to meet the practical requirements of fast adaptation at high robustness. As an example for the performance of the online adaptation, the effect on strip temperature prediction is illustrated in figure 3. Here, the temperature after the finishing train is predicted. The temperature model consists of an analytical model and a neural network correction factor. The root mean square error is plotted against the strip counter. Two pre-calculations are initiated at the instance of strip entry, each starting with the same trained neural network. One network is adapted online while the other is kept static.

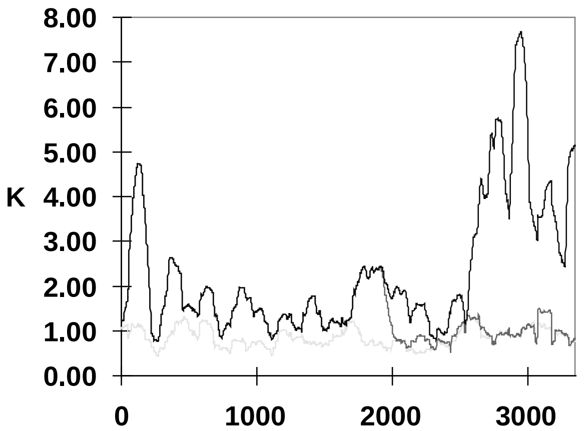

Fig. 3: Effect of on-line adaptation on the accuracy of strip temperature prediction

The network with online adaptation achieves a mean per-stand accuracy (fig. 3) of about one 1 Kelvin (lower curve). The accuracy of the non-adaptive model is initially only slightly worse than that of the adaptive model but it drifts off with time to up to 8 Kelvins (upper curve). The difference between the two models is due to the effect of online adaptation. At strip number 1900, the non-adaptive neural network was copied and re-started as an adaptive model. Within no more than 100 strips, the error of this network has decreased to the range of the error of the originally adaptive one.

Initialisation Learning

Usually neural networks have to be trained with a representative plant data set before they can generalise to new data and thus can securely be used in a controller. However, building a representative data set for a steel mill typically takes several thousands of strips (i.e. several weeks’ production). Such waiting times are often not acceptable when commissioning a new plant or a new controller. It is also not desirable to employ additional conventional modules, whose only job would be to guarantee sufficient operation in this training phase.

Consequently, "Initial(isation) Learning" methods have been developed that adapt to each single data point, starting from scratch, however resulting in reasonable on-line behaviour at new data points.
Initialisation Learning is supported efficiently by hybrid systems: The more elaborated the static analytical model is, the less the neural network has to learn. Small correction values can be found securely and rapidly by on-line adaptation. The analytical model is usually good enough to master the first few strips without support by a neural network.

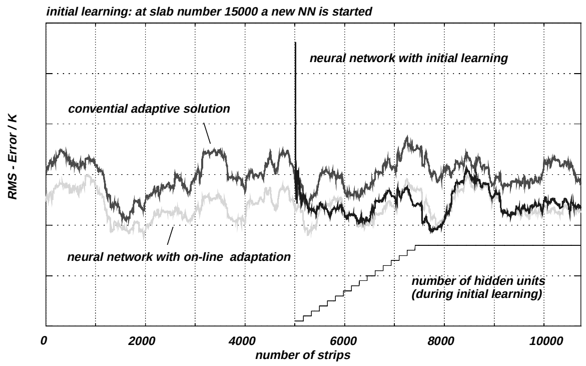

Fig. 4: Neural network "Initialisation Learning" applied to strip temperature prediction

For Initialisation Learning multiple on-line adaptive neural networks are used. The adaptive process starts using a very small network. Training data is stored throughout the whole initialisation phase. As soon as there is a certain amount of data, the smaller network is deleted and a new, bigger network is trained in the background with the complete stored data set and subsequently takes over on-line adaptation for the next production cycles. This method is repeated in several steps until, after several thousands of training examples, a network with the final size is used.

At hot strip mills, using Initalisation Learning, high quality strip temperature prediction was achieved after only a few operation days. As fig. 4 indicates, the quality after about 2000 strips was equal to the quality of off-line and/or on-line pre-trained networks and better than the conventional method.

5. Examples of current applications

For six years, neural networks from Siemens AG have been applied in steel process control (Röscheisen, *et al.*, 1992; Poppe and Martinetz, 1993; Poppe, *et al.*, 1995; Martinetz *et al.*, 1995; Schlang *et al.*, 1996; Jansen *et al.*, 1999, Döll *et al.*, 1999). Current neural modelling applications for predictive control of strip rolling mills include prediction of the temperature of the rolling stock, prediction of the spread in the roughing mill and the finishing mill, prediction of the rolling forces, prediction of mechanical properties, and others. For more than four years electric arc furnaces are controlled by neural networks. Neural networks are also employed for direct control: The neural "short-stroke controller" controls the width shape at the strip head and tail.

Some results from hot wide strip mills are explained in the following sections. In general, using a neural network based improved automation system, the product quality is increased and the amount of scrap is reduced avoiding unnecessary recycling .

Application in cold rolling mills

In cold rolling mills the material strength increases in each stand. This makes the process modelling considerably more difficult. That's why we split the modelling into two steps: a model for the material strength and a second one for the rolling forces in each stand.

Physically both models are coupled: if the material strength increases the rolling force will increase too.

The input to the material network is the chemical composition of the steel, the output some characteristic parameters which describe the material strength. These target values can not be measured directly. They are calculated from the rolling forces by the solution of an optimisation problem.

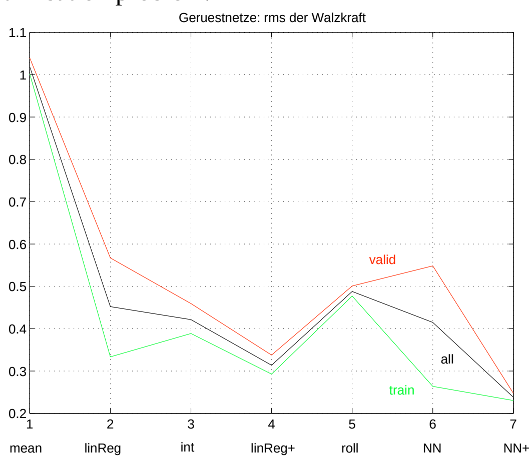

Fig. 5: Normalised root-mean-square error of the rolling force in cold rolling mills

The material parameters and some other parameters (geometry, slip...) are the inputs to an analytical rolling model which describes the physics in the roll gap. With this combination we get good prediction results. If some additional stand networks are introduced the modelling errors can be decreased: the stand networks learn the individual modelling error of each stand.

Fig. 5 shows the results for some simulations based on data of the cold rolling mill at Voest: the normalised root-mean-square error (rms) of the rolling force for a typical stand is shown as a function of different conventional and neural approaches. *Mean* is the *rms* of a simple prediction of the mean value, *roll* the error of the analytical model without any correction, *linReg* the result for correction with a linear regression, *NN* a static neural net. *Int*, linReg+ and *NN+* are the same methods expanded by an on-line adaptation. Fig. 5 shows that the best performance both for the static models and the on-line adaptive ones is obtained by neural networks. A comparison of the best linear approach *linReg+* and the neural network modelling *NN+* shows an improvement in generalisation accuracy of 25%.

Prediction of strip temperature in the finishing mill and the cooling section

In order to obtain adequate material properties the strip temperature has to be met exactly at the different processing states. Hybrid models can predict the temperature at different stages of the rolling process. Figure 6 shows a typical temperature distribution in the mill.

In the **finishing mill** the stock temperature at each roll gap can not be known a priori, but must be calculated. This is done by an analytical model in combination with a neural correction network. The mathematical model calculates the variation of stock temperature from its entry to its exit from the finishing mill, based on temperature measurement following its pass through the roughing mill. During the next strip pass, this temperature curve is checked by measurements at two points, behind the second and the last stand.

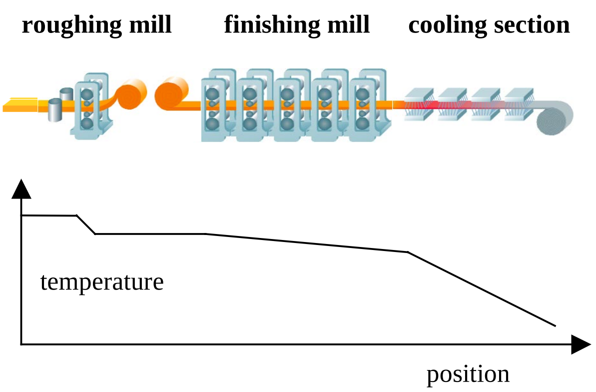

Fig. 6: rolling stock temperature (arbitrary units) in a hot rolling mill

This procedure results in the post-calculation errors for use of on-line adaptation of the neural network. Thus the networks are capable of forecasting the systematic error component within the framework of post-calculation.

The coiler temperature of can be predicted by a hybrid system.

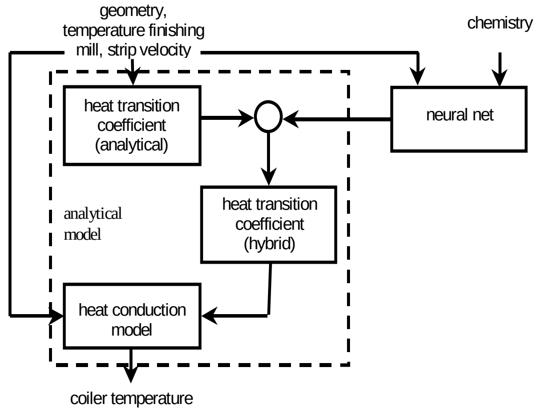

Fig. 7: A hybrid system for temperature prediction in the cooling section

The analytical model consists of two parts (see fig. 7): a sub-model for the heat transition coefficient (cooling water/strip) and a model based on finite differences for the heat conduction within the strip. The neural network learns an e.g. material dependent correction of the heat transfer coefficient.
The model is used to solve the “inverse” problem: given a desired temperature at the coiler the amount of needed water in the cooling section is calculated by a model based optimisation. The result for a mill with an extremly wide spectrum in different products and a very short cooling section is shown in fig. 8. Neural networks helped to reduce the resulting error in temperature prediction from 22 to 15 Kelvins.

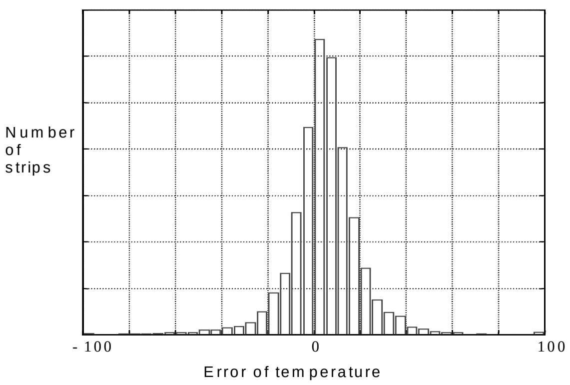

Fig. 8: The error of predicted vs. measured temperature at the end of the cooling section. Results of a short cooling section which handles over 250 different steel qualities

Short-Stroke-Control

The rolling of strips or plates causes width variations along the strip/plate. Equal width along the strip/plate is desired to yield a good product quality, to save material, and to comply with technological requirements for further processing. Local width variations are a particular problem at the instationary regions at the strip/plate head and tail.

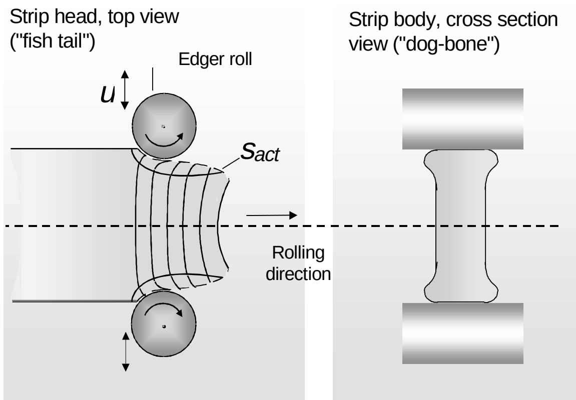

Fig. 9: Width deviations at strip head and tail

If, during an edging pass, for example, the edger rolls operate with a constant screw-down *u* (Figure 9), the strip ends show a significant under-width *s* as compared to the middle parts, the strip ends after edging resemble a "fish-tail". Further width deformations occur in subsequent passes. Various, complex superpositions of the width deformations are occur in different pass schedules (using combinations of edging and flat passes, forward and reverse passes, longitudinal and broadside rolling of plate).

In the roughing stand of a hot strip mill, hydraulic actuators for the edger rolls allow for a local influence on the width. A set of “short strokes” of the hydraulic actuators onto the strip ends are calculated in each pass in order to yield a desired width shape for the finished strip. In the case of Short Stroke Control (SSC) for strip ends, analytical models for the width shape are used. Due to the analytical structure, they provide a good extrapolation from the measured non-rectangular width shape to the desired rectangular width shape. However, the calculation of a suitable control using these analytical forward-models in real time is very difficult in the case of complex pass schedules and multiple technological constraints, such as found in a reversing rougher. Therefore, a neural network is trained as an inverse model under technological constraints.

Details of the complex training procedure of the neural SSC are depicted in Figure 10:

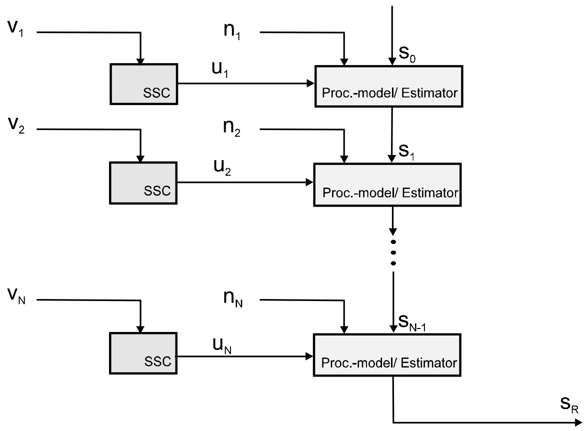

Fig. 10: The concept of a cyclic SSC,
v: precalculated process variables,
n: postcalculated process variables,
u: actuation (short-stroke), s: width shape

The neural control module (*SSC*) is used for every roughing cycle *i*. The short stroke *u* is directly derived from the outputs of the neural network based on the process parameters *p*. A cycle is defined according to the roughing mill configuration and the pass schedule used at the particular mill.

For training the SSC, the analytical model (*proc. model/gradient estimator*) calculates the width shape *s*. A width shape error Δs (derivation from rectangular shape) occurs for each cycle. Subsequently the model is used for estimation of the width error gradient with respect to each single SSC curve involved in the roughing process (Error backpropagation). Techno-logical constraints are introduced into the adaptation.

The neural SSC is one of the most recent and complex of a family of successfully applied neural controllers.

6. Conclusions and further prospects

The long term objective of further application development is the intelligent steel production plant. This plant should one day operate using neural networks and other methods from artificial intelligence at all higher automation levels, including scheduling and management systems. Besides control, automatic diagnosis of automation and technological faults has become a broad field of application of intelligent algorithms. The large potential of these approaches can be exploited to create integrated production techniques that improve the efficiency and competitiveness of entire industrial facilities while reducing demand for resources.

7. Acknowledgement

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Fig 11: Rolling mills, equipped (or in the process of being equipped) with neural control by Siemens AG

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