Advanced Soft Sensor Technology to be Used for Cold Rolling Mills

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Abstract

The use of data-driven soft sensors instead of expensive or even non-existent hardware sensors has become increasingly popular in the last two decades. Among others, they allow to reliably substitute the direct measurements with their predictions based on several related measured variables. The reason for such an indirect solution lies mostly in the absence or technical unsuitability of a reliable direct measurement of the variable of interest. This is the case of the real value of the rolling gap which substantially influences strip thickness when processed on a cold rolling mill. Although several successful approaches are being widely used for the thickness control, complementary solutions are sought permanently to improve control quality in anomalous situations and to further reduce off-tolerance parts of the rolled strip. Four partners have joined their expertise to obtain a qualitatively new soft sensor of this type in the framework of an international research project.

1. Introduction

Thickness control (Automatic Gauge Control - AGC) for cold rolling mills ranks with evergreens among applications of the control theory and has been continuously investigated for many decades. The main obstacle for a straightforward efficient control consists in practical impossibility to measure precisely the output thickness directly in the rolling gap. Instead, the thickness is measured with a substantial transport delay, see Fig. 1. An indirect measurement based on the measured rolling force, the so called uncompensated rolling gap and the knowledge about the mill stretch during rolling was introduced almost 60 years ago and has been widely used as the BISRA gauge or the gaugemeter principle. Since then, numerous other AGC approaches have been developed. They use, in addition to the above-mentioned signals, measurements of the input thickness, strip input and output speeds, strip tensions, etc.

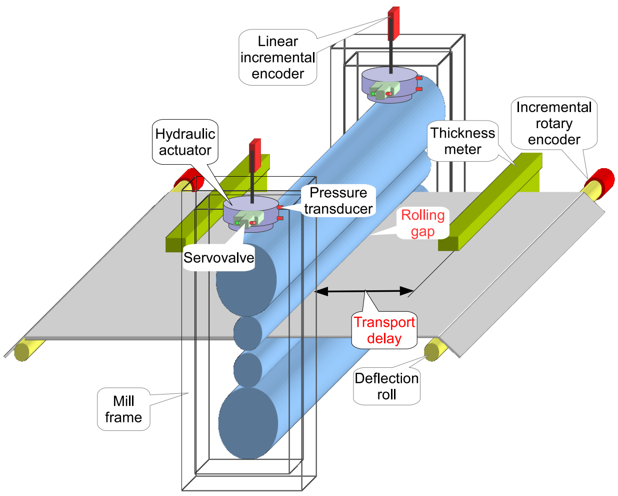

Figure 1. Schematic drawing of a reversing cold rolling mill.

Modern AGC are based on more or less complex mathematical models of the rolling process. The modelling and consequently the related control quality are strongly dependent on reliable and precise measurement of exploited variables. As an example, the so called mass-flow control based on a simple relation between ratios of strip input and output speeds and thicknesses, may benefit from precise measurement of speeds by laser velocimeters, while the ordinary type of measurement by incremental rotary encoders might by insufficient.

2. Motivation and basic ideas

2.1. Motivation

The aim of the project consortium is to contribute to a yet better AGC by developing a reliable soft sensor of the key process variable. Motivation for the introduced solution is based on several ideas:

- Although the modern AGC works well in most cases, possibilities for further improvement still exist (beginning of a strip, rolling of welded parts and various non-standard situations).
- Explicit precise prediction of the thickness in the rolling gap may be beneficial both for operators and for the AGC. Remark: Some types of the AGC do not provide this value externally.
- Even imperfectly measured signals provide partial information which the soft sensor can benefit from.
- Since different proven models use different sets of measured variables (not necessarily with empty intersection), their parallel evaluation may lead to more reliable and stable predictions, especially in the case of degradation or failure of some of the hardware sensors.

2.2. Outline of the solution

The key idea of the solution consists in simultaneous evaluation of several process models, independently providing their predictions of the output thickness in the rolling gap. Continuous mixing of models' outputs then results in a total prediction whose quality is expected to outperform single predictions. The main difficulty to be taken into account, consists in combining actual data with "old" estimated models given by the above-mentioned transport delay. Entire solution consists in a consistent exploitation of several complementary techniques:

- Signal monitoring and fault detection;
- Advanced enhancement of critical signals;
- Stable and reliable on-line estimation of models parameters;
- Continuous Bayesian decision making and model mixing.

Discussion of these points follows.

3. Solution and its components

Complete solution of the soft sensor consists in elaboration of particular building blocks and their integration into the functional system. The following sections thus refer to the block scheme in Fig. 2.

3.1. Performance monitor

Basic pre-processing of a signal consists in monitoring of its performance in a dedicated module. The module can be realized by a Programmable Logic Controller – PLC and utilized also independently.

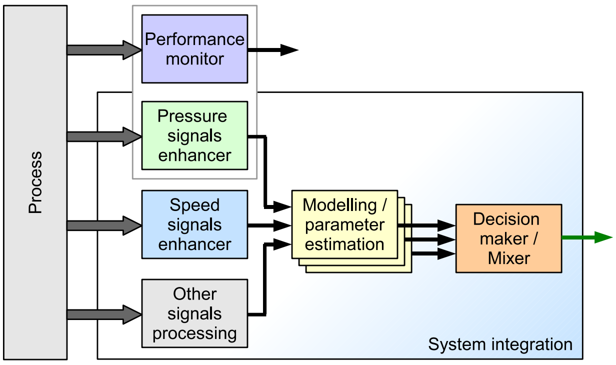

Figure 2. Block diagram of the developed soft sensor.

The purpose of the performance monitor is to detect anomalies as soon as possible, focus on three commonly encountered problems: appearance of oscillations, degradation of sensor dynamics and increase of the high-frequency noise. Therefore performance monitor includes detectors of the above-mentioned situations. Their algorithms rely on a minimal set of the parameters that have to be defined a priori (by the designer or the operator). Other parameters are automatically adjusted in the learning period. Performance monitor thus includes a kind of the adaptation scheme.

The fault detection scheme of the oscillation detector consists in continuous evaluation of the difference between the output of the internal model and the measured variable. Threshold amplitude of the oscillations which is the detector able to distinguish depends on the level of the measuring noise.

Sensor dynamics degradation detector watches over changes in the dynamic response of the sensor due to e.g. fatigue of material of its components or additional coating on a sensor. The principle of operation is to follow the cut-off frequency of the sensor and to detect its significant decrease which may indicate degradation of the dynamics.

3.2. Pressure signals enhancer

For rolling mills with the hydraulic screwdown, the rolling force can be measured directly by dedicated load cells or indirectly calculated from measured hydraulic pressures. In the latter case, measurements are influenced by hydraulic shocks generated by abrupt movements of servovalves.

An ordinary low pass filter which might be used to smooth the measured signal introduces time delays in the filtered output which are undesirable in our case. A way to alleviate this problem [5] is to assume that the measured signal is a result of a stochastic process the state reconstruction of which can be done by the extended Kalman filter. The time varying filter gain can be computed from the Riccati equation.

However, in order to reduce the computational load we take a fixed value for the filter gain. By manipulating the gain one can balance between the speed of the state reconstruction and variance of the reconstruction error.

It is well known [7] that under certain conditions, in particular provided the model is good enough approximation of the real process, the estimation error is exponentially bounded in the mean square sense.

The underlying model for the reconstruction of the pressure signal is obtained by the physical modelling of the pressure dynamics in the actuator in dependance of the piston position and servo-valve position. Two unknown parameters of the model can be found by means of identification along with the parameters of the noise covariances.

The role of the pressure signal enhancer is threefold. First, at each sampling instance it delivers denoised value of the measured signal and its variance. Second, it calculates the predicted value and based on that detects possible outliers in the signal by employing the 3σ rule. Third, a module in the enhancer detects possible incipient faults in either of the pressure and position sensors. This is done by applying the on-line CUSUM test to the residual signal. This provides additional information about the status of the process instruments. An example of the enhancer output is shown in Fig. 3.

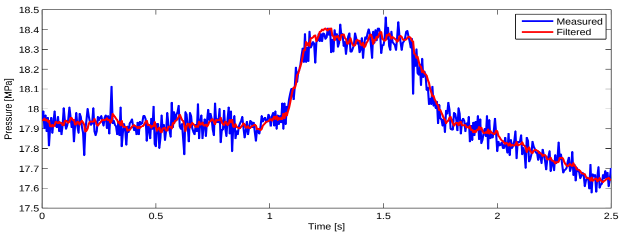

Figure 3. Measured pressure and its denoised version.

3.3. Speed signals enhancer

Information about strip speeds are crucial for most of the process models. If expensive laser velocimeters are not available, speeds are measured by incremental rotary encoders connected to deflection rolls – see Fig. 1. In such a case, the quality of a measurement depends on mechanical preciseness of the measurement system and on quality of the IRE itself.

There were elaborated several techniques for monitoring and enhancement of the IRE signals, some of them were published in [4]. The most promising (unpublished) solution is a subject of a patent application.

3.4. Other signals processing

Among the number of other measured signals, the input and output thicknesses are the most critical. Quality of their measurements depends primarily on the type the gauges. The contact thickness meters provide the best accuracy and dynamics, however their measurement can be deteriorated by a potential dirt or residues of the cooling emulsion on the strip or even by jittering of the strip in extreme cases. A functional ad hoc monitor was developed to detect such situations. A theoretically consistent method is yet to be developed.

Remaining signals are processed by conventional means, such as simple filters or limiters.

3.5. Modelling, parameter estimation

The recursive parameter estimation is provided within the consistent and versatile Bayesian framework. The parameters are considered to be random variables obeying certain distribution. Since the ignorance of their explicit evolution model prevents to use the Kalman filter or its variants, the Bayesian regression model represented by the normal inverse-gamma distribution [6] is employed. To achieve adaptivity, the partial forgetting method [2] allowing to track parameters with different variability rates is applied on it. This results in a quite universal and fast modelling method with only a very minor need of numerical approximation, which in turn allows to evaluate several white/grey/black box models in parallel.

A purpose-built algorithm [3] was developed to respect constraints of used parametric models. The method relies on parallel execution of the full model and its subset and on continuous switching among them.

3.6. Decision maker, mixer

The focused industrial environment imposes significant difficulties on true realtime modelling. The quality of measurements, their delayed delivery and the impossibility of evaluation of almost exact physical models forces the users to run multiple parallel regression models (here called *low-level models*) and to adaptively switch among them. This switching level is called the *averaging model*. The prediction process ends with the *high-level model*, reflecting the specific industrial requirements. This hierarchical modelling framework [1] represents a very scalable and universal solution, allowing to independently change any of the modelling levels and to use, e.g., particle filtering methods, Kalman filters etc. when necessary or possible.

To develop the averaging model, two similar approaches were tested: (i) dynamic Bayesian model averaging and (ii) dynamic Bayesian mixture modelling. Both approaches evaluate the underlaying low-level regression models. The main difference consists in the fact that while the Bayesian averaging considers these low-level models to be completely independent, the mixture modelling follows the policy “only one is true at the moment”. Both of them then produce a convex combination of regression models' outputs weighted by the respective models' evidences (in terms of likelihoods).

The purpose of the high-level model is to further stabilize the modelling and prediction process, particularly for further use of the outcomes in control. Inclusion of this level is justified by practical experience with averaging models, which may produce biased results. In our application, the high-level model is represented by a simple Bayesian regression model, evaluated in the same way as the low-level models, but with different input data – the averaging model's output and the real measurement. However, another models and data can be used as well.

3.7. System integration

Although the basic development of single algorithms is accomplished within the Matlab environment, particular building blocks of the system are intended to be finally realized in the form of specialized software modules, mainly written in the C language or its derivatives. The whole solution is to be integrated into the distributed real-time system. The timing-critical tasks are executed on the kernel level of the RT-Linux operating system, while the other tasks run under the user-level Linux or MS Windows systems. Some of the remote logical input and outputs are realized by a low-level PLC modules while outputs of the PLC-based performance monitor can be used also independently for common monitoring purposes.

4. Tests and results

The project now enters the last third of its duration and the achieved intermediate results allow to suppose that the main aim will be reached in time. The most important algorithms are more or less developed and are being separately tested. Fig. 4 illustrates the intermediate progress: prediction of the output thickness deviation mixed from two particular predictors is coming close to the measured value. Remark: in real situation, the prediction can be compared with the measured variable only after the time delay given by the distance between the rolling gap and the thickness meter. The predicted value was shifted in time in the plot to allow clear comparison.

5. Conclusion

Four partners with different expertise joined in a consortium to develop a new type of a soft sensor for cold rolling mills. Partial solutions of the system building blocks are already elaborated and the last phase of the project consists in system integration and testing.

Testing of the system within simulated environment

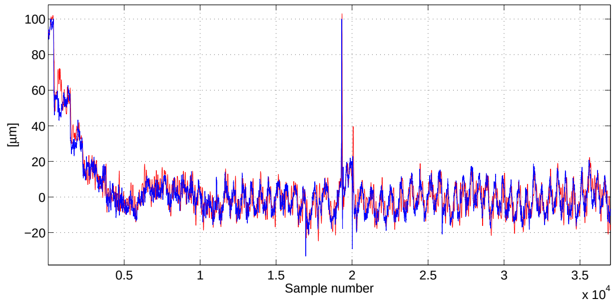

Figure 4. Test results: deviation of the output strip thickness (blue) and its prediction (red).

will be followed by experiments on a selected real cold rolling mill.

Acknowledgements

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