# MIXING MODELS TO IMPROVE GAUGE PREDICTION FOR COLD ROLLING MILLS

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Abstract:
Several techniques exist for evaluation or prediction of the strip gauge in the rolling gap. The method presented here consists in mixing several well known techniques to utilize all available information for weighted gauge prediction. Multiple use of recursive parameter estimation together with consistent handling of transport delays are essential for a working solution. 

Keywords: rolling mill, prediction, industrial control, feedback control

## 1. INTRODUCTION

Cold rolling of metal strips is connected with the well known problem – impossibility to measure the thickness (gauge) of processed material directly in the rolling gap.

Position of rolls or the screwdown position differs from the outgoing thickness because of several reasons from which elongation of the mill housing during rolling is crucial.

The thickness of the outgoing material can be measured reliably only in some distance from the roll bite (rolling gap), typically one meter or more. This arrangement prevents the feedback thickness controller to compensate for fast thickness variations because of the significant transport delay.

There exist several well elaborated solutions of this problem. They utilize some of the other quantities such as the rolling force, the ingoing strip thickness, ingoing and outgoing strip speeds and tensions and the above mentioned screwdown position for the thickness control (AGC – Automatic Gauge Control). It is evident that quality of control is influenced by quality of measurement of those signals. Strict criteria for the thickness deviations require application of accurate and expensive sensors which can impose a problem.

The main idea of the proposed solution is to predict the strip thickness in the rolling gap by combination of several methods relying on existing signals.

In the following $H_1$, $H_2$ stand for strip thicknesses on the input and output side of the rolling mill respectively, $h_1$, $h_2$ are deviation of thicknesses from their nominal values $H_{1\text{nom}}$, $H_{2\text{nom}}$ respectively, $v_r$ means ratio of the input and output strip speeds, $F$ is the rolling force, $z$ stands for uncompensated rolling gap and $d$ is the key transport delay related to the measurement of $H_2$. Discrete time is related to the strip movement, time $k$ corresponds to the piece of the strip just passing

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through the rolling gap. Because of the transport delay, the newest value of $H_2$ ($h_2$) at disposal is $H_2(\kappa)$ ($h_2(\kappa)$), where $\kappa = k - d$.

## 2. CURRENT PRACTICE

The section shortly summarizes the well known methods which are used for prediction and/or control of the strip thickness (AGC). Detailed information can be found e.g. in (Rath, 2000).

*Gaugemeter control* (GM)

*Gaugemeter* is being used for several decades. It works with the stretch of the mill housing during rolling. Thickness is calculated according to the equation

$$H_2(k) = z(k) + f(F, k) \ . \tag{1}$$

where $k$ is the discrete time and the stretch function $f(.)$ was determined experimentally. Straight utilization of the GM method counts with reliable measurement of the rolling force $F$.

*Massflow control* (MF)

The Massflow principle is based on continuity of material flow through the stand

$$\frac{H_2(k)}{H_1(k)} = v_r(k) \ . \tag{2}$$

The method is very sensitive to preciseness of measurement of strip speeds. Standard measurement derived from rotation of deflection rolls is inadequate in most cases. Practicable utilization relies on laser velocimeters which imply some expense.

*Monitor (feedback) control*

Feedback control based on the on-line output thickness measurement can minimize just mean value of the control error due to existing transport delay causing the dead-time control problem. Therefore the feedback loop is a prerequisite which should be combined with other methods to compensate abrupt disturbances.

*Feedforward/multi-variable (model based) control*

Although each of the above mentioned methods works with some kind of simple model a slightly more complex models are considered for the real model-based control. The model reflects relation among main process variables. Estimates of model parameters are used for evaluation of coefficients of the control law.

## 3. MAIN IDEA

When expensiveness of the solution is not a problem and state-of-the-art sensors are available, tailoring of the above mentioned methods results in the best-quality thickness prediction and control. Despite the long-term preference of the adaptive multi-variable AGC (Ettler, 1986), customers' requirements motivate authors to cope with the thickness monitoring and control for ordinarily equipped rolling mills and with situations where some signals are unavailable.

Here an ordinary reversing rolling mill means the machine which is typically equipped with

- indirect measurement of the rolling force based on hydraulic pressures,
- measurement of strip speeds based on rotary pulse encoders connected to deflection rolls,
- indirect measurement of strip tensions from electric currents of coiler drives,
- strip thickness measurement by contact, radioisotope or X-ray gauges on both sides of the mill.

The idea consists in engagement of the imperfectly measured signals in gauge predictions according to particular above-mentioned principles. Then the final prediction is obtained as a weighted mixture of single predictions. The main obstacle – significant transport delay between the gap and the output thickness meter– should be overcome by slowness of parameter and weights changes.

### 3.1 Single predictions

Let us distinguish two cases:

**GM-MF** calculation of predictions according to relations 1 and 2. For this purpose, equations can be transformed to

$$h_{\mathrm{GM}}(k) = z(k) + f(F, k) - H_{2\mathrm{nom}} \tag{3}$$
$$h_{\mathrm{MF}}(k) = H_1(k)\ v_r(k) - H_{2\mathrm{nom}} \tag{4}$$

**MM** Multiple Model) prediction engaging models with the defined structure and unknown parameters.

Particular outputs will be mixed to improve the final prediction.

### 3.2 Process models

Let us introduce a common form of the model

$$h_2(k) = \mathbf{p}(k)\mathbf{d}^T(k) + e(k) \ , \tag{5}$$

where $\mathbf{p(k)}$ is a vector of unknown parameters, $\mathbf{d(k)}$ is data vector and $e(k)$ means a zero mean white noise. Let us consider a four-model example with following data vectors:

$$\mathrm{M}_1: \ \mathbf{d}_1(k) = [z(k), f(F,k), 1] \tag{6}$$

$$\mathrm{M}_2: \ \mathbf{d}_2(k) = [v_r(k)h_1(k), v_r(k), 1] \tag{7}$$

$$\mathrm{M}_3: \ \mathbf{d}_3(k) = [\Delta\bar{z}(k), \bar{h}_2(k), 1] \tag{8}$$

$$\mathrm{M}_4: \ \mathbf{d}_4(k) = [h_1(k), z(k), v_r(k), 1] \ , \tag{9}$$

where $\bar{h}_2(k)$ stands for the mean value of $h_2$ over $d$ samples, $\Delta\bar{z}(k) = \bar{z}(k) - \bar{z}(k-d)$ means average increment of $z$ over $d$ samples and vector $\mathbf{d}_4(k)$ represents just one simple possibility of the multivariate model. More complex models (higher order, additional variables) are avoided here for the sake of lucidity.

Parameters of models with data 6 to 9 are estimated recursively for time $\kappa$. Evaluation of single predictions $\widehat{h}_{2,i}, \ i = 1,2,3,4$ for this spot is derived from the equation 5. Proven recursive algorithm utilizing robust matrix decomposition and the forgetting factor (Kulhavý and Zarrop, 1993) is used for parameter estimation.

### *3.3 Weighted prediction*

Model structure 5 is applied again for model of the weighted prediction the weights of which are now expressed as unknown parameters $\mathbf{p}_w$:

$$h_2(\kappa) = \mathbf{p}_w(\kappa)\mathbf{d}_w^T(\kappa) + e(\kappa) \ . \tag{10}$$

Data vectors $\mathbf{d}_w(\kappa)$ for GM-MF and MM predictions respectively are constructed according to

$$\mathbf{d}_w(\kappa) = [h_{\mathrm{GM}}(\kappa), h_{\mathrm{MF}}(\kappa), 1] \tag{11}$$

$$\mathbf{d}_w(\kappa) = [\widehat{h}_{2,1}(\kappa), \widehat{h}_{2,2}(\kappa), \widehat{h}_{2,3}(\kappa), \widehat{h}_{2,4}(\kappa), 1] \tag{12}$$

In practice, the estimator of $\mathbf{p}_w$ utilizes some normalizing rules which are not specified here. Then, $d$-samples-old values of parameter vectors $\mathbf{p}_i$ and identified weights $\mathbf{p}_w$ are used in the rolling gap (time instant $k$) for evaluation of particular predictions and consequently for the final prediction $\hat{h}_g(k)$:

$$\hat{h}_g(k) = \mathbf{p}_w(\kappa)\mathbf{d}_w^T(k). \tag{13}$$

For verification, the $d$-delayed weighted prediction $\hat{h}_g(\kappa)$ is being compared with the corresponding newest measured value $h_2(\kappa)$.

Whole system is schematically shown on Fig. 1

To allow comparison of predictions, prediction error $e_n$ is introduced

$$e_n = 1/n \sum_{\kappa=1}^{n} ((h_2(\kappa) - \widehat{h}(\kappa))^2) \ , \tag{14}$$

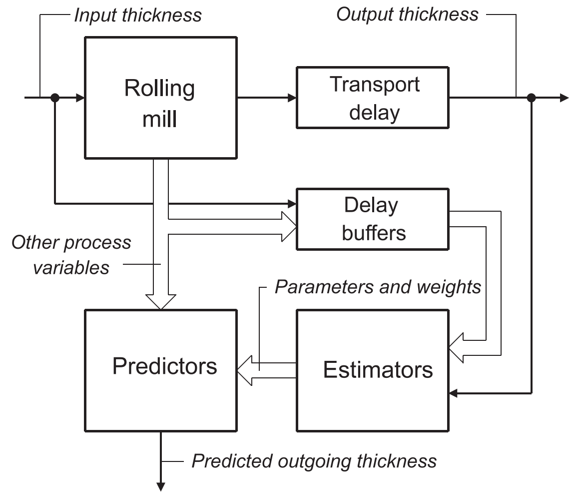


Fig. 1. Schematic diagram of the predicting system.

where $\widehat{h}$ represents any prediction of thickness deviation and $n$ stands for number of data samples.

## 4. RESULTS AND DISCUSSION

Proposed idea was tested both off-line on data from several cold rolling mills and on-line on a medium-size four-high rolling mill. Two typical records were selected for demonstration purposes: the first capturing relatively abrupt thickness changes at the end of the second pass and the latter representing slight periodic deviations within the tolerance range. The records are referred to as $\mathrm{file}_1$ and $\mathrm{file}_2$.

### *4.1 Mixing direct GM and MF outputs*

In this section let us investigate the benefit of mixing two well established approaches: the GM and MF principles. It should be recalled that the following concerns rolling mills without direct measurement of the rolling force and without any special velocimeters. In that case signals standing at disposal suffer from specific disturbances:

- The rolling force calculated from the hydraulic pressures contains unwanted dynamic components influenced by the operation of the roll positioning system. Fig. 2 compares the directly measured rolling force with the force calculated from the pressures for the mill equipped with the both systems.
- Accuracy of measurement of the strip speeds and their ratio $v_r$ depends on mechanical properties of deflection rolls, their coupling with optical encoders and can be even degraded by the strip slippage.

Signals $F$, $v_r$ can be improved by engaging suitable filtering but at the price of an undesirable

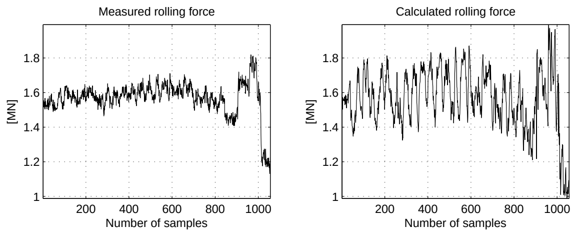


Fig. 2. Comparison of the rolling force $F$ measured directly by the force sensor and $F_p$ calculated from hydraulic pressures.

delay. Mixing GM and MF predictions calculated according to 1 and 2 brings improvement as shown on Fig. 3 and Fig. 4 for $\text{file}_1$ and $\text{file}_2$ respectively. Table 1 indicates improvement of predictions corresponding to Figures 3, 4.

Table 1. Comparison of the prediction error $e_n$ for GM and MF prediction and the weighted prediction GM-MF.

| | GM | MF | GM-MF |
|---|---|---|---|
| $\text{file}_1$ | 701.4 | 2933.6 | **271.3** |
| $\text{file}_2$ | 89.6 | 19.8 | **3.6** |

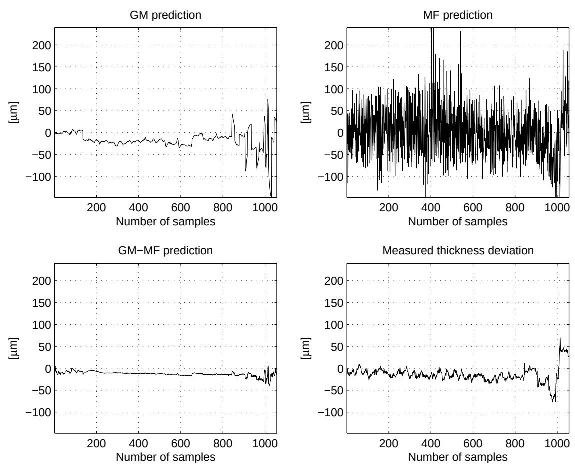


Fig. 3. Predictions made according to classical relations GM and MF compared with the GM-MF prediction and the measured thickness deviation for $\text{file}_1$. The measured value was shifted appropriately to allow direct comparison.

### *4.2 Mixing models with estimated parameters*

Replacement of direct relations 1, 2 by models $M_1$, $M_2$ with data vectors 6, 7 respectively makes the predictions smoother and much more reliable as shown in Tables 1 and 2. Model $M_3$ coming from the feedback controller and $M_4$ as a simple representative of the multi-variable model (with data vectors 8 and 9 respectively) were added to make set of four models for weighted prediction. Although estimated in time $\kappa$, parameters of all models were changing slow enough to allow their utilization for prediction in the rolling

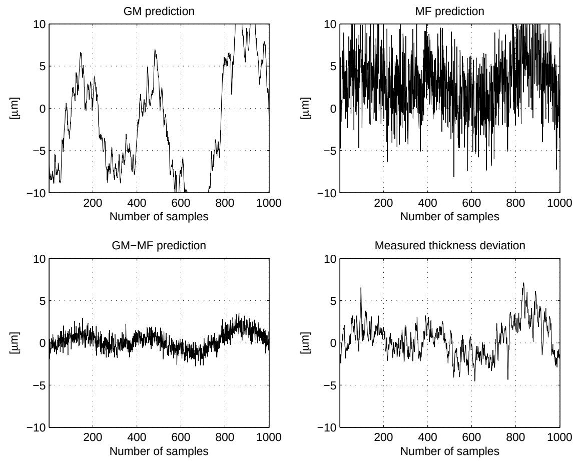


Fig. 4. Comparison as for the Fig. 3, here for $\text{file}_2$.

gap (time $k$). The same holds for the weights or parameters of the MM model with data vector 12. Values of the prediction error are summarized in Table 2 showing the benefit of the weighted prediction. Even more important is comparison of the time progress of the MM prediction with the measured value of $h_2$ made in time $\kappa$ depicted on Fig. 5. Fig. 6 compares prediction errors for the GM-MF and MM predictions.

Table 2. Comparison of the prediction error $e_n$ for particular models $M_1$ - $M_4$ and the weighted prediction MM.

| | $M_1$ | $M_2$ | $M_3$ | $M_4$ | MM |
|---|---|---|---|---|---|
| $\text{file}_1$ | 49.8 | 56.7 | 272.3 | 48.9 | **33.7** |
| $\text{file}_2$ | 3.9 | 1.9 | 5.2 | 1.8 | **1.6** |

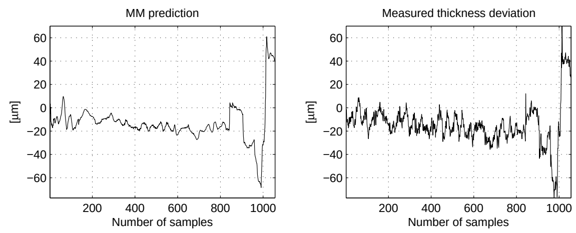


Fig. 5. MM prediction and the measured thickness deviation for $\text{file}_1$. The measured value was shifted appropriately to allow direct comparison.

### *4.3 Seeming alternative – the "super" model*

Use of a single model MS with data vector obtained as a union of data vectors of all models may seem to be the most straightforward combination way. This approach is often applicable. Generally, it has tendency to over-parametrization and consequently to unreliable prediction. This property is even accented for the considered system with a significant transport delay.

Experiments prove the expectation as summarized in Table 3. Moreover, utilization of several

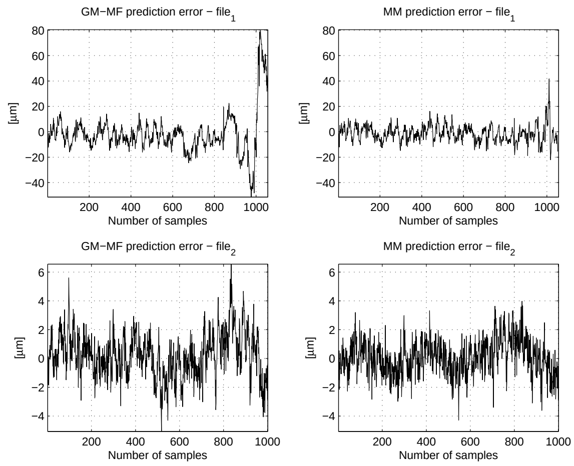


Fig. 6. Prediction errors $h_2(\kappa) - \hat{h}(\kappa)$: left plots for GM-MF prediction, right plots for MM prediction, for file$_1$ and file$_2$ respectively.

models with defined structures enables to cope more safely with discontinuous use of thickness meters and problems like that.

Table 3. Comparison of the prediction error $e_n$ for the "super" model MS and the weighted prediction MM.

| | MS | MM |
|---|---|---|
| file$_1$ | 36.7 | **33.7** |
| file$_2$ | 1.9 | **1.6** |

## 5. CONCLUSIONS

A method mixing outputs from several models for evaluation of prediction of the gauge within the rolling gap was introduced. Benefits of the method were verified off-line on data from several reversing cold rolling mills which process various materials. Provisionally, the system was tested on-line as well though its output was not used within the control system yet. Further research will be focused on two main aspects:

- Robustness of the solution to allow to close the feedback loop and
- Fully probabilistic approach to cope with the problem of changing quality of measured signals and possible discontinuity of thickness measurement.

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