FORCE PREDICTION IN COLD ROLLING MILLS BY POLYNOMIAL METHODS

Nicu Roman, I. Bogdan, Dorel Aiordachioaie, Emil Ceanga, Ion Bivol*

„Dunărea de Jos" University of Galați, Romania
Faculty of Electrical and Electronics Engineering
47, Domneasca, 800008, Galati, Romania
Phone/Fax (+40) 236 46 01 82
Email : Ion.Bivol@ugal.ro

Abstract: A method for steel and aluminium strip thickness control is provided including a new technique for predictive rolling force estimation method by statistic model based on polynomial methods.

Keywords: Cold rolling, Predictive model, Feed-forward control, Statistic Polynomial Methods.

1.INTRODUCTION

This paper discusses a method for steel and aluminum strips thickness control providing enhanced performance quality. The rapid growth in mini mills and small sized flat product plants, especially in Asia, has encouraged the growth in single stand reversing mills. At the same time there are increased demands on improved quality in thickness tolerances. Typically a single stand mill has a pair of driven work rolls supported between larger diameter backup rolls. The strip thickness is reduced between 15 and 50 percent each time it passes between the work rolls and is subject to high compressive forces. In the roll gap region plastic deformation occurs and slipping between the strip and roll surface takes place. The necessary compressive force is applied by hydraulic cylinders. Multiple passes may be needed to obtain the desired final thickness. Each pass involve rolling a coil from the uncoiling mandrel to the coiling mandrel as fast as possible and with desired thickness, flatness and surface quality. Keeping the strip thickness within a tight tolerance band is one of the crucial jobs in cold rolling. The more the thickness variation can be reduced, the closer the mill can be operated at the minimum permissible thickness.

A minimum variance control technique is suitable to reduce the thickness deviations from desired value. This technique implies to elaborate a prediction model for rolling forces deviations. In the following a brief description of the cold rolled process and of the usual thickness control laws are presented. Finally, a polynomial method for prediction of the rolling force deviation based on measured rolling force is proposed.

1.1. A brief introduction to cold rolling process

The main electrical drive equipment of a reversing mill is: the rolls drive, the coil and the uncoil drive. An essential element for controlling the rolling processes is the roll gap adjusting system. Older mills have mechanical screw down systems, equipped with electrical motors and automatic gap control. The modern mills have hydraulic adjusting systems. They provide a much faster and more accurate operation than a screw down. To control the rolling process the following sensors are used:

- the hydraulic cylinder position;
- the rolling force load cells or a measurement of the cylinder pressure used instead;
- strip speed sensors with laser Doppler or with special measurement wheels
- thickness sensors which offer the entry and the resulting exit thickness
- strip accurate tension sensor is expensive, so the most common method is to compute the tension from the motor armature current, the actual coil diameter and the strip cross-section area.

The incoming strip has two mainly disturbances: thickness variations and hardness variations. Due to the rolling forces in the rolling process the stand gap

* Corresponding Author

This paper was recommended for publication by Sergiu Caraman

will increase and the outgoing strip will have a thickness deviation from the desired value.

The main method consists in the roll hydraulic adjustment system. Another additional method is the control of tension applied to the incoming and outgoing strips. The rolling speed and the torque of the main rolls drive system have also an influence. There are different solutions for thickness control systems. In the modern rolling mills the thickness control is accomplished by the system called Automatic Gauge Control (AGC) based on roll gap control, strip tension control and mill speed control. Since the entry thickness deviations give information about the strip, before it passes the rolling cylinders (the thickness sensor being before the stand) the AGC system applies the thickness compensation in a feed forward manner.

In this paper we handle with thickness control technique named BIRSA [4] system based on rolling force deviations. During the rolling process a correction signal is calculated from measured and predicted rolling force to compensate the thickness deviations. The rolling force prediction stand for a feed forward control. Considering the stand as a spring, the changes in strip thickness Δh, rolling mill cylinders ΔS and rolling force ΔF, fulfill Hook’s law:

$$\Delta h = \Delta S + \frac{1}{M}\Delta F \qquad (1)$$

where M is the stand elasticity modulus. The control law for Δh null, is:

$$\Delta S = -\frac{\Delta F}{M} \qquad (2)$$

the predicted force model feed forward the roll force pattern red from force sensors and dictates the exact time of control output allowing proper compensation for the response time of the hydraulic servo system which execute the correction ΔS^*

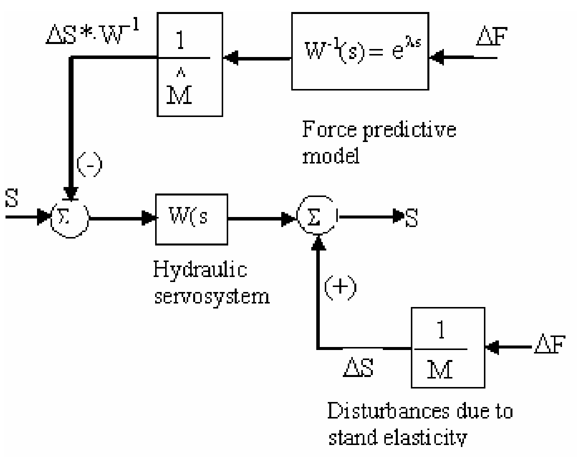

Fig. 1. BIRSA model for force deviations compensation.

In fig. 1 ΔS represents the disturbances due to the stand elasticity. These disturbances are compensate by ΔS^*W^{1}(s) command.

II..PREDICTIVE MODEL FOR ROLLING FORCE

The signals that characterize the rolling process like thickness deviations ΔH and Δh, force and torque deviations ΔF and ΔC are random variables. The natural quantity to study in a random or stochastic process is the power spectrum (the Fourier transform of the autocorrelation function of the signal) and not the harmonic spectrum (i.e. the Fourier transform of the signal). The thickness deviations ΔH and Δh are obtained directly from the thickness transducer because H^* and h^* are the desired constant thickness and

$$\Delta H = H^* - H \qquad (3)$$

and

$$\Delta h = h^* - h \qquad (4)$$

The force F and torque C are the absolute measurements. The mean values of F and C are variable. It is a natural way to consider the moving average of the signal $s(t)$

$$\bar{s}(t) = \frac{1}{\Delta}\int_{t-\Delta}^{t} s(\tau(\tau)), \qquad t_0 + \Delta \le t \qquad (5)$$

The signal deviation or noise Δs are

$$\Delta s = s(t) - \Delta s(t) \qquad (6)$$

As a measure of the amplitude of the signal $s(t)$ we use the moving root mean square (RMS) average.

$$s^2(t) = \frac{1}{\Delta}\int_{t-\Delta}^{t} s^2(\tau)d\tau, \qquad t + \Delta \le t \qquad (7)$$

The moving average and moving RMS calculation are always performed a specified time constant (averaging time, or window width) represented by a certain number N, of data points. The calculation is strongly affected by the value you choose for the window width. The window width is fixe or variable (moving window). An important difference in RMS and noise calculation is that the RMS calculation releates to the power content of the total signal (including the mean), while the noise calculation ignore the mean and are derived only from varying components of the signal.

In the rolling process standard deviation of sheet thickness is the most important quality criteria. Is a natural way to adopt the minimum variance thickness control technique to accomplish that criteria.

Minimum variance control implies a prediction model.

In the case of thickness control with the BIRSA algorithm the control is based on force predictive model. The force signal

$$\Delta F = F(t) - \overline{F}(t) \tag{8}$$

where $\overline{F}(t)$ is the moving average of $F(t)$ directly determine the thickness deviations $\Delta H(t)$.

The prediction of $\hat{\Delta F}$ with λ sample periods is allows the compensation of lag time introduced by hydraulic system which compensate the thickness deviations. First of all the autocorrelation function $R_f(\tau)$ of ΔF signal must by calculated. The model H(z) of force prediction yield the relation:

$$R_f(z) = H(z)H(z^{-1})R_e \tag{9}$$

where R_e is the autocorrelation function of white noise. The prediction force model is based on predetermined force autocorrelation function R_f and the actual ΔF measurements.

Let $\Delta F(t)$ be a stationary process with zero mean value and autocorrelation function:

$$R_f(z) = \frac{A(z)}{B(z)} \tag{10}$$

R_f is a causal function given as ratio of polynomials A and B. We must find the filter H which approximate the non causal prediction function:

$$\Lambda = z^{-\lambda},\ \lambda = 1,2,3... \tag{11}$$

That means the filter H has to predict the force deviation ΔF with λ samples periods.

The prediction algorithm is the following:

1. Let the polynomials A, B be partitioned as product of stable/unstable terms:

$$A = A^+A^- \tag{12}$$

$$B = B^+B^- \tag{13}$$

$$R = R^+R^- \tag{14}$$

Where for example A^+ is a strictly stable polynomial.

2. From polynomial equation

$$Z^{\lambda}\theta + B^+\Pi = A^+ \tag{15}$$

we find the minimal degree solutions Π and θ.

3. The optimal filter is:

$$H = \frac{\theta}{A^+} \tag{16}$$

The prediction error, E, is the difference between the filter desired responses:

$$\Delta F_d = \Lambda \cdot \Delta F \tag{17}$$

where ΔF is the force measured signal, and the filter output:

$$\hat{\Delta F} = H \cdot \Delta F \tag{18}$$

That is:

$$E = (\Omega - H)\Delta F \tag{19}$$

The error autocorrelation function is:

$$R_e = (\Omega - H)(\hat{\Omega} - \hat{H})R_f \tag{20}$$

The least square error is:

$$J = \sum_{i=0}^{\infty} e_i^2 \tag{21}$$

We have:

$$E(z) = \sum_{i=1}^{\infty} e_i z^i \tag{22}$$

$$\hat{E}(z) = \sum_{h=0}^{\infty} e_h z^{-h} \tag{23}$$

$$E(z)\hat{E}(z) = \sum_{i=1}^{\infty} \sum_{h=0}^{\infty} e_i e_h z^{i-h} \tag{24}$$

By Cauchy integral formula:

$$\oint_{\Gamma} z^{i-h} \frac{dz}{z} = \begin{cases} 1 & if \quad i = h \\ 0 & if \quad i \neq h \end{cases} \tag{25}$$

finally we have:

$$\sum_{i=0}^{\infty} \sum_{h=0}^{\infty} e_i e_h = \sum e_i^2 \tag{26}$$

and the least square criteria (21) is:

$$J = ctE\hat{E} = \frac{1}{2\pi j} \oint_{\Gamma} R_e(z) \frac{dz}{z} \tag{27}$$

The minimum variance error condition is:

$$\Delta J = \frac{1}{2\pi j} \oint_{\Gamma} \Delta R_e \frac{dz}{z} = 0 \tag{28}$$

From (21) we have:

$$\Delta R_f = (H-\Omega)R_f\Delta\hat{H} + (\hat{H}-\hat{\Omega})R_f\Delta H \tag{29}$$

From (28,29) results:

$$I_1 + I_2 = 0 \tag{32.a}$$

where

$$I_1 = \oint_\Gamma (H-\Omega)R_f\Delta\hat{H}\frac{dz}{z} = 0 \tag{32.b}$$

With the substitution $w=z^{-1}$ the I_2 integral is the same as I_1. Then we obtain:

$$I_1 = \oint_\Gamma R_f^- \frac{z^\lambda\theta - A^+}{z^\lambda B^+}\Delta\hat{H}\frac{dz}{z} \tag{33}$$

With the condition (17) we have:

$$I_1 = -\oint_\Gamma R_f^- \frac{\pi}{z^\lambda}\Delta\hat{H}\frac{dz}{z} \tag{34}$$

That integral is always zero if the contour of integration Γ is located in D^+ domain and not inclosed the poles.

III AN EXAMPLE

We consider stochastic stationary process with zero means and autocorrelation function :

$$R = \frac{4z(1+1{,}25z)(z+1{,}15)}{(1-0{,}6z+0{,}2z^2)(z^2-0{,}6z+0{,}2)} \tag{35}$$

We must calculate the filter H which predict the measured signal with λ=2 samples period. First we find the minimal degree solution of polynomial equation (17) with respect to polynomials θ and Π.

$$z^2\theta + (1-0{,}6z+0{,}2z^2)\pi = 2(z+1{,}25) \tag{36}$$

Minimal degrees of polynomials θ and Π are |θ| =1, |Π|=1 and we have:

$$\Pi_0 = 2{,}5 \tag{37}$$

$$-0{,}6\ \Pi_0 + \Pi_1 = 2 \tag{38}$$

$$\theta_0 + 0{,}2\ \Pi_0 - 0{,}6\ \Pi_1 = 0 \tag{39}$$

$$\theta_1 + 0{,}2\ \Pi_1 = 0 \tag{40}$$

The minimal solution is:

$$\theta = 1{,}6 - 0{,}7z \tag{41}$$

$$\Pi = 2{,}5 + 3{,}5z \tag{42}$$

The optimal filter results from (18):

$$H = \frac{0{,}64-0{,}28z}{1+0{,}8z} \tag{43}$$

That is:

$$\hat{y}_i = -0{,}8\hat{y}_{i-1} + 0{,}64x_i - 0{,}28x_{i-1} \tag{44}$$

The error variance is:

$$J = ct\pi\hat{\pi} = \pi_0{}^2 + \pi_1{}^2 = 18{,}5 \tag{45}$$

In fig 2 are represented the filter predicted signal, $\hat{y}$, and the measured signal x.

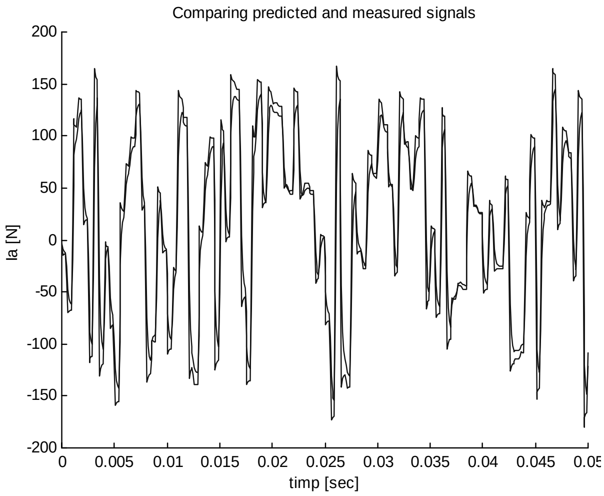

Fig. 2 The filter predicted signal in conditions of example 1.

The key point for the optimal filter calculation is the autocorrelation function. Practically this function is calculated in discrete form by experimental data:

$$R = \sum_{i=-n}^{n} R_i z^i = \frac{c}{z^2} \tag{46}$$

Where c is a symmetrical polynomial of 2n degree:

$$c = R_n + R_{n-1}z + \ldots + R_0 z^n + R_1 z^{n+1} + \ldots + R_n z^n \tag{47}$$

We assume that c polynomial has not zeros in the contour Γ: $|z|=0$. Let be the general representation of the autocorrelation function by

$$R(z) = \frac{A(z)\hat{A}(z)}{B(z)\hat{B}(z)}, \quad A = A^+, \quad B = B^+ \tag{48}$$

The polynomial relation (17) is:

$$z\theta + B\pi = A \tag{49}$$

We represent the polynomials A and B as:

$$A(z) = A(0)\prod_{i=1}^{n}(1-\alpha_i z), \quad |\alpha_i| < 1$$
$$B(z) = B(0)\prod_{i=1}^{m}(1-\beta_i z), \quad |\beta_i| < 1 \tag{50}$$

And we obtain the generalized form of filter as:

$$H = \frac{\theta}{A} = z^{-1}\left[1 - \frac{\pi(1-\beta_i z)}{\pi(1-\alpha_i z)}\right] \tag{51}$$

IV. EXPERIMENTAL RESULTS

The force prediction model with several sampling periods is based on the autocorrelation function of force ΔF deviations from moving average values.

Because multiple passes are needed to obtain the desired final thickness the force deviations autocorrelation function is calculate from data measured at first rolling pass. If in the first pass no correction on rolling mill cylinders are applied ($\Delta S^{*}=0$) , from relation (1) results

$$\Delta h = \frac{1}{M}\Delta F \qquad (52)$$

In that case the autocorrelation functions for thickness deviations Δh and force deviations ΔF are the same taken in account the scaling factor M. That fact is very important because on can use for calculation of the autocorrelation function Δh or ΔF signals.

In fig. 3 are represented then measured data Δh at first rolling pass with compressed time axis (fig. 3a) and with zoomed time axis (fig, 3b). Using 36,900 measurements the correlation function $R(\tau)$ – fig 3c and power density spectrum S(f) – fig 3d was calculated.

In fig. 4 the same calculations was developed using the measurements at the autocorrelation function taken from second rolling pass. The natural quantities to study in a random or stochastic process is the autocorrelation function and the power spectrum S(f) i.e. the Fourier transform of the autocorrelation function and not the harmonic spectrum(i.e. the Fourier transform of the signal).

The thickness Δh or force ΔF deviations has non – harmonic and harmonic components. The harmonic part is deterministic and referred to a discreet spectrum and is characterised by the locations f1, f2, in the power spectrum. For example in the power spectrum calculated from measured data at the second rolling pass (fig. 2b) the impulsive component with f=3 Hz correspond to a deterministic deviation due to the rolling cylinders exentricity.

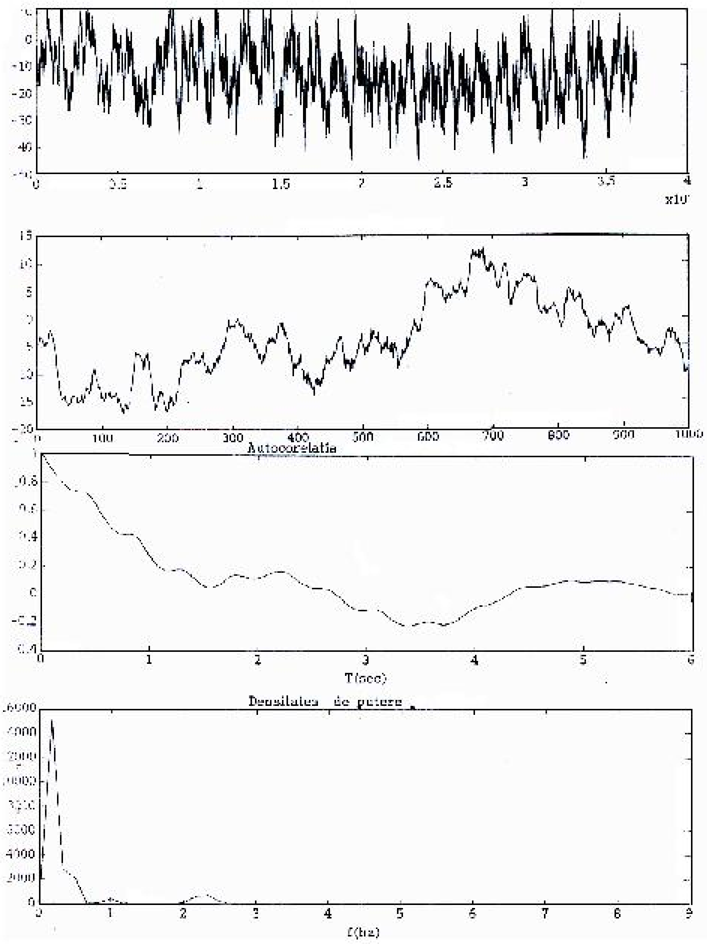

Fig. 3 The autocorrelation function and power spectrum calculates from Δh measurements at first rolling pass.

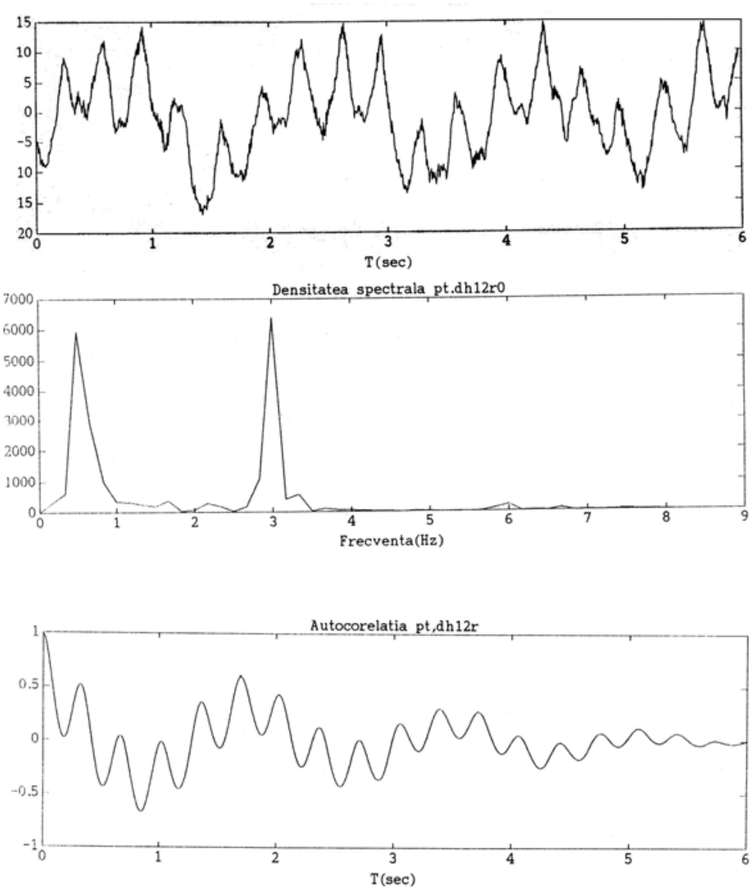

Fig.*4* The autocorrelation function and power spectrum calculates from Δh measurements at second rolling pass

.

In Figure 5 are presented experimental results obtained in Galfinband and Technosteel Iasi rolling mills thickness control system. It can be seen the influence of the feed-forward control over the Δh. The following technologies have been used for implementing the control system:

- Allen-Bradley Control Logix Programmable Controller
- Allen-Bradleu operator displays
- Relliance Electric DC Drives
- ControlNet industrial network

Figure 6 presents the architecture of the control system used at Technosteel Iasi rolling mill.

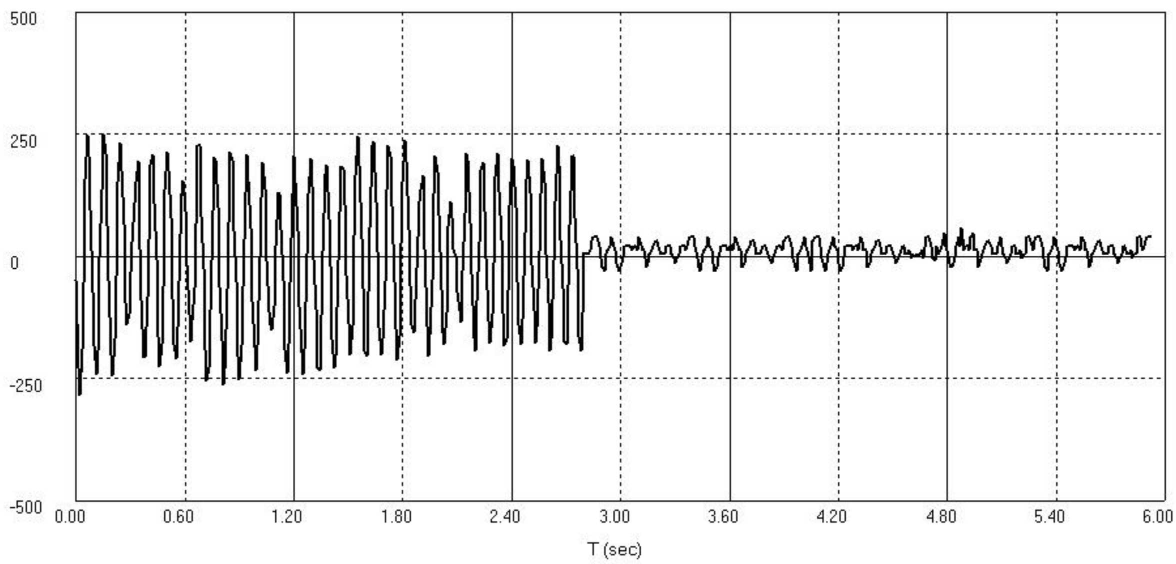

Fig. 5 Δh measurements with and without feed-forward control.

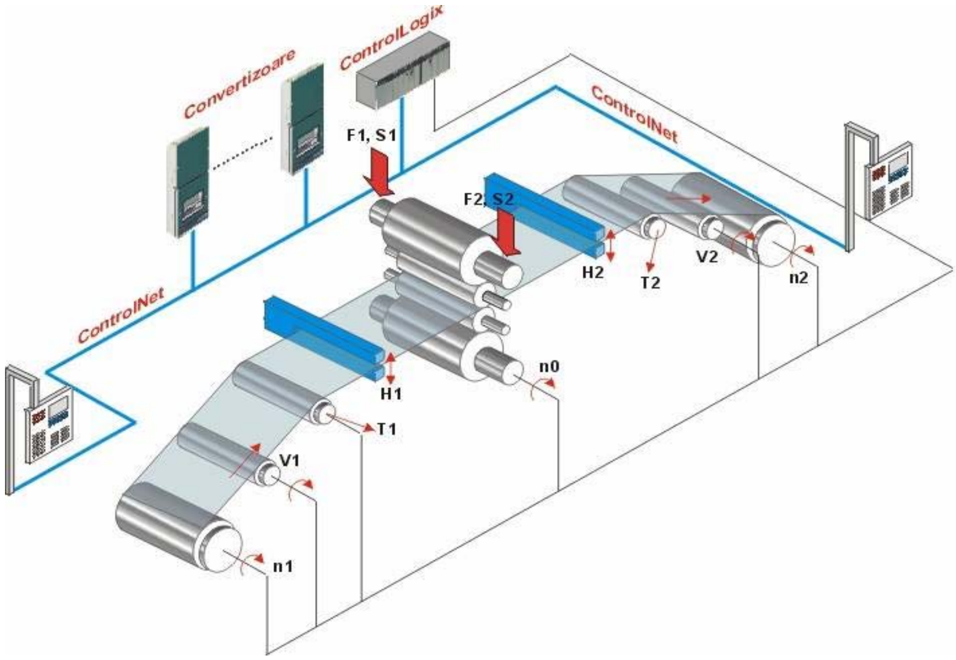

Fig. 6 Architecture of the control system - Technosteel Iasi rolling mill.

V.CONCLUSIONS

The thickness deviations from desired values has statistic and harmonic components. The harmonic components are deterministic and d' not make object of this paper. A predictive model is developed for statistical rolling force deviations based on autocorrelation function calculated from measured data. If the thickness control system is off line (no thickness correction are applied) the autocorrelation functions of force deviations and thickness deviations are the same taking into account a scaling factor. The thickness deviations compensation is accomplish in a feed forward manner using measured thickness deviations or predicted rolling force deviations. In this paper a rolling force predictive model is developed for feed forward control of strip thickness. The experimental results obtained in Galfinband and Technosteel Iasi rolling mills thickness control system are presented.

REFERENCES

[1] Meixing Ji, M.S. OPTIMIZATION OF MULTI-STAGE METAL FORMING PROCESSES, Dissertation, Ohio State University, 2006
[2] Y.Y. Yang,s.a., Roll Force and Torque Prediction Using Neural Network and Finite Element, ISIJ International, Vol 43(2003), No. 12, pp 1957-1966.
[3] Nicu ROMAN, Tiberiu NICOLAU, Ionel Radu MIHALCEA, Emil CEANGĂ, Sergiu CARAMAN, Ioan BIVOL Metode de reglare numerica a grosimii benzilor cu optimizarea parametrilor si constantelor specifice procesului de laminare la rece, Al 12 – lea SIMPOZION A.A.I.R.23 - 24 septembrie 2004 – Mamaia
[4] Francis Wagner, ROLL ECCENTRICITY CONTROL WITH THE FORCE FEED FORWARD AGC SYSTEM Rolling Mill Automation Hatch Associates Consultants, Inc., Buffalo, NY, USA
[5] Kurt Schlacher ,Stefan Fuchshumer ,Gernot Grabmair , Johann Holl ,Georg Keintzel, ACTIVE VIBRATION REJECTION IN STEEL ROLLING MILLS.
[6] Jingrong Liu, Design and Analysis of Intelligent Fuzzy Tension Controllers for Rolling Mills a thesis presented to the University of Waterloo, 2003.
[7] Gunnar BENGTSSON, IMPROVED AGC CONTROL IN COLD ROLLING USING LEARNING TECHNOLOGY. First Control Systems AB, Ängsgärdg. 4, S-72130 Västerås, Sweden
[8] FORMÁNEK, Ivo, Modern Control Systems of Cold Rolling Mills , XXIX. ASR '2004 Seminar, Instruments and Control, Ostrava, April 30, 2004 53
[9] K.J. Astrom and B. Wittenmark, Computer Controlled Systems. Prentice Hall, New Jersey, 1997.
[10] Kucera. Discret Linear Control: The Polynomial Equations Approach. Wiley, Chichester, 1979.
[11] A. G. Ivahnenko. Polynomial Theory of Complex Systems, IEEE Transactions on Systems, MAN, and Cybernetics, Vol. SMC-1, No 4, Oct. 1971.
[12] A. M. Yaglon, Correlation Theory of Stationary and Random Functions. New York: Springer Verlag, 1987.
[13] W. J. Eduards, P. J. Thomas, A Review of Thickness Control on Reversing Cold Rolling Mills, Control '95 Conference Institution of Engineering, Melbourne, Oct. 1995.