Intelligent Control of Aluminium Rolling Mills Using Two Dimensional Adaptive Filters

Branislav Vuksanovic and Amar Bousbaine

***Abstract*—The thickness of the aluminium sheets emerging from a rolling mill usually contains several unwanted frequency components. These tend to come from the cyclic and eccentric effects of the rotating machinery. In addition to these effects, the measurement of sheet thickness is made using radiation sources - either nucleonic or X-Ray which, by their very nature, introduce a random "noise" component into the measurement. The control technology currently used in the aluminium rolling mills is not able to successfully isolate and compensate for the periodic components present in the thickness profile of the rolled sheets. Due to this problem, there are difficulties in accurate production and the related losses for aluminium industry are significant. This paper discusses novel idea of applying adaptive filtering algorithm to reduce periodic variations in the produced thickness profiles in a typical aluminium rolling mill. As the modifications and testing of new control algorithms on the existing rolling mills systems are neither simple nor a cost effective exercises, proposed algorithm is simulated and tested using some typical signals and system parameters measured on a number of rolling mills in the industrial situation. The obtained results prove the effectiveness of the proposed approach and encourage further investigations and field trials of adaptive filtering and active control technology in the rolling mills industry.**

***Index Terms*—Adaptive digital filters, adaptive algorithm, active control, delayed least mean squares algorithm, actuation signal.**

I. Introduction

When rolling metal sheet the control of the thickness is very important. There are many reasons for this [1], [2]. For example if the material is to be used for making cans the thickness of the metal influences how long the can will be after it is punched out from the sheet. Tolerances of 0.8% at 0.3mm would not be uncommon and at foil gauges of a few microns the tolerance might be 3.2%. Typically sheet is rolled in a series of operations from a starting gauge to a final gauge. In aluminium rolling for example slabs might be originally cast at 400mm or more and then rolled down to thickness of only a couple of microns. Each of these operations will involve a pass through a rolling mill. Rolling mills might consist of a single stand with a set of rollers to make the deformation or might contain several stands – a reduction being taken at each stand. Fig. 1 shows a single stand mill where the metal strip enters on the left, passes between the work rolls and then gets coiled up on the right hand side.

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Each time strip is rolled errors can be introduced in the thickness. These can take a number of forms. The material might not be rolled to the correct thickness, it might contain transient errors (spikes) or it may contain periodic errors. These periodic errors can arise from hardness variations or eccentricity effects. All three types can also be present simultaneously.

Fig. 1. Aluminium rolling mill.

Eccentricity effects are perhaps the most common manifestation of cyclic errors. Fig. 2 shows how those periodic errors might arise during the rolling process.

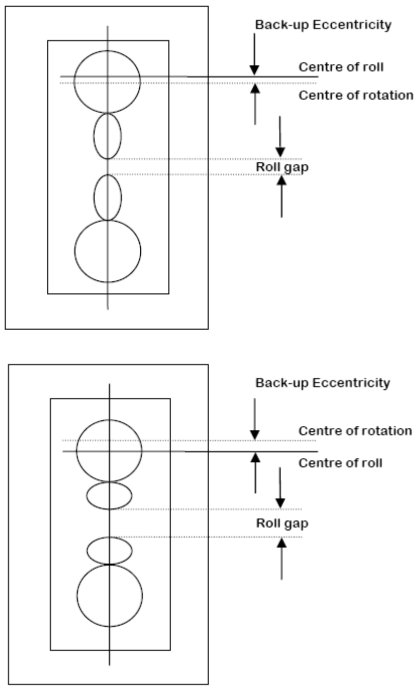

Fig. 2. Generation of periodic errors during the rolling process.

Here the workrolls are shown as being oval and the

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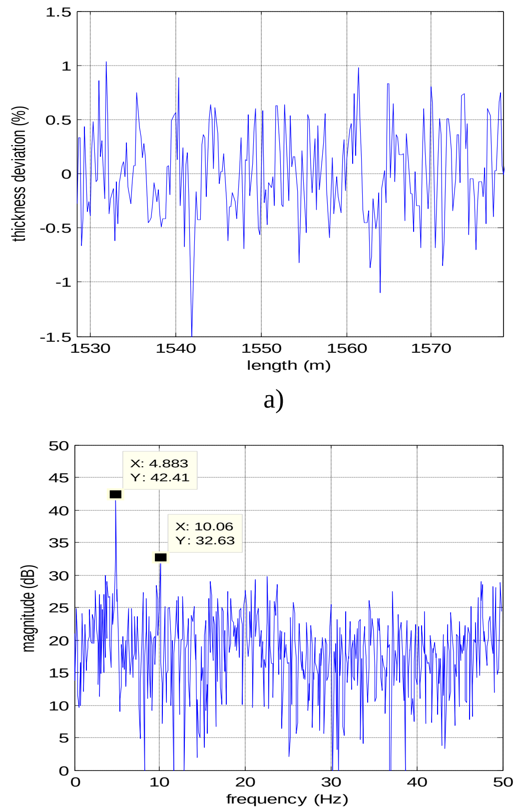
back-up rolls are shown as having a different centre of rotation to their geometric centre. The net effect of this is to cause the roll gap to vary as the rolls rotate. This in itself will introduce gauge variations at the frequencies of the back-up rolls and twice the workroll frequency into the exit thickness. On the next pass these errors will be incoming errors.

Fig. 3 shows the variation in the thickness of the one section of aluminium sheet after a pass through the mill at the rolling speed of 1222 m/min. Frequency of measurement, i.e. sampling frequency was 100 Hz. From the frequency domain plot of the same signal, it is easy to depict a very strong presence of a periodic component at 4.88 Hz (42.4 dB) in this signal and a weaker one at 10.06 Hz (32.6 dB).

Current thickness control technology does not allow effective removal of these incoming errors so some fraction of the error will remain after rolling. Recently, there have been some attempts to address this problem through the employment of modern control technology [3]. Since a reduction has been taken the strip length will be longer, so in the length domain the error will have been elongated. On the next pass a fresh set of eccentricity effects will be re-introduced so after a few passes there will be a large number of frequency components measured by the exit gauge.

Typical cold rolling loads range from a hundred tonnes for a small foil mill to a thousand tonnes on a steel cold mill. The load within the cylinder or its extension can be controlled well with bandwidths of up to 20Hz. For low thicknesses the cylinder load is fixed and exit thickness is controlled by adjusting entry stress or mill speed. These actuators have a smaller bandwidth – just a few hertz. Signal processing and control techniques able to reduce part of signal spectrum or cancel individual frequencies present in the spectrum have been developed and tested in the field of digital signal processing known as active noise control (ANC) [4]. A simple ANC algorithm is investigated in this paper and adopted in order to reduce the periodic components in the sheet profiles produced by the rolling mills in the aluminium industry. The basic idea behind the active noise control is to reduce the unwanted noise, for example sound in the acoustic environment by combining it with a negative replica – sound of same amplitude but opposite phase. Two signals destructively interfere in the environment reducing certain frequency components of the original signal. Active sound control system uses an actuator, typically a loudspeaker, to inject a secondary sound into the environment and an error sensor, usually a microphone, to monitor the actuator performance and adjust the control system parameters for optimal system performance. The emphasis of this paper is on the possible application of simple yet effective control algorithms used in ANC for the control of rolling mills on thicker materials where the mill runs in gap control.

The paper is organised in the following way. Section II introduces necessary mathematics to describe a problem of removing a single frequency component from the measured signal. Modification of this this method used to illustrate the way this approach can be used in the control system on the rolling mill is presented in Section III. Section IV gives some preliminary results by applying this approach to signals measured on the rolling mill, on site in average working conditions. Section V summarises obtained results and methods and gives some recommendations for the possible industrial implementation of the proposed system.



a)

b)

Fig. 3. Variation of the thickness of the rolled aluminium sheet in a) spatial and b) frequency domains.

II. Suppressing a Single Frequency Periodic Interference in the Signal

As a starting point, we consider a thickness signal $d(n)$ where the periodic interference $v(n)$, is mixed with the other variations in measured thickness described here with $s(n)$. Those are usually of a more random nature. Thickness $d(n)$ can therefore be expressed as:

$$d(n) = s(n) + v(n) = s(n) + k\cos(2\pi f_i n - \varphi) \quad (1)$$

where

f_i- interference frequency
k – amplitude of the periodic interference
φ – interference phase

While the rest of the signal, i.e. component $s(n)$ can contain other types of irregularities and noise, this work concentrates on the reduction of the periodic interference component $v(n)$ from the observed signal $d(n)$. Simple approach to remove the interference $v(n)$ from the signal is to estimate parameters f_i, k and φ, generate the interference signal using those estimates and subtract it from the observed signal $d(n)$. While the frequency of the interference is usually easy to estimate using the spectral analysis of the signal, estimation of the other two parameters of the interfering signal – amplitude k, and phase φ is not a straight forward task. Problem gets even more complicated if we allow for the variations of each of those three parameters during the mill operation procedure. A possible solution to this problem is described in the rest of this section and used as a basis for a controller proposed in this paper.

We start by rewriting the expression for the interference *v(n)* using the well-known trigonometric identity

$$\cos(\alpha-\beta)=\cos\alpha\cos\beta+\sin\alpha\sin\beta:$$

$$\begin{aligned} v(n) &= k\cos(2\pi f_i n-\varphi) \\ &= k\cos(2\pi f_i n)\cos\varphi + k\sin(2\pi f_i n)\sin\varphi \\ &= x_1(n)w_1 + x_2(n)w_2 \end{aligned} \tag{2}$$

where $w_1 = k\cos\varphi$ and $w_2 = k\sin\varphi$ are two parameters containing the amplitude and phase information and therefore need to be estimated and $x_1(n)=\cos(2\pi f_i n)$ and $x_2(n)=\sin(2\pi f_i n)$ are two sinewave sequences with 90◦ phase shift between them.

Forming two vectors:

$$\mathbf{x}(n)=\begin{bmatrix}x_1(n) & x_2(n)\end{bmatrix}^T \text{ and } \mathbf{w}=\begin{bmatrix}w_1 & w_2\end{bmatrix}^T$$

the above equation simplifies to:

$$v(n)=\mathbf{x}(n)^T\mathbf{w} \tag{3}$$

This equation can also be viewed as a very simple two-dimensional filter with two-dimensional input signal $\mathbf{x}(n)$. Vector $\mathbf{w}$ is the vector containing two filter coefficients w_1 and w_2.

The optimal values of two filter coefficients can be determined by minimising the cost function $J(\mathbf{w})$ which represents the squared deviation between the observed sequence *d*(*n*) and the interference signal *v*(*n*), i.e.

$$J(\mathbf{w})=\sum_n\left(d(n)-v(n)\right)^2=\sum_n\left(d(n)-\mathbf{x}(n)^T\mathbf{w}\right)^2 \tag{4}$$

It is usually more effective to iteratively obtain the optimal values of elements of vector $\mathbf{w}$ by using the adaptive algorithm. Least Mean Squares (LMS) adaptive algorithm is computationally efficient and simple to implement. Derivation of this algorithm for the case of this simple two-dimensional filter follows the same steps as derivation of the ordinary LMS algorithm [5].

Two 2D LMS filter equations used to obtain the error signal *e*(*n*) and update two coefficients of vector $\mathbf{w}$ are:

$$\begin{aligned} e(n) &= d(n)-\mathbf{x}(n)^T\mathbf{w}(n-1) \\ &= d(n)-\begin{bmatrix}x_1(n) & x_2(n)\end{bmatrix}\begin{bmatrix}w_1(n-1)\\ w_2(n-1)\end{bmatrix} \end{aligned} \tag{5}$$

$$\begin{aligned} \mathbf{w}(n) &= \mathbf{w}(n-1)+\mu e(n)\mathbf{x}(n) \\ &= \begin{bmatrix}w_1(n-1)\\ w_2(n-1)\end{bmatrix}+\mu e(n)\begin{bmatrix}x_1(n)\\ x_2(n)\end{bmatrix} \end{aligned} \tag{6}$$

where parameter μ in the weights update equation (6) represents the so called adaptive step size and controls the rate of change of adaptive filter coefficients and the rate of convergence of the system. Equation (5) shows how the error signal *e*(*n*), used to update filter coefficients is formed as a difference between the signal *d*(*n*), also known as desired signal and filter output *y*(*n*).

Described system for the single frequency suppression using a simple two-dimensional filter is shown in Fig. 4 below. Signal analyser block shown in the figure uses the measurement of the signal *d*(*n*) to determine fundamental frequency of the periodic interference present in the measured signal and the sine wave generator block then generates a sinusoidal reference signal at the desired frequency. This reference signal can easily be split into two orthogonal components $x_0(n)$ and $x_1(n)$ using a Hilbert transform as the 90° phase shifter.

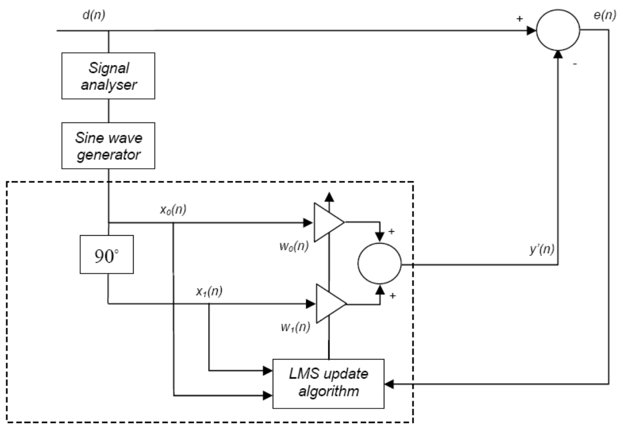


Fig. 4. Two-dimensional-two-coefficients filter for interference rejection.

III. Implementing 2D Adaptive Filter Control Scheme in Practice

Simplified aluminium rolling mill system containing two thickness control gauges is shown on Fig. 5 below.

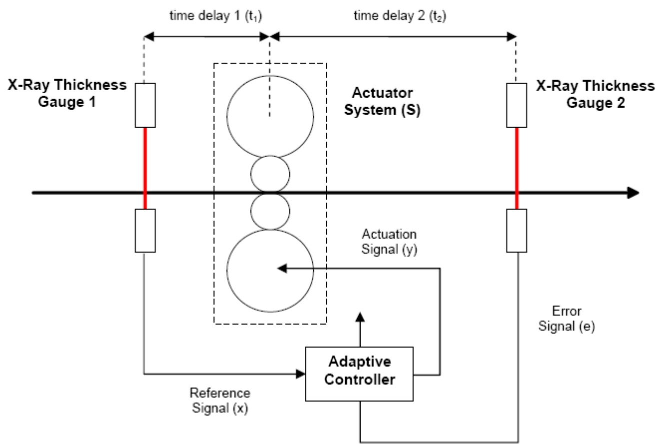


Fig. 5. Aluminium rolling mill control system.

Entry thickness gauge 1 measures the thickness of the aluminium sheet at the entrance of the system while exit thickness gauge 2 measures the thickness after the actuating system *S*. Corresponding time delays between each measurement and the actuating system are denoted t_1 and t_2 on the figure. Task of the adaptive controller is to reduce the unwanted periodic components present in the measurement obtained with gauge 1. Second thickness gauge measures the residual (error) signal which is used to adapt the controller coefficients in order to minimise this error. Fig. 6 shows the block diagram of the whole system where $W(z)$ denotes the transfer function of adaptive controller, $S(z)$ now represents the physical characteristics of the actuating system and D_1 and D_2 are two transport delays corresponding to time delays t_1 and t_2. At the summation point delayed reference signal $x(n)$ is combined with the action of actuator system $y'(n)$ to produce the error signal $e(n)$. Note that the signal $e(n)$ gets delayed through the transportation delay D_2 before it is available for the update of the adaptive filter coefficients. Actuator system action $y'(n)$ is initiated by the control output of the adaptive filter $y(n)$, i.e. $y'(n)$ is the actuating signal processed by the actuator system $S(z)$.

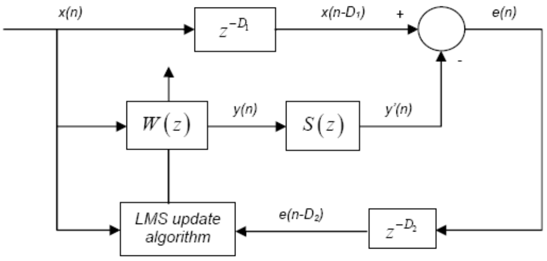


Fig. 6. Block diagram of aluminium rolling mill control system.

To simplify this scheme and reduce the number of delays in the system we can move delay D_2 from the error path simultaneously into reference and control signal paths. In this way, delay of signal $x(n)$ to summation point becomes $D=D_1+D_2$, while the transfer function of the secondary path $S(z)$ combines with delay D_2 to form the new, so called secondary system path with transfer function $S_{D_2}(z)$.

This scheme, incorporating two-dimensional adaptive filter derived in the previous section as a controller $W(z)$ is now shown on Fig. 7. Reference signal, delayed by the amount D which is the sum of two delays D_1 and D_2 is denoted with $d(n)$.

It is important to note that the LMS algorithm, described with equations (5) and (6) given in the previous section can exhibit unstable behaviour in the system containing delay between the filter output and the summation point shown in Fig. 7. To compensate for the destabilising effects of this delay contained in $S_{D_2}(z)$ the LMS update algorithm needs to operate on delayed versions of the orthogonal reference signals $x_0(n)$ and $x_1(n)$.

The complete system can therefore be described with the following set of equations:

$$y(n) = \mathbf{x}(n)^T \mathbf{w} \tag{7}$$

$$\begin{aligned} e(n) &= d(n) - \mathbf{x}(n)^T \mathbf{w}(n-1) \\ &= d(n) - \begin{bmatrix} x_1(n) & x_2(n) \end{bmatrix} \begin{bmatrix} w_1(n-1) \\ w_2(n-1) \end{bmatrix} \end{aligned} \tag{8}$$

$$\begin{aligned} \mathbf{w}(n) &= \mathbf{w}(n-1) + \mu e(n) \mathbf{x}(n-D_S) \\ &= \begin{bmatrix} w_1(n-1) \\ w_2(n-1) \end{bmatrix} + \mu e(n) \begin{bmatrix} x_1(n-D_S) \\ x_2(n-D_S) \end{bmatrix} \end{aligned} \tag{9}$$

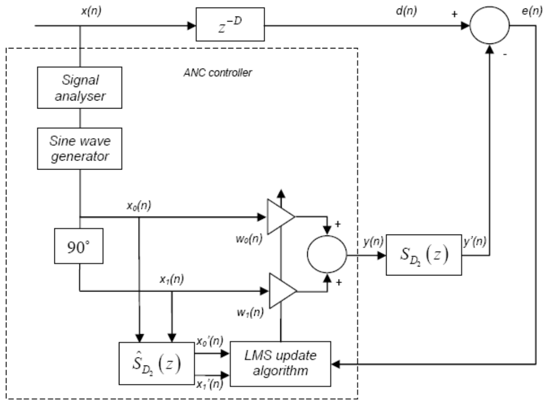


Fig. 7. 2D filter as a control system for aluminium rolling mill.

Weights update equation (9) is usually referred to as delayed LMS algorithm where DS represents delay present between the adaptive controller output and the residual error input, i.e. overall delay of the secondary path $S_{D_2}(z)$.

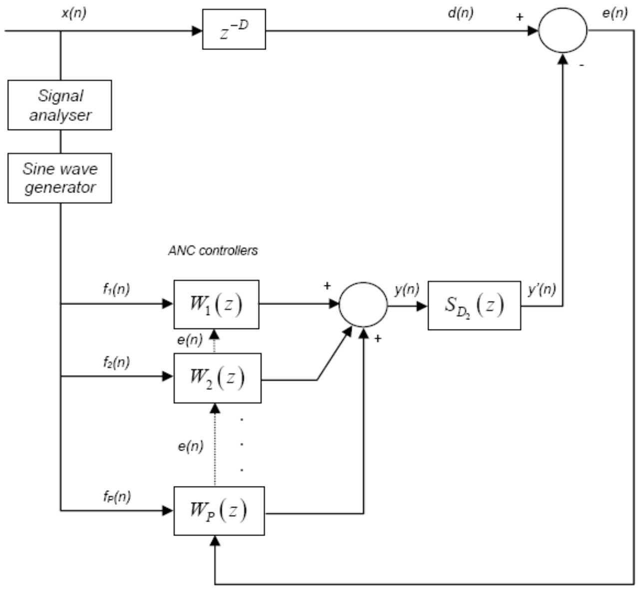


Fig. 8. Multiple frequency canceller using parallel connection of 2D filters.

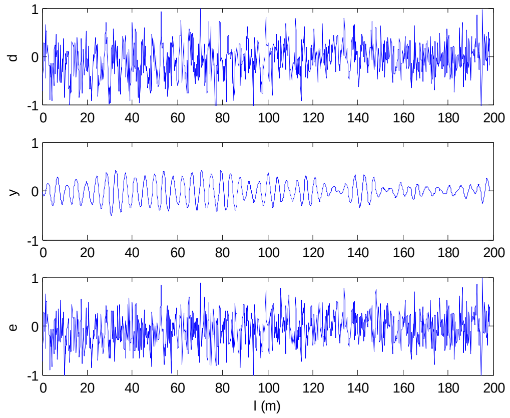
A. *Multi-Frequency Controller*

In order to cancel multiple frequency components present in the measured signal, a parallel combination of a number of simple 2D filters can be used. *P* of those filters needs to be used to control and reduce *P* frequency components from the measured signal as shown in Fig. 8 [6]. A set of *P* sinusoids still needs to be synthesized from the information provided by the signal analyser and each of those signals now needs to be fed to a corresponding 2D filter from the parallel structure shown in Fig. 8.

IV. RESULTS

Fig. 9 and Fig. 10 demonstrate the effectiveness of the approach discussed in this paper by simulating the action of the control system using two different signals measured in the rolling mill. First a controller depicted on Fig. 7 has been used to cancel a single periodic component from the signal *d*(*n*) shown on the top plot of Fig. 9.

From the frequency plot of the same signal strong presence of component at 5 Hz is evident and controller is therefore tuned to cancel this component as effectively as possible. For that purpose the estimate of the secondary path delay $\hat{D}_S$ is set to the value of 18 samples, which is identical to the value of the real secondary path delay present in the system at *f*=5 Hz in this example. Some errors in the estimation of the secondary path are allowed but can influence the achieved attenuation levels and convergence rate of the control system. Large errors can ultimately affect the stability of the control system [7]. The adaptive step size for the algorithm in this test was set to μ=0.06. Second plot from the Fig. 9 shows the signal *y*(*n*) produced by the controller and the third plot shows the resulting signal *e*(*n*) – modified variation in the thickness of the sheet. Frequency plot of this profile shows the complete disappearance of the component at the frequency of 5 Hz.



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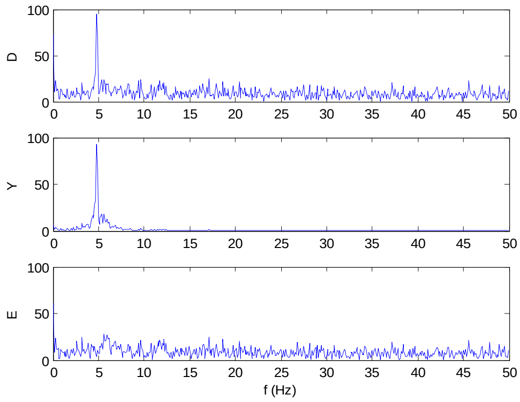
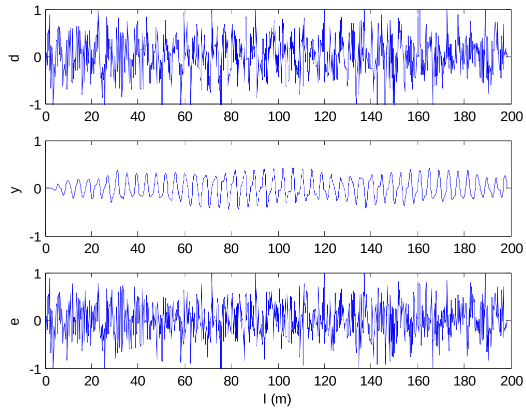


b)

Fig. 9. Original signal *d(n)*, controller output *y(n)* and residual signal *e(n)* for single frequency cancellation in a) spatial and b) frequency domains.

Fig. 10 shows the cancellation of two frequency components present in another sheet. Control system uses two adaptive filters in parallel connection as depicted in Fig. 8 (i.e. P=2 in this case). Here the first adaptive filter has been set to cancel 5 Hz frequency component and the second adaptive filter was set to cancel the weaker, 10 Hz frequency component also present in the signal. Other controller parameters are: $\hat{D}_{S_1}=14$, $\hat{D}_{S_2}=18$, $\mu_1=\mu_2=0.02$. Delay of secondary path used in this simulation was 14 samples at 5 Hz and 18 samples at 10 Hz, so the exact estimation of the secondary path characteristic and delays at two frequencies of interest has been assumed in this simulation as well. Complete reduction at both frequencies of interest can again be observed at the bottom plot of Fig. 10.



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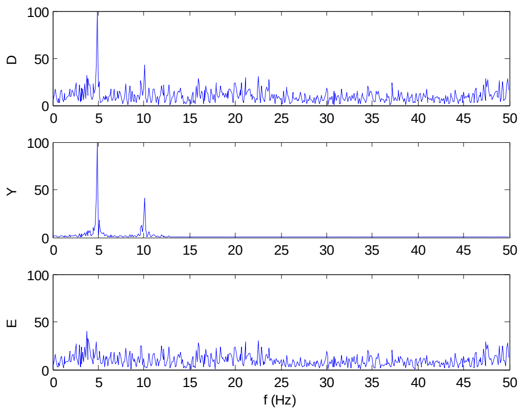

b)

Fig. 10. Original signal d(n), controller output y(n) and residual signal e(n) for multiple frequency cancellation in a) spatial and b) frequency domains.

V. CONCLUSIONS

This paper proposes a simple and effective active control method for the reduction of periodic variations in the thickness of the metal sheets rolled by the mills. Proposed method employs a simple two coefficients adaptive filter with filter coefficients updated at each sampling period using delayed version of the well-known least mean squares (LMS) method. This approach is simple, computationally efficient and exhibits stable behaviour with relatively high convergence rate providing certain stability conditions indicated in this paper are satisfied.

If the frequency of the periodic component present in the thickness signal can be correctly estimated, the only other control parameters that need to be adjusted at the start of the system operation are adaptive step size μ and the estimate of the secondary path delay $\hat{D}_S$. Ideally, with accurately estimated secondary path delay, system will converge rapidly and remain stable. The exact estimation of the delay in secondary path for particular frequency of interest can be hard to achieve in practice. However, some errors in the secondary path delay estimation can be tolerated. This will require further simulation and analysis of obtained results before the implementation of the algorithm on the real rolling mill system is attempted.

Proposed control system has been implemented in Matlab and tested using signals and system parameters measured in the real industrial situations. Results are encouraging and the next step of implementing and testing the proposed approach in practice can be considered.

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