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Sequential Control Performance Diagnosis of Steel Processes ⋆

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Abstract: A sequential method for Control Performance Diagnosis using a classification tree to predict possible root-causes of poor performance is presented. The classification tree methodology is used to combine process pre-assessment (nonlinearities detection, delays estimation and controller assessment), control performance assessment (CPA) and analysis of variance (ANOVA) into an integrated framework. An initial process data set is analysed and the results are used as decision thresholds for the classification tree. The methodology is capable to identify root-causes such as poor tuning, inadequate control structure, nonlinearities, process mismatch and disturbance changes. The proposed methodology is applied to individual loops of a tandem cold rolling mill.

Keywords: Sequential diagnosis, control performance assessment (CPA), multi-scale principal component analysis (MSPCA), model predictive control (MPC), rolling mill.

1. INTRODUCTION

Root-cause diagnosis or causal analysis is a challenging task in control performance assessment (CPA) and its synthesis has rarely been addressed (Huang, 2008). Diagnosis is normally carried out after a given performance metric has shown that the process is performing poorly, and is then used to identify possible causes of poor performance. Poor performance can be caused by several sources such as improper or inadequate controller tuning, lack of maintenance, inappropriate control structure, poor or missing feedforward compensation, equipment malfunction or poor design, and distributed oscillations, etc. (Huba et al., 2011). These root-causes can also produce shared effects in monitoring systems for sensors, actuators, controller and model mismatch (Huang, 2003). Diagnosis methods have been tailored to monitor individual root-causes. The majority of the development in causal analysis has been focused on distributed oscillations for industrial applications with thousands of control loops such as petrochemical industries. Advances in plant-wide disturbance detection and propagation path diagnosis has been reported (Bauer et al., 2007; Bauer and Thornhill, 2008). These methods are usually accompanied by Nonlinearities Detection (NLD) methods and oscillation detection methods.

Recent developments in model predictive control (MPC)-based approaches for CPA use statistical decision processes and pattern recognition to not only calculate the performance metrics, but also identify the root-causes in multi-variable systems (Tian et al., 2011). These diagnosis methodologies require a priori knowledge of the possible causes. More simple performance metrics such as minimum variance CPA (MV-CPA) (also known as the Harris index) and generalized minimum variance CPA (GMV-CPA) for feedback/feedforward control, decompose the output variance according to the source of disturbance and control structure, providing indirect performance diagnosis (Desborough and Harris, 1993). A detailed diagnostic method is presented using variance decomposition for CPA of feedback/feedforward control systems under the assumption that the controller(s) are properly tuned (Chen and Yea, 2005). The so-called diagnosis-tree-based analysis method identifies possible faults by using a sequence of hypothesis tests over ANOVA.

Applications of CPA and diagnosis methods can be found in a large number of processes. Successful implementations of CPA have been reported in the fields of refining, petrochemicals and chemicals as well as pulp and paper (Jelali, 2006). Nonetheless, applications in metallurgical processes were reported to be limited since these processes are highly complex, nonlinear, multi-variable and also subject to dynamic disturbances. In this work, the use of diagnosis-tree-based analysis and the pre-analysis of nonlinearities, time delays and poor performing controllers within the sequence of hypothesis tests is integrated. The proposed methodology is employed to assess and diagnose control performance in the simulation study of a tandem cold rolling mill.

The rest of the paper is organized as follows: Section 2 presents the mathematical framework of process pre-assessment and ANOVA based on MV-CPA. In Section 3, the decision tree is formulated on a set of hypothesis tests that represent individual root-causes. Section 4 describes the rolling mill control system. Assessment simulation results of this system are presented in Section 5 and conclusions are given in Section 6.

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2. PROCEDURE FOR CONTROL ASSESSMENT AND DIAGNOSIS

A comprehensive assessment and diagnosis of a control process requires pre-analysis of the process to examine system nonlinearites, variations in time delays and poor controller tuning; calculation of adequate performance metrics; and identification of sources for poor performance.

2.1 Process Pre-Assessment

Any linear performance metrics applied to a process with nonlinearities will give inaccurate performance values that can lead to a misconceived control loop performance assumption. Nonlinearities usually produce unwanted oscillations. A pre-diagnosis of nonlinearities becomes necessary not only to guarantee the accuracy of the performance metric, but also to assess under-performing controllers. Profit analysis provided in (Kadali and Huang, 2002) for feedback and feedforward control systems can be used to assess the existing controllers if the closed-loop operating data has been previously filtered. Filtering removes the variance caused by disturbances. A priori knowledge of time delays can also be used for estimating the minimum achievable variance, the estimation of which provides insights into other aspects of the process such as the need of high performance dead-time controllers (Lynch and Dumont, 1996) or, the lack of properly tuned derivative terms in the controller for time-delay compensation (Choudhury and Alleyne, 2009).

Detection of Nonlinearities. In this work, detection of nonlinearities is carried out with the Choudhury's method (Choudhury et al., 2004). This method, conceived as a diagnostic aid for poor performance, is based on the presence of phase coupling in the output error signal, a distinctive characteristic of nonlinear time series. Phase coupling leads to higher order spectral features that can be detected in the bicoherence signal. Two indexes are derived from the bicoherence, the non-gaussianity index (NGI) and the nonlinearity index (NLI):

$$NGI := \overline{\hat{bic}^2} - \overline{bic^2_{crit}} \tag{1}$$

$$NLI := \left| \hat{bic}^2_{max} - \left(\overline{\hat{bic}^2} + 2\sigma_{\hat{bic}^2} \right) \right| \tag{2}$$

where $\hat{bic}^2$ is the estimated bicoherence, σ is the standard deviation of the bicoherence and the subscripts $crit$ and max stand for critical and maximum values, respectively. Average bicoherence values ($\overline{bic^2}$) are used in both indexes. The bicoherence is defined as follows:

$$bic^2\left(f_1, f_2\right) := \frac{\left|B\left(f_1, f_2\right)\right|^2}{E\left\{\left|Y\left(f_1\right)Y\left(f_2\right)\right|^2\right\}E\left\{\left|Y\left(f_1+f_2\right)\right|^2\right\}} \tag{3}$$

$B\left(f_1, f_2\right)$ is the bispectrum at frequencies $\left(f_1, f_2\right)$ and is given by:

$$B\left(f_1, f_2\right) := E\left\{Y\left(f_1\right)Y\left(f_2\right)Y\left(f_1+f_2\right)\right\} \tag{4}$$

$Y\left(f_i\right)$ with $i = 1, 2$ are the Fourier transforms of the output data y_t at frequency f_i, and E is the expectation function. The process is Gaussian if $NGI \leq 0$ and linear if $NLI = 0$. We use threshold values i.e. $NGI < 0.001$ and $NLI < 0.01$ for analysis, under which the output signal can be assumed to be Gaussian and linear at a 95% confidence level (Choudhury et al., 2004).

Time-delay Estimation. Among various methods for time delay estimation, correlation methods are widely used to determine the delay between two signals. This method computes the cross-correlation function (Knapp and Carter, 1976):

$$R_{yu}\left(b\right) := E\left\{y\left(t+b\right)u\left(t\right)\right\} \tag{5}$$

where b is the time delay, $u\left(t\right)$, $y\left(t+b\right)$ are the control input and process output variables, respectively. It is difficult to estimate time delay from routine operating data without introducing external excitations or abrupt changes in the control signals (Jelali, 2006). These changes can also be caused by smooth nonlinearities or perturbations, therefore it is important to pre-filter the signals to reduce estimation errors. For ergodic processes, the cross-correlation function can be estimated as follows:

$$\hat{R}_{yu}\left(b\right) = \frac{1}{N}\sum_{t=b+1}^{N} y\left(t\right)u\left(t-b\right) \tag{6}$$

The time delay that maximizes the cross-correlation is given by $\hat{b} = \max_b \hat{R}_{yu}\left(b\right)$.

Controller Pre-assessment with Disturbance Filtering. Controller pre-assessment is a specific diagnosis method of poor performing controllers, implemented before CPA (Recalde et al., 2013). An output performance index is formulated as the ratio of the output covariance matrix obtained using a MPC benchmark to the plant output covariance matrix:

$$\eta_y^f = \frac{\det\left\{R_{\hat{Y}^o}\right\}}{\det\left\{R_{\hat{Y}}\right\}} \tag{7}$$

where f stands for filtered, o refers to optimal benchmark values, $R_{\hat{Y}^o} := cov\left(\hat{Y}^o\right)$ is the output covariance matrix and det is the determinant of the matrix to obtain a scalar value. The input energy index can be calculated as in (7) by using the input covariance matrices R_{U^o} and R_U as follows:

$$\eta_u^f = \frac{\det\left\{R_{U^o}\right\}}{\det\left\{R_U\right\}} \tag{8}$$

The process data can be de-noised using multi-scale principal component analysis (MSPCA). The MPC controller is obtained by minimizing the following cost function:

$$J_{min} = \min_U \left\{\hat{Y}^T\hat{Y} + U^T R U\right\}. \tag{9}$$

Filtered data are used for model identification through a recursive subspace identification with QR decomposition. The indexes in (7) and (8) vary between 0 and 1, showing good controller performance when they are closed to 1 and vice versa.

To diagnose the root-causes for poor controller performance, the following indexes are defined to quantify the percentage of improvement by feedback (fb) control retuning:

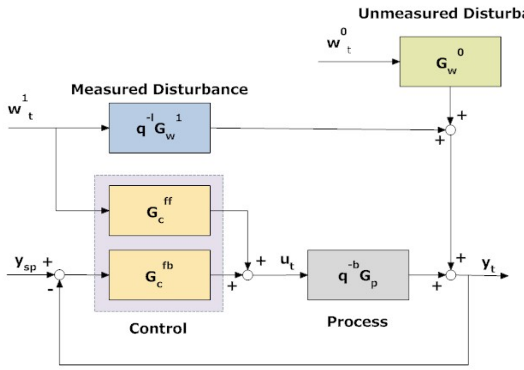

Fig. 1. Feedback/feedforward control structure

$$I_y^{fb} = \frac{R_{\hat{Y}}^{fb} - R_{\hat{Y}^o}^{fb}}{R_{\hat{Y}}^{fb}} \times 100; \;\; I_u^{fb} = \frac{R_{\hat{U}}^{fb} - R_{\hat{U}^o}^{fb}}{R_{\hat{U}}^{fb}} \times 100\% \quad (10)$$

When measured disturbances are available, it is possible to calculate the percentage of improvement from feedforward (ff) control. If this percentage is insignificant, inadequate control structure should be considered as the root-cause of poor performance.

2.2 Control Performance Assessment

CPA works on the output variance, and possibly the offset or tracking error that can be extracted from routine operating data. Performance metrics appear as the ratio of a low variance given by a well-tuned or optimal controller to the plant output variance (σ_y^2) as follows:

$$\eta_y = \frac{\sigma_{mv}^2}{\sigma_y^2} \quad (11)$$

where σ_{mv}^2 is the variance achieved under minimum variance (MV) control and represents the lowest theoretical variance a control system can achieve. This index is called MV-CPA or the Harris index (Harris, 1989).

With a reliable estimation of delays and pre-analysis of nonlinearities, MV-CPA can be used to diagnose sources of poor performance. For instance, the ANOVA (Desborough and Harris, 1993), initially conceived as an indirect method for feedback/feedforward controller analysis, has been extended by (Chen and Yea, 2005) to diagnose process-related and disturbance-related poor performance. Consider the following system as shown in Fig. 1:

$$y_t = q^{-b} G_p \left(q^{-1}\right) u_t + \sum_{i=0}^{1} q^{-il} G_w^i \left(q^{-1}\right) w_t^i \quad (12)$$

where y_t is the process output, u_t is the control input, w_t^i, with $i = 0, 1$ and $w^i \sim N\left(0, \sigma_w^i\right)$, are the unmeasured and measured disturbances, respectively. b, l are the input and disturbance delays. G_p, G_w^0 and G_w^1 are models of the process, unknown disturbance and known disturbance, respectively. The control action is given by the following feedback and feedforward controllers:

$$u_t = G_c^{fb} \left(q^{-1}\right) e_t + G_c^{ff} \left(q^{-1}\right) w_t^1 \quad (13)$$

with error $e_t = y_{sp} - y_t$, setpoint y_{sp}, feedback controller G_c^{fb} and feedforward controller G_c^{ff}. For a SISO system, the output of the closed-loop system will be:

$$\begin{aligned} y_t = & G_w^0 w_t^0 + q^{-l} G_w^1 w_t^1 + q^{-b} G_p G_c^{ff} w_t^1 \\ & - \frac{q^{-b} G_p G_c^{fb} G_w^0}{1 + q^{-b} G_p G_c^{fb}} w_t^0 \\ & - \frac{q^{-b} G_p G_c^{fb} \left(q^{-l} G_w^1 + q^{-b} G_p G_c^{ff}\right)}{1 + q^{-b} G_p G_c^{fb}} w_t^1 \end{aligned} \quad (14)$$

In (14), the first and second terms are called feedback invariant (fbi) and feedback/feedforward invariant (fbi/ffi), respectively, since they are not affected by the controllers (Desborough and Harris, 1993). The third term is only affected by the feedforward controller and is called feedback-invariant/feedforward-dependent (fbi/ffd). In time-delayed systems, these three terms together provide the theoretical minimum variance that a system can achieve (Chen and Yea, 2005). The last two terms are directly affected by the feedback action and the feedforward action and are called feedback dependent (fbd) and feedback/feedforward dependent (fbd/ffd), respectively. The output variance can therefore be expressed as follows:

$$\begin{aligned} \sigma_y^2 = & \sigma_{mv}^2 + S_{fbd}\left(b, G_w^0, G_p, G_c^{fb}\right) \sigma_{w_t^0}^2 \\ & + S_{fbi/ffd}\left(b, G_w^1, G_p, G_c^{ff}\right) \sigma_{w_t^1}^2 \\ & + S_{fbd/ffd}\left(b, l, G_w^1, G_p, G_c^{fb}, G_c^{ff}\right) \sigma_{w_t^1}^2 \\ \sigma_{mv}^2 = & S_{fbi}\left(b, G_w^0\right) \sigma_{w_t^0}^2 + S_{fbi/ffi}\left(b, l, G_w^1\right) \sigma_{w_t^1}^2 \end{aligned} \quad (15)$$

$S_{fbi}, S_{fbd}, S_{fbi/ffi}, S_{fbi/ffd}$ and $S_{fbd/ffd}$ are residuals estimates. Each term in equation (15) is calculated individually. Time series models of G_w^0 and G_w^1 are identified and truncated to obtain the residual estimates.

3. SEQUENTIAL DIAGNOSIS USING A CLASSIFICATION TREE

Performance diagnosis can be achieved as a comparison between the actual variance residual given by (15) and the lowest variance residuals (Chen and Yea, 2005; Tian et al., 2011; Huang, 2003; Kadali and Huang, 2002). A decrease in control performance triggers the first hypothesis test. To verify the accuracy of the index value, nonlinearities and time-delay variations have to be tested. Controller pre-assessment is the next hypothesis test. Indexes for controller improvement (profit analysis) may reveal poor control tuning and inadequate control structure. The remaining sources of performance degradation are poor or missing feedforward compensation, process and disturbance variations and possible model mismatch. Hypothesis tests based on each component of ANOVA can identify these remaining sources (Chen and Yea, 2005).

The resulting hypothesis tests can be arranged into a binary tree-like graph and form a decision tree. The decision tree is capable to classify new tree inputs (new data assessment values) within a given class or root-cause. Each internal node in the tree is a decision-making unit that applies a hypothesis test to the inputs. The process continues until an internal node that corresponds to a specific class is reached.

To form the decision tree, use the assessment values of a given nominal model (a model with the lowest known variance) to form a predictor vector and link it to a given root-cause. The tree will use the predictor-class pair to optimally define a set of thresholds for the hypothesis tests. To obtain a specific set of thresholds use several predictor-class pairs. The sequential combination of process pre-assessment indices and ANOVA components described in Section 2 provides the decision tree as shown in Fig. 4.

4. PROCESS DESCRIPTION

Tandem cold metal rolling mill process is composed of several stand mills to produce a steel coil with specific strip thickness and flatness/shape. Every stand is driven by work rolls supported by backup rolls of larger diameters. The work rolls reduce the strip thickness of the material by plastic deformation. The necessary force to reduce the strip thickness is applied by hydraulic rams that constitute the system actuators. These actuators are powered by the variable speed AC machines and controlled by PWM drivers. In-contact surfaces (work rolls and strips) are constantly cooled down with air lubricant.

The control objective is to produce flat sheets of metal with a desired geometry, including strip flatness. It is crucial to control strip flatness, while reducing excursions in strip thickness and tensions. The control structure should be simple for design and implementation (Pittner and Simaan, 2011). Additionally, the controllers must be capable of handling other conditions during normal operation such as 1) acceleration and deceleration line speed; 2) set-point changes in thickness and tensions. The control objectives may be defined at each individual stands. Instrumentation in cold rolling mills consists of load cells to measure roll force F, work roll speed V, roll gap actuator position S, and in some instances, actual strip input speed V_{in} and output speed V_{out}.

A typical cold rolling mill control system is given in Fig. 2. This figure represents a four-stand four-high cold rolling mill with the following control loops: automatic flatness control (AFC), inter-stand tensions by gap control (ITGC), mass flow control (MFC), hydraulic gap control (HGC), motor speed control (MSC) and feedback/feedforward thickness control (FBC/FFC). Instrumentation consists of thickness sensors at the input of the first stand and output of the first and third stands; speed sensors at the input and output of the first stand; inter-stand tensiometers; and stressometer at the exit of the third stand. Due to physical distances between stands, variable time-delays are present in the process, the values of which depend on the speed of the line as well as the scheduling strategy (Pittner and Simaan, 2011).

In a steel line, there are various sources that may degrade the performance of the processes and sub-processes, e.g.:

- *Type of processes.* Metal processing lines are generally divided into sub-processes. Each sub-process modifies the properties of the product. These changes cannot be tracked automatically.
- *Transition or scheduling strategies.* Every single piece of the final product depends on the customer-order specifications. Variations in product properties can be traced back to the starting point, consequently, delays of production, continuity and idle times must be scheduled.

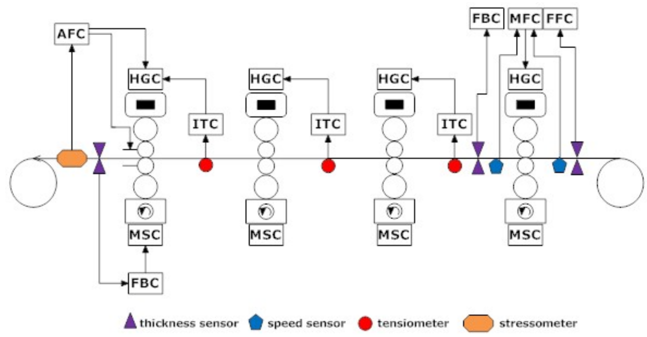

Fig. 2. Illustrative tandem cold rolling mill control structure (redrawn after (Jelali, 2007))

- *Variable operating points.* The whole steel line is setpoint-dependent. To obtain customer-order specifications, every sub-process uses individual setups (Pittner and Simaan, 2011). Models for setup variations are highly nonlinear and difficult to implement.
- *SISO controllers.* It has been reported that most of the sub-processes have SISO controllers poorly tuned and with a half-life of about six months (Jelali, 2006).
- *Other sources.* Common sources include sensor and actuator faults, model uncertainties and disturbances. A significant part of these uncertainties comes from inaccurate values of friction coefficients. Disturbances can be internal or external, for example, from roll eccentricity (Pittner and Simaan, 2011).

5. INDUSTRIAL CASE STUDY

A model has been establish for the simulation study of a three-stand two-high rolling mill. A multi-loop architecture is implemented to control the process using a combination of PID and other controllers. Thickness, mass flow and speed control are implemented in every stage. The thickness of the last stand is analysed. The time delay at the thickness sensor can be monitored. Controllers are assumed to be properly tuned. Roll eccentricity is added at every stand to increase disturbances in simulation. The strip thickness is reduced from 15mm to 5mm.

The output strip thickness of the third stand is presented in Fig. 3. The simulation length is 350s. A set-point change in strip thickness from 4mm to 5mm is introduced at $t =$ 280s in stand 3. Similar set-point changes are carried out in stand 1 (15mm - 4.6mm) at $t = 100$s; and stand 2 (15mm - 4.3mm) at $t = 190$s. The changes in set-points in stands 1 and 2 are reflected in the strip thinkness at stand 3 due to the mass conservation principle. Operating data can be collected and analysed in every stand. CPA is only applied to the last stand. Roll eccentricity is changed to test the decision tree under disturbance. When roll eccentricity is increased, the output strip thickness becomes oscillatory after $t = 220$s, therefore the simulations are presented up to time $t = 220$s. Three sets of simulation results are compared in the following.

5.1 Nominal Model

Fig. 3 represents the nominal model. The term nominal refers to indexes values from the first dataset analysed and

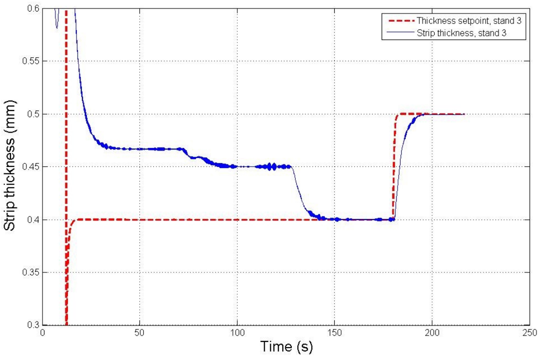

Fig. 3. Output strip thickness at stand 3 with the nominal model

Table 1. Complete assessment of output thickness in stand 3: nominal (N), reduced (R) and increased (I) eccentricity models

	Nonlinearities detection		Delay estimation			
	NGI	NLI	b	$\hat{b}$		
N	0.41	1.23	1.03	1.04		
R	4.15	-7.73	1.03	1.27		
I	0.49	0.10	1.03	0.98		
Profit Control Analysis						
	$var\,(u)$	$var\,(y)$	η^{f}_{y+u}	I^{fb}_{u} (%)	I^{fb}_{y} (%)	
N	0.25	0.62	1.54	0	38.31	
R	0.25	0.51	1.27	0	49	
I	0.32	0.51	1.28	0	48.66	
ANOVA						
	mv	variance inflation due to:			linear	nonlinear
		fb	ff	ff/fb	η_y	η^{nonl}_{y}
N	17.73	71.56			0.80	0.79
R	21.57	93.02			0.81	
I	46.39	228.75			0.83	0.69

used as benchmark. Results of pre-assessment and ANOVA are presented in Table 1. mv stands for minimum variance; N, R and I stands for nominal, reduced eccentricity and increased eccentricity, respectively. Time delays in every stand can be monitored by dividing the distance between the sensor and the stand by the output speed of the stand. A positive NGI rejects the Gaussian hypothesis. A positive NLI rejects the linearity hypothesis. These results suggest the use of CPA nonlinear indexes to avoid inaccurate performance values. A nonlinear index is calculated, using the method described in (Harris and Yu, 2007).

The cumulative index (η^{f}_{y+u}) is a sum of the output index and the energy index, which is used to ease the hypothesis test since the diagnosis depends only on the percentages of improvement indexes. The profit analysis suggests a reduction of the output variance of 38.30% if the controller is fine tuned. The nonlinear index suggests that the results obtained with the linear index are inaccurate. At this point, no further diagnosis can be provided. Feedforward control assessment is not undertaken since no feedforward control data is available. Results from Table 1 are used as decision thresholds in the decision tree shown in Fig. 4.

5.2 Model with Reduced Eccentricity

The output strip thickness with reduced eccentricity is given in Fig. 5. The results of the assessment calculations are included in Table 1. In this case, the estimated time delay is larger than the average value. Using the decision tree, NGI rejects the Gaussian hypothesis but NLI accepts the linearity hypothesis. The system is therefore non-Gaussian but linear. The use of linear indexes is thus recommended.

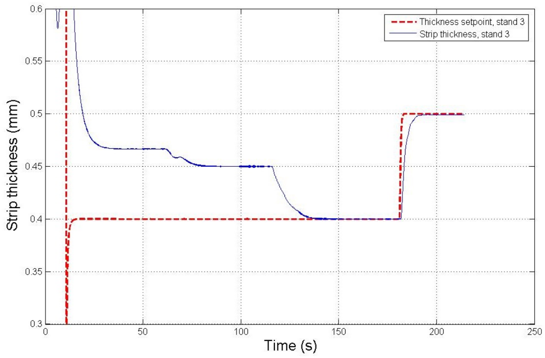

Fig. 5. Output thickness at stand 3 for the model with reduced eccentricity

The profit analysis is consistent with the previous simulation. A larger improvement in output variance is suggested. The ANOVA results show that the Harris index is slightly higher than the one from the nominal model. The decision tree suggests that the performance has been improved and no further diagnosis can be carried out with the existing thresholds. The results from the reduced eccentricity model are used to replace the nominal values as new indices thresholds. With the new tree, diagnosis is carried out on the nominal model. The new hypothesis tree suggests that the performance degradation in the nominal model is due to changes in disturbance and process models. The latter is caused by the rejection of the linearity hypothesis in the nominal model and also variations in the estimated time delay.

5.3 Model with Increased Eccentricity

The output strip thickness in stand 3 with increased eccentricity is presented in Fig. 6 with assessment results included in Table 1. The estimated time delay is a bit smaller than the calculated time delay. The hypothesis tree suggests that the nominal model presents nonlinearities, therefore the use of nonlinear index is recommended. The profit analysis is consistent with the previous simulation. The variance increase in the controlled signal indicates an increase of disturbance. This result is also verified by the decision tree.

The ANOVA results show that the Harris index is unrealistic in this case. The nonlinear index offers a better quantitative assessment. It can be concluded from the decision tree that causes for performance degradation are again changes in process and disturbance models. In practice, only the results of the decision tree are used for guidance. Nonetheless, an expert user can use the results in Table 1 to obtain a more complete assessment.

6. CONCLUSION

In this work, a sequential control diagnosis methodology has been developed by combining pre-assessment of time

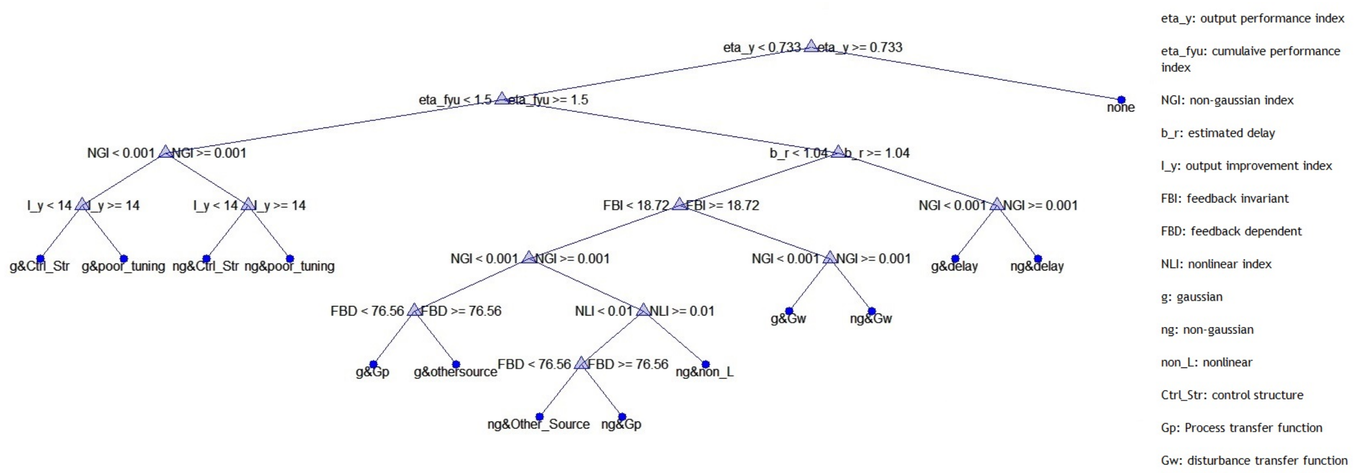

Fig. 4. Hypothesis tree design using Matlab classification tree function

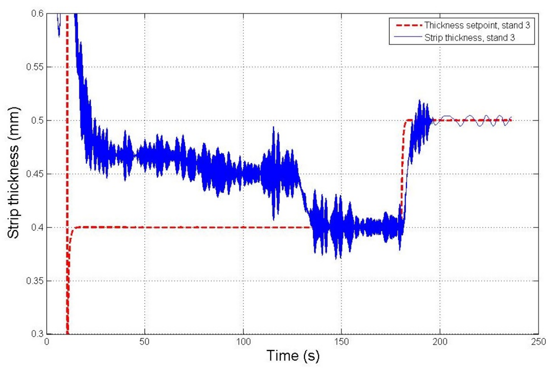

Fig. 6. Output thickness at stand 3 for the model with increased eccentricity

delays, nonlinearities, controllers and ANOVA. The diagnosis is formulated as a classification tree, where a possible root-cause of poor control performance is predicted. The diagnostic results are easy to interpret and the decision thresholds can be modified to cope with new emerging performance problems when more information about the process becomes available.

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