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Control Performance Assessment for Block-Oriented Nonlinear Systems

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***Abstract*— Control performance assessment or CPA is a useful tool to establish the quality of industrial feedback control loops. While many current CPA techniques are developed solely for the linear systems, [1–3] has recently considered CPA for nonlinear systems. This paper continues this trend by extending CPA into a popular class of nonlinear systems, specifically block-oriented nonlinear models. For these systems, a semi-parametric method is proposed to estimate the minimum variance performance lower bound and simulation examples illustrate that the proposed methodology is efficient and accurate enough to provide the statistics for nonlinear CPA.**

I. Introduction

An interesting statistic much debated recently is the number of control loops per operator on an industrial plant, the trend of that statistic, and the reasons behind it. On a recent visit to a major dairy plant, we found over 500 control loops were under the maintenance supervision of a single instrument engineer. Our anecdotal evidence suggests that this is not unusual, so it is not surprising that engineers are overwhelmed by the sheer number of loops that need attention on any typical industrial processing plant. Consequently many loops are mis-tuned, if tuned at all, or exhibit degraded performance as noted by audits [4, 5].

CPA, developed over the last 20 years is well recognized as an effective tool to help engineers to improve control performance and is now widely applied in the refining, petrochemicals, pulp and paper, and the mineral processing industries as noted by [6–8], while a recent practical overview is given in [9]. However given that many industrial processes are inherently nonlinear, CPA results based on linear dynamic models was shown in [10] to over-estimate the performance index, and thereby lull the control engineer into a false sense of security.

In this paper we will estimate the minimum variance performance lower bound (MVPLB) to a common class of block-oriented nonlinear models. The MVPLB is lowest achievable output variance of a control loop and therefore is commonly used as a CPA performance benchmark. Nonlinear block-oriented models consist of the interconnection of a linear time invariant (LTI) systems with static, or memoryless, nonlinearities. This class includes Hammerstein models, Wiener models and combinations of the two, [11].

Such block-oriented nonlinear descriptions are very useful modelling input nonlinearities such as equal percentage valve characteristics, quantisation due to pulse-width modulated controllers, or output nonlinearities such as thermocouple or thyristor transducer calibration curves, and/or the digital quantisation due to a crude A/D converter. Hammerstein models can be found in chemical engineering [12, 13], biochemical engineering [14], and physiology [15] while Wiener models have been used to model distillation columns [16], fluid catalytic cracker units [17], pH processes [18, 19] as well as various biological systems [20]. Applications of the Hammerstein-Wiener and Wiener-Hammerstein models can be found in [21–24].

For this class of nonlinear systems, [1] proved that a minimum variance feedback invariant exists and the minimum variance performance can be estimated from routine operating data. This paper focusses on developing a new approach to estimate the MVPLB or Harris index for block-oriented nonlinear systems. In order to estimate the MVPLB, a polynomial ARMA model is used to fit the closed-loop nonlinear systems. This approximation turns out to be suitable for moderate nonlinearities such as bilinear systems, but is less suitable for hard nonlinearities which often occur in the block-oriented nonlinear systems [20]. In this paper, instead of identifying the entire closed-loop to estimate the MVPLB, we proposed a semi-parametric method based on spline smoothing.

In general, outputs from block-oriented nonlinear systems with an additive linear disturbance can be decomposed into two parts: a nonlinear component and a linear remainder. A smoothing spline curve is used to model the nonlinear part where the determination of the extent of smoothing depends on a Gaussianity and linearity test on the residuals between the output and the spline curve. Once the spline curve is identified, statistics such as the MVPLB and Harris index can be estimated for the residuals using standard linear time series identification techniques.

The layout of the paper is as follows. In Section II, block-oriented nonlinear systems with additive disturbances are introduced. Section III describes the existence of a feedback invariant, the MVPLB and Harris index of the block-oriented nonlinear systems. Section IV outlines the proposed methods which can be used to estimate the MVPLB and Harris Index. In section V, three simulations are used to illustrate the proposed methodology. This is followed by a discussion and conclusions highlighting both the limitations and potential of the proposed methods.

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II. Process Description

The nonlinear systems under consideration here are restricted to the cases where we can separate a static nonlinear element from the linear dynamics. Specifically, we consider the four following topologies:

The **Hammerstein Model** consists of the cascade connection of a static nonlinearity followed by a LTI system and is described by

$$y_t = \frac{B(q^{-1})}{A(q^{-1})} q^{-f} v_t + d_t, \text{ with } v_t = N_1(u_t) \tag{1}$$

as represented in Fig. 1 with $N_2(x_t) = x_t$. The **Wiener Model** reverses the order of the linear and the nonlinear blocks and is described by

$$y_t = N_2(x_t) + d_t, \text{ with } x_t = \frac{B(q^{-1})}{A(q^{-1})} q^{-f} u_t \tag{2}$$

as represented in Fig. 1 with $N_1(u_t) = u_t$. The **Hammerstein-Wiener Model** is where two static nonlinear elements N_1 and N_2 bracket a linear dynamic element as shown in Fig. 1 and is described as

$$y_t = N_2(x_t) + d_t \tag{3}$$

with

$$x_t = \frac{B(q^{-1})}{A(q^{-1})} q^{-f} v_t \text{ and } v_t = N_1(u_t) \tag{4}$$

and as the name suggests is simply a Hammerstein model concatenated with a Wiener model.

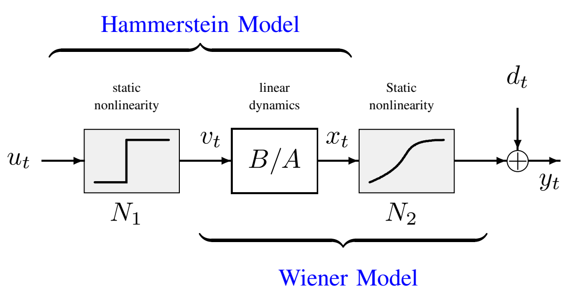

Fig. 1. The Hammerstein–Wiener model structure

The Wiener-Hammerstein Model, being the reverse of the above, is where two linear dynamic elements L_1 and L_2 bracket a static nonlinear element N, as shown in Fig. 2 and is described as

$$y_t = \frac{B_2(q^{-1})}{A_2(q^{-1})} q^{-f} x_t + d_t \tag{5}$$

with

$$x_t = N(v_t) \text{ and } v_t = \frac{B_1(q^{-1})}{A_1(q^{-1})} u_t \tag{6}$$

$A(q^{-1})$ and $B(q^{-1})$ are polynomials in the backward shift operator q^{-1}, and f is the time delay of the process. u_t and y_t are the process input and output respectively; the internal signals v_t and x_t are nonmeasurable. The functions N_1, N_2 represents the static nonlinearities. The disturbance d_t is modeled as the output of a linear Autoregressive-Integrated-Moving-Average (ARIMA) filter driven by white noise a_t of zero mean and variance σ_a^2 of the form

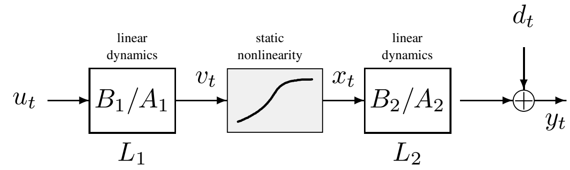

Fig. 2. The Wiener-Hammerstein model structure

$$d_t = \frac{\theta(q^{-1})}{\phi(q^{-1})\nabla^h} a_t = \psi(q^{-1}) a_t \tag{7}$$

where $\nabla \stackrel{\text{def}}{=} (1 - q^{-1})$ is the difference operator and h is a non-negative integer, typically less than 2. The noise polynomials $\theta(q^{-1})$ and $\phi(q^{-1})$ are considered without loss of generality monic and stable.

III. MVPLB for Block-oriented Nonlinear Models

All four models considered in section II can be written in the following form

$$y_t = \frac{\alpha(q^{-1})}{\beta(q^{-1})} q^{-f} N(u_t, .., u_{t_u}) + d_t \tag{8}$$

which is known as a linear autoregressive–nonlinear moving average model with exogenous inputs (LARNMAX), [25], where it was proved in [1] that a feedback invariant exists.

The feedback invariant, $e_{t+f|t}$, being independent of the manipulated variable action, is the f-step ahead prediction error as,

$$\begin{aligned} y_{t+f} &= \frac{\alpha(q^{-1})}{\beta(q^{-1})} N(u_t, .., u_{t_u}) + d_{t+f|t} + e_{t+f|t} \\ &= y_{t+f|t} + e_{t+f|t} \end{aligned} \tag{9}$$

where

$$e_{t+f|t} = (1 + \psi_1 q^{-1} + \cdots + \psi_{f-1} q^{-(f+1)}) a_{t+f} \tag{10}$$

and

$$y_{t+f|t} = \frac{\alpha(q^{-1})}{\beta(q^{-1})} N(u_t, .., u_{t_u}) + \frac{P_f(q^{-1})}{\phi(q^{-1})\nabla^h} a_t \tag{11}$$

$P_f(q^{-1})$ is a polynomial in the backshift operator obtained by solving the Diophantine equation:

$$\frac{\theta(q^{-1})}{\phi(q^{-1})\nabla^h} = 1 + \psi_1 q^{-1} + \cdots + \psi_{f-1} q^{-f+1} + q^{-f} \frac{P_f(q^{-1})}{\phi(q^{-1})\nabla^h} \tag{12}$$

These equations follow immediately from the definition of the conditional expectation and standard results for prediction of linear time series [26, 27].

Therefore, under minimum variance control [26–28], $\frac{\alpha(q^{-1})}{\beta(q^{-1})}N(u_t,..,u_{t_u}) + d_{t+f|t} = 0$, so the process output, $y^{\rm MV}_{t+f}$, will depend on only the most recent f past disturbances,

$$y^{\rm MV}_{t+f} = e_{t+f|t} \tag{13}$$

The MVPLB, as measured in the mean square sense, can be written as:

$$\sigma^2_{MV} = \text{var}\{y^{\rm MV}_{t+f}\} = (1 + \psi^2_1 + \cdots + \psi^2_{f-1})\,\sigma^2_a \tag{14}$$

from which the popular performance index, the Harris index, can be calculated as

$$\eta = \frac{\sigma^2_{MV}}{\sigma^2_y} \tag{15}$$

While it depends somewhat on the specific plant and application, typically well-tuned loops operate with a Harris index between 0.5 and 0.7. Harris indices too low are of course a cause for concern indicating that the loop exhibits excessive variance and could stand retuning, or at least an inspection. Conversely Harris indices too high (i.e. close to 1) despite the fact that they indicate the loop is operating near minimum variance, are probably economically sub-optimal when considering the service life of the actuator.

If the process in Eqn. (8) is controlled by a linear/nonlinear feedback controller $u_t = \gamma(y_t - y_{\rm sp},..,y_{t_c} - y_{\rm sp})$, then the conditional b step ahead prediction error $e_{t+f|t}$ is feedback invariant and can theoretically be recovered from routine operating data [1]. This can be done by Substituting $a_t = y_t - y_{t|t-1}$ into Eqn. (11), we can obtain the f step ahead prediction of output, $y_{t+f|t}$, in a nonlinear auto-regressive (NAR) model form as,

$$A(q^{-1})y_{t+f|t} = B(q^{-1})\tilde{N}(y_t,...,y_{t_y}) + C(q^{-1})y_t \tag{16}$$

where $A(q^{-1}) = \theta(q^{-1})$, $B(q^{-1}) = \frac{\alpha(q^{-1})}{\beta(q^{-1})}\phi(q^{-1})\nabla^h(1 + \varphi_1 q^{-1} + \cdots + \varphi_{f-1}q^{-(f+1)})$ and $C(q^{-1}) = P_f(q^{-1})$.

IV. Estimating the MVPLB of Block-oriented Nonlinear Models

An obvious CPA strategy is simply to ignore the presence of the nonlinearity, and compute the MVPLB in standard manner assuming a purely linear system. Unfortunately if we do this, we incur a bias. To show this, let $\gamma(q^{-1})y_t$ be the linear approximator of $\tilde{N}(y_t,...,y_{t_y})$ in Eqn. (16)),

$$\begin{aligned} A(q^{-1})y_{t+f|t} &= \tilde{N}(y_t,...,y_{t_y}) + C(q^{-1})y_t \\ &= \gamma(q^{-1})y_t + C(q^{-1})y_t + \epsilon_t \end{aligned} \tag{17}$$

where ϵ_t is the bias of the approximator and only involves $y_{t-i}, i = 0, 1, \ldots$ values.

If we use a linear ARMA model in Eq. 17 to estimate $y_{t+f|t}$ and assume that the parameter estimation is perfect, the estimate, $\hat{y}_{t+f|t}$, can be written as

$$\hat{y}_{t+f|t} = y_{t+f|t} - \epsilon_t \tag{18}$$

By subtracting y_t from both sides of Eqn. (18), we will have the estimate of the b-step ahead prediction error, $\hat{e}_{t+b|t}$, as

$$\hat{e}_{t+b|t} = e_{t+b|t} + A^{-1}(q^{-1})\epsilon_t \tag{19}$$

and since ϵ_t and $e_{t+b|t}$ are uncorrelated, the estimate of the MVPLB can be calculated as

$$\hat{\sigma}^2_{MV} = \sigma^2_{MV} + \text{var}\left\{A^{-1}(q^{-1})\epsilon_t\right\} \tag{20}$$

thus showing that the estimate of the MVPLB and consequently the Harris index using the linear CPA techniques will be over-estimated. Further details of this derivation, and a discussion of the consequences is given in [29].

Clearly one solution is to estimate the block nonlinearities where there has been considerable activity, [13, 22, 23, 30, 31]. Even the popular System Identification Toolbox, [32], includes limited identification support for these types of models.

Despite the plethora of strategies employed in the above reports, many are flawed for nonlinear CPA. There are two main reasons for this: i) it is difficult to determine the model structure, and ii) the methods generally demand the input to be persistently exciting, something that is not generally available during routine closed loop operation.

Another alternative solution is to use an approximator to fit the nonlinear function $\tilde{N}(y_t,\ldots,y_{t_y})$ in Eqn. (16). A common approximator, polynomial function, was used to estimate the MVPLB for a class of nonlinear systems [1]. This method has two drawbacks: i) it is difficult to find a suitable approximator for an unknown nonlinear function, ii) some non-differentiable nonlinear functions cannot be approximated by common approximator. For these reasons, splines are often used instead of polynomial for function approximation [33]. A semi-parametric method based on spline techniques to estimate the MVPLB for the block-oriented nonlinear systems will be discussed in the following sections.

A. A semi-parametric or spline smoothing method for nonlinear CPA

A semi-parametric approach is to remove the nonlinearity, $\tilde{N}(y_t,\ldots,y_{t_y})$, in Eqn. (16) in the observable time series y by replacing it with smoothing splines. The degree of the spline curve smoothing (tolerance, τ) is adjusted iteratively to just make the resultant series linear. This approach consists of two steps: i) a non parametric B-spline to fit the nonlinearity from the output and ii) a linear ARMA model is used to fit the residuals between the output and B-spline, from which the Harris index can be estimated. This procedure is detailed in the following sections.

1) Removing the nonlinearity and testing for Gaussianity and linearity: The outputs from the block-oriented nonlinear systems can be generally decomposed into two distinct parts: a linear part and the nonlinear part. A heuristic way to remove the nonlinearity for the purposes of subsequently establishing the performance of the controller is by using some sort of local smoother such as a spline.

For this application we have employed a smoothing B-spline, [34], with a single smoothing parameter, τ, as implemented by the MATLAB function `spaps` in the spline toolbox. A large tolerance value will give a smoother approximate curve. A suitable tolerance is established by finding the largest smoothing parameter τ where the residual between the output y and the the spline is both Gaussian and linear. This implies an iterative search procedure using the statistical tests for determining whether an observed stationary time series is linear proposed by Hinich in [35]. It is possible that a series is linear without being Gaussian, but all of the stationary Gaussian time series are linear.

Let x_t denote a third-order stationary time series which can be expressed as a finite impulse response function

$$x_t = \sum_{i=0}^{M} h_i a_{t-i} \tag{21}$$

where a_t is a sequence of i.i.d. random variables with zero mean, constant variance σ_a^2 and $E[a_t^3] = \mu_3$. The power spectrum $A(\omega)$ and bispectrum $B(\omega_1, \omega_2)$ of this series are

$$A(\omega) = \sigma_a^2 |H(\omega)| = |H(\omega)H^*(\omega)| \tag{22}$$
$$B(\omega_1, \omega_2) = \mu_3 H(\omega_1)H(\omega_2)H^*(\omega_1 + \omega_2) \tag{23}$$

where

$$H(\omega) = \sum_{k=0}^{M} h_k \exp(-j2\pi\omega k) \tag{24}$$

and $H^*(\omega)$ is its complex conjugate. The squared bicoherence follows from Eqn. (24) such that

$$\text{bic}^2(\omega_1, \omega_2) = \frac{|B(\omega_1, \omega_2)|^2}{E[|X(\omega_1)X(\omega_2)|^2]\, E[|X(\omega_1 + \omega_2)|^2]} = \frac{\mu_3^2}{\sigma_a^6} \tag{25}$$

From Eqn. (25), it is easy to see the relationship between the squared bicoherence and Gaussianity/linearity. If y_t is Gaussian, the skewness, μ_3, is zero and thus $\text{bic}^2(\omega_1, \omega_2) = 0$. If y_t is linear, μ_3 is constant and thus $\text{bic}^2(\omega_1, \omega_2)$ is constant, but not necessarily zero. These properties form the basis for the Hinich Gaussianity and linearity tests.

2) Computing the CPA metrics: Given a suitable tolerance value, τ, to just make the residual time series linear and Gaussian, an ARMA model is identified to fit the residuals between the output and the spline curve from which σ^2_{MV} and hence the Harris index, η, can be estimated.

The generating of the closed loop data for a given system, the establishment of a suitable τ, and the subsequent ARMA model fitting and CPA metric computation is repeated 500 times to assess the reliability and robustness of this proposed strategy.

V. Simulation Experiments

The following simulations demonstrate the proposed strategy to estimate the Harris index given block-oriented nonlinear components in a feedback loop with a linear controller, G_c.

A. Hammerstein Models

This section employs a Hammerstein model following Eqn. (1) with static nonlinearity

$$N_1(u_t) = 1.2\left(u_t\, e^{-2u_t} + 0.1u_t\right), \tag{26}$$

linear model and PI controller

$$G = \frac{q^{-3}(1 - 0.5q^{-1})}{1 - 1.5q^{-1} + 0.7q^{-2}}, \quad G_c = \frac{0.2 - 0.15q^{-1}}{1 - q^{-1}}, \tag{27}$$

and an additive ARMA disturbance

$$d_t = \frac{a_t}{1 - 0.8q^{-1}} \tag{28}$$

where a_t is a sequence of i.i.d. Gaussian random variable with zero mean and constant variance $\sigma_a^2 = 0.1$. The nonlinearity $N_1(u_t)$ is depicted in the insert plot in Fig. 3.

Fig. 3 compares the results of the estimates of the Harris index obtained via linear, polynomial ARMA method, and the semi-parametric proposed in section IV-A for this Hammerstein model structure. 1000 data points were used in the closed loop series, and the procedure was repeated 500 times. The true value of η is given by the dashed horizontal line in Fig. 3.

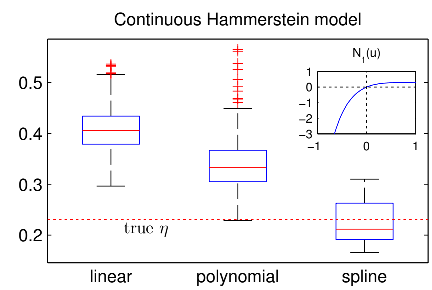

Fig. 3. Estimates of the Harris index, η, using various methods: linear, polynomial, and spline. See also Fig. 5.

In this instance, a suitable value is $\tau = 0.7$ which was established by the Hinich tests. Splines with a range of tolerance values, including 0.7, are compared in Fig. 4.

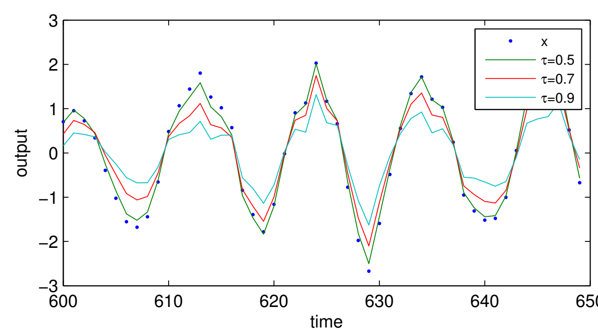

Fig. 4. Approximating smoothing spline curves with different tolerance values. The optimum $\tau = 0.7$ is established by the Gaussianity and linearity tests.

The results from Fig. 3 support both assertions that the linear and polynomial ARMA methods overestimate the performance index from 0.12 to 0.18, while the smoothing spline method delivers results close to the true values.

A slight, but important modification, is where we introduce a non-differentiable component into the nonlinearity. Fig. 5 compares the result of quantisizing the $N_1(u)$ from Eqn. (26) at two different levels. Once again the linear and polynomial methods significantly overestimate η, while the proposed spline method brackets the true value, even at a relatively coarse discretisation.

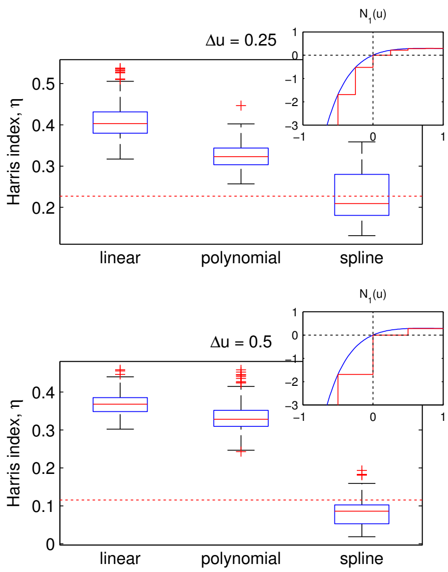

Fig. 5. Box plots for the case where $N_1(u)$ is non-differentiable: (a) discretised with $\Delta u = 0.25$, and (b) discretised with $\Delta u = 0.5$.

B. Wiener Model

The same linear dynamics and disturbance models used in section V-A are adopted for this Wiener model while the nonlinear static function is $y_t = N_2(x_t) = e^{x_t}$ and $\sigma_a^2 = 0.004$. The closed-loop set-point is 1 and a PI control $\frac{0.1-0.08q^{-1}}{1-q^{-1}}$ is used. The same procedures for estimating Harris index in section V-A are used. The estimates are plotted in Fig. 6 (left).

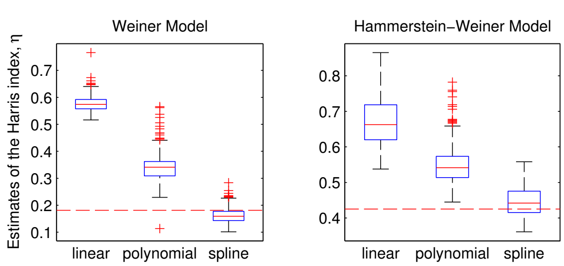

Fig. 6. Estimates of the Harris index for a (left) Wiener Model, and (right) a Hammerstein-Wiener model using different methods: for various methods: linear, polynomial, and spline

C. Hammerstein-Wiener Model

For this simulation, we use the same linear dynamics and disturbance models in section V-A. The nonlinear static function, $N_1(u_t)$, in front of the linear dynamics is an unsymmetric dead zone between -0.02 and 0.1. coupled with the same linear dynamics and nonlinear static function used in the Wiener model in Section V-B. The closed-loop set-point is 1.5 and a feedback PI control $\frac{0.2-0.19q^{-1}}{1-q^{-1}}$ is used. The same procedures for estimating Harris index in section V-A are used. The estimates are plotted in Fig. 6 (right).

As with the previous examples, again the estimates of the Harris index using linear CPA exhibit a significant positive bias and the estimates using polynomial techniques can reduce the over-estimates. Our semi-parametric method provides more accurate estimates.

D. Discussion

Compared to the estimates of the Harris index, or the MVPLB given in [2, 3] for the specific cases of valve stiction, these results are considerably improved. The error bounds are tighter, and the estimates are centered on the true value. This is probably due in part to the fact that valve stiction is a *dynamic* nonlinearity, coupled with the fact that it is a hard, non-differentiable, nonlinearity. Notwithstanding, it is pleasing to note that the spline, a smooth local interpolating function, could handle the non-differentiable hard nonlinearities.

It is interesting to note that under reasonable control, the Hammerstein model structure often erroneously passes the nonlinearity test. This is consistent with the observation that if the nonlinear model is smooth around the region that the plant is operating, and the fact that the low-pass characteristics of the plant dampen further the fluctuations, then the nonlinearity is suppressed. This is not the case for the Wiener model, both because it follows the plant, and due to the fact that in our example, the nonlinearity was unbounded.

VI. Conclusions

The contribution of this work is a reliable algorithm that allows one to estimate the achievable controlled performance of an industrial control loops containing block-oriented nonlinear components. The proposed method works well even in the case of non-smooth nonlinearities.

The method requires only observable signals and crude estimates of the plant dominant time constants and plant delay. The proposed method neither requires one to identify the model structure, nor estimate the closed-loop nonlinear model. By using spline curves to remove the nonlinearity of output data, the Harris index can be easily estimated from the resulting simple linear ARMA model.

Simulation results for a range of differentiable and non-differentiable nonlinearities show that our approach can provide reliable estimates for CPA on the block-oriented nonlinear systems in contrast to either simply ignoring the nonlinearity, or using a crude polynomial.

Acknowledgments

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