ROBUST PID TUNING USING CLOSED-LOOP IDENTIFICATION

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Abstract: Identification based PID tuning is studied. The proposed approach consists of the identification of linear or nonlinear process model and model based control design. The identification test can be performed in both open loop and closed-loop. The so-called ASYM method is used to solve the identification problem. The method identifies a low order process model with a quantification of model errors (uncertainty). The PID tuning is based on internal model control (IMC) tuning rules. Two case studies will be performed to demonstrate the methodology. The first one is the adaptive control of the dissolved oxygen of a bioreactor; the second one is the nonlinear PID control of a pH process.

Key words: PID control, adaptive control, identification, performance, robustness

1. INTRODUCTION

Although MIMO model based control such as MPC is becoming more popular in process control, most control loops are still PID controllers. PID tuning is also part of the pre-test in an MPC project. Therefore, good tuning of PID loops is very important to maintain good performance of the overall process control system.

PID tuning follows basically two approaches: Manual tuning and model based tuning. Manual tuning is effective for simple loops. The disadvantages are that the quality of the tuning is dependent on the knowledge of the control engineer and the control performance will be, in general, not optimal. Moreover, manual tuning will be difficult and inefficient for processes with complex dynamics and/or nonlinearity. For the control of complex industrial processes, a model-based control approach has been proven the most effective. There are many advantages of a model-based approach. The controller can have a high performance because the controller parameters can be optimized based on the process model. The quality of the tuning is independent of the tuning experience of the control engineer. More complex dynamics can be controlled. Nonlinear processes can be controlled using nonlinear models; time-variant processes can be controlled using an adaptive PID.

In this paper a model based PID auto-tuning method is outlined. The model is identified using open or closed-loop test data. Both linear and block-oriented nonlinear models can be obtained. Model error (uncertainty) is also estimated, which makes the robust tuning possible. Internal model control (IMC) tuning rules (Rivera *et. al.*, 1986) are used to determine the PID parameters. In Section 2, the identification method is introduced. Section 3 discusses the controller tuning and implementation. Two case studies are presented in Section 4. Conclusions are given in Section 5.

2. IDENTIFICATION OF LINEAR AND NONLINEAR MODELS

2.1 Cloced-loop Identification of Linear Models

Single-input single-output (SISO) system (process) identification using data from closed-loop operation will be introduced here.

The control system block-diagram is shown in Figure 2.1 where $u(t)$ and $y(t)$ are the process input and output signals at time t, $v(t)$ represents an unmeasured disturbance acting at the output, $r(t)$ is the setpoint of the controlled process. It should be clear that the open loop situation is a special case of closed-loop identification.

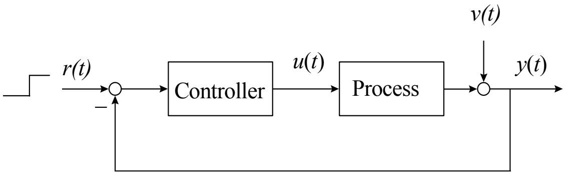

Figure 2.1 Process identification in closed-loop operation

A linear time-invariant discrete-time model that describes the relation between process input and output in terms of the backword shipt operator q^{-1} is given as follows:

$$\begin{aligned} y(t) &= G(q)u(t) + v(t) \\ v(t) &= H(q)e(t) \end{aligned} \qquad (2.1)$$

where

$$G(q) = \frac{B(q)}{A(q)} = \frac{b_0 + b_1 q^{-1} + \ldots + b_n q^{-n}}{1 + a_1 q^{-1} + \ldots + a_n q^{-n}}$$

is called process transfer function model, and

$$H(q) = \frac{C(q)}{D(q)} = \frac{1 + c_1 q^{-1} + \ldots + c_n q^{-n}}{1 + d_1 q^{-1} + \ldots + d_n q^{-n}}$$

is a disturbance shaping filter, n is called the order of the model, $\{e(t)\}$ is white noise with zero mean and variance λ^2 and

$$\{a_1, \ldots, a_n, b_0, \ldots, b_n, c_1, \ldots, c_n, d_1, \ldots, d_n\}$$

are the parameters of the model. This model structure is called Box-Jenkins model in the literature.

A process identification procedure consists of four steps: test design, parameter estimation, order selection and model validation. The following is the so-called ASYM method (Zhu, 2001) that solves these four problems.

1) Test Design

Often binary test signals are used for linear model identification. Tulleken (1990) has proposed the so-called generalized binary noise (GBN) signal for use in identification. The character of a GBN signal is determined by its power spectrum which is in turn determined by its amplitude and average switch time.

A good test design should meet two requirements: 1) the test signal should excites the process such that the identified model is most accurate for control, 2) the test will not disturb normal production, or, the disturbance is minimized. The spectrum of the test signal should be determined such that the control error of the identified model is minimal. An approximate optimal spectrum formula of the test signal at the setpoint of the closed-loop system is given as (Zhu and van den Bosch, 2000)

$$\Phi_r^{opt}(\omega) \approx \mu\sqrt{\Phi_r(\omega)\Phi_v(\omega)} \qquad (2.2)$$

where $\Phi_r(\omega)$ is the power spectrum of the reference signal r, $\Phi_v(\omega)$ is the power spectrum of the disturbance, and μ is a constant adjusted so that the signal power (or amplitude) is constrained. In practice, the average switch time of the GBN signal is adjusted so that its spectrum approximates the optimal one in (2.2). The amplitude is chosen so that the process output will stay within a given range.

2) Parameter Estimation

Parameters of $G(q)$ and $H(q)$ can be estimated in several ways. The well known prediction error method (Ljung, 1987) estimates the parameters of both $G(q)$ and $H(q)$ by minimizing the *prediction error* criterion according to (2.1). This approach is numerically difficult. Local minima and non-convergence can occur.

In the so-called ASYM method (Zhu, 2001), first a high order ARX (equation error) model is estimated:

$$\hat{A}^h(q)y(t) = \hat{B}^h(q)u(t) + \hat{e}(t) \qquad (2.3)$$

where $\hat{A}^h(q)$ and $\hat{B}^h(q)$ are polynomials.

The high order model in (2.3) is practically unbiased, provided that the process behaves linear around the working point. The variance of this model is high due to its high order. Using the asymptotic result of Ljung (1987) it can be shown that the asymptotic negative log-likelihood function for the reduced process model is given by (Wahlberg, 1989)

$$\int_{-\pi}^{\pi} | \{ | \hat{G}^h(e^{i\omega}) - \hat{G}\ (e^{i\omega}) |^2 \ \frac{\Phi_v(\omega)\lambda^2}{\Phi_u(\omega)\lambda^2 - |\Phi_{ue}(\omega)|^2} \, | \, \mathrm{d}\omega \qquad (2.4)$$

The reduced model $\hat{G}(q)$ is thus calculated by minimizing (2.4) for a fixed order.

3) Order Selection

The best order of the reduced model is determined using a frequency domain criterion ASYC which is relate to the noise-to-signal ratios and to the test time; see Zhu (2001). The basic idea of this criterion is to equalize the bias error and variance error of the transfer function in the frequency range that is important for control.

If the optimal order is higher than 2, a model reduction is used to reduce the order to 2 for PID tuning.

4) Model Validation

Model validation is to check whether the identified model is suitable for control. The main task of model validation is to check if the identification test data is rich enough for control purpose, and if not, provide a test redesign. In Zhu (2001), a stochastic model error bound has been derived based on the asymptotic properties of high order models. Denote $\Delta(e^{i\omega})$ as the high order model error, then the additive error bound $\overline{\Delta}(\omega)$ is given as:

$$|\Delta(e^{i\omega})| \leq \overline{\Delta}(\omega) := 3\sqrt{\frac{n_h}{N}\frac{\Phi_v(\omega)\lambda^2}{\Phi_u(\omega)\lambda^2 - |\Phi_{ue}(\omega)|^2}}$$

w.p. 99.9% (2.5)

where n_h is the order of the high order model, N is the number of samples, $\Phi_v(\omega)$ is the power spectrum of disturbance, $\Phi_u(\omega)$ is the power spectrum of input, $\Phi_{ue}(\omega)$ is the cross power spectrum between input and white noise sequence $\{e(t)\}$. When the optimal model order is higher than 2, the model order will be reduced to 2. In this case, the difference between the optimal model and the 2nd order model will be added to the upper bound (2.5).

One way to use upper bound (2.5) for model validation is as follows. First simulate the control system using the model and controller. Then check the robust stability of the system using the model, the upper bound and the controller parameters; see Section 3. If the controller simulation show good performance and robust test is passed, the identified model passes the validation and the controller can be implemented. If the robust test is failed, then, according to the upper bound formula (2.5), a test redesign can be done using the following rules:

- *Doubling the test signal amplitude will half the error over the whole frequency band.*
- *Doubling the test time will reduce the error by a factor of 1.414 over the whole frequency band.*
- *Doubling the average switch time of GBN signal will half the error at low frequencies and double the error at high frequencies.*

2.2 Identification of Block-Oriented Nonlinear Models

Commonly used block-oriented models are the Hammerstein model, the Wiener model and combined Hammerstein-Wiener models. A Hammerstein model is formed by a nonlinear gain at the input followed by a linear block, hence it can also be called a N-L model; see Figure 2.2. A linear block followed by a nonlinear gain forms a Wiener model or a L-N model; see Figure 2.3. One way to combine the Hammerstein Model and and the Wiener model is the so-called N-L-N Hammerstein-Wiener model; see Figure 2.4.

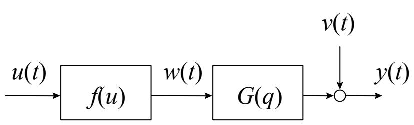

Figure 2.2 Hammerstein model

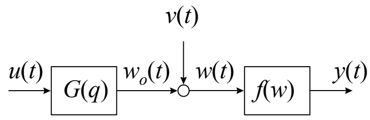

Figure 2.3 Wiener model

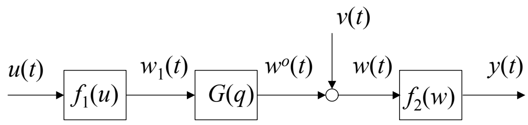

Figure 2.4 N-L-N Hammerstein-Wiener model

Here, $G(z^{-1})$ represents a linear time-invariant transfer function, $f(.)$ denotes the static nonlinear gain. It is assumed that: 1) the nonlinear function $f(.)$ is continuous, monotone and invertible; 2) the unmeasured disturbance $\{v(t)\}$ is a stationary stochastic process.

One can parametrize the linear part with the disturbance using the Box-Jenkins model; and parametrize the nonlinear function using cubic splines. Recently, identification algorithms have been developed for such models by extending the ASYM method; see Zhu (1999, 2000, and 2002).

3. ROBUST PID TUNING

3.1 Tuning for Linear PID

There are many model-based PID tuning rules, such as dominant pole placement, optimization by minimizing *integral square error* (ISE) or *integral absolute error* (IAE), and internal model control (IMC) tuning; see Åström and Hägglund (1995).

Here we will use the IMC tuning rules introduced by Rivera *et. al.* (1986). The idea of the IMC tuning is to use the two-step IMC design method to derive the PID parameters based on a low order (up to 2nd order) plus delay model of the process. The PID parameters are determined so that the closed-loop behavior approximates the behavior given by a first order filter

$$f(s) = \frac{1}{\tau_{cl}s + 1} \qquad (3.1)$$

For controller tuning, the user only needs to specify the time constant τ_{cl} of the filter, or the desired speed of the closed-loop system. In general, a large time constant leads to a slow response and a more robust controller; a small time constant leads to a fast response, but a less robust controller. Tuning formulae for typical process models are available in tables; see, e.g., Chien and Fruehauf (1990). Therefore, when a process model is identified, it is straightforward to obtain PID parameters. The closed-loop system can be simulated using the model and the controller. Industrial experience of the IMC tuning rules is very positive; see Chien and Fruehauf (1990).

Because model errors are inevitable in real process identification, a good control performance according to simulation does not necessarily mean good performance in reality. The robustness of the controlled system against model errors can be analyzed using the upper error bound in (2.5). Denote $\hat{G}(s)$ as the process model in continuous-time, $C(s)$ as the controller and $\overline{\Delta}(\omega)$ as the upper bound. Then it can be shown (see, e.g., Rivera *et. at*.,1986) that the controlled system is robustly stable for all the errors bounded by the upper bound if and only if

$$\frac{|C(i\omega)|}{|1+\hat{G}(i\omega)C(i\omega)|}\cdot\overline{\Delta}(\omega)<1 \quad \forall\omega\in[0,\infty] \qquad (3.2)$$

The performance of the true system will be close to the simulation if the left hand side of (3.2) is much smaller than 1, for example, smaller than 0.5.

3.2 Tuning for Nonlinear PID

When a Hammerstein model or a Wiener model is identified, the simplest tuning is to invert the nonlinearity and then use the same IMC tuning rules to find the linear part of PID controller. The robust stability analysis can also be used after the nonlinear compensation. Denote $\hat{f}^{-1}(.)$ as the identified nonlinear gain, then the block diagram for the nonlinear PID control using the Hammerstein model is given in Figure 3.1; and that using the Wiener model is shown in Figure 3.2.

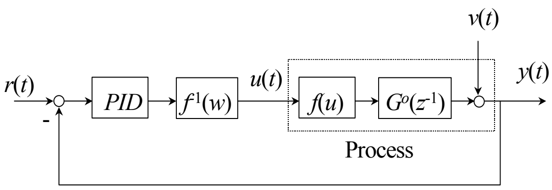

Figure 3.1 Nonlinear PID for Hammerstein model

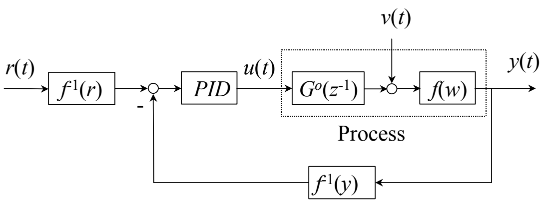

Figure 3.2 Nonlinear PID for Wiener model

4 CASE STUDIES

4.1 Adaptive Control of the Disolved Oxygen of a Bioreactor

The setup is a 20 liter fermentor (Figure 4.1). In this setup, base and acid are used to control the pH value; heating and (water) cooling are used to control temperature and airflow is used to control dissolved oxygen.

The production specifications for the three controlled variables are:

1) **pH** Normal range: setpoint ± 0.05. Worst case range: setpoint ± 0.05.

2) **Dissolved oxygen** Nornal range: setpoint ± 2.0%. Worst case range: setpoint ± 5.0%.

3) **Temperature** Normal range: setpoint ± 0.1 °C. Worst case range: setpoint ± 1.0 °C.

Each variable is controlled using a PID controller. Experience has shown that, when fixed PI controllers are used, the controls of pH and dissolved oxygen are difficult, but the control of temperature is easier.

The main disturbances to the dissolved oxygen are changes in the oxygen consumption rate during the fermentation, the addition of anti-form the changes of the medium properties.

Applikon ADI 1065 unit that is connected to the sensors and actuators controls the fermentor. The low level PID control loops are run in a PC. The supervisory controller sets the PID parameters. The supervisor controller runs in another PC under Matlab/Simulink/ Stateflow. The sampling time is 5 seconds.

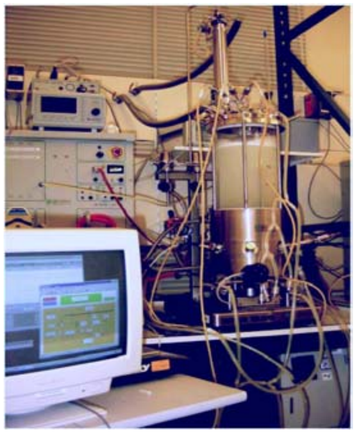

Figure 4.1. The bioreactor setup

The adaptive control scheme is as follows.

1) Control loop performance monitoring
Is control performance OK?
Yes, goto 1); no, goto 2)
2) Identification test; identifying model and error bound
3) Performing PID tuning and simulating closed-loop responses
4) Performing robust stability test
Is the control system robust?
Yes, goto 5);
No, goto 2) (for collecting more test data), or, goto 3) (detune the controller)
5) Implement the new PID parameters
Goto 1)

In this work, control performance monitoring (Huang and Shah, 1999) is not studied; only identification and PID tuning are shown.

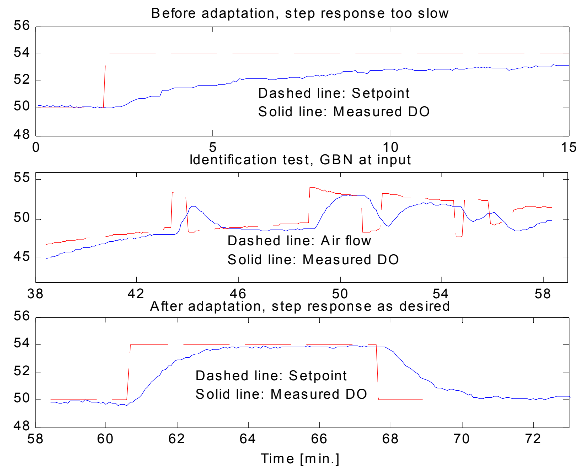

Figure 4.2 DO control loop before, during and after the adaptation

Figure 4.2 shows the signal plots of the real-time measurements during the test. First the existing PID tuning is made very slow; see the first plot of Figure 4.2. Then the identification test is started. A GBN signal is added at the process input. The test lasted for about 20 minutes; see the second plot of Figure 4.2. At the end of the 20 minutes, the input/output data is used to identify a model and its error bound, and PID parameters are computed. The desired settling time of the closed-loop is 1 minute. The closed-loop system is simulated and the robust stability is tested using the model and the control parameters see Figure 4.3. It shows that the new PID controller has good performance with robust stability. The new PID parameters are implemented in the low level controller and the step responses is measured after the adaptation; see the third plot of Figure 4.2.

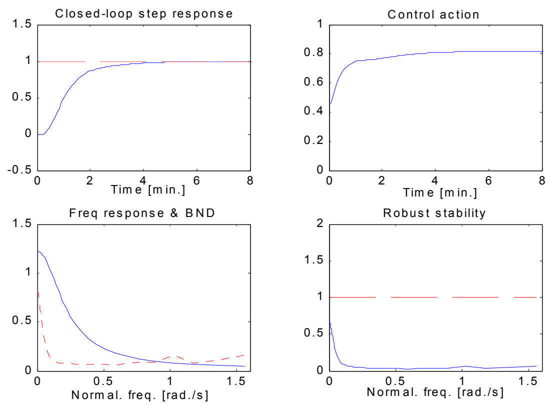

Figure 4.3 Identification and robust PID tuning

It can be seen that the performance of the adaptive control is very satisfactory. The simulation and the real-time measurements agree very well. Only a few seconds are needed to carry out the off-line identification, PID tuning and robust stability analysis.

When the closed-loop is in oscillation, the identified model is very poor. This results in a large error bound and the robust stability test will fail. Therefore the new control parameters will not be implemented. To solve this problem, and oscillation detection is performed before the identification test. The existing controller is detuned until the oscillation disappears.

The adaptive control of the pH and the temperature can be done in the same way.

4.2 Nonlinear PID Control of a pH Process

The pH process consists of a continuous stirred tank reactor (CSTR) with two input streams and one output stream. The scheme is shown in figure 4.4. The first input flow consists of solution of strong acid and the second flow consists of a solution of strong base. The acid flow has a constant rate and the rate of base flow can be adjusted using a controlled pump. These two flows react with each other and produce a pH value. The pH of the solution inside the CSTR is measured by using a pH sensor. The base flow rate is used to control the pH value of the solution inside the tank.

Closed-loop identification test has been carried out. Staircase test signal with different step length is applied at the pH setpoint. Wiener model is identified using the test data. The linear model has an order of 2, but a first order model is almost as good. The nonlinear part has degree 10. Figure 4.4 shows the identified nonlinear gain which decreases as the pH increases.

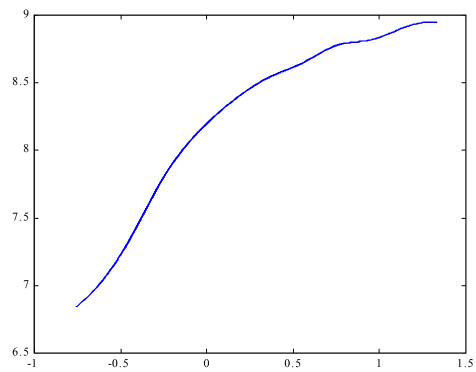

Figure 4.4 Identified nonlinear gain

Based on the identified Wiener model, a nonlinear PID controller is designed and tested for the pH process. In the control scheme, the inverse of the nonlinear gain is placed in the feedback path and before the setpoint as shown in Figure 3.2. Figure 4.5 shows the control result of the nonlinear PID (step responses); Figure 4.6 shows the result of linear PID. One can see that the system with linear controller becomes slower when the pH value is high, but with the nonlinear controller the performance is nearly the same for low and high pH values.

The control scheme is implemented in a LabView environment. See Erol (1999) for more details on the study.

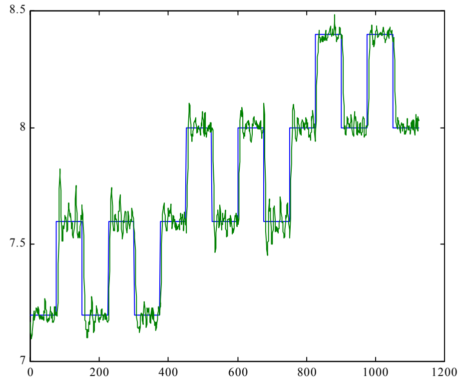

Figure 4.5 Step responses of the nonlinear PI controller

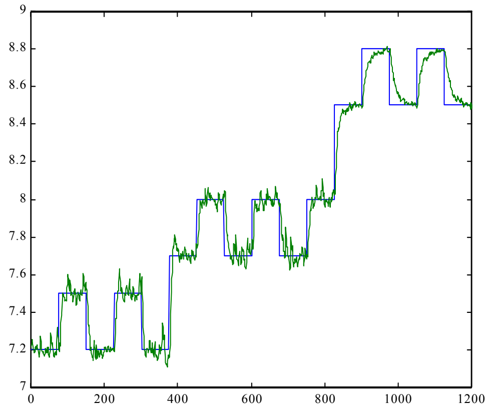

Figure 4.6 Step responses of the linear PI control

5. CONCLUSIONS

An identification based robust PID tuning method is proposed. Both linear and simple nonlinear models can be identified in a possibly closed-loop operation. An error bound of the linear model part can be estimated, which makes the robust tuning possible. The linear or nonlinear PID controller is determined using the so-called IMC tuning rules. The robust stability analysis is then carried out using the identified model, the error bound and the controller parameters. There are many ways to implement the proposed method to solve industrial control problems. The first way is to use the linear method in an auto-tuner to tune fixed PID controllers. The second way is to use the linear identification and PID tuning in an adaptive controller. The third way is to design a time-invariant nonlinear PID controller. The two case studies have shown the capability of the methodology. our experience, the use of such test signals is often permitted in industrial environments.

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