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IDENTIFICATION FOR CONTROL

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Glossary

Approximate identification: Modeling of a dynamic system with identification techniques where a model of limited complexity or limited model order is assumed to approximate the dynamic behavior of the system.
Closed loop data: Data gathered from a plant under feedback controlled conditions.
Controller: A sub-system that generates a control signal on the basis of a feedback or a feedforward connection.
Data: The time history measurement of the (possibly noisy) input and output of a plant.
Discrete time systems: Systems described in the discrete time domain. Typically used in computer controlled systems or systems that are sampled for identification purposes.
Feedback: Feedback is an connection principle of sub-systems in which the output of a sub-system is fed back to the input for control purposes.
Frequency response: The steady-state response of a system to sinusoidal signals of unity amplitude and variable frequency.
Identification: Modeling of a dynamic system on the basis of experimental data obtained from that system.
Identification for control: Modeling of a dynamic system with identification techniques where a model of limited complexity is used specifically for feedback and feedforward control design and evaluation purposes.
Model: Mathematical description of the dynamic behavior of a (sub)-system, e.g. in the form of a transfer function.
Open loop data: Data gathered from a plant without control or under open loop control

Process: A sub-system that is considered to be unknown and is subjected to an identification procedure in order to model the unknown sub-system.

SISO: Single-input-single-output.

System: A set of components, physical or otherwise, connected in a manner to form and act as an entire unit.

Transfer function: A mathematical complex valued function that characterizes the transfer behavior of a system in the complex plane. For discrete time systems it is the ratio of the Z-transform of the output in the absence of initial conditions, to the Z-transform of the input.

Z-Transform: A mathematical transformation that converts the calculus of time invariant discrete time dynamical systems into an algebra in the complex plane.

Summary

Control systems are generally designed on the basis of a quantitative model of the dynamical system or plant to be controlled. When identifying dynamical models for this particular purpose on the basis of experimental data, care has to be taken that the model is particularly accurate in those aspects that are most relevant for the model application, i.c. model-based control design. In order to design control systems with manageable complexity, many advanced control design algorithms require models of limited order. This stresses the necessity of identifying reduced order models that are control-relevant. For the identification of such models, closed-loop experiments have particular advantages. Additionally the interplay between modeling and control has led to a wide variety of iterative modeling and control approaches, where control-relevant identification is interleaved with control analysis and design, aiming at the gradual improvement of controller performance.

1. Introduction

1.1. Relation between modeling and control

When designing a feedback control system for a dynamical process, model information on the dynamical process generally plays a crucial role. The control system is basically designed and analyzed on the basis of a model of the process at hand. Dependent on the particular design procedure, different types of model information are required. Controller tuning methods as e.g. PID, and frequency domain loop shaping methods are often based on non-parametric (graphical) representations as e.g. step responses, frequency responses, disturbance spectra, etcetera. However more advanced design strategies which typically also apply to systems having multiple input and multiple output signals, require a full parametric dynamic model of the underlying process, together with a model of the disturbances acting on the measurement signals.

In the identification problem, as schematically depicted in Figure 1, measurement data of particular experiments are used to identify a dynamical model. In the control design stage, this model information is used to design a feedback control system, as schematically depicted in Figure 2, aiming at typical control performance properties as stability, disturbance rejection, tracking of particular reference inputs, etcetera.

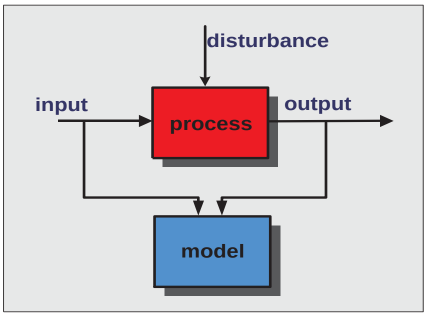

Figure 1: Identification on the basis of input-output data

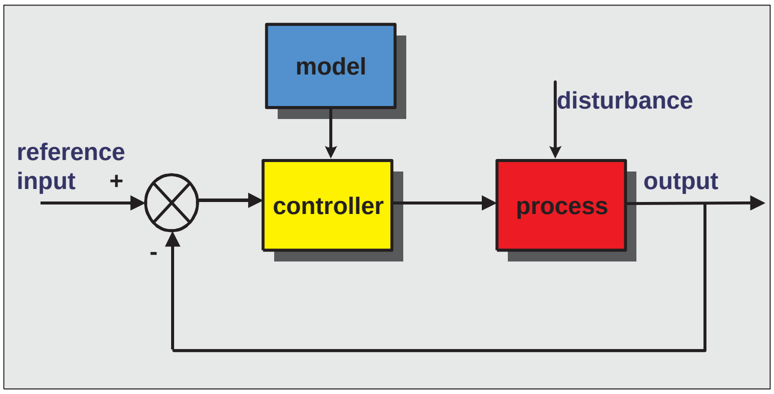

Figure 2: Feedback control system

When considering the question which identified model would be best suited to serve as a basis for subseqeunt control design there is one obvious answer. If the model exactly represents the process under consideration, including the disturbances acting on the process, then this model will be optimal for all model applications, including model-based control design. This principle of certainty equivalence (first construct an exact model, then use this model for control design) is hard to justify when the model has to be identified from measurement data. In this latter situation the identified model will contain uncertainties due to e.g.

- disturbances acting on the measurement data
- finite observation times
- limited excitation of input signals
- the approximative character of the class of models used

Practically it is often impossible to exactly characterize all phenomena that describe the dynamical behaviour of the process. As a result, models will necessarily be approximative. Additionally, many control design methods provide controllers whos order is essentially determined by the order of the underlying process model. In this way a high order process model will also lead to a high order controller, which may be infeasible from an implementation point of view. As a result, low order -approximate- models are needed for the control design. On the other hand, many complex industrial processes are controlled satisfactorily be low order (PID) controllers. This suggests that limited order models should suffice when serving as a basis for control design. When identifying these models from data, dedicated experiments and well chosen identification methods are required for control-relevant modelling.

1.2. When is a model good for feedback control?

Models that accurately describe the open-loop frequency response of the process, are not necessarily good for control, and models that seem bad from an open-loop frequency response point of view, can be good as a basis for control design. As a brief illustration of this we consider the following example.

In Figure 3 the frequency response of a dynamical process is given in black, together with two candidate models (red and blue curves). The blue model is very accurate in the lower frequency range ($\omega < 0.2\ rad/s$), but shows moderate deficiencies in the higher frequencies. The red model has a very poor low-frequent behaviour, but is accurate in the frequency range $0.2\ rad/s \leq \omega \leq 1\ rad/s$. The poor open-loop quality of the red model is also clearly visible in Figure 4(left) where the open-loop step response of the process and the two candidate models is shown.

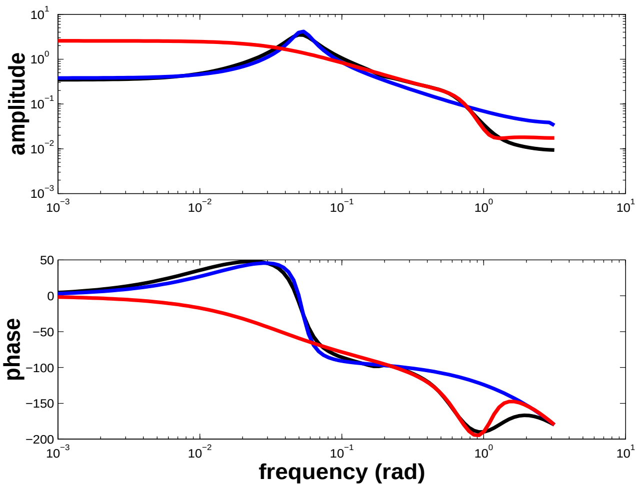

Figure 3: Frequency response of dynamical process (black) and two candidate models (red and blue).

When evaluating the properties of process and models in a closed-loop configuration, determined by a feedback controller achieving a closed-loop bandwidth of 0.7 rad/s, the red model appears to exhibit a closed-loop step response that is very similar to the response of the process, whereas the blue model deviates considerably from this. The closed-loop step responses are depicted in Figure 4 (right). As a general rule-of-thumb it can be stated that for model-based control

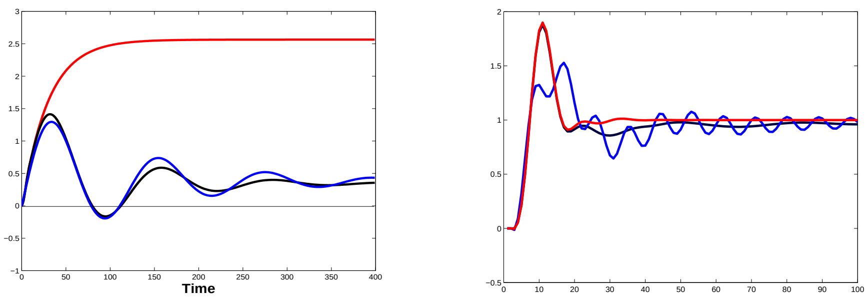

Figure 4: Open loop step response (left) and closed-loop step response (right) of the dynamical process (black) and of two candidate models (red and blue).

design, the process model should be particularly accurate around the bandwidth of the closed-loop system. However the required accuracy at other frequencies can not be specified on beforehand.

A simple experiment that will reveal plant information in the important frequency region is given by a relay feedback experiment, as depicted in Figure 5. A nonlinear feedback switch will

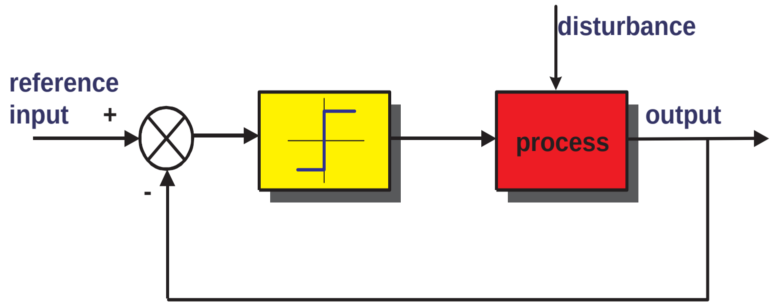

Figure 5: Relay feedback system

cause the output of the closed-loop system to oscillate when the reference signal is held constant. The frequency and amplitude of the oscillating signal carries the necessary information on the plants amplitude and frequency at which its phase shift is -180 degrees, being the crossing of the Nyquist curve of the plant with the negative real axis. For many industrial plants this provides knowledge on the maximum controller gain that can be allowed while guaranteeing stability of the closed-loop system.

2. Identification of approximate models

2.1. Prediction error identification

In the mainstream area of system identification, a prediction error approach is followed, considering a dynamical process description of the form

$$y(t) = G_0(q)u(t) + v(t); \qquad v(t) = H_0(q)e(t) \tag{1}$$

where G_0 and H_0 represent two linear time-invariant systems, y and u represent the output and input signal(s) of the process, e is a sequence of independent, identically distributed random variables (white noise), and q denotes the forward shift operator $q^{-1}u(t) = u(t-1)$. The noise representation H_0 is used to characterize the power spectral distribution of the additive noise v. For a parametrized model $\{G(q,\theta), H(q,\theta)\}$, with θ a real-valued parameter vector, the filtered one-step-ahead prediction error

$$\varepsilon_f(t,\theta) = L(q)H(q,\theta)^{-1}[y(t) - G(q,\theta)u(t)] \tag{2}$$

is used as a basis for the parameter estimate, employing a quadratic (least squares) identification criterion which is constructed on the basis of experimental data $\{y,u\}_{t=1,\cdots,N}$. The prefilter L is an additional design variable to be chosen by the user. Under mild conditions the parameter estimate will converge (for N tending to infinity) to a limiting estimate, which for model structures with fixed noise models, i.e. $H(q,\theta) = H(q)$, and for u and v uncorrelated, is given by

$$\theta^* = \arg\min_{\theta} \frac{1}{2\pi}\int_{\pi}^{\pi} |G_0(e^{i\omega}) - G(e^{i\omega},\theta)|^2 \frac{\Phi_u(\omega)|L(e^{i\omega})|^2}{|H(e^{i\omega})|^2} d\omega. \tag{3}$$

This shows that in this setup the process model $\hat{G}(q) = G(q, \theta^*)$ is obtained as the result of a minimization of an integrated quadratic error between G_0 and G, weighted with a particular weighting function determined by input spectrum, prefilter and noise model.

2.2. Closed-loop process-model mismatch

In case the model $\hat{G}$ is to be used for model-based control design, the approximation of G_0 by $\hat{G}$ should not be based on open-loop considerations. Instead, the approximation should be directed towards a closed-loop match between process and model, taking account of the controller $C(q)$ to be designed.

When a controller $C_{\hat{G}}$ is designed on the basis of a model $\hat{G}$, the desired match between system and model is reflected by a required similarity between the closed-loops of the controlled process (achieved loop) and that of the controlled model (design loop), as indicated in Figure 6.

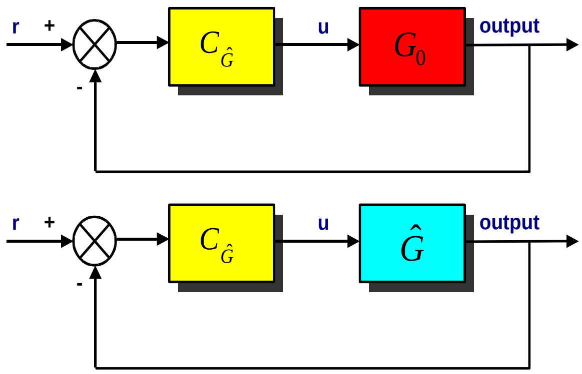

Figure 6: Achieved closed-loop (upper), and design closed-loop (lower).

Denoting the sensitivity functions of the closed-loops:

$$S_0 = [1 + G_0 C_{\hat{G}}]^{-1}, \qquad \hat{S} = [1 + \hat{G} C_{\hat{G}}]^{-1}$$

the (closed-loop) error to be considered is given by:

$$\frac{G_0 C_{\hat{G}}}{1 + G_0 C_{\hat{G}}} - \frac{\hat{G} C_{\hat{G}}}{1 + \hat{G} C_{\hat{G}}} = (G_0 - \hat{G}) \cdot C_{\hat{G}} S_0 \hat{S}. \tag{4}$$

This shows that from a closed-loop perspective the relevant process-model mismatch should not be considered in a simple additive form, but the additive error should be weighted with a weighting function given by $W := C_{\hat{G}} S_0 \hat{S}$. As a direct consequence the process model $\hat{G}$ should be accurate in the particular frequency region where the weighting function $C_{\hat{G}} S_0 \hat{S}$ is large.

A typical example is when the designed controller $C_{\hat{G}}$ contains an integrating (I) action, i.e. for low frequencies $|C_{\hat{G}}(e^{i\omega})| >> 1$. In this case the weighting function

$$|C_{\hat{G}} S_0 \hat{S}| \sim \left| \frac{1}{C_{\hat{G}} G_0 \hat{G}} \right| << 1 \quad \text{for low frequencies} \quad \omega << 1.$$

This implies that model errors $G_0(q) - \hat{G}(q)$ in the low frequency region have almost no influence on the closed-loop properties of the model. This is in accordance with the example that is shown in Section 1.2.

2.3. Identification of control-relevant approximate models

The feedback control performance criterion (4) suggests an identification criterion to be used for identifying the model $\hat{G}$ that (in a 2-norm setting) takes the form:

$$\theta^* = \arg\min_\theta \frac{1}{2\pi}\int_\pi^\pi |G_0(e^{i\omega}) - G(e^{i\omega},\theta)|^2 \left|\frac{C(e^{i\omega})}{1+C(e^{i\omega})G_0(e^{i\omega})}\right|^2 \left|\frac{1}{1+C(e^{i\omega})G(e^{i\omega},\theta)}\right|^2 d\omega. \quad (5)$$

When comparing this criterion with the identification criterion occurring in prediction error identification (3), it appears that they can be made equivalent by choosing an identification setup corresponding to e.g.

$$\Phi_u(\omega) = \left|\frac{C(e^{i\omega})}{1+C(e^{i\omega})G_0(e^{i\omega})}\right|^2 \quad \text{and} \quad (6)$$

$$L(q) = \frac{1}{1+C(q)G(q,\theta)} \quad (7)$$

$$H(q) = 1. \quad (8)$$

In this setting the desired input spectrum is generated by $u = CS_0r$. This input spectrum is achieved by doing closed-loop experiments with a reference signal that has a flat spectral density ($\Phi_r(\omega) = 1$), and the process is controlled by the controller C. The prefilter L that is required is dependent on the model parameter θ and can be implemented via an iterative update of the model estimation. The choice $H(q) = 1$ reflects a so-called output error model structure.

The identification setup described will generate experimental data and a resulting identified model that by construction has properties that reflect the control-relevant aspects of the underlying process. The appealing principle that occurs here, is the observation that the optimal experiment under which the process should be identified, is equal to the situation under which the model is used (namely in terms of its model-based controller).

In this line of reasoning, the optimal identification experiment is a closed-loop experiment with the -yet to be designed- controller $C_{\hat{G}}$ being implemented on the process. Since this controller is unknown before the model is identified, this suggests an iterative scheme of identification and control, which is further explained in section 4.

3. Identification from closed-loop data

The typical problem in closed-loop identification is the fact that the plant input signal u is correlated with the output noise disturbance v. This distinguishes the situation from open-loop experiments. In the so-called direct identification method one simply applies the standard (prediction error) identification procedure without taking special measures for the presence of a feedback controller. A parameter estimate is obtained similarly as in the open-loop case, described in section 2.1. The asymptotic identification criterion in the frequency domain, now is determined by the residual spectrum given by

$$\Phi_\varepsilon = \frac{|S_0|^2|G_0 - G(\theta)|^2}{|H(\theta)|^2}\Phi_r + \frac{|H_0|^2|S_0|^2}{|H(\theta)|^2|S(\theta)|^2}\lambda_0$$

where $S(q,\theta) = (1 + CG(q,\theta))^{-1}$ is the sensitivity function of the parametrized model. This expression is obtained by simply combining (1) and (2) with the controller equation $u = C(r-y)$. If G_0 can be modeled exactly within the chosen model set, i.e. $G_0 \in \mathcal{G}$, the first term of the residual spectrum can be made 0 but this is not necessarily a minimum solution because of the presence of $G(\theta)$ in the second term; any misfit in $H(q,\theta)$ in this term will be compensated for by $G(q,\theta)$ in $S(q,\theta)$.

The direct method can provide good estimates when one is willing/able to identify full order models for both plant and noise dynamics. In case one is identifying approximate models or when one refrains from modelling the full noise dynamics, the consequences are that G_0 is not identified consistently, and the criterion that governs the approximate identification of G_0 is not explicitly tunable by the user. I.e. it will not take a simple form as (3) with the additive error in G_0 weighted with a known weighting function.

Alternative methods are available that allow for a decoupling of the identification of G_0 and H_0 in a closed-loop setting:

- *Indirect identification.* In this approach the closed-loop system

  $$y(t) = T(q)r(t) + W(q)e(t)$$

  is identified from measurements of y and r, leading to models $\hat{T}(q)$ and $\hat{W}(q)$, that have to be converted to equivalent plant models $\hat{G}$ and $\hat{H}$ by solving the equations

  $$\hat{T}(q) = \frac{C(q)\hat{G}(q)}{1 + C(q)\hat{G}(q)}; \qquad \hat{W}(q) = \frac{\hat{H}(q)}{1 + C(q)\hat{G}(q)}$$

  for $\hat{G}$ and $\hat{H}$. This requires knowledge of the controller C.

- *Two-stage method.* In this approach one first identifies the system that generates the plant input:

  $$u(t) = M(q)r(t) + N(q)e(t)$$

  from measurements u and r, leading to models $\hat{M}$ and $\hat{N}$. A noise-free plant input signal is then reconstructed by

  $$\hat{u}^r(t) = \hat{M}(q)r(t)$$

  which subsequently is used in the second stage to identify the system

  $$y(t) = G_0(q)u^r(t) + H_0(q)S_0(q)e(t)$$

  where the non-measurable noise-free input signal $u^r := C(q)S_0(q)r(t)$ is replaced by its estimate $\hat{u}^r$. For this procecure no explicit knowledge of the controller is required. Extensions are also developed for situations where the controller is nonlinear.

Both alternatives allow the separate identification of plant model G_0 and noise model H_0. In the situations that plant and noise models are parametrized independently (or that a fixed noise model W_* is used) the asymptotic identification criterion for the estimation of G_0 takes the form (for the indirect method[1]):

$$\theta^* = \arg\min_\theta \frac{1}{2\pi}\int_{-\pi}^{\pi} |G_0(e^{i\omega}) - G(e^{i\omega},\theta)|^2 \frac{|C(e^{i\omega})S_0(e^{i\omega})S(e^{i\omega},\theta)|^2\Phi_r(\omega)}{|W_*(e^{i\omega})|^2} d\omega$$

[1]The expression for the two-stage method varies slightly.

which exactly matches the required criterion formulated in (5).This implies that in this case with an appropriate choice of Φ_r and W_* the criterion that is requested from a control-relevancy point of view, can be realized exactly by applying an indirect closed-loop identification.

Consideratons have so far been directed towards asymptotic approximative properties of estimates. This refers to the asymptotic bias properties of identified models. For analyzing the asymptotic variance of the transfer function estimates it is known that for both model order and number of data tending to ∞:

$$cov\begin{pmatrix} \hat{G}(e^{i\omega}) \\ \hat{H}(e^{i\omega}) \end{pmatrix} \sim \frac{n}{N}\Phi_v(\omega)\cdot \begin{bmatrix} \Phi_u(\omega) & \Phi_{eu}(\omega) \\ \Phi_{ue}(\omega) & \lambda_0 \end{bmatrix}^{-1}, \tag{9}$$

leading to

$$cov(\hat{G}) \sim \frac{n}{N}\frac{\Phi_v}{\Phi_u^r} \qquad cov(\hat{H}) \sim \frac{n}{N}\frac{\Phi_v}{\lambda_0}\frac{\Phi_u}{\Phi_u^r} \tag{10}$$

with Φ_u^r the power spectral density of u^r. This shows that only the noise-free part u^r of the input signal u contributes to variance reduction of the transfer functions. Note that for $u^r = u$ the corresponding open-loop results appear. The variance expressions hold for all of the closed-loop identification methods. It gives an appealing indication of the mechanisms that contribute to variance reduction. It also illustrates one of the basic mechanisms in closed-loop identification, i.e. that noise in the feedback loop does not contribute to variance reduction. Particularly in the situation that the input power of the process is limited, it is relevant to note that only part of this input power can be used for variance reduction. This has led to the following results

- If the input power is limited, and the controller is designed only on the basis of $\hat{G}$ and not of $\hat{H}$, the optimal identification experiment to minimize the variance cost of the control performance is an open-loop experiment with an input spectrum that is proportial to the sensitivity function of the to-be-designed closed-loop system, as in section 2.3.
- If during identification experiments the output power is limited, a closed-loop experiment becomes optimal.
- If the controller is designed on the basis of both $\hat{G}$ and $\hat{H}$, then a closed-loop experiment is optimal.

4. Iterative identification and control

The situation described in the previous subsections shows that control-relevant models are obtained when identification takes place under closed-loop experimental conditions with the -yet to be designed- controller $C_{\hat{G}}$ being implemented on the process. As this controller is unknown before the model is identified, an iterative scheme is required to arrive at the desired situation:

- *Step 1* Perform an identification experiment with the process being controlled by an initial stabilizing controller C;
- *Step 2* Identify a model $\hat{G}$ with a control-relevant criterion;
- *Step 3* Design a model-based controller $C_{\hat{G}}$;

- *Step 4* Implement the controller on the process and return to Step 1 while using the new controller.

This iterative scheme is depicted in Figure 7. A second motivation for applying an iterative

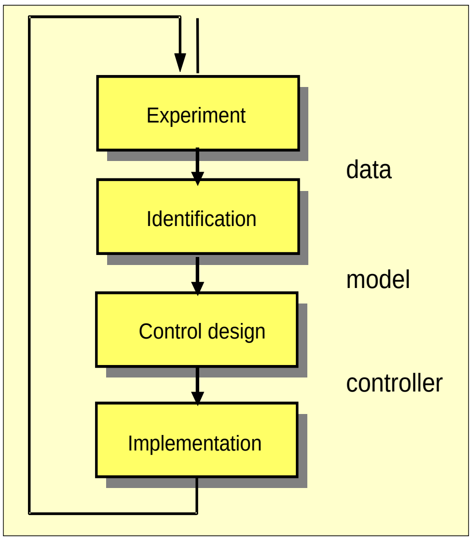

Figure 7: Iterative scheme of (closed-loop) identification and control design

scheme is the fact that when designing control systems, the performance limitations are generally not known on beforehand. As a result the sketched iterative scheme can also be considered to allow to improve the performance specifications of the controlled system, as one learns about the system through dedicated experiments. In this way improved knowledge of the process dynamics allows the design of a controller with higher performance, thus enhancing the overall control performance.

Another view towards the iterative scheme is obtained by considering a control performance cost function $\|J(G_0, C_{\hat{G}})\|$, related to a closed-loop system with process G_0 and controller $C_{\hat{G}}$[2]. J can e.g. be a weighted sensitivity function:

$$J(G_0, C_{\hat{G}}) = \frac{V}{1 + C_{\hat{G}} G_0} \tag{11}$$

aiming at a control system that satisfies: $|S_0(e^{i\omega})| < |V(e^{i\omega})|^{-1}$; alternative choices for J include LQ/LQG criteria, model reference control, robustness optimization and H_∞ control schemes. It is the aim of the control system to achieve a minimum value of $\|J(G_0, C_{\hat{G}})\|$, through an appropriate choice of $\hat{G}$ and $C_{\hat{G}}$. Employing the triangle inequality:

$$\begin{aligned} \Big| \|J(\hat{G}, C_{\hat{G}})\| - \|J(G_0, C_{\hat{G}}) - J(\hat{G}, C_{\hat{G}})\| \Big| &\leq \\ \leq \|J(G_0, C_{\hat{G}})\| &\leq \\ \leq \|J(\hat{G}, C_{\hat{G}})\| + \|J(G_0, C_{\hat{G}}) - J(\hat{G}, C_{\hat{G}})\|&, \end{aligned} \tag{12}$$

shows that the *achieved performance cost* $\|J(G_0, C_{\hat{G}})\|$ can be minimized by minimizing each of the two separate terms on the right hand side of (12). Since such a minimization over $\hat{G}$ involves the control design $C_{\hat{G}}$, this will generally be intractable. In the iterative approach

[2]In this notation it is presumed that the controller C can be a function of the noise model $\hat{H}$ also.

both terms are minimized separately: minimizing the *designed performance cost* $\|J(\hat{G}, C)\|$ over C for a fixed model $\hat{G}$ (control design), and minimizing the *performance degradation term* $\|J(G_0, C) - J(G, C)\|$ over G for a fixed controller C (control-relevant identification). In that case this degradation term can be given the interpretation of a control-performance induced modelling criterion:

$$\hat{G} = \arg\min_{G} \|J(G_0, C) - J(G, C)\|$$

which for the choice of J as given in (11) takes the form:

$$\hat{G} = \arg\min_{G} \left\| \frac{V(G_0 - G)C}{(1 + CG_0)(1 + CG)} \right\|.$$

Note that for a 2-norm this criterion has the same structure as the bias expression for the closed-loop identification methods as shown in (5).

By minimizing the performance degradation term, and making it much smaller than the designed cost $\|J(\hat{G}, C_{\hat{G}})\|$, it follows from the two triangle inequalities (12) that the achieved performance is forced to be close to the designed performance, i.e.

$$\|J(\hat{G}, C_{\hat{G}})\| \sim \|J(G_0, C_{\hat{G}})\|$$

which is exactly what a control design engineer is aiming at: designing a model-based controller that -after implementation on the real process- shows a performance cost that is similar to the performance of the controlled model.
In general no convergence guarantees are available for the iterative schemes as described, although robust versions (see next section) can be designed that guarantee non-divergence through monitoring the controller results before implementation.

The iterative scheme considered relates to so-called adaptive control where recursively at each time step a model update is identified and a new controller is designed. In the situation described above, there is no necessity to design model and controller updates at each time step, but only after seperate experimental runs. In this respect it reflects "extremely slow" adaptive control.

5. Extensions

When models are used as a basis for *robust* control design, both a nominal model and a model uncertainty characterization are required. In recent years attention has been given to the quantification of model uncertainty on the basis of experimental data. A starting point for a model uncertainty set, would be to collect all models that are not invalidated by the data and the prior information on the system, sometimes called the *Feasible System Set* (FSS) or the set of unfalsified models:

$$\mathcal{P}_{unf} := \{G \mid y(t) - G(q)u(t) = v(t), v \in \mathcal{V}\}$$

where $\mathcal{V}$ is a hypothesized set of disturbance signals on the output. Dependent on the particular character of $\mathcal{V}$:

- hard-bounded, as e.g. $\mathcal{V} = \{v \mid |v(t)| \leq c \ \forall t\}$, or

- soft-bounded, as e.g. $\mathcal{V} = \{v \mid v$ a stationary stochastic process with rational spectrum, not correlated with $u\}$,

the uncertainty set $\mathcal{P}_{unf}$ will be of a deterministic (hard-bounded) or a probabilistic (soft-bounded) nature. In the latter situation confidence bounds on estimated model parameters (parametric) or the model frequency response (non-parametric) are provided. Although the preference in robust control design goes to hard-bounded sets, the commonly used hard-bounded noise paradigms lead to uncertainty sets that in many cases are overly conservative. This is due to the fact that the correlation between input signal and noise signal is not bounded.

Incorporating estimated model uncertainty bounds in the iterative scheme of the previous section leads to an iterative scheme of identification and robust control, where the estimated model is composed of both a nominal model and an uncertainty bound, and the control design is a robust control design. Implementation of the controller is then preceded by a robustness test on stability and performance of the designed control system.

6. Conclusions

It is possible to design an identification setup in such a way that the resulting models automatically reflect those aspects of the undelying process that are most relevant for a subsequent model-based control design. In this situation the identification setup is a result of a chosen control performance cost. Optimization of the control and identification design can be achieved by iteratively estimating models (possible accompanied by uncertainty bounds) and designing and implementing enhanced controllers. Such an iterative procedure appeals to the learning principle, where subsequent experiments allow the better understanding of the relevant process dynamics, and the design of controllers with gradually improving performance.