

Figure 2.28 A Hammerstein model a), and a Wiener model b)

Fortunately there are special classes of models that are well suited for PID control. A system is represented as a combination of a static nonlinearity and a linear dynamical system. Such models are quite simple and they are nicely adapted to PID control but there are nonlinear systems that cannot be well modeled using this approach.

The nonlinearity can be before the linear part as shown in Figure 2.28a. This model is called a Hammerstein model. It is a good model for a system with a nonlinear actuator, for example a nonlinear valve.

The nonlinearity can also be placed after the linear dynamical system. This gives a Wiener model which is illustrated in the block diagram in Figure 2.28b. The Wiener model is a good representation for a system with a nonlinear sensor, for example a pH electrode.

If the process is nonlinear, the dynamics are varying with the operating conditions. Ideally, the controller should be tuned with respect to these variations. A conservative approach is to tune the controller for the worst case and accept degraded performance at other operating conditions. Another approach is to find a measurable variable that is well correlated with the process nonlinearity. Such a variable is called a scheduling variable. The controller is then tuned for a few values of the scheduling variable. Controller parameters for intermediate values may be obtained by interpolation. This approach to generate a nonlinear controller is called gain scheduling. It will be discussed in more detail in Section ??.

It is easy to compensate for the nonlinearity for a system that is described by a Wiener or a Hammerstein model by using a nonlinear controller composed of a PID controller and a static nonlinearity. The linear PID controller is designed as if the system was linear. When the process has a nonlinearity at the input we simply pass the control signal through the inverse of the nonlinearity. If the nonlinearity is at the output as for the Wiener model we simply pass the sensor signal through an inverse of the nonlinerity before feeding the measured signal to the controller. Many PID controllers have a facility to introduce a nonlinerity characterized as a piece-wise linear function.

2.6 Models for Disturbances

So far, we have only discussed models of process dynamics. Disturbances is another important aspect of the control problem. In fact, without disturbances and

process uncertainty there would be no need for feedback. There is a special branch of control, stochastic control theory, that deals explicitly with disturbances. This has had little impact on tuning and design of PID controllers. For PID control, disturbances have mostly been considered indirectly, e.g., by introducing integral action. As our ambitions increase and we strive for control systems with improved performances it will be useful to consider disturbances explicitly. In this section, therefore, we will present some models that can be used for this purpose. Models for disturbances are useful for simulation, diagnostics, and performance evaluation.

The Nature of Disturbances

We distinguish between three types of disturbances, namely, setpoint changes, load disturbances, and measurement noise. In process control, most control loops have setpoints that are constant over long periods of time with occasional changes. An appropriate model is therefore a piecewise constant signal. Setpoint changes are typically known beforehand. Good response to setpoint changes is the major issue in drive systems.

Load disturbances are disturbances that enter the control loop somewhere in the process and drive the system away from its desired operating point. Load disturbances typically have low frequency. Efficient reduction of load disturbances is a key issue in process control systems.

Measurement noise represents disturbances that distort the information about the process variables obtained from the sensors. Measurement noise is often high frequent. It is often attempted to filter the measured signals to reduce the measurement noise. Filtering does, however, add dynamics to the system.

The Character of Disturbances

One way to get a first estimate of the disturbances is to log the measured variable. The measured signal has contributions both from load disturbances and measurement noise. If there are large variations it is often useful to investigate the sensor to reduce some of the measurement noise. Filtering may also be useful. Filtering should be done in such a way that it does not impair control.

The process variations may have very different character. Some examples are given in Figure 2.29. The disturbances can be classifies as pulses (a), steps (b), ramps (c), and periodic (d). It is useful to compute statistics such as mean values, variances and maximum deviation. It is also useful to plot a histogram of the amplitude distribution of the disturbances.

Simple Models

It is useful to have simple models for disturbances for simulation and evaluation of control strategies. Models that are typically used are shown in Figure 2.29.

The impulse is a mathematical idealization of a pulse whose duration is short in comparison with the time scale. The signals are essentially deterministic. The only uncertain elements in the impulse, step, and ramp are the times when they start and the signal amplitude. The uncertain elements of the sinusoid are frequency, amplitude, and phase.

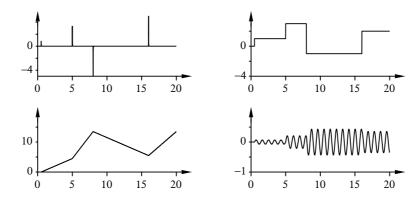


Figure 2.29 Different charachters of disturbances. Markera a,b,c,d

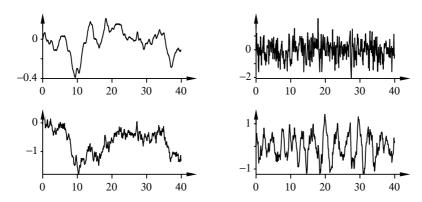


Figure 2.30 Examples of noise signals.

Random Fluctuations

There are well developed concepts and techniques for dealing with random fluctuations that are described as stochastic processes. There are both time domain and frequency domain characterizations. In the frequency domain the random disturbances are characterized by the spectral density function $\phi(\omega)$. The variance of the signal is given by

$$\sigma^2 = \int\limits_{-\infty}^{\infty} \phi(\omega) d\omega.$$

The spectral density tells how the variation of the signal is distributed on different frequencies. The value

$$2\phi(\omega)\Delta\omega$$

is the average energy in a narrow band of width $\Delta\omega$ centered around ω . A signal where $\phi(\omega)$ is constant is called white noise. Such a signal has its energy equally distributed on all frequencies.

There are efficient techniques to compute the spectral density of a given function. If the spectral density is known it is possible to evaluate how the variations

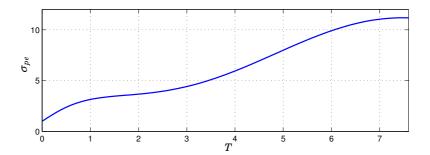


Figure 2.31 Prediction error σ_{pe} as a function of prediction time T.

in the process variable are influenced by different control strategies.

Prediction of Disturbances

When controlling important quality variables in a process it is often of interest to assess the improvements that can be achieved and to determine if a particular control strategy gives a performance that is close to the achievable limits. This can be done as follows. The process variable y(t) is logged during normal operation with or without control. By analyzing the fluctuations it is possible to determine how accurately the process variable can be predicted T time units into the future based on present and past values of y. let $\hat{y}(t+T|t)$ be the best prediction of y(t+T) based on $y(\tau)$ for all $\tau < t$. By plotting the variance of the prediction error $y(t+T) - \hat{y}(t+T|t)$ as a function of the prediction time we obtain the curve shown in Figure 2.31. For large prediction times the prediction error is equal to the variance of the process variable, approximately $\sigma_{pe}=12$ in the figure. The best control error that can be achieved is the prediction error at a prediction time T_p corresponding to the time delay of the process and the sampling time of the controller. This can be achieved with a so called minimum variance controller. The figure indicates that variances less that 5 can be obtained if T_p is less than 3.4. Further reductions are possible for smaller T_p but variances less than 1 cannot be achieved even if T_p is very short. By comparing this with the actual variance we get an assessment of the achievable performance. This is discussed in more detail in Chapter 10. There is efficient software for computing the prediction error and its variance from process data.

2.7 How to Obtain the Models

In previous sections we have briefly mentioned how the models can be obtained. In this section we will give a more detailed discussion of methods for determining the models. There are two broad types of methods that can be used. One is physical modeling and the other is modeling from data.

Physical modeling uses first principles to derive the equations that describe the system. The physical laws express conservation of mass, momentum and energy. They are combined with constitutive equations that describe material properties.

When deriving physical models a system is typically split into subsystems. Equations are derived for each subsystem and the results are combined to obtain a model for the complete system. Simple examples were given in Section 2.3. Physical modeling is often very time consuming. There are often difficult decisions on suitable approximations. The models obtained can, however, be very useful since they have a sound physical basis. They also give considerable insight into the dependence of the model on the physical parameters. A simple way to start is to model dynamics as first order systems where the time constants are the ratio of storage and flow.

Modeling from data is an experimental procedure. Data is generated by perturbing the input signal (the manipulated variable) and recording the system output. The experiment can also be performed under closed-loop conditions for example by perturbing the setpoint of a controller or the controller output. It is then attempted to find a model that fits the data well. There are several important issues to consider, selection of input signals, selection of a suitable model structure, parameter adjustments and model validation. Ideally the experimental conditions should be chosen to be as similar as possible to the intended use of the model. The parameter adjustment can be made manually for crude models or by using optimization techniques.

Static Models

Static models are easy to obtain by observing the relation between the input and the output in steady state. For stable well damped processes the relation can be obtained by setting the input to a constant value and observing the steady state output. The procedure is then repeated for different values of the input until the full range is covered. For systems with integration it is convenient to use a controller to keep the output at a constant value. The setpoint of the controller is then changed so that the full signal range is covered. Effects of disturbances can be reduced by taking averages.

The Bump Test

The bump test is a simple procedure that is commonly used in process control. It is based on an experimental determination of the step response. To perform the experiment the system is first brought to steady state. The manipulated variable is changed rapidly to a new constant value and the output is recorded. The measured data is scaled to correspond to a unit step. The change in the manipulated variable should be large in order to get a good signal to noise ratio but it should not be so large that the process behavior is not linear. The allowable magnitude is also limited by process operation. It is also useful to record the fluctuations in the measurement signal when the control signal is constant. This gives data about the process noise. It is good practice to repeat the experiment for different amplitudes of the input signal and at different operating conditions. This gives an indication of the signal ranges when the model is linear. It also indicates if the process changes with the operating conditions.

By inspection of the step response it is possible to make a crude classification of the dynamics of the system into the categories shown in Figure 2.2. A model with a few parameters is then fitted to the data.