Lecture 1

- System Identification
- System
- Model
- The system identification procedure
- Course outline

System Identification

Def. System identification is the field of *modeling* dynamic *systems* from *experimental data*.

- System identification is as much an art as a science.
- Many software packages are available.
- Dates back to Gauss (1809). Birth-year for modern identification theory 1965 (Åström and Bohlin, Ho and Kalman).

System

System ($\mathcal{S}$): A defined part of the real world. Interactions with the environment are described by inputs, outputs and disturbances.

Dynamic system: A system with a memory, i.e., the input value at time t will influence the output at future time instants.

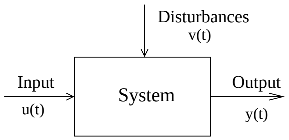


Figure 1: Schematic picture of a system.

Ex. A Solar Heated House

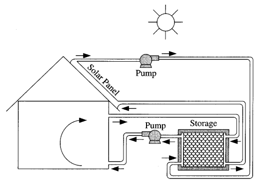


Figure 1.2 A solar-heated house.

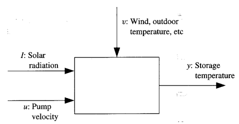
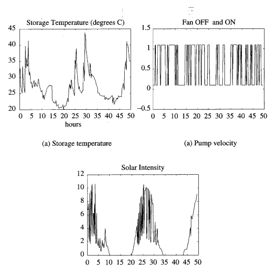


Figure 1.3 The solar-heated house system: u: input; I: measured disturbance; y: output; v: unmeasured disturbances.



(a) Storage temperature (a) Pump velocity

(a) Solar intensity

Figure 1.4 Storage temperature y, pump velocity u, and solar intensity I over a 50-hour period. Sampling interval: 10 minutes.

Ex. Speech

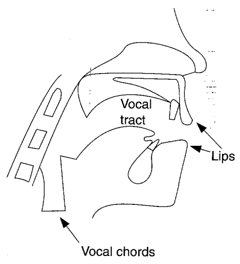


Figure 1.7 Speech generation.

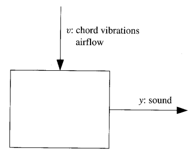


Figure 1.8 The speech system: y: output; v: unmeasured disturbance.

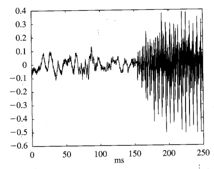


Figure 1.9 The speech signal (air pressure). Data sampled every 0.125 ms. (8 kHz sampling rate).

Models

Model ($\mathcal{M}$): A description of the system. The model should capture the essential information about the system.

Systems	**Models**
Complex	Approximative (idealization). Should capture the relevant information.
Building/Examine systems is expensive, dangerous, time consuming, etc.	Models can answer many questions about the system.

Applications

- Process design. Ex. Designing new cars, new airplanes.
- Control design. Simple regulators ⇒ simple models, and optimal regulators ⇒ sophisticated models.
- Prediction. Forecast the weather, predict the stock market, etc.
- Signal processing. Ex. Communication, echo cancellation.
- Simulation. Ex. Train nuclear plant operators, try new operation strategies.
- Fault detection.

Types of Models

- Mental, intuitive or verbal models. Ex. Driving a car.
- Graphs and tables. Ex. Bode plots and step responses.
- Mathematical models. Ex. Differential and difference equations, which are well-suited for modeling dynamical systems.

Mathematical Models

- **Analytical models**. Basic laws from physics are used to describe the behavior of a phenomenon.
  - You need to be an expert in the field. Know the physics.
  - Yields physical interpretation.
  - The models are often quite general. Often nonlinear.
- **System identification**. Experimental approach.
  - Black-box models (konfektionsmodeller). Choose a standard model and adjust its parameters to the data.
    - Easy to construct and use.
    - Less general. Often linear.
  - Grey-box models (skräddarsydda modeller). Derive the model and adjust its parameters to the data.
    - Combines analytical modeling and black-box identification.

Ex. Models

- Nonlinear versus linear
- Time continuous versus time discrete
- Deterministic versus stochastic.

The System Identification Procedure

1. Collect data (*experiment design*, $\mathcal{X}$). If possible choose the input signal such that the data become maximally informative. Reduce the influence of noise.
2. Choose the *model structure* ($\mathcal{M}$). Use priori knowledge and engineering intuition. Most important and most difficult step. (Do not estimate what you already know).
3. *Identification method* ($\mathcal{I}$). Determine the best model in the model structure (find optimal $\boldsymbol{\theta}$ using *e.g.*, the least squares method).
4. *Model validation*. Is the model good enough? Good is subjective, and depends on the purpose with the model.

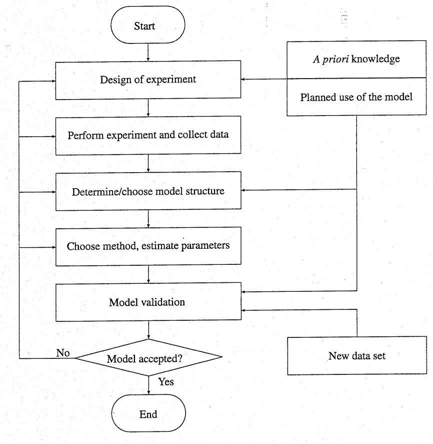


Figure 2: Schematic flowchart of system identification

Typical problems to answer

- How to design the experiment. How much data is needed?
- How to choose the model structure?
- How to deal with noise? Data contains noise, hence the measurements are unreliable.
- How do we measure the quality of the model.
- How will the purpose of the model affect the identification?
- How do we handle non-linear and time-varying effects?

System Identification Methods

- Non parametric methods. The results are curves, tables, etc. These methods are simple to apply. They give basic information about, *e.g.*, time delays and time constants of the system.
  - Ex. transient analysis (impulse or step responses) and frequency analysis (input is a sinusoid).
- Parametric methods. The results are the values of the parameters in the models. These methods can handle disturbances and they provide better accuracy. They are often computationally more demanding.

Course Outline

- Non parametric methods, input signals, model structures.
- Parametric methods. Linear regression (the least squares method), prediction error methods, instrumental variable methods.
- Model validation.
- Recursive identification.
- Identification in closed-loop.
- Practical aspects.

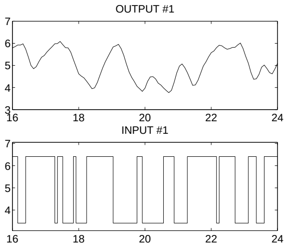
Conclusion

- System identification is the art of building mathematical models of dynamical systems from experimental data. It is an iterative procedure.
  - A real system is often very complex. A model is an approximation.
  - Data contain noise, hence the measurements are unreliable.
- Analytical methods versus system identification (black-box, grey-box)
- Non parametric methods versus parametric methods.
- Procedure: Collect data, choose a model structure, determine the best model within the model structure, validation.

An Example

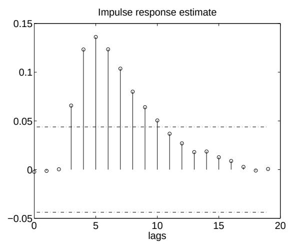
Identify a hairdryer: air is fanned true a tube and heated at the inlet. Input u: power of the heating device. Output y: air temperature.

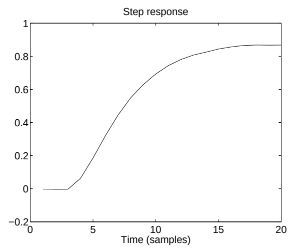
```
>> load dryer2
>> z2 = [y2(1:300) u2(1:300)];
>> idplot(z2,200:300,0.08)
```



Nonparametric modeling:

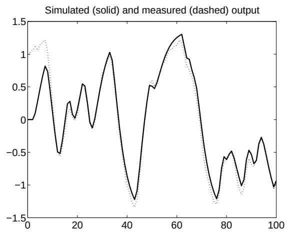
```
>> z2 = dtrend(z2);
>> ir = cra(z2);
>> stepr = cumsum(ir);
>> plot(stepr), ...
```





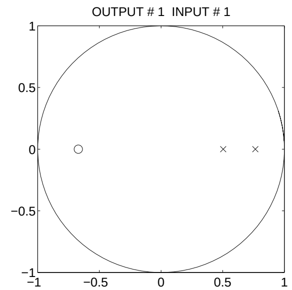
Parametric modeling: ARX model,
$y(t) + a_1 y(t-1) + a_2 y(t-2) = b_1 u(t-3) + b_2 u(t-4)$

```
>> th = arx(z2,[2 2 3]); th = sett(th,0.08);
>> u = dtrend(u2(800:900)); y = dtrend(y2(800:900));
>> yh = idsim(u,th);
>> plot([yh y]), ...
```



Pole zero plot of the model:

```
>> zpth = th2zp(th);
>> zpplot(zpth)
```



Compare the transfer functions obtained from nonparametric and parametric modeling:

```
>> gth = th2ff(th);
>> gs = spa(z2); gs = sett(gs,0.08);
>> bodeplot([gs gth])
```