System Identification

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Course Contents

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Course Contents

Each module contains a set of exercises / quiz that the student should answer before moving on to the next module.

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Module 1

Lecture 1

Objectives of this Module

- To introduce the learner to the subject of system identification and provide an overview of the same
- To introduce the notion of a model and the approach of empirical modelling
- To illustrate the central issues of identification by means of an example
- To outline a procedure for system identification
- To briefly review the various classes of mathematical models

Learning Benefits

At the end of this module, the student should be able to:

- Explain the term system identification and obtain an overview of the subject
- Define the term "model" and outline its uses
- Envisage the need for empirical modelling
- Understand the systematic approach in empirical modelling
- Have a feel for the challenges and limitations of identification

Lectures in this Module

The module contains four (4) lectures:

1. Introduction to Empirical Modelling
2. Step-wise procedure for identification
3. A Quick Tour of Identification
4. Mathematical Descriptions of Systems (Models)

Contents of Lecture 1

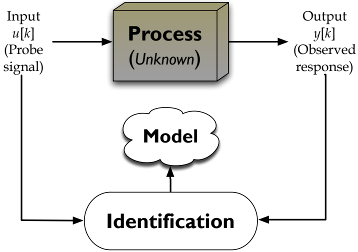
Through this lecture, we shall learn:

- Overview of identification
- Outline of the course

What is Identification?

Identification

Identification is the exercise of building (describing) a relationship between the cause (input) and effect (response) of a system (process) from observed (measured) data



The cause-effect relationship that we develop is termed as a model.

Developing models is crucial to several applications in engineering, science, medicine, social and economic systems.

Examples

1. **Spring-mass system**:
   The objective is to develop an empirical model between the displacement of spring is affected by the load (mass). Such a model can be used to design a suitable spring.
2. **Buffer (liquid level) system**:
   A model relating the changes in inlet flow to the changes in liquid level is built from experimental data. One of the prime uses of this model is in the control of liquid level.
3. **Chemical Reactor**:
   An engineer identifies a model relating the coolant flow and measuring the temperature response for the purpose of controlling the reactor.
4. **Cement Mill**:
   Fineness of cement is not measurable on-line but is rather inferred from other measurements. Identification yields a model, which acts as a "soft sensor" for

Model

A model serves as a good (mathematical) substitute for the process. Models are very useful - simulations using models are very economical, safe and powerful substitutes for experiments. Imagine testing the response of a process under faulty conditions, for which we cannot carry out experiments.

- No model is perfect! - we try to develop as accurate a model as possible.
- Qualitative understanding of a process (human-brain models) are also models.
- However, in automation we need quantitative models so that they can be coded!

A model usually consists of a set of differential (or difference) and algebraic equations

Uses of Models

Models are useful primarily for prediction, which is critical to the design, control, monitoring, soft-sensing, optimization and forecasting of processes.

The end-use requirements determine the model's complexity:

- **Modelling & Design**: To understand and analyse process behaviour; to simulate process systems.
- **Control**: To quantify the effect of manipulated variables and disturbances on the controlled variables.
- **Monitoring**: To obtain a template of the process variations under normal conditions; to perform root-cause diagnosis.
- **Soft-sensors**: To obtain inferential estimates of physical quantities.
- **Optimization**: To identify constraints among decision variables and make optimal decisions
- **Time-series analysis**: Forecasting, prediction, estimation.

Approaches to Modelling

Models obtained from fundamental laws (material & energy conservation, continuity equations, ...) are known as **first-principles models**. However, to build such models we require good knowledge of the physics of process, which is seldom available (for a large class of processes).

The alternative approach is to build models by conducting experiments - such models are known as **empirical models**.

Test drive

Taking a vehicle for a test drive is a simple example of how experiments are a natural way of understanding processes. As the vehicle is subjected to different test (road) conditions, its response is used by the test-driver to develop a "mental model" of the vehicle.

System Identification

> The subject of system identification is concerned with development of (black-box) empirical models from experimental data, with scope for incorporating *a priori* process knowledge

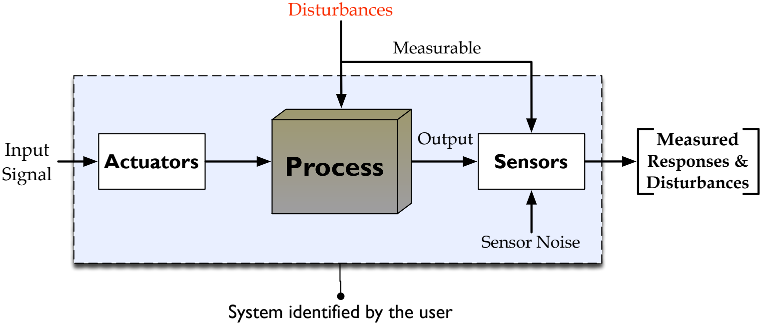
Several processes are too complex to be understood at a fundamental level. Given that industries collect large amounts of data, it is both intelligent and time-effective to build data-based (or data-driven) models.

A Note

- First-principles models are very useful for off-line applications (e.g., simulations).
  - In fact, these models are usually simplified / reduced before their usage in on-line applications.
  - Further, such models are never truly first principles - they contain some empirical correlations
- A point in favour of the experimental approach is that unmeasured dynamics and uncertainties are difficult to handle using a first-principles approach - they have to be empirically modelled.

System identified by the user

- While the attempt is to identify the process, the **actual system** identified consists of **process, actuators, sensors** and the **disturbances** (see schematic below).



- To recover the model of the process from the identified model is an advanced problem known under the name of **continuous-time identification**.

Stochastic and Deterministic Models

Inputs are known (and adjustable) quantities, whereas disturbances/noise are unknown and not accurately predicable (random quantities). This forces us to build two separate sub-models for explaining the output measurement.

- **Deterministic mode**l: This is that part of the model that explains the effect of physical / measured input(s) on the output(s).
- **Stochastic model**: That part of the model which accounts for the unmeasured disturbances and sensor noise

The overall model is a fusion of these two models

Liquid-Level System

For the liquid level system, the deterministic model explains the effects due to changes in inlet flow rate, while the stochastic model explains the effects of measurement noise and disturbances.

The subject of identification

Through a formal study of the subject of identification, we can answer many generic questions that arise in empirical modelling

- What type of models are possible? Which one(s) to choose?
- How do we "fit" a model that "explains" the variations observed in experimental data?
- How to "correctly" account for the deterministic and stochastic effects?
- Will the experiment influence the model that we fit? If yes, how?
- How we we set up and solve the problem of estimating the unknown model parameters?
- What kind of experiments should we design to obtain a good quality model? and several other related questions

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