Systems Dynamics

Course ID: 267MI – Fall 2022

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267MI –Fall 2022

Course Overview

Course Administration

Lecturers & examiners

- Thomas Parisini (parisini@units.it)
- Gianfranco Fenu (fenu@units.it)

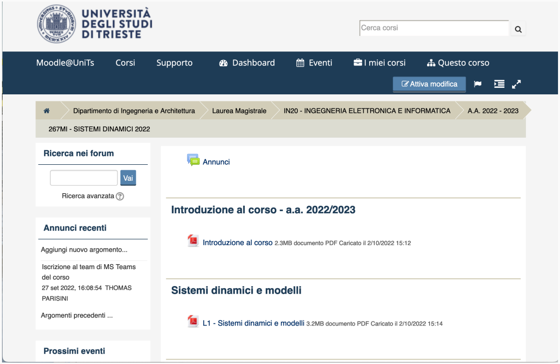
Course home page

- slides, exercises and computer code examples
- old exams

Systems Dynamics homepage

Course credits

- 9 CFU



Examination

- **Final exam**: a preliminary written examination followed by oral questions.
- The **final grade** depends on both the written part and the outcome of the oral discussion.
- Written examination and oral discussion usually usually take during the same exam session.

Examination (cont.)

Written examination

The exam paper consists of 3 – 4 essay questions:

- typical numerical application problems
- specific questions about theoretical aspects (theorems, properties, definitions) could be included

Oral questions

Oral questions deal with any possible topic, discussed and analysed in the lectures.

- A short discussion about the written examination results generally also takes place

Examination (cont.)

Homework (not compulsory)

- Advanced engineering specific projects are offered during the course, characterised by challenges more difficult to address than the usual ones.
- The aim is to stimulate learning advanced concepts during the course also to help the learning exercise
- These projects are then evaluated upon request by the students.
- It's allowed to solve the projects in groups, up to 3 persons.
- Working on homework problems is **not compulsory**

Examination (cont.)

Homework & final grade

- Homework contributes to the final grade, with an increment of the score up to 2 points.
- The grading of the homework is **independent** from the grading of the examination
- Homework expiration: the increment of the final exam score, using the homework grade, is allowed during the current academic year (**for the academic year 2022/2023** until the end of the examination session in **February 2024**). When the exam sessions of the current academic year are over, the homework grade expires.

Exam Sessions

Examination timetable

- 3 sessions in January–February
- 2 sessions in June–July
- 2 session in September

How to sign up for examinations

- In order to participate to the exam session you must sign up/register for the exam **(compulsory)**
- To sign up, use the students university career management system Esse3 to access to the on-line University Services.
- Please, **pay attention** to the dates of the registration periods and the examination periods!

Course Information

Prerequisites

- Linear algebra, calculus and complex analysis
- Course 034IN “Fundamentals of automatic control” (or equivalent for students enrolled from other universities/programs)
- Basic knowledge of probability and statistics is not mandatory, but highly helpful

Course organization

- Lectures
- Exercise sessions

Desiderata

Students who pass the course should be able to:

- carry out a complete and comprehensive analysis of the main properties of deterministic and stochastic discrete-time dynamic systems;
- design and implement parametric estimation and identification, and state estimation algorithms that use available data or data collected in real-time with reference to engineering application scenarios;
- ...

Desiderata (cont.)

Students who pass the course should be able to

- evaluate, among several options, what's the best choice of parametric estimation and identification, and state estimation algorithms starting from requirements and considering technological constraints;
- describe in a clear and plain way the functionalities of a parametric estimation and identification, and state estimation algorithm in the context of discrete-time dynamic systems and with the correct use of technical terminology

Lectures Plan

Lect.	Content
1	Course overview. Generalities: systems and models (defs, props, problems). Sampling and discrete-time representation of linear continuous-time dynamic systems.
2	Time-evolution of state and output of linear dynamic systems.
3	Stability of discrete-time dynamic systems.
4	Model identification from data.
5	A glimpse on prob. theory, random vars and discrete-time stochastic processes.
6	Definitions and properties of the estimation and prediction problems.
	. . .

Lectures Plan (cont.)

Lect.	Content
7	Dynamic models of stationary discrete-time stochastic processes.
8	Least-squares estimation.
9	Bayes estimation.
10	Solution of the prediction problem.
11	Identification Based on Prediction Error Minimization (PEM).
12	Batch PEM Identification Algorithms.
13	State estimation from observed data.

References

References on dynamic systems analysis:

P. J. Antsaklis and A. N. Michel.
Linear Systems.
Birkhäuser, 2006.

G. Calafiore.
Elementi di Automatica.
CLUT, Torino, 2007.
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Teoria dei Sistemi e del Controllo.
Zanichelli, 1989.
(in Italian).

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Teoria dei Sistemi.
CLUP, Milano, 1977.
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References (cont.)

References on data-based estimation and identification:

T. Söderström. P. Stoica.
System Identification.
Prentice Hall, 1989.

L. Ljung.
System Identification – Theory for the User.
Prentice Hall, 1999.

S. Bittanti.
Model identification and data analysis.
John Wiley & Sons, 2019.

S. Bittanti, M. Campi.
Raccolta di Problemi di Identificazione, Filtraggio, Controllo Predittivo.
Pitagora Editrice, Bologna, 1996.
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References (cont.)

References on data-based estimation and identification (cont.):

S. Bittanti.
Teoria della predizione e del filtraggio.
Pitagora Editrice, Bologna, 2000.
(in Italian).

S. Bittanti.
Identificazione dei Modelli e Controllo Adattativo.
Pitagora Editrice, Bologna, 1997.
(in Italian).

Motivating Application Examples

Prediction of Temperature at the Spout of a Glass Furnace Feeder

Prediction of Melted Glass Temperature

- A feeder is the final part of a plant used for melting glass.
- Main purpose: to realize a homogeneous temperature distribution of the glass at some absolute level that allows shaping of the glass.
- Structure: it is divided into several sections in which energy can be supplied to or extracted from the glass, using burners and cooling air.

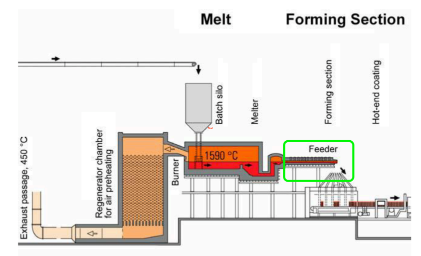


Figure 1: Typical industrial glass production plant, with in evidence the feeder [Source: Verallia Oberland AG]

Prediction of Temperature at the Spout of a Glass Furnace Feeder (cont.)

- The **model** shall capture and describe the **dynamic relations** between the inputs of the feeder (burners and cooling air in the various sections) and the outputs (some glass temperatures close to the outlet).
- The outputs are temperatures of the glass measured at some points in a cross section of the feeder just before the spout.

- Available data: 1247 samples for each input and output variable;
- 3 inputs:
  - input 1: gas input of the first feeder section;
  - input 2: cooling air input;
  - input 3: gas input of the second feeder section;
- 6 outputs: glass temperatures in a cross-section of the feeder, close to the outlet.

Prediction of Temperature at the Spout of a Glass Furnace Feeder (cont.)

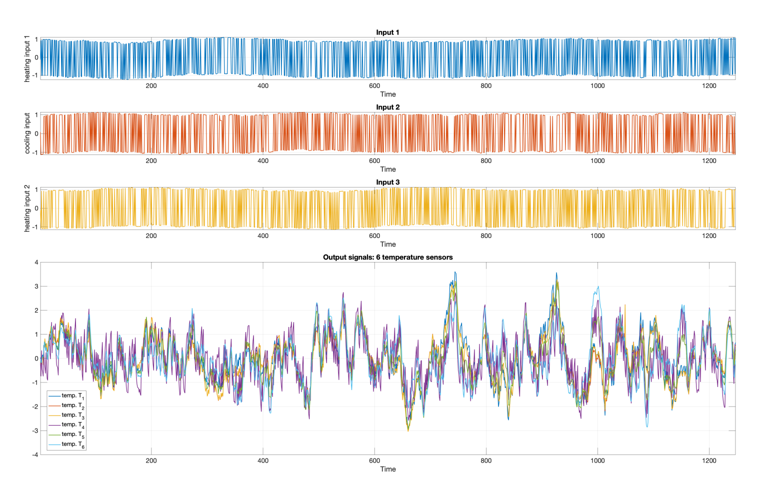


Figure 2: The data have been pre-processed: detrending, peak shaving, scaling.

Prediction of Temperature at the Spout of a Glass Furnace Feeder (cont.)

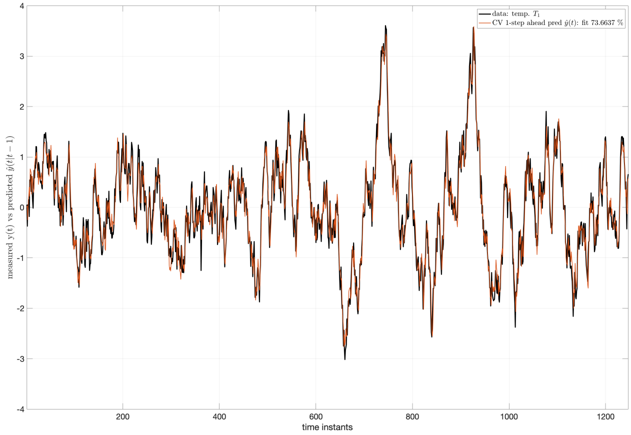


Figure 3: Prediction of the temperature T_1 using the best ARX model according the Cross-validation criterion: fit 73.66 %.

Prediction of Temperature at the Spout of a Glass Furnace Feeder (cont.)

The Model

Discrete-time ARX model: $A(z)y(t) = B(z)u(t) + e(t)$
Polynomial orders: $n_a = 7$, $n_b = [7,\ 5,\ 4]$, $n_k = [1,\ 2,\ 5]$

$$A(z) = 1 - 0.6969z^{-1} - 0.05691z^{-2} - 0.06532z^{-3} - 0.02166z^{-4} - 0.1276z^{-5} - 0.0871z^{-6} + 0.1011z^{-7}$$

$$B_1(z) = 0.02755z^{-1} + 0.07005z^{-2} + 0.05956z^{-3} + 0.03304z^{-4} + 0.02933z^{-5} + 0.03725z^{-6} + 0.02344z^{-7}$$

$$B_2(z) = -0.1006z^{-2} - 0.09078z^{-3} - 0.06914z^{-4} - 0.03442z^{-5} - 0.01503z^{-6}$$

$$B_3(z) = -0.04104z^{-5} - 0.04249z^{-6} - 0.01118z^{-7} - 0.008236z^{-8}$$

SOC Estimation

- A battery management system is responsible for monitoring the **state-of-charge (SOC)** of the battery, among other features.
- The SOC can be estimated using a **Kalman Filter**.

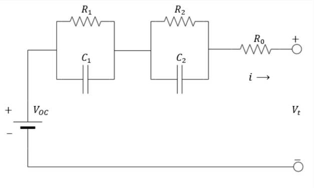


Figure 4: 2^{nd} order RC ECM battery model.

- common **battery model**: 2-RC Equivalent Circuit Model (ECM);
- parameters: the battery Open Circuit Voltage (OCV) as voltage source V_{OC} , the internal resistance R_0 and two parallel RC pairs;
- the ECM parameters depend on the actual SOC value and the battery temperature

A Kalman Filter Based Battery SOC Estimation (cont.)

Appropriate battery tests should be done to obtain data for OCV as a function of SOC for a desired range of battery temperatures.

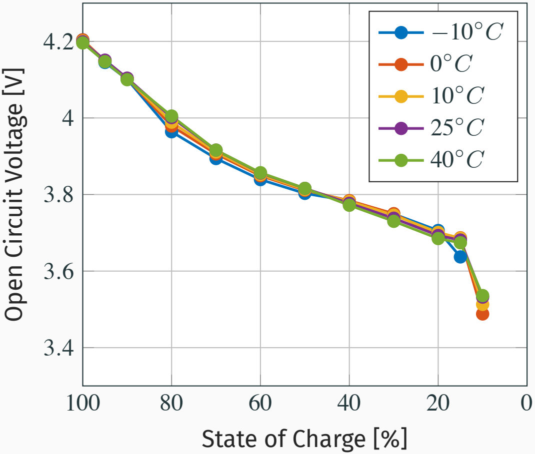


Figure 5: OCV vs. SOC of a Turnigy Graphene 5000mAh Li-ion Battery.

The tests data are used also to estimate the EMC parameters R_0, R_1, R_2, C_1 and C_2 at different temperatures as functions of SOC.

A model-based parameter optimization approach has to be applied.

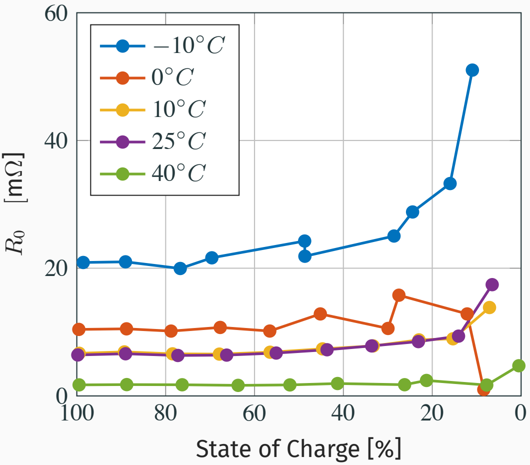


Figure 6: Resistance R_0 vs. SOC of a Turnigy Graphene 5000mAh Li-ion Battery.

Battery as dynamic system: the ECM dynamics is described by

$$\begin{cases} \mathrm{SOC}(k+1) &= \mathrm{SOC}(k) - \dfrac{\eta\,\Delta\, i(k)}{C_n} \\ V_1(k+1) &= e^{\frac{-\Delta}{R_1 C_1}} V_1(k) + R_1\left(1 - e^{\frac{-\Delta}{R_1 C_1}}\right) i(k) \\ V_2(k+1) &= e^{\frac{-\Delta}{R_2 C_2}} V_2(k) + R_2\left(1 - e^{\frac{-\Delta}{R_2 C_2}}\right) i(k) \\ V_{\mathrm{OC}}(k) &= g\Big(\mathrm{SOC}(k)\,,\; T(k)\Big) \\ V_t(k) &= V_{\mathrm{OC}}(k) - V_1(k) - V_2(k) - R_0\, i(k) \end{cases}$$

where Δ is the sampling time interval, k indicates the k-th time instant, η is the Coulombic efficiency, C_n is the battery nominal capacity, i is the battery current (negative when charging, positive when discharging), T is the battery temperature.

The equations are in **state space form** and describe a **non-linear system**: not only V_{OC} depends on the actual SOC and T values, but also the ECM parameters R_0, R_1 etc.

A Kalman Filter Based Battery SOC Estimation (cont.)

An Extended Kalman Filter as SOC Estimator

Assuming that both the state transition and the observation equation sets are affected by additive zero mean multivariate Gaussian noise

$$\begin{cases} x(k+1) = f\big(x(k), u(k)\big) + w(k) \\ z(k) = h\big(x(k), u(k)\big) + \nu(k) \end{cases}$$

where $x(k) = \left[\text{SOC}(k)\,,\ V_1(k)\,,\ V_2(k)\right]^T,\ u(k) = i(k)\,,\ z(k) = V_t(k)$

an **Extended Kalman Filter** may be successfully applied to estimate the SOC value at the k-th time instant, using the measurements of input and output at the same time instant.

A Kalman Filter Based Battery SOC Estimation (cont.)

An Extended Kalman Filter as SOC Estimator

The EKF structure

$$e(k) = \Big[z(k) - h\Big(f\left(\hat{x}\,(k-1|k-1)\ ,\ u(k)\right),\ u(k)\Big)\Big]$$

$$\hat{x}\,(k|k) = f\Big(\hat{x}\,(k-1|k-1)\ ,\ u(k)\Big) + \mathbf{K}_0(k)e(k)$$

$$\mathbf{K}_0(k) = \mathbf{P}(k)\,\mathbf{H}^T(k)\Big[\mathbf{H}(k)\,\mathbf{P}(k)\,\mathbf{H}^T(k) + \mathbf{R}\Big]^{-1}$$

$$\mathbf{P}(k+1) = \mathbf{F}\Big\{\mathbf{P}(k) - \mathbf{K}_0(k)\,\mathbf{H}(k)\,\mathbf{P}(k)\Big\}\,\mathbf{F}^T(k) + \mathbf{Q}$$

where

$$\mathbf{F}(k) = \frac{\partial f}{\partial x}\Big|_{\hat{x}(k-1|k-1)\,,\,u(k)} \qquad \mathbf{Q} = \mathbf{cov}(w)$$

$$\mathbf{H}(k) = \frac{\partial h}{\partial x}\Big|_{\hat{x}(k-1|k-1)\,,\,u(k)} \qquad \mathbf{R} = \mathbf{cov}(\nu)$$

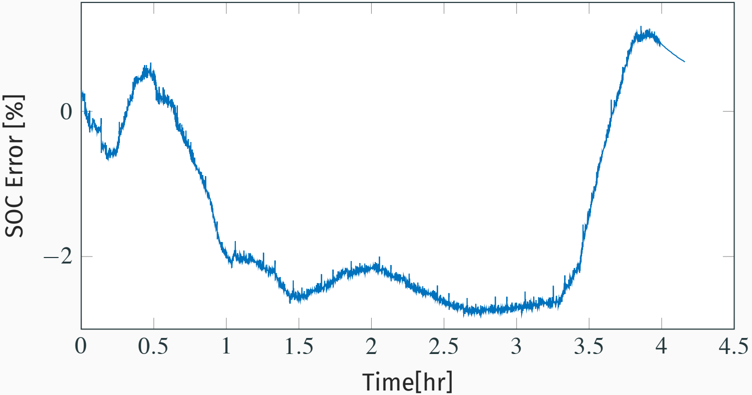
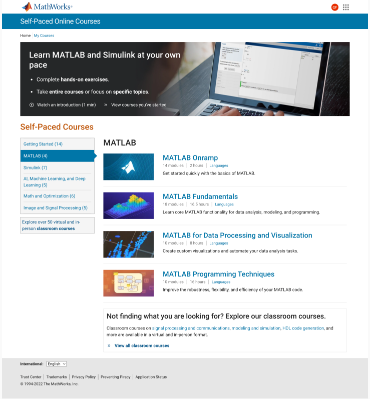


Figure 7: SOC estimation error using EKF filter, applied to a Turnigy Graphene 5000mAh Li-ion battery.

Online Tutorials and Courses on MATLAB

Online courses and tutorials for learning MATLAB fundamentals and programming techniques with online courses:
MATLAB Academy



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