2026
International Graduate School on Control

www.eeci-igsc.eu

M01 LUCCA 02/02/26-06/02/26	*Model Predictive Control: From Theory to Applications Through Numerical Methods*

Paolo Falcone
Electronic Engineering Department
Chalmers University of Technology, Sweden
https://www.chalmers.se/en/departments/e2
falcone@chalmers.se

Mario Zanon
IMT School for Advanced Studies
Lucca, Italy
https://www.imtlucca.it
mario.zanon@imtlucca.it

Abstract of the course

Model predictive control (MPC) is an optimization-based control approach that enables the control of complex nonlinear systems while optimizing a given performance criterion and imposing constraints both on the states and the control inputs of the system. While these advantages are compelling, the main drawbacks are the computational burden which can hinder real-time feasibility, and the fact that asymptotic stability and constraint satisfaction at all future times are not a direct consequence of optimality. A successful practical implementation therefore requires one to carefully formulate the MPC scheme.

This course blends together theory and practice, with the aim of providing the students with the tools that are necessary for designing MPC controllers in practice. On the theoretical side, we will discuss: (i) the theory behind asymptotic stability and recursive feasibility; (ii) the algorithms enabling real-time solvability of the optimization problem; (iii) the combination of MPC with learning algorithms. On the practical side, we will provide several examples of practical implementations, with emphasis on autonomous driving, which will be used to discuss how seemingly abstract theory can be applied to real-world cases. Furthermore, we will provide some hands-on advice on how to design the MPC controller, e.g., how to obtain the desired closed-loop behavior by suitable design of the cost, how to handle perturbations by careful constraint definition, etc.

Topics

- MPC formulation: stability and recursive feasibility
- Optimization: theory, algorithms and their practical implications
- MPC design: tuning, modelling, tricks
- Advanced topics: learning and MPC
- Applications with a focus on autonomous driving

2026
International Graduate School on Control

www.eeci-igsc.eu

M02 PARIS-SACLAY 09/03/26-13/03/26	*Nonlinear and Data-driven* *Model Predictive Control*

Frank Allgöwer
Institute for Systems Theory and Automatic Control
University of Stuttgart, Germany
https://www.ist.uni-stuttgart.de
allgower@ist.uni-stuttgart.de

Matthias A. Müller
Institute of Automatic Control
Leibniz University Hannover, Germany
https://www.uni-hannover.de
mueller@irt.uni-hannover.de

Abstract of the course

Model predictive control (MPC), also called receding horizon control, is a very successful and widely applied modern control technology. Its basic idea is as follows: at each sampling instant, the future behavior of the system is predicted over some finite horizon using some prediction model, and an open-loop optimal control problem is solved to determine the optimal input trajectory over this time horizon. Then, the first part of this optimal input is applied to the system until the next sampling instant, at which the horizon is shifted and the whole procedure is repeated again.
The main advantages of MPC and the reasons for its widespread success include (i) guarantees for closed-loop satisfaction of hard input and state constraints, (ii) the possibility to directly include the optimization of some performance criterion in the controller design, and (iii) its applicability to nonlinear systems with possibly multiple inputs.

In recent years, significant progress has been made in establishing various guarantees of nonlinear model predictive controllers such as closed-loop stability, robustness, and performance. The goal of this course is to give an introduction to the field of nonlinear model predictive control, covering both basic results as well as current research topics such as economic and distributed MPC. Also, purely data-driven predictive control schemes that do not use a (parametric) model of the system will be discussed. The lectures will be accompanied by programming exercises.

Topics

- Stability in MPC with terminal constraints
- Stability and performance in MPC without terminal constraints
- Robust MPC
- Economic MPC
- Data-driven MPC

2026
International Graduate School on Control

www.eeci-igsc.eu

M03 PARIS-SACLAY
16/03/2026 - 20/03/2026

Data-driven and sample-based methods in optimization and control

Summary of the course

In the realm of control engineering, we have traditionally focused on designing systems for stability and optimal performance, often relying on precise models of dynamic behavior. However, the increasing complexity and uncertainty inherent in modern cyber-physical systems demand a departure from purely model-centric approaches. This course is designed to equip you with the essential tools to navigate this evolving landscape.
We will begin by exploring fundamental *data-driven systems* formalisms, laying the groundwork for how these concepts apply to *data-driven control systems*.
The course will then delve into the practicalities of *forecasting and classifying* unknown system behaviors. A significant part of this section will also address *uncertainty quantification*, which is paramount for robust data-driven design.
Moving beyond prediction, we will address the crucial aspect of probabilistic certification. This involves understanding *sample complexity*, exploring concepts of *probabilistic scaling*, and applying iterative methods and the theory of finite families to provide rigorous guarantees on system performance despite data-driven uncertainties.
Finally, we will transition *to optimization in data-driven systems*. Here, we will investigate various first-order methods, delve into the intricacies of *stochastic optimization*, and examine the interplay between optimization and randomization in designing effective controllers. The course will conclude with a look at diverse Applications, including *quartile regression*, the generation of *probabilistic invariant sets*, and the implementation of *stochastic model predictive control*, demonstrating how these methodologies translate into practical solutions for complex control problems.

Teodoro Alamo
University of Seville

Fabrizio Dabbene
CNR-IEIIT

Outline

1. **Introduction**
   i. Data-driven systems formalisms
      a) Regression/classification
      b) Parametric/non-parametric
   ii. Deterministic vs randomized
   iii. Applications in data-driven control systems
2. **Forecasting and classifying**
   i. Kriging
   ii. Kernel methods
   iii. Uncertainty quantification
3. **Probabilistic certification**
   i. Sample complexity
   ii. Probabilistic scaling
   iii. Iterative methods and finite families
4. **Optimization in data-driven systems**
   i. First order methods
   ii. Stochastic optimization
   iii. Optimization and randomization
5. **Applications**
   i. Quartile regression
   ii. Probabilistic invariant sets
   iii. Stochastic model predictive control

2026
International Graduate School on Control

www.eeci-igsc.eu

M04 NANTES 07/04/2026-10/04/2026	*Stabilization of PDEs* *by means of linear or nonlinear feedback laws*

Swann Marx
CNRS, Nantes, France
https://sites.google.com/site/swamarx
Swann.marx@ls2n.fr

Christophe Prieur
CNRS, Grenoble, France
http://www.gipsa-lab.grenoble-inp.fr/~christophe.prieur/
Christophe.prieur@gipsa-lab.fr

Abstract of the course

Partial differential equations (PDEs) are essential for modeling complex systems, with applications ranging from electrical engineering to fluid mechanics and nuclear fusion. Controlling these infinite-dimensional systems requires advanced tools and methodologies. This course provides a comprehensive overview of stability conditions and control design techniques for PDEs. We will cover all major types of PDEs—parabolic, elliptic, and hyperbolic—with a focus on linear dynamics, including boundary control and boundary output with an abstract viewpoint. Among the different control objectives, design of linear and nonlinear stabilizing output feedback controllers is one of the key problems that will be solved during the classes for various systems. A core objective is solving the challenge of designing constrained stabilizing output feedback controllers, using methodologies such as spectral decomposition, the method of characteristics, and Lyapunov functionals—each chosen based on the equation class. Comparisons with existing classical methods for finite-dimensional systems will be drawn all along the courses.

Topics:

- Partial differential equations
- Transport equations
- Reaction diffusion equations
- Semigroup theory
- Lyapunov functionals
- Linear and nonlinear controllers
- Output feedback designs

2026
International Graduate School on Control

www.eeci-igsc.eu

M05 DELFT 13/04/2026-17/04/2026	*Formal Methods in Control Design: Abstraction, Optimization, and Data-driven Approaches*

Calin Belta
University of Maryland, USA
https://calinbelta.com/

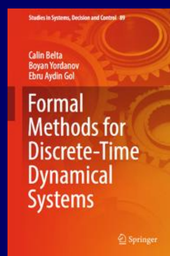
Antoine Girard
CNRS, CentraleSupélec, France
https://sites.google.com/site/antoinesgirard/

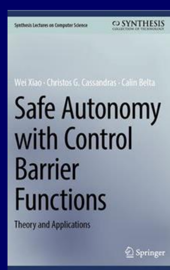
Summary of the course

In control theory, complicated dynamics such as systems of (nonlinear) differential equations are mostly controlled to achieve stability and to optimize a cost. In formal synthesis, simple systems such as finite state transition graphs modeling computer programs or digital circuits are controlled from specifications such as safety, liveness, or richer requirements expressed as formulas of temporal logics. With the development and integration of cyber physical and safety critical systems, there is an increasing need for computational tools for controlling complex systems from rich, temporal logic specifications. The main objective of this course is to present formal methods in control design. We will first present abstraction-based approaches. We will show how continuous dynamics can be formally related (using simulations, bisimulations, approximate bisimulations) to finite abstractions, how finite models can be controlled from temporal logic specifications, and how controllers for the abstractions can be refined into control strategies for the original continuous systems. We will then teach two optimization-based approaches. In the first, we will show how a constrained optimal control problem for a dynamical system with temporal logic specifications can be mapped to (mixed integer) linear or quadratic programs. In the second, we will enforce stability and temporal logic specifications using control barrier functions (CBF) and control Lyapunov functions (CLF). Finally, we will focus on systems with uncertain or unknown dynamics and will show how techniques from adaptive control and reinforcement learning can be used to enforce temporal logic requirements.

Outline

1. The need for formal methods in control design
2. Systems, behaviors and relations among them
3. Abstractions of continuous systems
   - 3.1 Discrete abstractions: partition-based approaches, Lyapunov-based approaches
   - 3.2 Continuous abstractions
4. Abstraction-based controller synthesis
   - 4.1 Safety, reachability, attractivity and recurrence specifications: fixed-point synthesis, quantitative and robust synthesis, compositional synthesis
   - 4.2 Linear temporal logic specifications: Finite temporal logic control, language-guided control systems, optimal temporal logic control
5. Optimization-based synthesis
   - 5.1 Synthesis based on temporal logic quantitative semantics
   - 5.2 Synthesis based on control barrier functions (CBF) and control Lyapunov functions (CLF)
6. Formal synthesis for systems with partially known and unknown dynamics
   - 6.1 Data-driven abstractions
   - 6.2 Data-driven synthesis using CBF and CLF
   - 6.3 Automata-based approaches to safe and interpretable reinforcement learning





2026
International Graduate School on Control

www.eeci-igsc.eu

M06 BIRMINGHAM
13/04/2026-17/04/2026

Game Theory with Engineering Applications

Dario Bauso
University of Groningen
https://www.rug.nl/staff/d.bauso/

Leonardo Stella
University of Birmingham
https://www.leonardostella.com/

Summary of the course

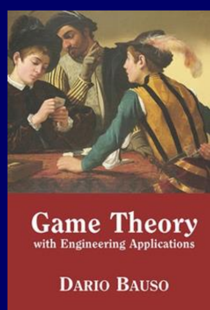
This course is an introduction to the fundamentals of cooperative and non-cooperative game theory. Motivations are drawn from engineering and networked systems (dynamic resource allocation, multi-agent systems, multi-agent learning, cyber-physical systems), and social models (including social and economic networks). The course emphasizes theoretical foundations, mathematical tools, modeling, and equilibrium notions in different environments.

Learning objectives:

1. Choose and implement the most appropriate models and methods to address competition in engineering systems.
2. Analyse the performance measures and optimally design the inputs under deterministic or stochastic, known and unknown parameters of multi-agent systems.
3. Perform numerical analysis and design of small-scale examples on paper.
4. Develop code using Python and MATLAB to perform numerical analysis and design on large-scale examples in game-theoretic engineering applications.

The course is organised in four main topic areas.

- Noncooperative games.
- Cooperative games.
- Evolutionary games.
- Learning in games.



D. Bauso affiliation: Since 2018 I have been with the Jan C. Willems Center for Systems and Control, ENTEG, Faculty of Science and Engineering, University of Groningen (The Netherlands), where I am currently Full Professor and Chair of Operations Research for Engineering Systems. Since 2005 I have also been with the Dipartimento di Ingegneria, University of Palermo.

L. Stella received the Laurea Magistrale degree (equivalent to MSc) in 2016 from Università La Sapienza, Italy, and the Ph.D. degree in 2019 from the University of Sheffield, UK. Since 2022, he is Assistant Professor in the School of Computer Science at the University of Birmingham (UK).

2026
International Graduate School on Control

www.eeci-igsc.eu

M07 TORINO
20/04/2026-24/04/2026

Optimization over networks and collaborative learning

Bahman Gharesifard
Queen's university
https://gharesifard.github.io/

Julien Hendrickx
UCLouvain
https://perso.uclouvain.be/julien.hendrickx/

Summary of the course

This course surveys decentralization in the context of optimization and learning, with focus on modern directions in large-scale machine learning.
We begin with an overview of decentralization in optimization, presenting classical techniques alongside recent communication-efficient methods, where optimization is carried out through structured local updates and fixed communication protocols. In particular, we cover some stochastic and adaptive methods.
We then develop some fundamental limits for distributed computation, highlighting oracle and communication lower bounds, and present some principled and automated analysis frameworks for deriving worst-case performance guarantees and guide the design of efficient methods.
An important theme is non-convex optimization, with applications to in decentralized and federated settings, where stochastic gradient descent (SGD) and adaptive variants are analyzed under heterogeneity, asynchrony, and partial participation. We study convergence guarantees, variance-reduced methods, and adaptive gradient strategies, connecting them to the practice of federated learning across devices with limited resources.
The last part of the course is devoted to robustness and resiliency, addressing Byzantine failures, adversarial models, and privacy-preserving mechanisms critical for federated and edge learning.

Detailed Information will be provided on
https://gharesifard.github.io/eeci/index.html

Outline

1. Decentralization in optimization and learning: an overview of the state-of-the-art
2. Fundamental limits in distributed computations and optimization
3. Focus classical decentralized deterministic technique
4. Focus on adaptive gradient method
5. Focus on stochastic method
6. Automated and principled approach to worst-case analysis
7. Robustness and resiliency in distributed optimization

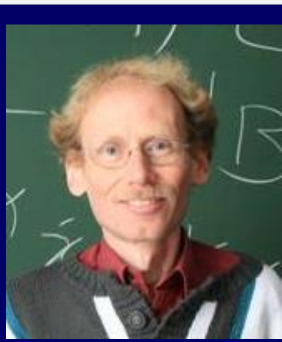
2026
International Graduate School on Control

www.eeci-igsc.eu

M08 BESANÇON
27/04/2026-30/04/2026

Modeling and control of distributed parameter systems: the Port Hamiltonian Approach

Yann Le Gorrec
Université Marie et Louis Pasteur, FEMTO-ST , SupMicroTech , Besançon, France
legorrec@femto-st.fr, http://legorrec.free.fr/wordpress/



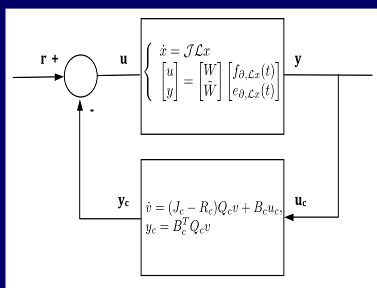
Hans Zwart
University of Twente , Department of Applied Mathematics, The Netherlands
h.j.zwart@utwente.nl
https://people.utwente.nl/h.j.zwart

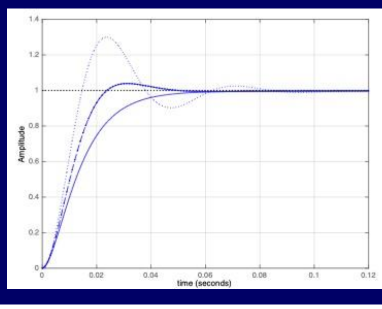
Abstract of the course

This course presents a system control-oriented approach to modeling, analysis, and control of distributed parameter systems (DPS), i.e., systems governed by partial differential equations (PDEs). This class of systems is more and more encountered in cutting edge engineering applications due to the increased use of complex, heterogeneous and smart systems. Analysis and control of DPS is thus of high theoretical and practical interest, especially when considering the evolution of computing capacities that allows to deal with very high order systems. The formalism used in this course is the port-Hamiltonian framework. Well-known in control of nonlinear systems governed by ordinary differential equations, this formalism based on the concepts of energy and power exchanges has been extended to distributed parameter systems. The aim of this course is to show how this formalism can be advantageously used to study and control DPS. For instance, to derive simple (boundary) control laws for the stabilization of un-(or weakly) damped (linear) distributed parameter systems.

Topics

The first part of the course is devoted to modelling. More precisely, it focuses on the derivation of structured models accounting for power exchanges occurring within the system and with its environment. In the second part, existence of solutions, boundary control and stability of linear port-Hamiltonian systems are studied. The third part is concerned with control design. The course ends with a tutorial aiming at applying the different concepts on a practical and realistic example in order to illustrate with simulations the interest of such an approach. The different parts of this course are also illustrated through physical examples such as transmission lines, beam equations, linearized shallow water equations, Korteweg-de Vries equations, reaction-transport problems including chemical processes, population dynamics, etc.





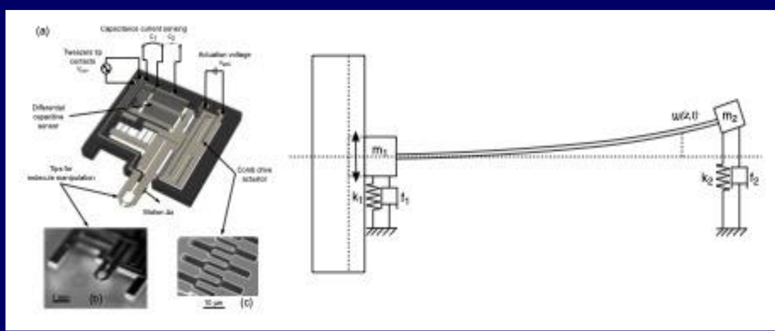
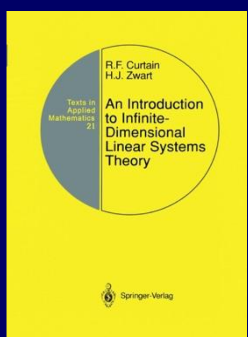


Fig: Modeling, simulation and control of flexible nanotweezers for DNA manipulation

Target audience

This course is devoted to engineers and applied mathematicians looking for an introduction to the modelling and control of distributed parameters systems using the port-Hamiltonian framework.

http://events.femto-st.fr/MCDPS-PHS



2026
International Graduate School on Control

www.eeci-igsc.eu

M09 HAMBURG
04/05/2026-08/05/2026

Data-based systems and control theory

Kanat Camlibel
University of Groningen
https://www.math.rug.nl/~kanat

Paolo Rapisarda
University of Southampton
https://ieeecss.org/contact/paolo-rapisarda

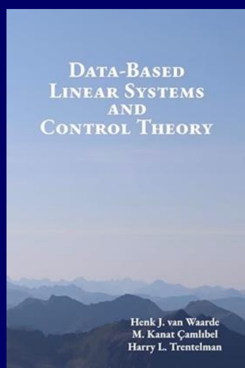
Henk van Waarde
University of Groningen
https://henkvanwaarde.github.io

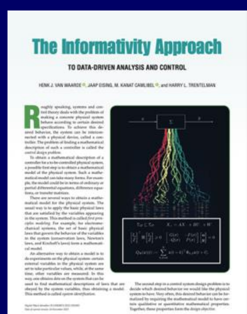
Summary of the course

A common approach to control design involves first obtaining a mathematical model of the to-be-controlled system. This model can take various forms, including ordinary or partial differential equations, difference equations, or transfer matrices. One way to derive a model is through first-principles modeling, which relies on fundamental physical laws governing the system, such as Newton's laws for mechanical systems or Kirchhoff's laws for electrical circuits. An alternative approach is system identification, where experimental data is used to derive a mathematical representation of the system based on observed input-output relationships. However, in many practical scenarios, obtaining an accurate model of a system can be challenging or even infeasible due to system complexity, unknown dynamics, or measurement noise. In such cases, data-driven control offers an alternative paradigm. Rather than relying on explicit mathematical models, data-driven methods synthesize control laws directly from measured data. Ensuring that data-driven methods provide the same stability and performance guarantees as traditional model-based control remains a significant challenge. This course provides a comprehensive introduction to the principles and methods of data-driven control. Students will delve into various methods, such as data-driven stabilization, regulation and predictive control, as well as their theoretical underpinnings like persistency of excitation, the fundamental lemma, and matrix versions of Yakubovich's S-lemma.

Outline

1. Historical perspective
   Subspace identification, fundamental lemma and its applications in data-driven tracking, data-enabled predictive control, and data-based closed-loop parametrization
2. Foundations of data informativity approach
   The data informativity framework, stability and controllability analysis from data, stabilization and linear quadratic regulation by using only data
3. Designing stabilizing controllers using noisy data
   Noise models based on quadratic matrix inequalities (QMIs), Schur complement and its consequences for QMIs, from S-lemma to matrix S-lemma, stabilizing controllers from noisy data
4. Advanced analysis and control
   H-infinity control design by using noisy data, dissipativity analysis from data, stabilization by using only input-output data
5. Analysis and design for continuous-time systems from measurements
   Generalized sampling, orthogonal polynomial bases, data informativity framework for continuous-time systems.
6. **Data informativity for system identification and experiment design**
   Necessary and sufficient conditions for system identification, the problem of experiment design , the shortest experiment for linear system identification





2026
International Graduate School on Control

www.eeci-igsc.eu

M10 TORINO
11/05/2026-15/05/2026

Big Data, Sparsity and GenAI in Control, Systems Identification and Machine Learning

Mario Sznaier
Electrical and Computer Eng.
Northeastern University,
Boston, USA
msznaier@coe.neu.edu

Abstract of the course

One of the hardest challenges faced by the systems community stems from the exponential explosion of data, fueled by recent advances in sensing technology. During the past few years a large research effort has been devoted to developing computationally tractable methods that seek to mitigate the ``curse of dimensionality" by exploiting sparsity.

The goals of this course are:

1) provide a quick introduction to the subject for people in the systems community faced with ``big data" and scaling problems, and

2) serve as a ``quick reference" guide for researchers, summarizing the state of the art .

Part I of the course covers the issue of handling large data sets and sparsity priors in systems identification, model (in)validation and control, presenting techniques that exploit a connection to semi-algebraic geometry, rank minimization and matrix completion. Several applications of these techniques will be discussed, including control and filter design subject to information flow constraints, subspace clustering and time-series classification, including activity recognition and anomaly detection.

Part II of the course focuses on recently developed Generative AI tools. In particular we will discuss how these new techniques can be applied to identification and control problems, what performance guarantees are currently available and open problems where a systems perspective can help.

Topics include:

- Review of convex optimization and Linear Matrix Inequalities
- Promoting sparsity via convex optimization. Convex surrogates for cardinality and rank
- Fast algorithms for rank and cardinality minimization
- Fast, scalable algorithms for Semi-Definite Programs that exploit sparsity
- Sparsity in Systems Identification:
    - Identification of LTI systems with missing data and outliers
    - Identification of Switched Linear and Wiener Systems
    - Identification of sparse networks
- Connections to Machine Learning: subspace clustering and manifold embedding
- Applications: Time series classification from video data, fault detection, actionable information extraction from large data sets, nonlinear dimensionality reduction
- GenAI and Control:
    - Diffusion models: theory and applications to trajectory planning in uncertain environments
    - Transformers and applications to filtering
    - Selective state space models (Mamba)

2026
International Graduate School on Control

www.eeci-igsc.eu

M11 LONDON 18/05/2026-22/05/2026	*Multi-agent optimization and learning: resilient and adaptive solutions*

Nicola Bastianello
KTH, Stockholm, Sweden
nicolba@kth.se
https://bastianello.me

Ruggero Carli
University of Padova, Italy
carlirug@dei.unipd.it
https://automatica.dei.unipd.it/ruggero-carli/

Luca Schenato
University of Padova, Italy
schenato@dei.unipd.it
https://automatica.dei.unipd.it/luca-schenato/

Course website https://sites.google.com/view/eeci-igsc-2026-multi-agent-opt

Summary

Recent technological advances have enabled the widespread adoption of intelligent devices in many applications, such as healthcare, edge computing, transportation, robotics, smart grids. These devices are equipped with communication and computational resources, which allow them to learn from the data they collect. However, in order to improve the accuracy of the models they train, the important paradigm of decentralized learning is being deployed. Therefore, there is a need for algorithmic advances that can support cooperative learning and optimization. The course will provide a thorough introduction to the state of the art in decentralized learning, both with federated and peer-to-peer communication architectures. The course will cover different algorithmic approaches, e.g. gradient-based and dual methods. A particular emphasis will be given to the practical challenges that arise in this context, such as asynchrony and limited communications.

Outline

1. Introduction and motivating examples (healthcare, edge/fog computing, transportation, robotics, smart grids)
2. Decentralized learning and optimization
    - From centralized to decentralized
    - Practical challenges
    - Decentralized cooperative architectures
3. Federated learning
    - Deep learning
    - Privacy and resilience to attacks
4. Consensus and distributed optimization
    - The consensus algorithm: standard, accelerated, push-sum/ratio, broadcast w/ faulty communications
    - Consensus-based distributed optimization: gradient tracking and Newton
    - Non-expansive operators for optimization: background, operator-based algorithms (proximal gradient, ADMM, primal-dual, …)
    - Application to decentralized asynchronous and lossy networks: a stochastic operators approach
5. Current trends
    - Reinforcement learning, Online distributed optimization, Data-driven optimization, Privacy, Human-in-the-loop
    - Frontiers in applications
6. Hands-on coding experiences

2026
International Graduate School on Control

www.eeci-igsc.eu

M12 PARIS
01/06/2026-05/06/2026

An overview on observer design methods for nonlinear systems

Vincent Andrieu
CNRS
sites.google.com/site/vincentandrieu/

Pauline Bernard
Mines Paris - PSL
sites.google.com/site/sitepmbernard/home

Summary of the course

The purpose of this course is to give an **overview** of the main synthesis techniques of state observers for nonlinear dynamical systems. The lecture will start by addressing some general comments on the ``estimation problem'', that is, reconstructing the full information of a dynamical process on the basis of partial observed data. We will then introduce a particular type of algorithm: the asymptotic observer. Some necessary conditions that ensure convergence of the estimate toward the state of the system will be introduced: the detectability and its infinitesimal characterization.

Then, based on a characterization of detectability, a first class of observers will be presented. Some methods to design such observers will be introduced based on numerical methods.

The next part of the course will consist in presenting the main three families of observers based on stronger observability properties:

- **Kalman** and **Kalman-like** observers for state-affine systems, based on a persistence of excitation of the gramian of observability;
- **High-gain observers** and **differentiators**, based on differential observability assumptions;
- **Kazantzis/Kravaris-Luenberger** observers, based on backward distinguishability conditions.

We will show that each class of observer relies on transforming the plant's dynamics in a particular normal form which allows the design of an observer. We will explain how each observability condition guarantees the invertibility of its associated transformation and the convergence of the observer. The most important and informative proofs will be detailed, and the advantages/drawbacks of each design discussed.

At the end of the course, we will study some implementation issues and open problems.
For instance, the case of time discretization of the output will be considered. Another issue related to the left inversion problem in observers will also be discussed.
Finally, we show how an estimate given by the observer may be used in combination with a stabilizing state feedback in order to guarantee asymptotic stabilization of the origin by means of output feedback.

Throughout the course, the various concepts encountered will be illustrated with examples and followed by homework assignments designed to enhance their understanding.

ELSEVIER
Annual Reviews in Control
Volume 53, 2022, Pages 224-248

Tutorial article

Observer design for continuous-time dynamical systems

Pauline Bernard a, Vincent Andrieu b, Daniele Astolfi b

Show more

Add to Mendeley Share Cite

https://doi.org/10.1016/j.arcontrol.2021.11.002

Get rights and content

2026
International Graduate School on Control

www.eeci-igsc.eu

M13 SEVILLE
08/06/2026-12/06/2026

Time-Delay and Sampled-Data Systems



Emilia Fridman
School of Electrical & Computer Engineering
Tel Aviv University, Israel
https://www.emilia.sites.tau.ac.il/
emilia@tauex.tau.ac.il

Pierdomenico Pepe
Dipartimento di Ingegneria e Scienze dell'Informazione e Matematica
University of L'Aquila, Italy
https://www.disim.univaq.it/PierdomenicoPepe/218/
pierdomenico.pepe@univaq.it

Alexandre Seuret
Departamento de Ingeniería se Sistemas y Automática
University of Sevilla, Spain
https://prisma.us.es/investigador/8241
aseuret@us.es

Abstract of the course

Time-delay appears naturally in many control systems. It is frequently a source of instability although, in some systems, it may have a stabilizing effect. A time-delay approach to sampled- data control, which models the closed-loop system as continuous-time with delayed input/output, has become popular in networked control systems (where the plant and the controller exchange data via communication network). The beginning of the 21st century can be characterized as the "time-delay boom" leading to numerous important results. The aim of this course is to give an introduction to systems affected by time-delays, in both the linear and the nonlinear framework. The emphasis of the course is on the Lyapunov-based analysis and design for time-delay, sampled-data and networked control systems.

Topics

Models of systems with time-delay and basic theory. Sampled-data and networked-control systems. LTI systems with delay: characteristic equation. Stability and performance analysis. Direct Lyapunov approach: Krasovskii and Razumikhin methods. An LMI approach to stability and performance. Control design: predictor-based control, LQR problem, LMI-based design. Stabilization by using delay. Systems with saturated actuators. Discrete-time delay systems. Networked control systems: a time-delay approach. A time-delay approach to averaging-based control. Nonlinear retarded systems with inputs: basic theory, stability, input-to-state stability. Stabilization by means of control Lyapunov-Krasovskii functionals. Universal stabilizers. Sampled-data stabilization of nonlinear retarded systems.

2026
International Graduate School on Control

www.eeci-igsc.eu

M14 LEUVEN 15/06/2026-19/06/2026	***Deep Learning for System Identification***

Dario Piga
Dalle Molle Institute for Artificial Intelligence,
SUPSI, Lugano, Switzerland
https://leon.idsia.ch/people

Marco Forgione
Dalle Molle Institute for Artificial Intelligence,
SUPSI, Lugano, Switzerland
https://leon.idsia.ch/people

Summary of the course

In recent years, deep learning has advanced at a tremendous pace and is now the core methodology behind cutting-edge technologies such as image classification and captioning, autonomous driving, natural language processing and generation. One exciting and challenging application field for deep learning is the learning of dynamical systems, also known as system identification. In this field, tailor-made model architectures and fitting criteria should be designed to: retain structural physical knowledge when available; introduce regularization to avoid overfitting or enforce known relationships among variables; and optimize training efficiency by leveraging parallelization as much as possible. The objective of this course is to introduce deep learning concepts and recently developed tools for system identification, including meta learning concepts for automated learning of the identification procedure itself. The course combines theoretical lectures and hands-on practical sessions in PyTorch.

Outline

1. Introduction to system identification and deep learning
2. Feedforward and recurrent neural networks for system identification
3. Numerical optimization algorithms for training neural networks
4. Integrating system theory in deep learning
5. Meta-learning

Target audience

Students, researchers, and practitioners who want to understand how complex system identification problems can be formulated and solved using modern deep learning techniques.

Basic knowledge of Python can be beneficial to better follow hands-on practical sessions.

2026
International Graduate School on Control

www.eeci-igsc.eu

M15 OXFORD 15/06/2026-19/06/2026	*Biological Control Systems*

Armin Baumschlager
Lonza, Switzerland

Corentin Briat
FHNW, Switzerland
www.briat.info

Jean-Baptiste Lugagne
University of Oxford, UK
jblugagne.gitlab.io

Summary of the course

Biological control is a growing field at the intersection of control theory, systems biology, and synthetic biology. While already being applied, it holds significant potential for further advances in healthcare, biomanufacturing, agriculture, and ecology. This course introduces researchers to the theoretical and experimental foundations of natural regulatory mechanisms in living organisms, and their practical implementations via synthetic biology and cell-machine interfaces.

This intensive week-long course is designed for students, scientists, and researchers with backgrounds in biology, engineering, or mathematics. It provides a comprehensive introduction to recent advances in biological control within systems and synthetic biology. Emphasizing a rigorous bottom-up approach, the course integrates foundational concepts from mathematics, control theory, and the life sciences, progressing toward practical implementation. Delivered by leading experts in the field, the program offers an interdisciplinary perspective that is essential for modern bioengineering but rarely addressed in conventional academic curricula. Designed to be interdisciplinary and highly interactive, this module provides participants with the conceptual framework and practical tools needed to understand, analyze, design, and implement control strategies in living systems. This will ultimately translate into advances in biomedical research and biotechnology.

Outline

Day 1. The course begins with an introductory presentation of the module followed by two parallel refresher tracks tailored to students' backgrounds. One track introduces key mathematical and control theory concepts for students with a life sciences background. The other introduces essential biological terminology and ideas for students with a technical background. The day wraps-up with a common discussion and Q&A session as a final preparation for the main part of the course.

Day 2. Theoretical foundations of biological control systems are presented. Topics include reaction networks, noise and stochastic models for genetics circuits, noise-induced behaviors, analysis of stochastic models and ergodicity, homeostasis and perfect adaptation, as well as primers on biological control systems such as single cell and cellular population control.

Day 3. Focus shifts to in-silico control. Students will explore the interface between synthetic biology, control engineering, and machine learning, particularly deep learning methods used in modeling and design of in-silico control for biological systems, for both single-cell and population control.

Day 4. The emphasis moves to in-vivo control strategies, combining experimental synthetic biology with principles of control theory to derive, analyze and implement controllers aimed to be implemented inside living cells using biological components.

Day 5. The final day is dedicated to open discussions on adjacent research questions, unresolved challenges, and real-world applications of biological control systems.

2026
International Graduate School on Control

www.eeci-igsc.eu

M16 OXFORD
22/06/2026-26/06/2026

Optimization and Control of Complex Multi-Agent Systems

Kostas Margellos
University of Oxford
https://eng.ox.ac.uk/people/kostas-margellos/

Alessandro Falsone
Politecnico di Milano
https://falsone.faculty.polimi.it/

Maria Prandini
Politecnico di Milano
https://prandini.faculty.polimi.it/

Summary of the course

Current operations in energy and transportation are experiencing a transition to new operational paradigms that exhibit certain complexity features. Complexity involves challenges associated with: (i) coordinating operations among heterogenous interacting entities without sharing information considered as private; (ii) robustness against uncertainty; (iii) the ability to deal with an interplay of continuous and discrete scheduling decisions. This course provides a theoretical and computational framework for coordination and optimal operation of complex systems, addressing the aforementioned features of complexity. We first draw motivation from the energy sector, formalizing several of the current operational challenges as multi-agent optimal control and optimization problems. We then introduce and analyze a portfolio of algorithms capable to deal with the three main complexity pillars, with emphasis on distributed optimization over networks, addressing also the case where both continuous and discrete decisions are involved. Finally, we consider the case where uncertainty affects the underlying systems and show how data-driven algorithms based on statistical learning theory and randomized optimization can be extended to a multi-agent setting.

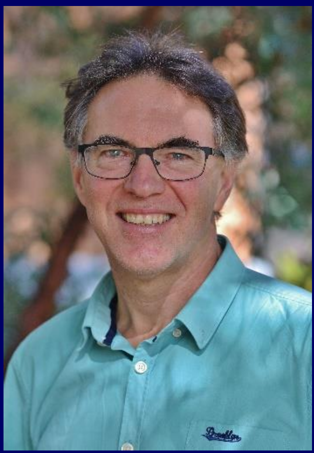
Course outline

1. Motivation of decision making in complex systems
   - Energy systems operations: Aggregation of distributed energy resources; demand response; electric vehicle scheduling; building energy management
2. Mathematical preliminaries on optimization and iterative algorithms
3. Distributed algorithms for multi-agent decision making
   - Continuous domains: Primal-based algorithms (proximal methods; projected sub-gradient methods) and primal-dual algorithms (distributed alternating direction method of multipliers; distributed dual decomposition) for constrained optimization over networks.
   - Discrete domains: Primal-dual algorithms for resource sharing problems
4. Data-driven algorithms for optimization under uncertainty
   - The scenario approach to optimization under a learning theoretic lens
   - Probabilistic robustness in multi-agent decision making problems
5. Research vistas

2026
International Graduate School on Control

www.eeci-igsc.eu

M17 ZARAGOZA 22/06/2026-26/06/2026	*Equivariant Systems Theory and Observer Design for Autonomous Systems*



Robert Mahony
Systems Theory and Robotics group
The Australian National University
Robert.Mahony@anu.edu.au
http://users.cecs.anu.edu.au/~Robert.Mahony/

Jochen Trumpf
Systems Theory and Robotics group
The Australian National University
jochen.trumpf@anu.edu.au

Tarek Hamel
Laboratoire d'Informatique de Signaux et Système de Sophia-Antipolis (I3S), CNRS-UNSA, France
thamel@i3s.unice.fr
http://www.i3s.unice.fr/~thamel/

Abstract of the course

The functionality of any autonomous system depends critically on its ability to estimate its dynamic state. For robotic systems, with limited sensor suites, highly dynamic motion, non-linear state space, and limited computational capacity, the state observer performance is even more important. A key technology enabler underlying the explosion of small scale commercial aerial robotic systems was the development of high quality, simple, robust, attitude observers based on the underlying equivariant symmetry structure of the attitude estimation problem.

This course provides an introduction to emerging field of *Equivariant Systems Theory* and applies these techniques to the design of observers for autonomous systems. The approach taken is highly practical, starting from matrix calculus and Lie theoretic foundations from an engineering perspective and working through a number of examples to demonstrate how to model equivariant systems and use the symmetry to derive robust observers. The course is based around an extensive suite of case studies drawn from aerial robotic applications including; attitude estimation, velocity aided attitude estimation, pose estimation, homography estimation, SLAM and Visual Odometry. Students will come out of the course with a strong understanding of how to derive and implement equivariant observers and filters for real world robotic systems.

Topics:

1) Perspectives on observer design for autonomous systems.
2) Matrix calculus and matrix ODEs.
3) Lyapunov observer design for systems with matrix Lie-group state.
4) Dealing with practical issues, velocity bias, asynchronous measurements and delays.
5) Equivariant Systems Theory.

Practical work in this course uses MATLAB (or equivalent scripting language such as Python) extensively. Students are required to have a working system on their own laptop for the course.

2026
International Graduate School on Control

www.eeci-igsc.eu

M18 PARIS-SACLAY
29/06/2026-03/07/2026

Bootcamp for Supervisory Control of Discrete-Event Systems, with Hands-On Python Software Tool

Kai Cai
Osaka Metropolitan University
https://www.caikai.org

Summary of the course

Supervisory control theory of discrete-event systems (DES) provides a rigorous framework for the analysis and control of complex, event-driven systems such as automated manufacturing, warehouse, traffic, and more recently AI-driven systems. Unlike continuous-time systems governed by differential equations, DES evolve through discrete states and event-driven transitions. This course introduces the fundamentals of DES and their supervisory control, from automaton models to closed-loop control synthesis, with a strong emphasis on hands-on learning. Students will explore automaton creation, system properties, synchronous product, controllability, and optimal supervisory control. A key feature of the course is the integration of **PyTCT**, a Python-based software tool developed for teaching, simulation, and design of supervisory controllers. Through guided exercises, students will not only understand theoretical concepts but also acquire hands-on skills to design correct, nonblocking, and optimal controllers for DES.

Outline

1. Introduction and Modeling of DES
- Discrete-event dynamics: states, events, transitions
- Automaton representation and modeling principles
- Software tool: PyTCT

2. Properties of Automata
- Reachability, coreachability, trimness, nonblocking
- Behavioral analysis and structural properties
- Implementation and verification with PyTCT

3. Composition of Systems
- Synchronous product of automata
- Modeling multi-component and multi-agent systems
- Conflict detection and resolution

4. Supervisory Control Loop
- Control requirements and specifications
- Supervisor synthesis for closed-loop systems
- Case studies: safety enforcement, resource allocation

5. Controllability and Optimality
- Controllability: definition and characterization
- Supremal controllable sublanguages
- Optimal supervisory control design using PyTCT

6. Advanced Topics
- Observability
- Distributed control of multi-agent systems
- Data-driven approaches