CS Group orientation meeting

Control Systems, Department of Electrical Engineering

September 20, 2019
Program

- 15.00-16.40 Presentations
- 16.40-16.50 Questions & answers - Student can talk to individual presenters
CS Group Overview
CS Group

Prof. Paul Van den Hof
Prof. Siep Weiland
Dr. Tijs Donkers
Dr. Mircea Lazar
Dr. Roland Toth
Dr. Leyla Özkan
Dr. Sofie Haesaert
Dr. Maarten Schoukens
Prof. Hans Butler (ASML)
Prof. Henk Jan Bergveld (NXP)
CS Group

Control is:

• Making systems smart (intelligent...)
• Combining (multi)physical modeling with data-driven (machine) learning
• Implementing smart (optimization) algorithms
• Dealing with interconnected / networked / distributed / multi-agent systems
• On the interface between EE / ME / Math / ChemEng / CompSc
• Dominant in key industries: high-tech systems, automotive systems, energy systems, industrial production, robotics, drones
• Becoming more complex/challenging because of multiple sensing/actuation
• A key player in AI for Engineering Systems (new TU/e institute EAISI)
• Always providing terrific job opportunities
Strategy and Vision

High Tech Systems

Energy

Process

Automotive
CS Group Labs

• Dynamic Networks: Data-Driven Learning and Control - Paul Van den Hof
• Dynamics and Control for Electrified Automotive Systems – Tijs Donkers
• Autonomous Motion Control Lab – Sofie Haesaert
• Formal methods for control of cyber-physical systems – Sofie Haesaert
• Machine Learning for Modelling and Control – Roland Toth & Maarten Schoukens
• Smart Process Operations and Control Lab (SPROC) – Leyla Özkan
• Constrained Control of Complex Systems (C3S) – Mircea Lazar
• Spatial-Temporal Systems for Control – Siep Weiland
• Control of High-Precision Mechatronic Systems - Hans Butler
Paul Van den Hof

Dynamic Networks: Data-Driven Learning and Control
Introduction – dynamic networks

Decentralized process control

Smart power grid

Autonomous driving

Metabolic network

Brain network

Hydrocarbon reservoirs

- www.envidia.com
- Hillen (2012)
- Mansoori (2014)
- Pierre et al. (2012)
Introduction

Overall trend:

• (Large-scale) interconnected systems
• With hybrid dynamics (continuous / switching)
• Distributed / multi-agent type monitoring, control and optimization problems
• Data is “everywhere”, big data era
• Modelling / machine learning problems will need to consider this
Introduction

Distributed / multi-agent control:

With both physical and communication links between systems $G_i$ and controllers $C_i$

How to learn models from data in such a setting?
Dynamic network setup

\[ r_i \text{ external excitation} \]
\[ v_i \text{ process noise} \]
\[ w_i \text{ node signal} \]
Dynamic network setup

Many new data-driven learning questions can be formulated:

- Learning of a local module (known topology)
- Learning of the full network dynamics
- Identifiability
- Topology estimation
- Sensor and excitation allocation
- Fault detection
- Experiment design
- User prior knowledge of modules
- Scalable algorithms
- Relation with distributed control
- Switching elements
- Physics-based models
Particular projects

• Machine learning tools for local module identification; algorithm development

• Structure learning (application in brain network)

• Data-driven modelling of interconnected systems for distributed/multi-agent control

• Physically coupled systems, e.g. power networks
Dynamics and Control for Electrified Automotive Systems
My research interests:

• Computational aspects of control
• The role of sampling in identification and control

Fundamentals:

• Distributed Optimization
• Model Predictive Control
• Linear Matrix Inequalities
• Hybrid Systems (discrete/continuous-time)
Vehicle Energy Management

Complete Vehicle Energy Management (CVEM) with Eco-driving

- Minimization of energy consumption
- Distributed optimization
- Optimal velocity profiles
- Non-convex optimization problems
Energy Management / Autonomous Vehicles

Eco-driving for Urban Environments
Battery Management

Modelling and Parameter Estimation

to better understand estimation methods
to better understand battery chemistries

Optimal fast charging / cell balancing
tradeoff between vehicle range and battery lifetime
Networked Control Systems

Communication network introduces delays, losses, etc.

- System identification in presence of delays, losses, etc
- Controller and communication protocol codesign / sampled-data control
Autonomous Motion Control Lab

New lab facilities

With scaled race cars, drones and a motion capturing system
Autonomous Motion Control Lab

MSc projects

- Energy optimal autonomous vehicle
- Identify vehicle model parameters
- Safely teaching an AI to fly a drone

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Sofie Haesaert

Formal methods for control of cyber-physical systems
Formal Methods for Control of Cyber-Physical Systems

Cyber-physical:
Increasing connectivity, functionality, complexity and autonomy in control systems

How do you engineer these systems?

Delivery drones (amazon)
Credit: drwe.com

Autonomous driving
Credit: Amber

Smart grid
Credit: unsplash

Long term autonomy
Credit: NASA/JPL-Caltech
Cyber-physical:
Increasing connectivity, functionality, complexity and autonomy in control systems

How do you engineer these systems?

1. Avoid human design errors by automating control design
   - No tuning/rules of thumb
   - Complex specifications
   - + performance specifications

2. Test design to find control errors
   - Design tests to find dangerous errors
   - After implementation
   - Find optimal solutions
Formal Methods for Control of Cyber-Physical Systems

1. Avoid human design errors by automating control design
   - No tuning/rules of thumb
   - Complex specifications
   - + performance specifications

2. Test design to find control errors
   - Design tests to find dangerous errors
   - After implementation
   - Find optimal solutions

Mathematics
- Proof-based methods
- Discrete math
- Temporal logics

Classical Control
- Lyapunov stability
- Optimal control
- Hybrid control

Computational aspect
- Use & create open source tools
- Python (and Matlab)
1. Automating control design

Digital Specifications
Temporal logic spec
e.g., $\psi := \text{avoid } A \text{ until } K$
and eventually visit $L$.

Automatically design control
Solve control problem
with digital spec.
+ continuous dynamics

Physical model
- Wind & temperature
- Component failure
- Human behavior

Abstraction
Physical domain
Digital
Refine solution

TU/e
Long term autonomy on Mars

Capability-aware temporal logic planning

Obtain samples & avoid hazards
- Get potential samples
- Avoid potential hazards

With rover-copter team
- Explore with copter
- Science tasks with rover

2. Design tests to find control errors

How do you test whether a system is safe?
- All operating conditions
- Model inaccuracies & degradation
- Environment scenarios

Testing problem
Efficiently design inputs for control systems to show erroneous behavior

Find optimal test strategy

Apply input

Get failure
1. Avoid human design errors by automating control design
   • “Safety-first performance second – automated control design”

2. Find control errors
   • “Experiment design for conformance testing”
   • “Testing as an (optimal) control problem”
Roland Toth

Machine Learning for Modelling and Control
Research Focus - Linear Parameter-Varying Systems

The Engineers’ Dream:
How to use “simple” linear control for NL systems with performance guarantees?

Local approximation principle

Local synthesis:
Gain scheduling (interpolated LTI control)

Global embedding principle

Global synthesis:
Multipath feedback linearization (NL control)
Research Focus - Linear Parameter-Varying Systems

Current topics:
• Automated model conversion tools
• Data–driven modeling tools (NL and LPV identification)
• Control design ($H_\infty$/$H_2$, MPC, Auto-PID)
• LPVcore toolbox

Current applications:
• High-tech systems (motion and thermal control: wafer stage, robots, ball-bot)
• Automotive (engine control, suspension)
Research Focus – High-tech systems

- High-precision motion-control and thermal control problems
  - nm-accurate moving magnet actuator

- Autonomous vehicles (learning, motion control, navigation, machine vision)
Research Focus – Machine Learning

• Machine learning based identification and control

  Reinforcement learning  ANN & GP based learning  Deep learning

• Symbolic regression based modeling & control

  AI-based Motion Control  Learning of Thermal and Mechanical dynamics  Safe Learning
Maarten Schoukens

Machine Learning for Modelling and Control
Nonlinearities & Data-Driven Modelling

Nonlinearities are Everywhere

1: asmpacific.com
2: ampleon.com
3: dialog-semiconductor.com
Nonlinearities & Data-Driven Modelling

How to Model, Design and Control Nonlinearities in a System?

1: asmpacific.com
2: ampleon.com
3: dialog-semiconductor.com
Nonlinearities & Data-Driven Modelling

Fusing machine learning and model-based control engineering!
Deep Learning for Dynamical Systems

Push the Frontier of the possible in Nonlinear Data-Driven Modelling

- Large-Scale Systems
- Parameter Initialization
- Structure Detection

Autoencoder-Based Deep Learning for Nonlinear System Identification

MSc Internship / Graduation project
Machine Learning For Feedforward Control

Gaussian Process Learning
+ Feedforward Control

Position-Dependent Dynamics
Friction
Manufacturing Variations
Parameter Variation over Time

Machine Learning based Motion Control of Wire Bonders

Improved Performance!

Ongoing MSc Internship
Radio Receiver Characterization

Applied System Identification

Performance Parameters Extraction

Microcontroller Implementation

Chip Response Identification

Ongoing MSc Internship
Many More

Non-linear modelling of an electric car motor

MSc Internship / Graduation project

(Leuven, Belgium)

Non-linear state-space estimation of photo-electrochemical water splitting cells

MSc Internship / Graduation project

Differ

Dutch Institute for Fundamental Energy Research

(Online) Identification of Vehicle Model Parameters (Autonomous Motion Lab)

MSc Graduation project

Siemens

TU/e
Break
Leyla Özkan
SMART PROCESS OPERATIONS and CONTROL Lab

CS Orientation

Leyla Ozkan, Assistant Professor

Electrical Engineering Department
SMART PROCESS OPERATIONS and CONTROL Lab

CS Orientation

Leyla Ozkan, Assistant Professor

Electrical Engineering Department
(Fine) chemicals
Pharmaceuticals
Bio based

Energy Systems
Contractors & suppliers
Waste water treatment
Waste incineration

Food industry

Petrochemicals
Refinery
glas, steel cement ceramics

Gelderlander.nl

www.glasbrancheorganisatie.nl
en.wikipedia.org
beeldbank.rws.nl
www.saangineers.com
www.gelderlander.nl

Sasol, Secunda SA

Petrochemicals

Shorehill Capital
Disruptions, Major Trends & Challenges (Past-Present)

- Oil embargo of 70’s (Model Predictive Control)
- Climate Change (Low Emissions) (Data Analytics)
- Industry 4.0 (Data Analytics)
- Circular Economy (Near Zero Waste) (Multiple sources)
- Green Transition (Multiple sources)
- Electric Cars (decoupling of energy from chemicals)
- Energy Transition (electrochemistry)

- Tightly integrated physical network
- Wide range of feedstock
- Dynamic multiple energy sources and market prices (agile operation)
- Decentralized production (batch operations)
- Dynamics is unavoidable
Modeling for Model Based Operation Support Technology

- Multiphase (liquid, gas, solid, emulsions)
- Complex dynamics (reactions, varying timescales)
- Large number of physical parameters

- Rigorous Modeling, Hybrid Modeling
- Identifiability analysis and model maintenance
- Simple models suitable for online operation
- Keeping physical knowledge intact
- Experiment design for parameter estimation and model adaptation

![membranes](image)

- milk
- acidification
- crystallization
Model Based Operation Support Technology

Topics of interest:

- Performance monitoring
- Maintenance prediction
- Autonomous testing:
  - Autonomous test-signal design
  - Productivity preserving testing
  - Stealth MPC
- Autonomous MPC tuning:
  - Loop shaping for MPC
  - Autonomous auto-tuning

Extensive testing
Model Based Operation Support Technology

- Several layers of decision making
- Limited interaction/information exchange between layers
- Different models and objectives for each layer

- Smart Interaction between scheduling and control for
  - Flexible operation
  - Increased uptime
  - Improved closed loop performance at unit/enterprise level

Current and Future Projects
Real-Time Scheduling and Control of Complex Dynamical Systems (RESCCoDyS)
NWO-Open Programme Application Collaboration
DSCS TUDelft and CS TU/e
Supported by: ASML, Vande Vult, OCE, TBA Group:
  - Smart Interaction between planning and control for
  - Flexible operation,
  - Increased uptime
  - Improved closed loop performance at unit/enterprise level
Model Based Operation Support Technology

• Moment Based Model Predictive Control for Robust Operation
  • Controller operates in Real Time
  • Applied to Large Scale Industrial Systems
  • Low Complexity
  • Risk Aware
Integration of Design, Operations and Control

Flexible production;
Dynamics considered in the design stage

MSMPR Crystallizer

Optimal sensor and actuation;

Intensified Reactor
Project Example: Model Learning Predictive Control for Batch Processes

- Developing models suitable for online use
  - LPV models based on physical knowledge
- Learning technology to adjust model and batch recipe
Project Examples: Plasma Controlled Thermoacoustic

Thermoacoustic coupling in a combustion chamber

Pulsed nanosecond discharge, showing periodic plasma behavior

1. Modeling of Flame dynamics with ozone
2. Modeling for control
3. Control design
Project Examples: Parameter estimation for process system models

**Challenges**

- Determination of most important parameters
- Optimal input design for parameter identification
- Improvement of model identifiability in closed-loop

Unconstrained optimal input design for parameter estimation
Dynamic Modeling

\[ \frac{dC}{dt} = S_c r X \]
\[ \frac{dX}{dt} = \mu X \]
\[ r_{M,i} = \phi_i k_i^{\max} \prod_j \frac{C_j}{K_{C,i} + C_j} \]

- Based on Physical principles
- Large number of parameters
- Highly non-linear

Transformation of substrates into products by microorganisms

Control strategies

- Model Predictive Control
- Distributed Control
- Forced Periodic Operation

Soft sensors

- Data-driven
- Online data
- Model-based
- Observers

Project Examples: Modeling, Control and Monitoring of bio-processes

Transformation of substrates into products by microorganisms

Optimization

Project Examples: Modeling, Control and Monitoring of bio-processes
Predictive Control in Brainport Smart District

Optimizing and control of Energy and Water consumption while preserving occupant’s comfort.
Project Example: Model Predictive Control for Simple Distillation Columns

- Modeling for Control
  - (wave equation, two-time constant model, data driven)
- Model based control design

Internships/graduation projects on the demonstration column in one of the CE-labs (with reservation)

CS-DC, STW 1.158
We like to cooperate

Internal & external academic groups

Students

SPROC
Smart Process Operations and Control Lab
Dr. Mircea Lazar

Constrained Control of Complex Systems (C3S)
Introduction

Real-life systems are subject to safety-critical constraints!

An airplane cannot descent beneath the earth
Introduction

How can you handle constraints?
Lyapunov functions

- **Lyapunov functions**: 1892 ... 2019
Lyapunov functions

- **Lyapunov functions:** 1892 ... 2019

- **MSc topics:**
  - Stabilizing control of high-frequency power converters
  - Cancer therapy based on multiple Lyapunov functions
  - Safety verification of intelligent feedforward controllers for industrial linear motors (including controller design using neural networks and ILC)
  - Learning Lyapunov functions from data
  - ...

![Diagram of Lyapunov functions](image)
Lyapunov functions

**Tools:**
- Construction of Lyapunov functions
- Domain of attraction estimation
- Stabilization of equilibria

\[ \dot{V}(x) = V(x) f(x) < 0, \forall x \in S \]

**Application:**
- Evolutionary disease models
  - tumor growth
  \[ \begin{align*}
  \dot{N}_N &= R_N N_N - \frac{R_N}{K_N} N_N^2 - \frac{R_N \alpha_{NT}}{K_N} T_N N_N \\
  \dot{N}_T &= R_T N_T - \frac{R_T}{K_T} N_T^2 - \frac{R_T \alpha_{TN}}{K_T} T_N N_N
  \end{align*} \]
- Therapy outcome prediction
- Therapy design - immunotherapy
- Model validation stage – *collaboration with SPS, EE or other departments and medical centers*
Introduction

How else can you handle constraints?
MPC

• Model predictive control: 1978 ... 2019
MPC

- Model predictive control: 1978 ... 2019

- MSc topics:
  - Learning MPC (mechatronics, drones, robots)
  - Distributed MPC (power systems, thermal control, platooning)
  - Data-driven MPC (skip the model, use data directly)
  - MPC for fuel efficiency optimization in hybrid trucks
  - ...

Siep Weiland

Spatial-Temporal Systems for Control
Controlling complexity

Growth of complexity of engineered systems

- Increasing demands on accuracy
- Spatial-temporal models
- Multi-physics aspects in manufacturing
- Networks of interconnected systems
- Complex control architectures
- Scope of systems and control field enlarges

Research themes:

- Model order reduction
- Model reduction for parameterized systems
- Scalable, flexible, versatile modeling tools
- Modular approaches in modeling
- Preservations of physical laws
- Design optimization
- Distributed optimization
- Identification/control of networked systems
- ...
3D concrete printing in outdoor environments

Topic:
Nozzle position control for 3D outdoor concrete printing

Tasks:
Implementation of control strategy
- Extend model with cable dynamics
- Develop dual stage control system
- Implementation on prototype

Collaboration: Rohaco (Nieuwegein)
Coaches: Siep Weiland, Jelle Overtoom, TUDelft

3D printing of concrete (TU/e)
Thermal FEM model order reduction on Philips products

Accurate thermal modeling for design optimization

Topic: Model reduction for parametrized systems

Tasks: Development and application of model reduction strategies for parametrized systems.

Collaboration: Philips Innovation Services

Coaches: Siep Weiland, Joris Oosterhuis, Rob van Gils
Validation and control of low heat capacity drying belt

Topic:
Drying of paper in a printing process

Tasks:
Heater control for consistent quality
- control architecture
- modeling and model validation
- optimization

Collaboration: Oce, Venlo

Drying of paper in an industrial printing process

Coaches: Siep Weiland, Amritam Das, Amol Khalate
Design and implementation of control strategies in thermo-fluidic components

Topic:
Real-time implementation of control in a benchmark print-head.

Tasks:
Control design on a benchmark printhead
- Formulate performance criteria
- Choice of control architecture
- Implementation and validation

Collaboration: Oce (Venlo)
Coaches: Siep Weiland, Amritam Das, Amol Khalate
Nonlinear state-space estimation of PEC water splitting cells

Topic:
Understanding splitting H\textsubscript{2}O in H and O

Tasks:
- Understanding physiochemistry
- Develop system identification algorithms
- Use voltage modulation to estimate parameters

Collaboration: Differ

From solar energy to storable fuel

Coaches: Siep Weiland, Maarten Schoukens, Matthijs van Berkel