CHEM-E7190
2020-2021

Aalto University

Process dynamics and control

CHEM-E7190 (was E7140), 2020-2021

Francesco Corona (¬_¬)

Chemical and Metallurgical Engineering
School of Chemical Engineering

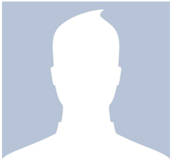
Overview

We study the mathematical principles and basic computational tools of state-feedback and optimal control theory to manipulate the dynamic behaviour of process systems

- Understanding of feedback control
- Examples from process systems
- (Catchy image from the internet)

The approach is general with application domains in many (bio)-chemical technologies

Overview (cont.)



Process control and automation at Aalto University

Francesco Corona

- ⇝ Professor of process control and automation
  - Once and future chemical engineer
  - Camouflaged as computer scientist

Research+teaching on **computational** and **inferential thinking** of process systems

- ⇝ **Automatic control and machine learning**
  - **Three doctoral students**
  - **Three master's students**
- ⇝ Production planning and optimisation

Formal methods from automatic control, statistics, and optimisation, plus applications

Overview (cont.)

- ⇝ Dynamic process modelling and state-space representations
- ⇝ Introduction to state-feedback and optimal control
- ⇝ Introduction to state estimation

Outcome 1

- How to write and analyse a mathematical description of a process system

⇝ The model will be expressed as a set of differential equations

Outcome 2

- How to design/synthetise controllers to manipulate the process system

⇝ The design will be based on optimal state-feedback control

Outcome 3

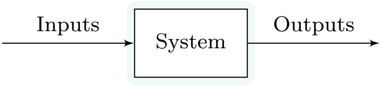
- How to design estimators to reconstruct the process state from data

⇝ The design will be based on optimal state feedback control

Trajectory

Input-output (I/O) process modelling of process systems

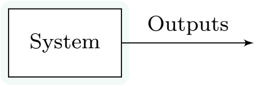
I Control variables and disturbances
O Measurement variables, the data
⇝ The system evolves in time
⇝ (System/model/process)



Ordinary differential equations and matrix algebra

- Force-free response (no inputs)
- Numerical integration

⇝ Stability

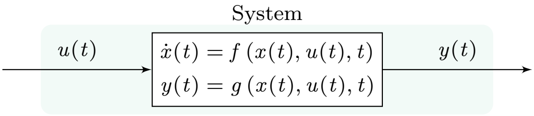


Trajectory (cont.)

State-space (SS) process modelling

I/O Inputs u, outputs y

S State variables x



The dynamics of the state vars are represented by some function f

- Function f returns $\dot{x}(t)$ at time t, given $x(t)$, $u(t)$, and t

How the state vars are transformed into measurements, function g

- Function g returns $y(t)$ at time t, given $x(t)$, $u(t)$, and t

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In general, function f and g may change in time (f and g will change with time t)

- Typical of process operated under varying conditions
- Important, but we will not discuss those explicitly

$\rightsquigarrow$ $\dot{x}(t) = f(x(t), u(t), \cancel{t})$

$\rightsquigarrow$ $y(t) = g(x(t), u(t), \cancel{t})$

Trajectory (cont.)

Functions f often derived from a process modelling effort: Mass and energy balances

$$\underbrace{[\text{Stuff in}] - [\text{Stuff out}] + \backslash - [\text{Stuff generated/consumed}]}_{f(x,u)} = \underbrace{[\text{Stuff accumulated}]}_{\dot{x}}$$

Functions g often determined by the automation system: Sensors and instruments

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By definition, the system/model itself is an approximation of the true/real process

$\rightsquigarrow$ We will often need to accept even additional approximations

- Oftentimes, this is a necessary step to be able to proceed
- Otherwise, the mathematics would be too complicated

Trajectory (cont.)

Approximated process dynamics (linear and time-invariant)

- Function f becomes two matrices

$$f(x(t), u(t)) \approx Ax(t) + Bu(t)$$

- Function g becomes two matrices

$$g(x(t), u(t)) \approx Cx(t) + Du(t)$$

System

$$u(t) \longrightarrow \boxed{\begin{aligned}\dot{x}(t) &= Ax(t) + Bu(t)\\ y(t) &= Cx(t) + Du(t)\end{aligned}} \longrightarrow y(t)$$

Linearisation of nonlinearities around steady-states

- $\rightsquigarrow$ First-order Taylor approximations
- $\rightsquigarrow$ The work-horse of modernity
- $\rightsquigarrow$ Leading tech, since 1700's

Trajectory (cont.)

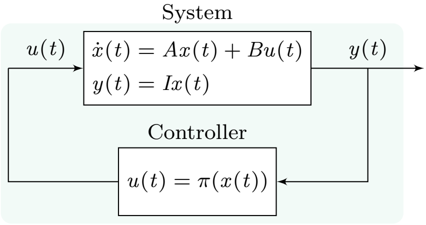
From (approximated, linear) process dynamics to state-feedback control

We will make some initial assumptions

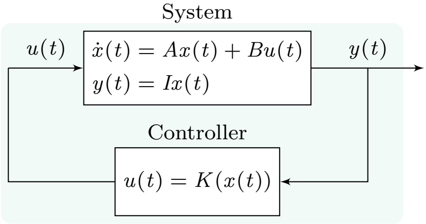
- We can measure the states $x(t)$
- We define control actions $u(t)$

$\rightsquigarrow$ The (static) controller, π

$\rightsquigarrow$ Controllability



State-feedback optimal control (again linear dynamics, plus quadratic costs)



We introduce performance measures

- Control accuracy

$$\left\| x(t) - x_{\text{target}} \right\|_Q^2$$

- Control effort

$$\left\| u(t) - u_{\text{reference}} \right\|_R^2$$

Trajectory (cont.)

Optimal state-feedback, estimation, and control (again, linear and quadratic)

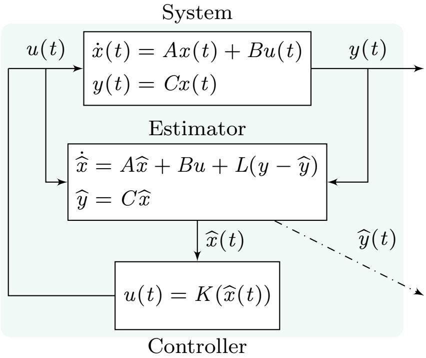
We will relax some initial assumptions

- Cannot measure the states $x(t)$
- Must estimate them, from data

$\rightsquigarrow$ The estimator, φ

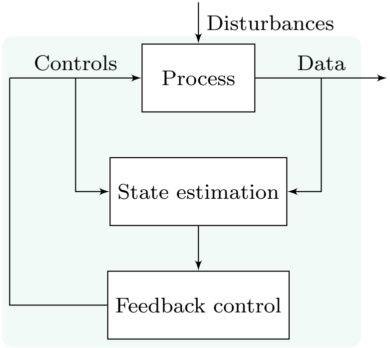
$\rightsquigarrow$ Observability

We then define control actions, $u(t)$



Trajectory (cont.)

Optimal state-feedback, estimation, and control (the general framework)



A general structure, each block can be treated using different technologies

- First-principles (physics)
- Empirical (data-derived)

It scales (it can be solved) reasonably well with the process size (complexity)

Process machine learning, methods for sensing, learning, reasoning, and actuating

Trajectory (cont.)

Sensing, ‘observing, getting measurements’

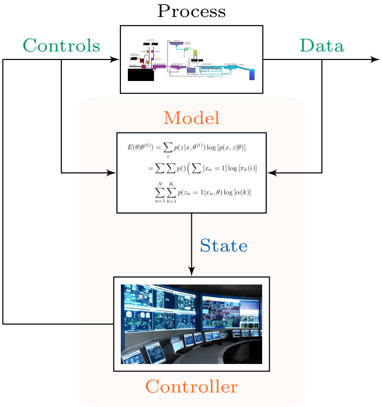
Learning, ‘making statistical inferences’

Reasoning, ‘making optimal decisions’

Actuating, ‘implementing decisions’

Process ML is applied **automatic control**, **optimisation**, **statistics**

⇝ For **chemical engineering**



Key factor is that the approach needs be automatic, interpretable, general and efficient

- Full-scale industrial and environmental systems (that is, constraints)

Why should I care? An example: Control4Reuse

Present wastewater treatment technologies are designed to produce a disposable WW

- Discharged wastewater is expected to be poor in solids and nutrients
- Low carbon (C), nitrogen (N) and phosphorus (P) concentration

Increasing water scarcity requires us to reuse treated WW, a non conventional resource

- At present there exists no standardised solution for urban WWTPs that explicitly aim at delivering a treated wastewater that fulfils the requirements for reuse

⇝ In agriculture (high N and P contents and absence of micro-pollutants, pathogens and antibiotic resistant bacteria (ARB), and antibiotic resistance genes (ARG)

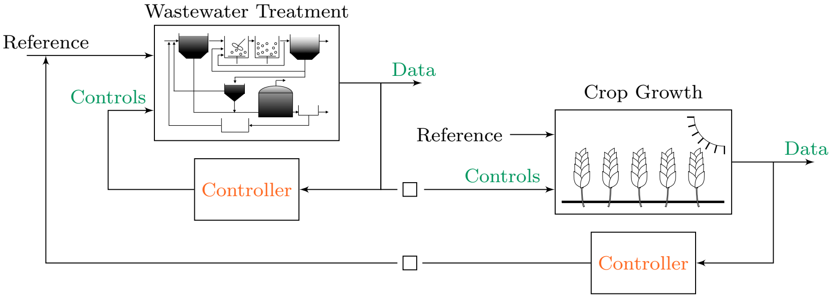
Most of water withdrawal goes to agriculture

Can we operate a large-scale WWTP to produce water for reuse, on demand?

Wastewater not as a waste but as a resource

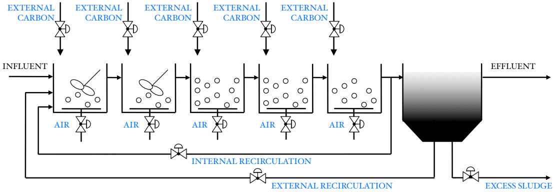
Water JPI

Control4Reuse (cont.)

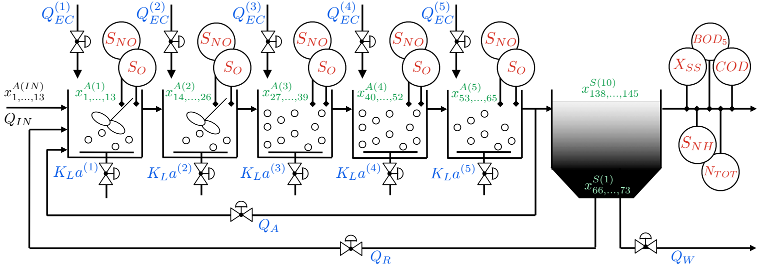


Benchmark Simulation Model no. 1 (BSM1)

- 5 bio-reactors (ASMs)
- 1 settler (TAKACS')



Control4Reuse (cont.)



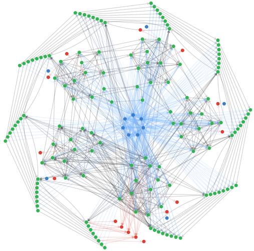
Analysis of the dynamics and control flexibility of activated sludge plants

⇝ **Full-state controllability**

⇝ **Full-state observability**

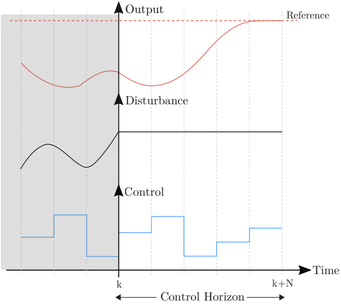
⇝ **Online optimal control**

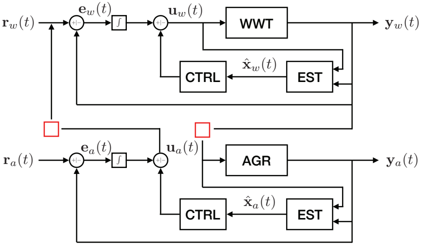
Neto et al. ECC (2020) and IFAC (2020)



Control4Reuse (cont.)

- ASPs are controllable but unobservable, in a structural sense
- ASPs are uncontrollable and unobservable in a classical sense





- A cascade of optimal controllers

There will be a guest seminar on how to control wastewater treatment plants for reuse

- Most probably, on NOV 27 (you'll get properly notified about the exact date)

Overview

CHEM-E7190 is a set of **lectures (approx. 24h)** and **exercises (approx. 24h)**

- The primary objective is to provide a modern view on process control system
- The boundary between lectures and exercises will be intentionally fuzzy

W01 (44)	**Introduction, process models**		
27/10 (14-16)	L (was E)		Intro + Process system analysis
29/10 (10-12)	L (was E)		Process system analysis (II)
W02 (45)	**State-space models, simulation**		
03/11 (12-14)	L		Dynamical processes as ODEs
03/11 (14-16)	E		Exercises (Matrix algebra)
05/11 (10-12)	E		Exercises (Modelling + simulation)
06/11 (12-14)	L		Dynamical processes as ODEs
W03 (46)	**Process dynamics, linearisation**		
10/11 (12-14)	L		Linearisation of nonlinear process models
10/11 (14-16)	E		Exercises (Simulation + linearisation)
12/11 (10-12)	E		Exercises (Steady-states + linearisation)
13/11 (13-15)	L		Controlled processes and state-feedback
W04 (47)	**Process control using state feedback**		
17/11 (12-14)	L		State-feedback and controllability
17/11 (14-16)	E		Exercises (Open-loop stability)
19/11 (12-14)	E		Exercises (Controllability + reachability)
20/11 (12-14)	L		Linear quadratic regulator, LQR
W05 (48)	**State estimation and feedback control**		
24/11 (12-14)	L		State estimation and observability
24/11 (14-16)	E		Exercises (Evalues placement + closed-loop stability)
26/11 (12-14)	E		Exercises (LQR controllers)
27/11 (12-14)	L		Dynamics and control of ASP (Guest seminar)
W06 (49)	**Estimation, conclusion**		
01/12 (12-14)	L		State estimation, Luenberger observers
01/12 (14-16)	E		Exercises (Observability + detectability)
03/12 (12-14)	E		Exercises (Luenberger observers)
04/12 (14-16)	L		Recap + Outro

Lectures/exercise schedule will be modified to accommodate the class needs

Overview (cont.)

To pass E7190 you must return all the exercises (80%) and participate (20%)

Exercises (80%)

- One (1) written report with your solutions
- Include your results and your code
- Include high-quality diagrams
- Discuss your solution/code

⇝ Pick your DL, notify FC

⇝ By **DEC 04, 23:59:59**

Upload a (1) single (1) file, only use PDFs[1]

Participation (20%)

- Engage with the course activities
- Comment on the lecture notes
- Find and report typos/bugs

We encourage you to collaborate in figuring out answers and help others solve the problems, yet we ask you to submit your work individually and to explicitly acknowledge those with whom you collaborated. We are assuming that you take the responsibility to make sure you personally understand the solution to work arising from collaboration

[1] If you have multiple files, merge them. If you use MSWord or else, save as PDF.