Knowledge-Based Control Systems
(SC4081)

Lecture 1: Introduction

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Lecture Outline

1. General information about the course
2. Conventional control – a refresher
3. Intelligent control
4. Introduction to fuzzy sets
Course Information
Knowledge-Based Control Systems (SC4081)

• **Lecturers:**
  - Alfredo Núñez, weeks 3.01, 3.02 and 3.03
  - Hans Hellendoorn, Wednesday week 3.04
  - Robert Babuška, Monday week 3.05
  - Jens Kober, Wednesday week 3.05

• ** Assistants:**
  - Sachin Navalkar
  - Vahab Rostampour

• **Lectures:** (9 lectures = 18 hours)
  – Monday (15:45 – 17:30) in lecture hall Chip at EWI
  – Wednesday (15:45 – 17:30) in lecture hall Chip at EWI
• **Examination**: (check yourself the dates and times!):
  
  – 15 April 2015, 9:00-12:00.

  Exam constitutes 60% of the final grade, remaining 40% are two assignments: **literature and Matlab assignment**

• To obtain the credits of this course:
  
  Each activity must be approved.
Matlab Assignment

Objectives:

- Get additional insight through Matlab implementation.
- Apply the tools to practical (simulated) problems.

The assignment consists of three problems: fuzzy systems, fuzzy control and neural networks modeling.

Work in groups of two students, more information later.

Will be handed out on **February 25, 2015**, report deadline **April 8, 2015**
Literature Assignment

Objectives:

- gain knowledge on recent research results through literature research
- learn to effectively use available search engines
- write a concise paper summarizing the findings
- present the results in a conference-like presentation

Deadline paper – **March 18, 2015**
Symposium: Reserve the whole day **April 1, 2015**, Oude Lagermuseum

Work in groups of four students.

Choose subject via Blackboard → SC4081 → Literature assignment – Do it this week!
Goals and Content of the Course

knowledge-based and intelligent control systems

1. Introduction to intelligent control
2. Fuzzy sets and systems
3. Data analysis and system identification
4. Knowledge based fuzzy control
5. Artificial neural networks
6. Control based on fuzzy and neural models
7. Basics of reinforcement learning
8. Reinforcement learning for control
9. Applications
Course Material

- **Lecture notes:** Robert Babuška: *Knowledge-Based Control Systems*. TU Delft, 2010 (available from NextPrint)

- **Items available for download at:**
  - www.dcsc.tudelft.nl/~SC4081
    - Transparencies as PDF files
    - Demos, examples, assignments with Matlab/Simulink

- **Blackboard**

  The entire content of the lecture notes will be examined!
Where to run Matlab

- At your home PC: Matlab Classroom Kit (you can download it from Blackboard).

- Computer rooms at 3mE.

- Computer rooms of other faculties (e.g., at Drebbelweg)
Prerequisites, Background Knowledge

- Mathematical analysis
- Linear algebra
- Basics of control systems (e.g., Control Systems)
Conventional Control

A Refresher
Process to Be Controlled

\[ d \]

\[ u \] \hspace{2cm} \text{Process} \hspace{2cm} y \]

\[ y : \text{variable to be controlled (output)} \]
\[ u : \text{manipulated variable (control input)} \]
\[ d : \text{disturbance (input that cannot be influenced)} \]

\textbf{dynamic system}
Examples of “Processes”

● technical (man-made) system
Examples of “Processes”

• technical (man-made) system
• natural environment
Examples of “Processes”

- technical (man-made) system
- natural environment
- organization (company, stock exchange)
Examples of “Processes”

- technical (man-made) system
- natural environment
- organization (company, stock exchange)
- human body
Examples of “Processes”

- technical (man-made) system
- natural environment
- organization (company, stock exchange)
- human body
- . . .
Classical Control Design

Disturbances

Process

u

y
Classical Control Design

Disturbances

\[ u \to \text{Process} \to y \]

Modeling

Mathematical model
Classical Control Design

Goal (reference) => Controller => Disturbances

Synthesis

Mathematical model

Modeling

Controller

Process

u

y
How to Obtain Models?

- **physical (mechanistic) modeling**
  1. first principles \(\rightarrow\) differential equations (linear or nonlinear)
  2. linearization around an operating point

- **system identification**
  1. measure input–output data
  2. postulate model structure (linear–nonlinear)
  3. estimate model parameters from data (least squares)
Modeling of Dynamic Systems

$x(t)$ ... state of the system

summarizes all history such that if we know $x(t)$ we can predict its development in time, $\dot{x}(t)$, for any input $u(t)$

linear state-space model:

$$\dot{x}(t) = Ax(t) + Bu(t)$$
Modeling of Dynamic Systems

\( x(t) \) ... state of the system

summarizes all history such that if we know \( x(t) \) we can predict its development in time, \( \dot{x}(t) \), for any input \( u(t) \)

linear state-space model:

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Bu(t) \\
y(t) &= Cx(t) + Du(t)
\end{align*}
\]
Continuous-Time State-Space Model

\[
\dot{x}(t) = Ax(t) + Bu(t) \\
y(t) = Cx(t) + Du(t)
\]
Discrete-Time State-Space Model

\[
x(k + 1) = \Phi x(k) + \Gamma u(k) \\
y(k) = C x(k) + D u(k)
\]
Discrete-Time State-Space Model

\[
x(k + 1) = \Phi x(k) + \Gamma u(k) \\
y(k) = C x(k) + D u(k)
\]
Input–Output Models

Continuous time:
\[ y^{(n)}(t) = f \left( y^{(n-1)}(t), \ldots, y^{(1)}(t), y(t), u^{(n-1)}(t), \ldots, u^{(1)}(t), u(t) \right) \]

Discrete time:
\[ y(k + 1) = f(y(k), y(k - 1), \ldots, y(k - ny + 1), \ldots, u(k), u(k - 1), \ldots, u(k - nu + 1)) \]
System Identification

\[ \text{Process} \]

\[ u \rightarrow \text{Process} \rightarrow y \]
System Identification

Input data

$u \rightarrow y$

Process
System Identification

Input data

\[ u(1), u(2), \ldots, u(N) \]

Process

Output data

\[ y(1), y(2), \ldots, y(N) \]
System Identification

Given data set \( \{(u(k), y(k)) \mid k = 1, 2, \ldots, N\} \):

1. **Postulate model structure, e.g.:**

\[
\hat{y}(k + 1) = ay(k) + bu(k)
\]
System Identification

Given data set \( \{(u(k), y(k)) \mid k = 1, 2, \ldots, N\} \):

1. **Postulate model structure, e.g.:**
   \[
   \hat{y}(k + 1) = ay(k) + bu(k)
   \]

2. **Form regression equations:**
   \[
   y(2) = ay(1) + bu(1) \\
y(3) = ay(2) + bu(2) \\
\vdots \\
y(N) = ay(N - 1) + bu(N - 1)
   \]

   in a matrix form: \( y = \varphi[a \ b]^T \)
3. Solve the equations for \([a \ b]\) (least-squares solution):

\[
y = \varphi [a \ b]^T
\]
3. Solve the equations for \([a \ b]\) (least-squares solution):

\[
\mathbf{y} = \varphi [a \ b]^T \\
\varphi^T \mathbf{y} = \varphi^T \varphi [a \ b]^T
\]
3. Solve the equations for \([a \ b]\) (least-squares solution):

\[
y = \varphi [a \ b]^T
\]

\[
\varphi^T y = \varphi^T \varphi [a \ b]^T
\]

\[
[a \ b]^T = [\varphi^T \varphi]^{-1} \varphi^T y
\]
3. Solve the equations for \([a \ b]\) (least-squares solution):

\[
\begin{align*}
y &= \varphi [a \ b]^T \\
\varphi^T y &= \varphi^T \varphi [a \ b]^T \\
[a \ b]^T &= [\varphi^T \varphi]^{-1} \varphi^T y
\end{align*}
\]

Numerically better methods are available (in MATLAB \([a \ b] = \varphi \ \backslash \ y\)).
Classical Control Design

Goal (reference) → Controller → Process → y

Disturbances → Process

Synthesis → Controller

Modeling → Mathematical model
Design Procedure

- **Criterion** (goal)
  - stabilize an unstable process
  - suppress influence of disturbances
  - improve performance (e.g., speed of response)

- **Structure** of the controller

- **Parameters** of the controller (tuning)
Taxonomy of Controllers

- Presence of feedback: feedforward, feedback, 2-DOF
- Type of feedback: output, state
- Presence of dynamics: static, dynamic
- Dependence on time: fixed, adaptive
- Use of models: model-free, model-based
Feedforward Control

Controller:

- (dynamic) inverse of process model
- cannot stabilize unstable processes
- cannot suppress the effect of \( d \)
- sensitive to uncertainty in the model
Controller:

• dynamic or static (≠ inverse of process)
• can stabilize unstable processes (destabilize stable ones!)
• can suppress the effect of \( d \)
Proportional Control

Controller:

- **static gain** $P$: $u(t) = Pe(t)$
Controller:

- **dynamic**: \( u(t) = Pe(t) + I \int_0^t e(\tau)d\tau + D \frac{de(t)}{dt} \)

- \( P, I \) and \( D \) are the **proportional, integral and derivative gains**, respectively
$u(t) = Pe(t) + I \int_0^t e(\tau)d\tau + D\frac{de(t)}{dt}$
PID Control: Internal View

\[ u(t) = P e(t) + I \int_0^t e(\tau) d\tau + D \frac{de(t)}{dt} \]
State Feedback

Controller:

- **static**: $u(t) = Kx(t)$
- $K$ can be computed such that $(A + BK)$ is stable
- $K_{ff}$ takes care of the (unity) gain from $r$ to $y$
Model-Based Control

- state observer
- model-based predictive control
- adaptive control
Motivation for Intelligent Control
Pro’s and Con’s of Conventional Control

+ systematic approach, mathematically elegant
+ theoretical guarantees of stability and robustness

− time-consuming, conceptually difficult
− control engineering expertise necessary
− often insufficient for nonlinear systems
Additional Aspects

- control is a multi-disciplinary subject

- human factor may be very important
  - pilot
  - plant operator
  - user interface (e.g., consumer products)

- quest for higher machine intelligence
When Conventional Design Fails

- no model of the process available
  - mathematical synthesis and analysis impossible
  - experimental tuning may be difficult

- process (highly) nonlinear
  - linear controller cannot stabilize
  - performance limits
Example: Stability Problems

\[ \frac{d^3 y(t)}{dt^3} + \frac{d^2 y(t)}{dt^2} + \frac{dy(t)}{dt} = y^2(t)u(t) \]

Use Simulink to simulate a proportional controller (nlpid.m)
Example: Stability Problems

\[
\frac{d^3 y(t)}{dt^3} + \frac{d^2 y(t)}{dt^2} + \frac{dy(t)}{dt} = y^2(t)u(t)
\]

Use Simulink to simulate a proportional controller (nlpid.m)

Conclusions:

• stability and performance depend on process output
• re-tuning the controller does not help
• nonlinear control is the only solution
Intelligent Control

techniques motivated by human intelligence

- fuzzy systems (represent human knowledge, reasoning)
- artificial neural networks (adaptation, learning)
- genetic algorithms (optimization).

⇒ computational intelligence, soft computing
Knowledge Representation by If–Then Rules

If $x$ is *Medium* then $y$ is *Large*
Artificial Neural Networks

Function approximation by imitating biological neural networks.

Learning, adaptation, optimization.
Genetic Algorithms

Optimization by imitating natural evolution.
Intelligent Control

- Fuzzy knowledge-based control

- Fuzzy data analysis, modeling, identification

- Learning and adaptive control (neural networks)

- Reinforcement learning
Direct Fuzzy Control

Goal (reference) $\rightarrow$ Human operator $\rightarrow$ Process $\rightarrow$ Disturbances $\rightarrow$ y

$\rightarrow$ u $\rightarrow$
Direct Fuzzy Control

Goal (reference) → Human operator

Disturbances → Process

Knowledge acquisition

Fuzzy if-then rules
Direct Fuzzy Control

Goal (reference) \[ \rightarrow \] Fuzzy controller \[ \rightarrow u \] Disturbances \[ \rightarrow \] Process \[ \rightarrow y \]

Implementation

Fuzzy if-then rules
Fuzzy Sets and Fuzzy Logic

Relatively new methods for representing uncertainty and reasoning under uncertainty.

Types of uncertainty:

- chance, randomness (stochastic)
- imprecision, vagueness, ambiguity (non-stochastic)
Vagueness in If–Then Rules

If temperature in the burning zone is OK, and oxygen percentage in the exhaust gases is Low, and temperature at the back-end is High, then reduce fuel Slightly and reduce fan speed Moderately.
Fuzzy Sets and Fuzzy Logic

Proposed in 1965 by L.A. Zadeh
(Fuzzy Sets, Information Control, vol. 8, pp. 338–353)

- generalization of ordinary set theory
- ’70 first applications, fuzzy control (Mamdani)
- ’80 industrial applications, train operation, pattern recognition
- ’90 consumer products, cars, special HW, SW.

The term “fuzzy logic” often also denotes fuzzy sets theory and its applications (e.g., fuzzy logic control).
Applications of Fuzzy Sets

Fuzzy Set Theory

Fuzzy Mathematics
- fuzzy measures
- fuzzy relations
- fuzzy topology

Fuzzy Logic & AI
- Approximate reasoning
- expert systems

Fuzzy Systems

Classification, clustering
- multi-criteria optimization
- mathematical programming

Fuzzy Decision Making
- fuzzy signal processing
- noise cancellation
- image processing

Fuzzy modeling
- identification
- validation

Fuzzy control
- control design
- applications