COURSE DESCRIPTION CARD - SYLLABUS

Course name
MACHINE LEARNING METHODS IN CONTROL SYSTEMS [S5AEEITK>MUMSS]

Course

Proposed by Discipline
–

Year/Semester
2/3

Level of study
Doctoral School

Course offered in
English

Form of study
full-time

Requirements
elective

Number of hours

Lecture
8

Laboratory classes
0

Other
0

Tutorials
0

Projects/seminars
0

Number of credit points
2,00

Coordinators

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Lecturers

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Prerequisites

Knowledge: knows and understands in enhanced level the selected areas of mathematics: linear algebra, has an background knowledge of methods of analysis and design of control systems. Skills: has the ability to self-educate in order to improve and update one's professional competences, can design control systems using selected engineering tools (e.g. Matlab). Social competencies: is aware of responsibility for own work and willingness to conform to the principles of teamwork and taking responsibility for jointly implemented tasks.

Course objective

The aim of the course is to acquaint PhD students with modern machine learning methods applied to the modelling, analysis, and control of dynamic systems. The course enables understanding of the principles of integrating machine learning techniques with classical control structures, such as Model Predictive Control (MPC), adaptive control, and Fault-Tolerant Control (FTC). Particular emphasis is placed on the practical aspects of algorithm implementation in MATLAB and Python environments, including the use of Reinforcement Learning (RL) methods for designing optimal and adaptive control systems. The course also aims to develop the ability to: - independently select and apply ML/RL methods in scientific research in the field of automation and robotics, - critically analyse scientific literature concerning the application of artificial intelligence in control, - nterpret and evaluate simulation results. The expected learning outcome is that the PhD student will be prepared to independently conduct research on data-driven control and to integrate machine learning algorithms into modern control and diagnostic systems.

Course-related learning outcomes

Knowledge

W1. The PhD student knows contemporary machine learning (ML) and reinforcement learning (RL) methods applied to the design, identification, and control of dynamic systems.
[P8S_WG/SzD_W02]

W2. The PhD student understands the principles of integrating machine learning methods with classical control structures (PID, LQR, MPC, ADRC) and is familiar with current research trends in this field.
[P8S_WG/SzD_W03]

Skills

U1. The PhD student can select and implement an appropriate ML or RL method in MATLAB or Python environments for modelling, prediction, or control of a dynamic system.
[P8S_UW/SzD_U01]

U2. The PhD student can critically analyse and interpret scientific research results and publications related to the application of machine learning in control, assessing their cognitive and practical value.
[P8S_UW/SzD_U02]

Social competences

K1. The PhD student is ready to engage in interdisciplinary scientific discussions on the application of ML/RL methods in automation and robotics and to critically evaluate their own contribution to the development of this field.
[P8S_KK/SzD_K02]

K2. The PhD student understands the importance of responsibility for research integrity and the role of knowledge in solving complex engineering and scientific problems.
[P8S_KK/SzD_K03]

Methods for verifying learning outcomes and assessment criteria

Learning outcomes presented above are verified as follows:

Assessment methods and criteria

The final grade is based on an individual or two-person project carried out by the PhD student, involving the application of a selected machine learning (ML) or reinforcement learning (RL) method in the context of control systems.
The project topic may be:
- assigned by the lecturer, based on current issues discussed during the course (e.g. ML-MPC, RL-based control, NARX/NARMAX identification, FDD/FTC diagnostics), or
- independently proposed by the PhD student, provided that it falls within the thematic scope of the course and has a sound scientific justification.

The project includes the preparation of:
- a short report (3–5 pages) describing the problem, the selected method, simulation results (MATLAB / Python) and a brief literature review,
- a presentation of the project during the final class, including discussion of the results and reference to current research trends,
- participation in a final discussion session, evaluating different approaches to the use of ML/RL methods in control systems.

Assessment criteria:
- technical and scientific quality of the project and justification of the selected method – 40%,
- correctness and clarity of simulation results – 30%,
- presentation quality and defence of the project during discussion – 20%,
- active participation during classes and in the analysis of scientific publications – 10%.

Passing requirements:
- presentation of the project during the final meeting,

- submission of the written report in electronic form,
- attendance in at least two-thirds of the total course hours.

Programme content

The course provides an overview of contemporary machine learning (ML) methods applied in automation, robotics, and process control. It begins with the discussion of fundamental concepts of machine learning — including supervised, unsupervised, and reinforcement learning — together with typical applications in automation and control engineering.
Connections between classical system identification methods and data-driven approaches are presented, including NARX, NARMAX, and recurrent neural network (LSTM) models. Particular attention is given to the integration of these models with Model Predictive Control (MPC) frameworks and the use of Reinforcement Learning (RL) algorithms in adaptive and optimal control.

In the subsequent part of the course, participants are introduced to data-driven methods applied to the control and diagnostics of dynamic systems, including strategies ensuring safety and fault tolerance (Fault Detection and Diagnosis – FDD, Fault-Tolerant Control – FTC). Current research directions are also discussed, especially the use of ML techniques for modelling and anomaly detection.

The aim of the course is to enable PhD students to understand current research trends, become familiar with ML tools used in control system design, and develop the ability to independently analyse and critically evaluate scientific publications in this field.

Course topics

1. Introduction to machine learning methods in automation and robotics
- Classification of machine learning methods: supervised, unsupervised, and reinforcement learning.
- Typical applications of ML in automation: state prediction, parameter estimation, adaptive control, and optimization of drive systems and industrial processes.
- Relationship between classical control theory and ML-based approaches (the role of data and models).
- Fundamental concepts: training data, generalization, overfitting, cross-validation, and model interpretability.
- Examples of control systems using ML models in the feedback loop.

2. Data-based models in control and system identification
- Identification of dynamic systems based on experimental data.
- Nonlinear model structures
- Practical examples: identification of drive systems, thermal processes, and nonlinear dynamic systems.

3. Machine learning in model predictive control (ML-MPC)
- Concept of Model Predictive Control (MPC) and its limitations: model accuracy and computational complexity.
- Integration of ML with MPC: surrogate models
- Practical examples: temperature regulation, control of electric drives, and chemical process control.

4. Reinforcement Learning (RL) in control systems
- Definition of agent, environment, reward function, and policy.
- Tabular algorithms: Q-learning
- Applications of RL in simple control systems (e.g. inverted pendulum balancing, adaptive PID control).
- Analysis of the advantages and limitations of RL compared with classical adaptive control.
- Deep Reinforcement Learning (DRL): main concepts and architectures.
- Algorithms: DQN, DDPG, PPO, SAC, Actor–Critic, and Policy Gradient.
- Practical examples: control of a mobile robot, adaptive control of an electric drive.

5. Machine learning in diagnostics and fault-tolerant control
- Concept of fault-tolerant control systems (Fault-Tolerant Control, FTC).
- Data-driven methods for fault detection and diagnosis (FDD).

6. Machine learning in anomaly detection
- Application of ML methods for analysing sensor data and detecting anomalies in dynamic systems.

Teaching methods

The course is conducted in a lecture - seminar format, combining elements of lectures, multimedia presentations, and discussions based on recent scientific publications.
The primary form of instruction is a problem-oriented lecture illustrated with simulation examples in MATLAB/Simulink and Python environments (using libraries such as NumPy, TensorFlow, PyTorch, and Scikit-learn), demonstrating the practical aspects of implementing machine learning methods in control systems.

Bibliography

Basic
1. Åström, K. J., & Murray, R. M. (2020). Feedback Systems: An Introduction for Scientists and Engineers (2nd ed.). Princeton University Press.
https://fbsbook.org
2. Sutton, R. S., & Barto, A. G. (2018). Reinforcement Learning: An Introduction (2nd ed.). MIT Press.
https://www.andrew.cmu.edu/course/10-703/textbook/BartoSutton.pdf
3. Brunton SL, Kutz JN. Data-Driven Science and Engineering: Machine Learning, Dynamical Systems, and Control. Cambridge University Press; 2019.
https://www.databookuw.com/

Additional
4. Wu, Z., Christofides, P. D., & Wu, W. (2025). A Tutorial Review of Machine Learning–Based Model Predictive Control Methods. Reviews in Chemical Engineering. De Gruyter. https://doi.org/10.1515/revce-2024-0055
5. Verheijen, P. J. T., De Schutter, B., & Heemels, W. P. M. H. (2024) Handbook of Linear Data-Driven Predictive Control. https://research.tue.nl/en/publications/handbook-of-linear-data-driven-predictive-control-theory-implemen
6. Tang, C., et al. (2024). Deep Reinforcement Learning for Robotics: A Comprehensive Review. arXiv preprint arXiv:2408.03539.
https://arxiv.org/abs/2408.03539

Breakdown of average student's workload

	Hours	ECTS
Total workload	50	2,00
Classes requiring direct contact with the teacher	8	0,00
Doctoral student's own work (literature studies, preparation for laboratory classes/tutorials, preparation for tests/exam, project preparation)	42	2,00