POZNAN UNIVERSITY OF TECHNOLOGY

EUROPEAN CREDIT TRANSFER AND ACCUMULATION SYSTEM (ECTS)

COURSE DESCRIPTION CARD - SYLLABUS

Course name
MODEL ORDER REDUCTION [S5IMECH>RWM]

Course

Proposed by Discipline
–

Year/Semester
3/6

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

dr hab. inż. Witold Stankiewicz
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Prerequisites

KNOWLEDGE: the student has a basic knowledge of computer-aided engineering methods and the basics of programming. Basic knowledge of the strength of materials and fluid mechanics. Basic knowledge of mathematics and numerical methods. SKILLS: the student is able to plan and carry out experiments, including measurements and computer simulations, interpret the obtained results and draw conclusions. Can write a simple program in any programming language or Matlab / Octave environment. SOCIAL COMPETENCES: the student is able to interact and work in a group.

Course objective

The aim of the course is to present a method of reducing complex systems to several important parameters (degrees of freedom) in order to use the models obtained in this way to control processes or model the behavior of a structure / system. The presented methods (including modal decomposition, projection) are used, for example, in the active reduction of flow-induced drag, modeling vibrations of structures, image analysis and recognition, machine learning (ML) and artificial intelligence (AI).

Course-related learning outcomes

Knowledge:
A doctoral student knows and understands:
1) global achievements in the field, including theoretical foundations as well as general and selected

specific issues of model order reduction, modal analysis, and machine-learning-based modelling of physical phenomena (P8S_WG/SzD_W01),
2) key development trends in machine learning-based modelling of dynamical systems (P8S_WG/SzD_W02).

Skills:
A PhD student who graduated from doctoral school can:
1) explore literature, select the promising projection-based and ML-based models/techniques, and creatively apply them to model and solve physical phenomena (P8S_UW/SzD_U01),
2) critically analyze and assess scientific research results, work of experts and other creative activities together with their contribution into knowledge development (P8S_UW/SzD_U02).

Social competencies:
A doctoral student is ready to:
1) recognize the importance of model order reduction techniques for addressing problems involving physical phenomena (P8S_KK/SzD_K03).

Methods for verifying learning outcomes and assessment criteria

Learning outcomes presented above are verified as follows:

Learning outcomes are verified through a written test (50%) and a short research-oriented written assignment (50%), relating selected methods presented in the course to the doctoral student's research.

The test assesses the understanding of key concepts and methods, while the assignment is assessed based on the relevance and justification of the selected methods and critical discussion of their applicability, advantages, and limitations.

The final grade is based on the total score: 5.0: 90-100%, 4.5: 80-89%, 4.0: 70-79%, 3.5: 60-69%, 3.0: 50-59%.

Programme content

Computational cost of modeling and simulation of physical systems. Applications of low-dimensional and reduced-order models. Dimensionality reduction, feature extraction, and modal analysis. Physics-based and data-driven model reduction. Model construction, calibration, and identification of dynamical systems. White-box, gray-box, and black-box models. Models for feedback control and real-time applications. Machine learning and physics-informed approaches to reduced-order modeling. Operator learning.

Course topics

Computational cost of high-fidelity modeling and simulation of physical systems and the motivation for reduced-order modeling. Applications of low-dimensional and reduced-order models. Dimensionality reduction and modal analysis: Principal Component Analysis (PCA), Proper Orthogonal Decomposition (POD), Dynamic Mode Decomposition (DMD), Locally Linear Embedding (LLE), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA), and physics-based modes. Construction of reduced-order models using Galerkin projection and interpolation. Model calibration and parameter estimation. Identification of dynamical systems, including sparse identification of nonlinear dynamics (SINDy) and neural ordinary differential equations (Neural ODEs). White-box, gray-box, and black-box models. Reduced-order models for feedback control and real-time applications. Genetic algorithms and other optimization methods for model calibration and identification. Machine-learning-based reduced-order models. Physics-informed models and operator learning.

Teaching methods

Lecture: multimedia presentation including illustrations and examples.

Bibliography

Basic:
A. Géron. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow. Concepts, tools, and techniques to build intelligent systems, 2nd ed., O'Reilly / Helion, 2019.

B.R. Noack, M. Morzyński, and G. Tadmor. Reduced-order modelling for flow control. CISM Courses and Lectures 528. Springer-Verlag, 2011.

R. King (editor). Notes on Numerical Fluid Mechanics and Multidisciplinary Design. Volume 95: Active Flow Control. Springer, Berlin Heidelberg, 2007.

T. Duriez, S.L. Brunton, and B.R. Noack. Machine Learning Control - Taming Nonlinear Dynamics and Turbulence. Fluid Mechanics and Its Applications, 116. Springer-Verlag, 2016

Additional:

R. T. Q. Chen, Y. Rubanova, J. Bettencourt, D. Duvenaud, Neural Ordinary Differential Equations, Advances in Neural Information Processing Systems, 31, 2018

Yu Yong, et al. A review of recurrent neural networks: LSTM cells and network architectures. Neural computation 31 (7), 1235-1270, 2019.

Brunton, S. L., Proctor, J. L., Kutz, J. N. Discovering governing equations from data by sparse identification of nonlinear dynamical systems. PNAS, 113(15), 3932–3937, 2016.

B.R. Noack, W. Stankiewicz, M. Morzyński, P.J. Schmid. Recursive dynamic mode decomposition of transient and post-transient wake flows.
Journal of Fluid Mechanics 809, 843-872, 2016.

W. Stankiewicz, K. Kotecki, M. Morzyński, R. Roszak, W. Szeliga.
Model order reduction for a flow past a wall-mounted cylinder. Archives of Mechanics 68 (2), 161-176, 2016.

T. Lassila, A. Manzoni, A. Quarteroni, G. Rozza. Model Order Reduction in Fluid Dynamics: Challenges and Perspectives. Reduced Order Methods for Modeling and Computational Reduction, 235–273, 2014.

W. Stankiewicz, R. Roszak, M. Morzyński. Genetic algorithm-based calibration of reduced order Galerkin models. Mathematical Modelling and Analysis, 16 (2), 233–247, 2011.

B.R. Noack, K. Afanasiev, M. Morzyński, G. Tadmor, and F. Thiele, A hierarchy of low-dimensional models for the transient and post-transient cylinder wake. J. Fluid Mech., 497, pp. 335–363, 2003

S. Hochreiter, J. Schmidhuber, Long Short-Term Memory, Neural Computation, 9(8), 1735–1780, 1997.

N. Aubry, P. Holmes, J. Lumley, and E. Stone. The dynamics of coherent structures in the wall region of a turbulent boundary layer. J. Fluid Mech., 192:115-173, 1988.

C.A.J. Fletcher. Computational Galerkin Methods. Springer, New York, 1984.

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