ME 462/597: ADVANCED COMPUTER CONTROL, FALL 2023

3:30 PM – 4:50 PM Tuesday, Thursday, 3100 LUMEB, per lecture/lab class format below

Course credits: ME462: 4 hours, ME597: 2 hours

Prerequisite: ME360 or equivalent (ME460 is not a prerequisite)

Instructor: Professor Joseph Bentsman, 3054 LUMEB, 244-1076, jbentsma@illinois.edu

Course objective. This course aims at building the foundation of modern real-time-computable control design with the elements of machine learning (ML) through progression from the basic theory to the advanced state-of-the-art control algorithms proven successful in applications. Both discrete time (DT) and continuous time (CT) formats are employed and linked through discrete-continuous (sampled-data) concepts. The laboratory part of the course provides exposure to 1) the basic controller code development in Python and C(++), including tutorials for students with no prior C(++) coding background, 2) the Matlab toolboxes related to the course topics, 2) the implementation of these algorithms on modern computing platforms (GPUs and FPGAs), 3) the elements of machine learning proven useful in enhancing these algorithms, and 4) the applications in aerospace, power generation, manufacturing, and other areas.

Format of the class instruction will be half-flipped – the recorded lectures along with the lecture slides will be posted online on Canvas course website by 3:30 pm on Monday and Wednesday the day before each lecture. Everyone is expected to listen to these lectures in preparation for the weekly material review session, which will be held in class every Thursday following the regular class schedule. The lab presentations will be held in class on Tuesdays according to the lab schedule, and the recorded lab presentations will also be posted on Canvas along with the lab slides. The homework help sessions with be held weekly online – the time to be arranged.

Lecture style. The lecture focus will be on clear control problem statement, analytical expressions of the control laws solving the problem, and applicability limitations. The corresponding codes, code development guidelines, Matlab-based controller design tools, and applications will be provided in the labs. Rigorous mathematical proofs will be given in the lectures for only a few key results – LQR, Kalman Filtering, Recursive Least Squares for system identification, GPC, Wavelet decomposition, Projection-based parameter estimation and adaptive control, and possibly several others.

Lecture schedule: The lectures will be posted on Canvas by 3:30pm MW and will be available after posting through the rest of the semester. The lecture slides will be provided at the lecture posting and will be available for download. The weekly material review session will be held in class every Thursday by the course instructor.

The labs will be presented in class on the scheduled lab weeks on Tuesday 3:30 pm - 5 pm and posted by 6 pm on that day. The lab schedule is listed below. The labs (slides, and recordings) will be available after posting through the rest of the semester.

The lab part has 8 labs, 2 hours each.

The ME597 (CRN 23198) addition (recommended for graduate students) will cover several additional advanced topics listed in the ME597 lecture topic schedule, with the corresponding homework and lab assignments, worth two extra credit hours. Adding this option should be communicated to the instructor in the beginning of the course.

Registration for ME597 only. Students with advanced graduate standing can register for ME597 only. The requirements will then include submitting all the assignments within the ME597 lecture topics schedule and ME597 Labs 7 and 8 description, both given further below.

Grading: Final Project (also serves as the final exam) - 20%, weekly/biweekly homeworks (total 12) - 50%, labs (total 8) - 30%.

Course Requirements: All lab reports and homeworks should be turned in on time.

For the undergraduate students, starting from the Nonlinear filtering topic in Week 11, some reduction of the assignment difficulty might be provided, if necessary, without affecting the course grade, to allow quality completion of all the previous assignments.

Students registering for ME597 only are required to do the homework assignments and the labs related only to the ME597 lecture topics given above.

ME462 lecture topics schedule:

Weeks 1, 2. System-theoretic properties of DT and sampled-data systems: Sampling of continuous time systems with zero order hold. DT systems in state space. Sampled-data systems. Stability, controllability, reachability, stabilizability, observability, detectability. Canonical forms. Intersampling behavior.

Weeks 3, 4. DT control fundamentals: pole placement design, observer design, output feedback, disturbance rejection, servo design: Design of DT feedback systems using pole-placement. Closed-loop state estimation. Prediction estimator. Deadbeat observer. Closed-loop observer. Dynamic output feedback. Certainty equivalence principle. Internal model principle, disturbance rejection using internal models, integral action. Tracking design.

Week 5. Linear DT optimal control based on state-space models: Finite and infinite horizon optimal control laws. Riccati difference and algebraic equation (RDI and ARE). Receding horizon implementation. Linear quadratic (LQ) control. Optimal current and predictor estimation, Kalman filter. Linear quadratic Gaussian (LQG) control. CT and DT LQG loop transfer recovery (LQG/LTR).

Weeks 6, 7. Linear DT self-tuning optimal control with constraints using polynomial models: Polynomial division based H_2 predictors. Generalized Predictive Control (GPC) and its relation to LQG. GPC with control rate and magnitude constraints. Recursive least squares (RLS) and multi-step predictive identification (MSPI). Self-tuning control using MSPI/GPC structures under control rate constraints.

Weeks 8, 9, 10. Introduction to Machine Learning (ML) - universal approximators and neural networks. Multiresolution nonlinear DT self-tuning control with constraints using ML techniques: Universal approximators – perceptron, feedforward Neural Networks (NNs), gradient descent algorithm for NN training. Multiresolution analysis, dyadic dilations. Sinc/rect time-frequency multiresolution decomposition example. Radial Marr vector scaling and wavelet functions, NARMAX wavelet modeling. Training wavelet network for nonlinear parameter identification using normalized gradient descent algorithm. ML-based multiresolution suboptimal self-tuning control with constraints.

Weeks 10, 11. DT Linear Model Predictive Control (LMPC) synthesis under constraints using Quadratic Programming: Introduction to Dynamic Programming and MPC as its moving horizon approximation. Linear MPC with constraints. MPC synthesis under equality and inequality constraints for embedded applications using sparse formulation and Quadratic Programming.

Weeks 11, 12. Nonlinear filtering, Introduction to Reinforcement Learning (RL): Extended Kalman Filter and its use with LMPC (other nonlinear estimators are covered in Lab 6). Introduction to Reinforcement Learning with actor-critic value/policy iterations. Link between MPC and RL.

Week 13. Robust control: CT and DT linear H_∞ control. Single and double Riccati equations H_∞ design.

Weeks 14, 15. DT/sampled-data robust adaptive control: Brief review of robust adaptive control techniques of current interest. Projection operator. DT L1 adaptive control. Performance enhancements through ML, MPC, and other techniques.

ME597 lecture topics schedule:

Week 10. Introduction to Machine Learning (ML): ML applications with Gauss-Newton and Levenberg-Marquardt algorithms. ML with wavelet-based multiresolution convolutional neural networks.

Week 11. DT Linear Model Predictive Control (LMPC): Interior point primal-dual approach, barrier functions, soft constraints. Mehrotra's algorithm.

Week 12. CT/Sampled-Data Constrained Nonlinear MPC (NMPC): Nonlinear state estimation – moving horizon estimator (MHE). Constrained NMPC based on Pontryagin's Maximum Principle. Combination of the MHE with constrained NMPC for output feedback. Reduced computational complexity implementation for embedded applications.

Week 13. Robust control: H_∞ design using linear matrix inequalities (LMI). Structured singular value and μ-synthesis. Nonlinear H_∞ controller design.

Weeks 14. Robust adaptive control. LQG/SPR (strictly positive real) approach with projection operator based adaptation.

Weeks 15. Robust adaptive control. Nonlinear H_∞ robust adaptive control. Combination of L1 adaptive control with constrained interior point primal-dual MPC.

ME462 Laboratory schedule and topics:

Lab 1, Week 2 (Tuesday, Aug. 29):

1) Brief review of system representation concepts and the corresponding Matlab Control Systems toolbox functions: State space and input-output models of DT systems. Sampling of CT systems with zero order hold. DT systems in state space. Relation between state space and transfer function matrix representations. Shift operators. Polynomial matrices. Pole-zero cancellations. Systems with unstable inverses.

2) Introduction to current computer control thinking, parallel programming, and highly parallelizable computer control hardware platforms: field-programmable gate arrays (FPGAs) and graphical processing units (GPUs). Setting up access to NCSA GPU lab.

3). Examples of modeling and control of systems of current interest – autonomous vehicles, robotic systems, industrial systems. Introduction to distributed parameter (PDE-based) systems - Timoshenko-beam/hydraulic-actuator testbed – its Matlab Simulink software implementation and FPGA industrial controller implementation.

Lab 2, Week 3 (Tuesday, Sept. 5):

1) Introduction to thermal and wind power plant models and their control - preview of several topics to be studied, including identification and H_∞ design. **ME597** – Comparison of numerical algorithms for H_∞ design, including D-K iterations and LMI-based methods.

2) Familiarization with Matlab and Python FPGA and GPU programming tools, and an introduction to basic C++. Discussion on how to decide on hardware and software architecture of controllers based on application-dependent constraints.

Lab 3, Week 5 (Tuesday, Sept. 19):

1). Introduction to aircraft and UAV models, including those for unmanned aircraft, F-16, and quadcopters. Equations of motions, lateral and longitudinal dynamics decoupling, system uncertainties.

2). Matlab simulation. Control objectives.

3). CT and DT LQG and LQG/LTR servo design for a selected system with the help of Matlab Control Systems toolbox, as well as the design of an LQG/LTR algorithm from scratch in Python.

Lab 4, Week 7 (Tuesday, Oct. 3):

1). Introduction to Matlab Model Predictive Control toolbox. Implementation of GPC algorithms from scratch in Python. Brief discussion of GPC implementation using gpc2mpc function in Matlab.

2). Introduction to Matlab System Identification toolbox, as well as common system identification models and techniques.

3). Development of the Python code for the real-time implementation of MSPI/GPC self-tuning controller with control rate constraints.

Lab 5, Week 9 (Tuesday, Oct. 17):

1). Introduction to Matlab Global Optimization toolbox: genetic algorithms, particle swarm optimization (PSO), simulated annealing. Basic Machine Learning - controller tuning by global optimization algorithms. GPU global optimizer programming. Discussion of classical and modern optimization techniques for machine learning, starting with Jacobian-based methods (Newton-Raphson iterations) all the way to state-of-the-art Jacobian-free methods (Jacobian-free Newton-Krylov), as well as stochastic gradient descent (SGD). Construction of a toolbox in Python capable of running these optimization algorithms for future labs. Performance comparisons and implementational considerations on embedded hardware and GPUs.

2). Introduction to Wavelet toolbox and generation of NARMAX wavelet-based model from noisy nonlinear system data using local Machine Learning algorithm - normalized gradient descent.

3) Deep learning: introduction to neural networks (NN): multi-layer perceptron, wavelet-based convolutional (CNN), recurrent (RNN), and generative adversarial (GAN), Matlab Deep Learning toolbox. Tensorflow code for CNN.

Lab 6, Week 11 (Tuesday, Oct. 31):

1) Review of nonlinear filtering (NF) and related Matlab filtering tools: Kalman extended (EKF), Kalman unscented (UKF), particle filter (PF). GPU implementation of an extended Kalman filter algorithm.

2) Review of Matlab Optimization and MPC toolboxes for systems with constraints.

3) Combining MPC with NF for output feedback. Python code development of the quadratic programming (QP) based MPC for systems with constraints. GPU implementation of QPMPC with NF.

Lab 7, Week 13 (Tuesday, Nov. 14):

1). Reinforcement Learning policies – Q-learning, DP-learning, and formulating/solving Markov Decision Processes (MDPs). Reinforcement Learning Toolbox and example. Reinforcement Learning using NNs for value/policy functions approximation. Discussion and small implementation exercise of Q-learning on a GPU.

2) Introduction to Matlab Robust Control toolbox: coupled Riccati linear H_∞ design for a selected system.

Lab 8, Week 15 (Tuesday, Nov. 28):

1) Introduction to robust adaptive control – current approaches will be briefly surveyed. L1 approach will be used for implementation. Discussion on coupling L1 methods with learning-based techniques and MDPs. **ME597** – introduction to H-infinity and LQG/SPR robust adaptive control.

2) Discussion of individual projects for a final exam: combination of global optimizers and deep learning with self-tuning and robust adaptive control. Application of digital control algorithms parallelization on FPGAs and GPUs for solving computationally intensive control problems. This includes also students who registered only for **ME597**.

3) In-class demo of some real-life control implementations on MCUs, CPUs, GPUs, and FPGAs.

<u>ME597 lab schedule and topics:</u>

Lab 7, Week 13 (Tuesday, Nov. 14):

1) ML with wavelet-based multiresolution convolutional neural networks in Python.

2) LMI-based linear H_∞ design and μ synthesis for a selected system.

Lab 8, Week 15 (Tuesday, Nov. 28):

1) Introduction to H-infinity and LQG/SPR robust adaptive control.
2) Application of GPUs in solving complex controller design problems.

3) Discussion of individual projects for a final exam: combination of global optimizers and deep learning with self-tuning and robust adaptive control. Application of digital control algorithms parallelization on FPGAs and GPUs for solving computationally intensive control problems.

Textbooks:

Required:

1) *Computer-Controlled Systems: Theory and Design*, *Third edition*, by K. J. Astrom and B. Wittenmark, Dover, 2011. A very inexpensive edition from Dover.

2) *Digital Control of Dynamic Systems, Third edition*, by G. F. Franklin, J. D. Powell, and M. Workman, Addison-Wesley, 1997. Officially available free of charge from https://www.researchgate.net/publication/31849881_Digital_Control_of_Dynamic_Systems-Third_Edition .

3) *Robust Control Design with MATLAB, Second Edition*, D.-W. Gu, P. H. Petkov, and M. M. Konstantinov, Springer, 2013. Officially available free of charge through Granger Library.

Strongly recommended:

1) *Signals, Instrumentation, Control, and Machine Learning: an Integrative Introduction*, J. Bentsman, World Scientific Publishing, 2022. (don't confuse with 2016 book, which is not suitable). This is ME360 background, with about quarter of the book used in ME462.

Advanced Online Accessible Texts to be used: The advanced part of the course , weeks 7-15, will use selected material from papers given in class and several books, many officially accessible online, most through Grainger library:

5) *Adaptive Optimal Control: The Thinking Man's GPC*, Prentice Hall, R. Bitmead, M. Gevers, V. Wertz, Prentice Hall, 1990.

6) *Model Predictive Control, 2nd edition*, by E. F. Camacho and C. Bordons, Springer, 2013.

7) *Adaptive Approximation Based Control: Unifying Neural, Fuzzy and Traditional Adaptive Approximation Approaches*, by J. A. Farrell and M. M. Polycarpou, Wiley 2006.

8) *L_1 Adaptive Control Theory: Guaranteed Robustness with Fast Adaptation*, N. Hovakimyan and C. Cao, SIAM, 2010.

9) *Machine Learning Refined: Foundations, Algorithms, and Applications, 2nd edition*, J. Watt, R. Borhani, A. Katsaggelos, Cambridge University Press, 2020.

Reference books:

1) *Feedback Systems: An Introduction for Scientists and Engineers, 2nd Edition*, K. J. Astrom and R. M. Murray, 2020,
http://www.cds.caltech.edu/~murray/books/AM08/pdf/fbs-public_24Jul2020.pdf ,
https://fbswiki.org/wiki/index.php/Category:Errata
with supplements given in
https://fbswiki.org/wiki/index.php/Main_Page

2) *Modern Control Engineering, Fifth edition*, by K. Ogata, Prentice Hall, 2010.

3) *Optimal Control, Third edition*, by F. L. Lewis, D. Vrabie, and V. L. Syrmos, Wiley, 2012.

4) *Optimal and Robust Estimation*, *Second edition*, by F. L. Lewis, L. Xie, and D. Popa, CRC Press. 2008.

5) *Handbook of Model Predictive Control*, S. V. Rakovic and W. S. Levine Editors, Birkhauser, 2019.

6) *Model Predictive Control: Theory, Computation, and Design, Second Edition,* Rawlings, J.B., Mayne D.Q. M. M. Diehl, M. M. (2019), Nob Hill Publishing.
https://sites.engineering.ucsb.edu/~jbraw/mpc/

7) *Optimal Sampled-Data Control Systems,* T. Chen and B. Francis, Springer, 1995.

Research papers, Theses, and Reports:

A set of references in these formats highlighting the most recent developments, as well as the classical results, will be provided throughout the semester.