# Syllabus

## MEGR 7090/8090 Special Topics: Dynamic System Learning and Estimation

Department of Mechanical Engineering and Engineering Science
UNC Charlotte
Fall 2024

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*Important Links*:

| | |
|---|---|
| Announcements/discussion: | TBD |
| Course content: | https://arturwolek.github.io/MEGR8090_Estimation/ |
| Homework submission/grades: | https://canvas.charlotte.edu |
| Virtual suggestion box: | https://forms.gle/yCWe4aAGtKzxLeHz9 |

*Classes Meet In Person*:
Class hours: Tues./Thurs.: 2:30pm – 3:45pm (Duke 345)

**Prerequisites** This course has no official prerequisites, however it will be geared toward graduate students who have familiarity with most of the following topics:

- dynamic systems (e.g., MEGR 3121/3122: Dynamic Systems I/II)
- control systems (e.g., MEGR 3237: Intro to Controls — preferred but not required)
- linear algebra
- multi-variable calculus and differential equations
- probability theory
- experience programming in MATLAB (or a similar programming language)

A background in graduate-level nonlinear/linear systems theory, dynamics, optimization, or machine learning is a plus (but again not required). The course content will aim to be as self-contained as possible—students who only have partial familiarity with the topics above (e.g., four out of six topics) are still encouraged to participate in this class.

**Course Overview** The process of developing models of dynamic systems from experimental data is called *system identification* or *system learning*, and using measurements of a system's output to infer its internal state is called *state estimation*. The need for system identification/learning and state estimation is ubiquitous in science and engineering, and this course will explore these topics in the context of dynamic systems modeled as ordinary differential equations. We will survey a broad range of topics including classical techniques and selected machine-learning-based methods. The class will include both theory and practical implementation. Students will complete regular homework assignments that include MATLAB programming and a final project based on their own research. A (tentative) outline of the course topics is as follows:

- **Course introduction**: state estimation vs. system identification/learning
- **Linear algebra review**: notation, vector spaces, matrix algebra, rank, inverse, nullspace, etc.
- **Continuous systems**: state transition matrix, LTI/LTV and nonlinear systems, linearization
- **Discrete systems**: exact/approximate discretization of continuous systems
- **Numerical simulation**: simulating continuous and discrete systems (e.g., Euler's method/ode45)
- **Observability**: LTV/LTI system observability, unobservable subspace, empirical observability Gramian

- **Luenberg observer**: observer design, consistency, and convergence
- **Probability review**: Gaussian random vectors, confidence ellipse, Mahalanobis distance, etc.
- **Stochastic systems**: process and measurement noise, continuous vs. discrete noise, simulation
- **Regression methods**: least-square parameter estimation, stepwise model determination
- **Random vector transformations**: linear/nonlinear transformations, mean/covariance propagation
- **Kalman filters**: discrete-time Kalman Filter, Kalman-Bucy filter, EKF, UKF
- **Parameter estimators:** online parameter estimation (augmented KF), maximum likelihood methods
- **Bayesian filters**: recursive Bayesian estimator, particle filters
- **Neural networks**: feedforward regression networks and sequence-modeling networks
- **Gaussian processes**: kernel selection, regression, hyperparameter optimization
- **Data-driven dynamic systems**: dynamic mode decomposition (DMD)

**Course Objectives** The goal of this course is to expose students to a variety of techniques for state estimation and system identification/learning of dynamic systems. After completing this course students should be able to:

1. Simulate linear and nonlinear dynamic state-space systems with process and measurement noise and analyze their observability
2. Design state-space filters (e.g., Kalman filters, Bayesian filters) to estimate the state of a dynamic system from noisy measurements and understand when to use different types of filters
3. Identify unknown parameters and determine model structure of state-space models from data, using least-square regression, maximum likelihood estimation, stepwise regression and other techniques
4. Implement neural network and Gaussian process regression to learn the dynamics of a system from input/output time-series data

**Assessment** Homework and exams will be based on the required reading materials and what was said in class. The typical UNCC graduate-level grading scale will be used. The grade will be determined based on the following scheme:

| **Course Element** | **Percentage** |
|---|---|
| Class Participation | 5 % |
| Homework | 75 % |
| Final Project | 20 % |

**Textbooks and Course Materials** Typeset lecture notes synthesized from a variety of references will be provided in PDF format. The course can be completed using only these lectures notes; however, students may consider obtaining the following text which overlaps with a large portion of the course.

- "Optimal State Estimation: Kalman, $H_\infty$ and Nonlinear Approaches," D. Simon, John Wiley & Sons, 2006. Free electronic copy available for download from UNCC Library [Link] (search for title). Physical copy available for purchase (e.g., from Amazon [Link])

Other relevant textbooks include:

Systems Theory/Probability:

- W. J. Rugh, *Linear System Theory*. Prentice-Hall, Inc., 1996
- J. P. Hespanha, *Linear Systems Theory*. Princeton university press, 2018
- D. Bertsekas, *Introduction to Probability*. Athena Scientific, 2008
- G. Strang, *Linear algebra and its applications.* Belmont, CA: Thomson, Brooks/Cole, 2006

State Estimation:

- D. Simon, *Optimal State Estimation: Kalman, H infinity, and Nonlinear Approaches*. John Wiley & Sons, 2006
- R. F. Stengel, *Optimal Control and Estimation*. Courier Corporation, 1994
- B. P. Gibbs, *Advanced Kalman Filtering, Least-squares and Modeling*. John Wiley & Sons, 2011
- J. L. Crassidis and J. L. Junkins, *Optimal Estimation of Dynamic Systems*. Chapman and Hall/CRC, 2004
- A. J. Haug, *Bayesian Estimation and Tracking: a Practical Guide*. John Wiley & Sons, 2012

System Identification / Learning:

- M. B. Tischler and R. K. Remple, *Aircraft and Rotorcraft System Identification*. AIAA, 2012
- E. A. Morelli and V. Klein, *Aircraft System Identification: Theory and Practice*
- C. M. Bishop and N. M. Nasrabadi, *Pattern Recognition and Machine Learning*. Springer, 2006
- K. P. Murphy, *Probabilistic Machine Learning: an Introduction*. MIT press, 2022
- C. K. Williams and C. E. Rasmussen, *Gaussian Processes for Machine Learning*. MIT Press, 2006
- S. L. Brunton and J. N. Kutz, *Data-driven Science and Engineering: Machine Learning, Dynamical Systems, and Control*. Cambridge University Press, 2022