EE/CPE/NIS 608 – Applied Modeling and Optimization

Instructor Name: R. Chandramouli

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Office Hours: Thursday 2:00 pm to 3:30 pm or by appointment

Text Book: No textbook. Class lecture notes and supplementary reading material.

Prerequisites: Background in calculus and linear algebra. MATLAB, Python, or similar scientific programming.

Course Description: This is an introductory course on mathematical modeling of optimization problems and techniques for finding solutions. The course covers mathematical modeling, unconstrained optimization problems, constrained optimization, convex optimization, non-convex optimization, linear and non-linear optimization, line search, gradient descent, penalty function and barrier methods, convergence analysis, applications in machine learning, decision making, wireless communications, signal processing, and other areas.

Course Learning Outcomes:

- The student will be able to model an optimization problem
- The student will be able to solve unconstrained and constrained optimization problems
- The student will be able to recognize a convex optimization problem
- The student will be able to apply numerical techniques such as gradient descent
- The student will be able to choose a software toolbox to solve an optimization problem
- The student will be able to apply optimization techniques to machine learning and other areas

Topics Covered Each Week (tentative):

- Mathematical modeling (identifying objective function, constraints, feasible region, etc.)
- Unconstrained optimization (necessary and sufficient conditions, feasibility, etc.)
- Constrained optimization (Lagrange multiplier method, conditions for failure, etc.)
- Constrained optimization (KKT method, examples, Weierstrass theorem, etc.)
- Convex programming (Identifying convex problems, modeling convex problems, etc.)
- Numerical algorithms (design, convergence analysis, stability analysis, etc.)
- Mid-term exam

- Gradient descent algorithm, analysis, and examples
- Newton-type algorithms, analysis, and examples
- Barrier and penalty function methods, analysis, and examples
- Applications to machine learning
- Linear programming
- Mid-term exam
- Other applications
- Final Project

Grading:

Final grade will be based on the average cumulative score.

Mid-term exam 1 – 30%
Mid-term exam 2 – 30%
Final project – 40%

Academic Integrity:

Stevens' graduate student code of academic integrity applies.

Learning Accommodations:

Stevens' policies to accommodate students with documented disabilities applies.