East Coast Optimization Meeting 2019

Dates

April 4-5, 2019

Location

George Mason University,
Johnson Center (3rd floor)
Room 334 (Meeting Room E), and
Room 336 (Meeting Room F).

Organizing Committee

Harbir Antil (George Mason University)
Drew P. Kouri (Sandia National Laboratories)
Denis Ridzal (Sandia National Laboratories)

Sponsors

National Science Foundation
Air Force Office of Scientific Research (AFOSR)
Department of Mathematical Sciences, George Mason University
College of Science, George Mason University
Association for Women in Mathematics, GMU Chapter
Society for Industrial and Applied Mathematics, GMU Chapter

Schedule for April 4, 2019

Time	Speaker
7:30 am - 8:15 am	Breakfast and Registration
8:15 am - 8:30 am	Opening remarks
8:30 am - 9:20 am	Alexander Shapiro (Georgia Tech)
9:30 am - 10:20 am	Alexander Shapiro (Georgia Tech)
10:20 am - 10:50 am	**Coffee break**
10:50 am - 11:50 am	Alexander Shapiro (Georgia Tech)
12:00 pm - 1:15 pm	**Lunch**
1:15 pm - 2:00 pm	Guzin Bayraksan (Ohio State University)
2:00 pm - 2:45 pm	Matthew Norton (Naval Postgraduate School)
2:45 pm - 3:15 pm	**Coffee Break**
3:15 pm - 5:30 pm	**Contributed talks (15 min including questions)** Sumaya Alzuhairy (University of Maryland, Baltimore County) Andreas Van Barel (KU Leuven) Anirban Chaudhuri (Massachusetts Institute of Technology) Ratna Khatri (George Mason University) Boris Kramer (Massachusetts Institute of Technology) Chen Li (Courant Institute, New York University) Mae Markowski (Rice University) Bismark Singh (Sandia National Laboratories) Deepanshu Verma (George Mason University)
6:00 pm - 8:30 pm	**Conference Dinner - Research Hall, 163**

Schedule for April 5, 2019

Time	Speaker
7:30 am - 8:15 am	Breakfast
8:30 am - 9:20 am	Jean-Paul Watson (Sandia National Laboratories)
9:30 am - 10:20 am	Jean-Paul Watson (Sandia National Laboratories)
10:20 am - 10:50 am	**Coffee break**
10:50 am - 11:50 am	Jean-Paul Watson (Sandia National Laboratories)
12:00 pm - 1:10 pm	**Lunch**
1:10 pm - 1:55 pm	Guanghui (George) Lan (Georgia Tech)
1:55 pm - 2:40 pm	Jie Xu (George Mason University)
2:40 pm - 3:00 pm	**Coffee Break**
3:00 pm - 5:30 pm	**Contributed talks (15 min including questions)** Stephanie Allen (University of Maryland, College Park) Azam Asl (Courant Institute of NYU) Robert Bassett (Naval Postgraduate School) Logan Beaver (University of Delaware) Getachew K. Befekadu (Morgan State University) Behdad Chalaki (University of Delaware) Jiahua Jiang (Virginia Tech) Joane Joseph (Princeton University) Elahesadat Naghib (Princeton University) Robert Ravier (Duke University)

Keynote Speakers

1. Alexander Shapiro (Georgia Tech University)

TUTORIAL:

Title. Stochastic Programming

Abstract. Optimization problems involving stochastic models occur in many areas of of science and engineering. These lectures are aimed at presenting theoretical foundations and recent advances in theory and applications of the stochastic programming approach to such problems. In particular we discuss modeling questions, computational complexity of solving static and multistage stochastic problems, risk averse and distributionally robust approaches and some popular numerical algorithms.

Reading material: Lectures on Stochastic Programming: Modeling and Theory, by Shapiro, A., Dentcheva, D. and Ruszczynski, A., SIAM, Philadelphia, 2009

This first edition can be downloaded from: `https://www2.isye.gatech.edu/~ashapiro/publications.html`

PUBLIC LECTURE:

Title. Computational complexity of stochastic programs

Abstract. The traditional approach to solving stochastic programming problems involves discretization of the underlying probability distributions. However, the number of required discretization points (called scenarios) grows exponentially both with increase of the number of random parameters and number of stages. In order to deal with this exponential explosion, randomization approaches based on Monte Carlo sampling techniques were developed. In this talk we discuss computational complexity of some of such methods from theoretical and practical points of view.

2. Jean-Paul Watson (Sandia National Laboratories)

TUTORIAL:

Title. Practical Computational Issues in Stochastic Programming

Abstract. In this tutorial, we focus on practical issues central to the solution of stochastic programming problems - specifically emphasizing mixed-integer models, e.g., those with discrete decision variables. Due to their empirical difficulty, extensive forms of stochastic programs commonly cannot be solved directly. We will survey the "zoo" of decomposition methods for stochastic programming, focusing on key stage-based and scenario-based methods. We will additionally emphasize bounding methods and deployment on high-performance computing platforms. The tutorial will also survey key computational approaches to answering the question: How many scenarios do we need when solving a stochastic program? The tutorial will conclude with a discussion of issues relating to

scenario generation (construction) and reduction. Throughout the tutorial, illustrative examples from the domain of power systems operations and planning will be provided.

PUBLIC LECTURE:

Title. On the Rigorous Evaluation of Stochastic Approaches to Power Systems Operations

Abstract. While there is significant recent research on stochastic optimization approaches to power systems operations, e.g., unit commitment and economic dispatch, there are still major impediments to their adoption in practice. In our experience, developed over years of attempting to deploy such approaches, one key issue is accurate evaluation of any proposed approach, relative to existing deterministic operational methodologies. In this talk, we discuss the challenges in such evaluation, and report on a novel methodology addressing what we feel to be deficiencies with current approaches. In the talk, we focus on issues relating to data availability and segmentation, probabilistic scenario generation, and the impact of probabilistic scenarios on operational performance.

Invited Speakers

1. Guzin Bayraksan (Integrated Systems Engineering, The Ohio State University)

   Title: Effective Scenarios in Multistage Distributionally Robust Optimization with Total Variation Distance

   Abstract: Traditional multistage stochastic optimization assumes the underlying probability distribution is known. However, in practice, the probability distribution is often not known or cannot be accurately approximated. One way to address such distributional ambiguity is to use distributionally robust optimization (DRO), which minimizes the worst-case expected cost with respect to a set of probability distributions. In this talk, we study multistage convex DRO with a finite set of scenarios. We illustrate that not all but only some scenarios might have an effect on the optimal value, and we formally define this notion for multistage DRO. In particular, we investigate problems where the distributional ambiguity is modeled stagewise by the total variation distance on conditional probability distributions. We show the resulting problem is a multistage risk-averse optimization with nested coherent risk measures formed by a convex combination of the worst-case and conditional value-at-risk. We conduct perturbation analysis with respect to a collection of scenarios being excluded and propose easy-to-check sufficient conditions for effectiveness. We explore effectiveness of scenario paths as well as scenarios conditional on the history of the stochastic process. Computational experiments illustrate the results on finance and energy problems.

2. Guanghui (George) Lan (H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology)

   Title: Stochastic optimization for learning over networks

   Abstract: Stochastic optimization methods, e.g., stochastic gradient descent (SGD), have recently found wide applications in large-scale data analysis, especially in machine learning. These methods are very attractive to process online streaming data as they scan through the dataset only once but still generate solutions with acceptable accuracy. However, it is known that classical SGDs are ineffective in processing streaming data distributed over multi-agent network systems (e.g., sensor and social networks), mainly due to the high communication costs incurred by these methods.

   In this talk, we present a few new classes of SGDs which can significantly reduce the aforementioned communication costs for distributed or decentralized machine learning. We show that these methods can significantly save inter-node communications when performing SGD iterations. Meanwhile, the total number of stochastic (sub)gradient computations required by these methods are comparable to those optimal ones achieved by classical centralized SGD type methods.

3. Matthew Norton – Department of Operations Research at The Naval Postgraduate School

   Title: Formulating Machine Learning Problems with Risk Management Tools

   Abstract. Formulating Machine Learning (ML) problems can often be difficult. We discuss how recently introduced concepts from risk management can be used to enhance the ML researcher's toolbox, allowing them to formulate new or improved ML problems. We focus on two particular concepts, Buffered Probability of Exceedance (bPOE) and the Risk Quadrangle. First, we show that bPOE can be used to develop a family of performance metrics that can naturally be optimized, with some turning out to form the basis of many well-known Support Vector Machine formulations. These metrics also allow us formulate tractable learning problems with performance constraints, such as classification with false alarm rate constraints, which is a traditionally difficult problem to handle. Secondly, we show how the Risk Quadrangle, specifically the concept of Generalized Deviation Measures, can be used to enhance existing Deep Learning architectures. We show that the Batch Normalization layer, a standard layer in state-of-the-art architectures, can be enhanced by considering alternatives to mean and standard deviation suggested by the Quadrangle. These new ideas address a disconnect between the choice of network non-linearities and the normalization layer that precedes it, improving convergence during training and, sometimes, increasing testing accuracy as well.

4. Jie Xu – Department of Systems Engineering & Operations Research at George Mason University

   Title: Efficient Simulation Sampling Allocation Using Multi-Fidelity Models

   Abstract: Computer simulation is frequently used to predict the performance of a complex and stochastic system and select the best system configuration from a set of alternatives. For a large-scale complex system, high-fidelity simulation is usually time-consuming and expensive. In this talk, we provide a new framework that integrates information from models of different fidelity levels to increase efficiency for selecting the best. A Gaussian mixture model is introduced as the prior distribution model for information from multi-fidelity models. Posterior information obtained by a clustering analysis incorporates both cluster-wise information and idiosyncratic information for each system configuration. We then propose a new budget allocation method to efficiently allocate high-fidelity simulation replications. Numerical experiments show that the proposed multi-fidelity framework achieves a significant boost in computational efficiency.

Contributed Talks

1. Stephanie Allen (University of Maryland, College Park)
   Solving a Stochastic Network Protection Problem with Complementarity Constraints using the Pyomo and PySP Open Source Packages

2. Azam Asl (Courant Institute, New York University):
   Analysis of Limited-Memory BFGS on a Class of Nonsmooth Convex Functions

3. Sumaya Alzuhairy (University of Maryland, Baltimore County):
   Efficient Multilevel Methods for the Optimal Control of Large-scale Stochastic Partial Differential Equations

4. Robert Bassett (Naval Postgraduate School):
   Likelihood Smoothing via the Moreau Envelope

5. Andreas Van Barel (KU Leuven):
   MG/OPT and multilevel Monte Carlo for robust PDE constrained optimization

6. Logan Beaver (University of Delaware):
   Distributed Optimal Control for Autonomous Agents

7. Getachew K. Befekadu (Morgan State University):
   Optimal decision problems with backward stochastic viability property

8. Behdad Chalaki (University of Delaware):
   Coordination of vehicles at interconnected intersections using an optimal control

9. Anirban Chaudhuri (Massachusetts Institute of Technology):
   Information Reuse for Importance Sampling in Reliability-Based Design Optimization

10. Jiahua Jiang (Virginia Tech):
Truncation and Recycling Methods for Lanczos Bidiagonalization and Hybrid Regularization

11. Joane Joseph (Princeton University):
Shaped Pupil Coronagraph Design for Subaru High-Contrast Imaging with Reduction of the Inner Working Angle for Earth-like Planet Detection

12. Ratna Khatri (George Mason University)
Role of Fractional Laplacian in Inverse Problems

13. Boris Kramer (Massachusetts Institute of Technology):
Conditional-Value-at-Risk estimation via reduced-order models

14. Chen Li (Courant Institute of NYU)
Sparse optimal control of PDEs under uncertainty

15. Mae Markowski (Rice University):
Scenario Reduction with Surrogate Models for Risk-Averse PDE-Constrained Optimization Problems

16. Elahesadat Naghib (Princeton University):
Fourier Constrained Optimization

17. Robert Ravier (Duke University):
The Role of Prediction in Optimization of Time-Varying Parametrizable Objective Functions

18. Bismark Singh (Sandia National Laboratories):
Modeling flexible operating regions with chance constraints for stochastic unit commitment

19. Deepanshu Verma (George Mason University):
External Optimal Control of Fractional Parabolic PDEs

Abstracts

Solving a Stochastic Network Protection Problem with Complementarity Constraints using the Pyomo and PySP Open Source Packages

Stephanie Allen

University of Maryland College Park

Stochastic network protection problems aim to fortify networks to minimize the potential losses that could be realized in the event of crises and disasters. When focusing on transportation networks, it is important to integrate equilibrium/complementarity constraints into the model to capture the dynamics of the network, but these constraints add both theoretical and computational difficulties to the process of solving the model. This project focuses on implementing Fan and Liu's 2010 stochastic network protection model with complementarity constraints in Python using the Pyomo and PySP packages. Pyomo is an open source optimization package initially developed by Sandia National Laboratory. It combines the accessibility of an algebraic modeling language with the open source advantages of being based in Python. PySP allows users to form and solve stochastic programming models using Pyomo. In our search of literature and open source code, we found very few instances of Pyomo implementations that incorporated both stochastic and complementarity elements, meaning that an implementation of Fan and Liu's model in Pyomo would be a helpful contribution to the set of Pyomo open source examples on GitHub.

Analysis of Limited-Memory BFGS on a Class of Nonsmooth Convex Functions

Azam Asl

Courant Institute of NYU

The limited memory BFGS (L-BFGS) method is widely used for large-scale unconstrained optimization, but its behavior on nonsmooth problems has received little attention. L-BFGS can be used with or without "scaling"; the use of scaling is normally recommended. A simple special case, when just one BFGS update is stored and used at every iteration, is sometimes also known as memoryless BFGS. We analyze memoryless BFGS with scaling, using any Armijo-Wolfe line search, on the function

$f(x) = a|x^{(1)}| + \sum_{i=2}^{n} x^{(i)}$, initiated at any point x_0 with $x_0^{(1)} \neq 0$. We show that if $a \geq 2\sqrt{n-1}$, the absolute value of the normalized search direction generated by this method converges to a constant vector, and if, in addition, a is larger than a quantity that depends on the Armijo parameter, then the iterates converge to a non-optimal point $\bar{x}$ with $\bar{x}^{(1)} = 0$, although f is unbounded below. As we showed in previous work, the gradient method with any Armijo-Wolfe line search also fails on the same function if $a \geq \sqrt{n-1}$ and a is larger than another quantity depending on the Armijo parameter, but scaled memoryless BFGS fails under a *weaker* condition relating a to the Armijo parameter than that implying failure of the gradient method. Furthermore, in sharp contrast to the gradient method, if a specific standard Armijo-Wolfe bracketing line search is used, scaled memoryless BFGS fails when $a \geq 2\sqrt{n-1}$ *regardless* of the Armijo parameter. Finally, numerical experiments indicate that similar results hold for scaled L-BFGS with any fixed number of updates.

Efficient Multilevel Methods for the Optimal Control of Large-scale Stochastic Partial Differential Equations

Sumaya Alzuhairy

University of Maryland Baltimore County

We investigate the design and analysis of multilevel preconditioners for optimal control problems constrained by elliptic equations with stochastic coefficients. Assuming a generalized polynomial chaos expansion for the stochastic components, our approach uses a stochastic Galerkin finite element discretization for the PDE, thus leading to a discrete optimization problem. The key aspect is solving the potentially very large linear systems arising when solving the system representing the first-order optimality conditions. We show that the multilevel preconditioning technique from the optimal control of deterministic elliptic PDEs has a natural extension to the stochastic case, and exhibits a similar optimal behavior with respect to the mesh size, namely the quality of the preconditioner increases with decreasing mesh-size at the optimal rate. Moreover, under certain assumptions, we show that the quality is robust also with respect the two additional parameters that influence the dimension of the problem radically: polynomial degree and stochastic dimension.

Likelihood Smoothing via the Moreau Envelope

Robert Bassett

Naval Postgraduate School

Maximum likelihood estimation (MLE) is a widely used technique for making decisions from data. But as statistical models have become increasingly complex, practitioners in machine learning and related fields have observed that approximately maximizing a likelihood function gives an estimator which often outperforms the MLE. In this talk we discuss the statistical properties of approximately maximizing a smoothed likelihood, and prove the asymptotic efficiency of this estimator. The likelihood function is smoothed with the Moreau Envelope, a technique which generalizes proximal gradient descent, ADMM, and other modern optimization methods.

MG/OPT and multilevel Monte Carlo for robust PDE constrained optimization

Andreas Van Barel

KU Leuven

We present an algorithm based on the MG/OPT framework (a multigrid optimization framework) to solve optimization problems constrained by PDEs with uncertain coefficients. For stochastic problems, the relevant quantities, such as the gradient and Hessian, contain expected value operators. In order to be able to deal with high dimensional or irregular stochastic spaces, these are evaluated using a multilevel Monte Carlo (MLMC) method. Each of the MG/OPT levels then contains multiple underlying MLMC levels. A finer MG/OPT level also corresponds to a finer discretization level, since the gradient is returned on a finer discretization level. The MG/OPT hierarchy allows the algorithm to exploit the structure inherent in the PDE, speeding up the convergence to the optimum (regardless of the problem being deterministic or stochastic). In contrast, the MLMC hierarchy exists to exploit structure present in the stochastic dimensions of the problem. One can observe a large reduction in the number of samples required on expensive levels, and therefore in computational time.

Distributed Optimal Control for Autonomous Agents

Logan Beaver

University of Delaware

This talk gives an overview of an optimal control method developed for use at the University of Delaware Scaled Smart City (UDSSC). Agent coordination and formation is a high DOF problem, one natural approach to overcoming the curse of dimensionality is to use the meager computational ability of each agent to build a distributed controller. A natural metric to minimize is the energy consumption of each agent; to have many agents each must have minimal actuation, sensing, and power capabilities. Optimizing each agent's power use can significantly extend the lifetime of the system and improve its performance significantly.

Optimal decision problems with backward stochastic viability property

Getachew K. Befekadu

Morgan State University

In this talk, we are mainly concerned with an optimal decision problem for systems governed by stochastic differential equations, in which an optimal decision is made in such a way to minimize a vector-valued accumulated cost over a finite-time horizon that is associated with the solution of a certain multi- dimensional backward stochastic differential equation (BSDE). Here, we also require that such a solution for the multi-dimensional BSDE to satisfy almost surely a backward stochastic viability property with respect to a given closed convex set, where such a requirement further allows us to provide a sufficient condition in differential form based on the convexity of the distance function of the convex set. As a result of this, we establish the existence of an optimal solution, in the sense of viscosity solutions, for the corresponding system of semilinear parabolic partial differential equations that is associated with the optimal decision problem. Finally, we briefly comment on the implication of our result.

Coordination of vehicles at interconnected intersections using an optimal control

Behdad Chalaki

University of Delaware

Nowadays, using connected and automated vehicles (CAVs) in the transportation network has been more promising, due to the next generation of information and communication technologies. In this talk, I will present a framework for coordination of CAVs at two interconnected intersections, which is one of the bottlenecks in the transportation network. I will talk about using optimal control, and scheduling theory to minimize both energy consumption and travel time of each vehicle in a decentralized approach.

Information Reuse for Importance Sampling in Reliability-Based Design Optimization

Anirban Chaudhuri

Massachusetts Institute of Technology

This work introduces a new approach for importance-sampling-based reliability-based design optimization (RBDO) that reuses information from past optimization iterations to reduce computational effort. RBDO is a two-loop process—an uncertainty quantification loop embedded within an optimization loop—that can be computationally prohibitive due to the numerous evaluations of expensive high-fidelity models to estimate the probability of failure in each optimization iteration. In this work, we use the existing information from past optimization iterations to create efficient biasing densities for importance sampling estimates of probability of failure. The method involves two levels of information reuse: (1) reusing the current batch of samples to construct an a posteriori biasing density with optimal parameters, and (2) reusing the a posteriori biasing densities of the designs visited in past optimization iterations to construct the biasing density for the current design. We demonstrate for the efficiency of the proposed method for a benchmark speed reducer problem and a combustion engine problem.

Truncation and Recycling Methods for Lanczos Bidiagonalization and Hybrid Regularization

Jiahua Jiang

Virginia Tech

Krylov methods for inverse problems have the nice property that regularization can be decided dynamically. However, this typically requires that the entire Krylov space is kept in memory, which is problematic for large problems that do not converge quickly. We propose strategies for truncating the search space while maintaining the possibility of dynamic regularization (for various regularization methods). In addition, these strategies have advantages if a sequence of related regularized solves is required.

Shaped Pupil Coronagraph Design for Subaru High-Contrast Imaging with Reduction of the Inner Working Angle for Earth-like Planet Detection

Joane Joseph

Princeton University

The Subaru telescope detects exoplanets at contrasts of 6x10-9 by using a shaped pupil coronagraph. To allow for detection of Earth-like planets which would be found closer to the target star, we present a new pupil design that attains a smaller IWA and increases the throughput, while maintaining the current contrast. The tradeoff is a smaller OWA, decreasing the discovery space at the outer regions of the image plane. We also explore the potential benefits of setting the desired level of throughput and maximizing the contrast, as opposed to the current method of fixing the contrast and maximizing the throughput.

Role of Fractional Laplacian in Inverse Problems

Ratna Khatri

George Mason University

We will discuss the application of fractional Laplacian in two kinds of inverse problems. The first problem arises from imaging science, in which we propose the use of fractional Laplacian as a regularizer, and develop a residual neural network scheme to learn the regularization parameters. In the second problem we discuss external source identification with fractional PDE constraints. Classical models only allow the source/control to be placed on the boundary or inside of the observation domain. We introduce a new class of inverse problems which allow the source/control to be placed outside and away from the observation domain.

Conditional-Value-at-Risk estimation via reduced-order models

Boris Kramer

Massachusetts Institute of Technology

We present two reduced-order model based approaches for the efficient and accurate evaluation of the Conditional-Value-at-Risk (CVaR) of quantities of interest (QoI) in engineering systems with uncertain parameters. CVaR is used to model objective or constraint functions in risk-averse engineering design and optimization applications under uncertainty. Estimating the CVaR of the QoI is expensive. While the distribution of the uncertain system parameters is known, the resulting QoI is a random variable that is implicitly determined via the state of the system. Evaluating the CVaR of the QoI requires sampling in the tail of the QoI distribution and typically requires many solutions of an expensive full-order model of the engineering system. Our reduced-order model approaches substantially reduce this computational expense.

Sparse optimal control of PDEs under uncertainty

Chen Li

Courant Institute, NYU

We study optimal control problems under uncertainty with a sparsity-driven objective function. We add sparsity by incorporating the L^1-norm of the mean of the pointwise squared controls in the objective which leads to a shared sparsity structure of stochastic optimal controls. To solve the corresponding nonsmooth optimization problem, we propose an iterative reweighting algorithm. The algorithm is based on a reformulation of the problem and iterates over a reweighting function, which is only defined over the physical space and thus avoids sampling of the random space. Combined with low-rank operator approximations, this results in a monotone first-order method. To accelerate the method, we introduce a reduced formulation which only depends on the reweighting function and derive a novel preconditioned Newton conjugate gradient method. The shared sparsity structure of the optimal controls and the performance of the algorithms are studied numerically using control problems governed by the Laplace and Helmholtz equations.

Scenario Reduction with Surrogate Models for Risk-Averse PDE-Constrained Optimization Problems

Mae Markowski

Rice University

This talk synthesizes ideas from scenario reduction and multi-fidelity discretizations of partial differential equations (PDEs) for the efficient solution of risk-averse,

PDE-constrained optimization problems. These problems may arise in engineering applications when one seeks design parameters that minimize the costs to a system under uncertainty. Instead of minimizing the expected costs to the system, risk-averse formulations use risk measures like the Conditional Value-at-Risk (CVaR) to penalize deviations of actual costs that are above expected costs and yield solutions that are robust to uncertainty. However, solving risk-averse optimization problems is computationally expensive, as they require sampling in the tail of the objective's complicated and unknown probability distribution, which depends on the random variables that enter the system, on the PDE, and on the cost measure. Recently, efficient solution strategies for risk-averse optimization problems have involved iterative approximations to the so-called "risk regions" in the parameter space, i.e. those parameters that result in high costs to the system. For example, some have used iterative scenario reduction techniques for finite-dimensional stochastic programs. Others in the PDE-constrained optimization community have utilized surrogate models like reduced-order models to replace expensive function evaluations with less expensive ones. I unite the concepts from these two communities and discuss how surrogate models of the PDE can be used in combination with scenario reduction techniques to lower the computational cost of solving risk-averse PDE-constrained optimization problems.

Fourier Constrained Optimization

Elahesadat Naghib

Princeton University

Fourier constrained optimizations (FCO) naturally appear in applications such as signal processing, and optics. In addition, they appear in continuous relaxations of some fundamental combinatorial problems, such as Packing and Covering. This work proposes a framework to formulate and efficiently solve FCO's, and presents its application in providing tractable numerical solutions for the density of packing with copies of an arbitrary convex-body. We also present density upper-bounds for packing with convex bodies that to the best of our knowledge were not known before.

The Role of Prediction in Optimization of Time-Varying Parametrizable Objective Functions

Robert Ravier

Duke University

In online optimization, decisions about candidate optima are frequently made sole on presently available information. Fewer works take advantage of potential predictions. In this talk, we discuss recent work concerning predictions in online optimization for parametrizable objective functions, i.e. optimization problems where the time dependence is based on the value of a parameter at a given time. We show that, under mild assumptions, dynamic regret can be improved in this setting provided sufficiently accurate predictions. We also utilize methods for online nonparametric model selection to propose a method for simultaneous prediction and optimization, and study its performance via numerical examples. If time permits, we will discuss preliminary result in the distributed setting.

Modeling flexible operating regions with chance constraints for stochastic unit commitment

Bismark Singh

Sandia National Laboratories

We present a novel chance-constrained unit commitment formulation to address renewables production uncertainty. For most thermal generators, underlying technical constraints that are treated as "hard" by unit commitment models are in fact based on engineering judgments, such that system operators can request operation outside these limits in non-nominal situations, e.g., to ensure reliability. We incorporate such practical considerations into a chance-constrained unit commitment formulation, specifically by at most occasionally allowing minor deviations from minimum and maximum thermal generator power output levels. We demonstrate that the extensive form of our formulation is computationally tractable for medium-sized systems given modest numbers of renewables production scenarios. Additionally, we show that the formulation is able to potentially save significant annual production costs by allowing infrequent and intermittent violation of bounds imposed on thermal generator production limits. Finally, we conduct a sensitivity analysis of the optimal solution under two restricted regimes and observe similar qualitative results.

External Optimal Control of Fractional Parabolic PDEs

Deepanshu Verma

George Mason University

In this talk we consider optimal control with fractional parabolic PDEs as constraints where the control is placed outside the domain. We tackle the Dirichlet, the Neumann and the Robin cases. The need for these novel optimal control concepts stems from the fact that the classical PDE models only allow placing the source/control either on the boundary or in the interior where the PDE is satisfied. However, the nonlocal behavior of the fractional operator now allows placing the control in the exterior. We introduce the notions of weak and very-weak solutions to the parabolic Dirichlet problem. We present an approach on how to approximate the parabolic Dirichlet solutions by the parabolic Robin solutions (with convergence rates). The numerical examples confirm our theoretical findings and further illustrate the potential benefits of nonlocal models over the local ones.

List of Participants

1. Stephanie Allen (University of Maryland, College Park)
2. Harbir Antil (George Mason University)
3. Sumaya Alzuhairy (University of Maryland, Baltimore County)
4. Ali Andalibi (George Mason University)
5. Robert Argus (George Mason University)
6. Azam Asl (Courant Institute, New York University)
7. Yemeen Ayub (George Mason University)
8. Andreas Van Barel (KU Leuven)
9. Robert Bassett (Naval Postgraduate School)
10. Guzin Bayraksan (The Ohio State University)
11. Getachew K. Befekadu (Morgan State University)
12. Mojeed Olamide Bello (Morgan State University)
13. Tyrus Berry (George Mason University)
14. Logan Beaver (University of Delaware)
15. Patrick Bishop (George Mason University)
16. Nicole Buczkowski (University of Nebraska, Lincoln)
17. Vijay Chakilam (George Mason University)
18. Behdad Chalaki (University of Delaware)
19. Anirban Chaudhuri (Massachusetts Institute of Technology)
20. Atis Degro (George Mason University)
21. Andrei Draganescu (University of Maryland, Baltimore County)
22. Maria Emelianenko (George Mason University)
23. Christian Emiyah (Morgan State University)
24. Kiefer Green (George Mason University)
25. Andrew Giuliani (Courant Institute, New York University)
26. Igor Griva (George Mason University)
27. Alejandro Figueroa (George Mason University)
28. SeongHee Jeong (Louisiana State University)
29. Jiahua Jiang (Virginia Tech)

30. Joane Joseph (Princeton)
31. Mona Hajghassem (University of Baltimore)
32. Ratna Khatri (George Mason University)
33. Zainab Koreshi (George Mason University)
34. Drew P. Kouri (Sandia National Laboratories)
35. Boris Kramer (Massachusetts Institute of Technology)
36. Ksenia Kyzyurova (Brown University)
37. George Lan (Georgia Tech University)
38. Chen Li (Courant Institute, New York University)
39. Jiaxing Liang (University of Maryland, College Park)
40. Sijing Liu (Louisiana State University)
41. Rainald Löhner (George Mason University)
42. Mae Markowski (Rice University)
43. John Maxwell (George Mason University)
44. Ahmad Mousavi (University of Maryland, Baltimore County)
45. Elahesadat Naghib (Princeton University)
46. Tracey Oellerich (George Mason University)
47. Hayley Olson (University of Nebraska, Lincoln)
48. Michael Orlitzky (University of Maryland, Baltimore County)
49. Patrick O'Neil (BlackSky)
50. Long Nguyen (George Mason University)
51. Matthew Norton (The Naval Postgraduate School)
52. Robert Ravier (Duke University)
53. David Reed (George Mason University)
54. William Reese (North Carolina State University)
55. Denis Ridzal (Sandia National Laboratories)
56. Alexander Shapiro (Georgia Tech University)
57. Bismark Singh (Sandia National Laboratories)
58. Jeff Snider (George Mason University / MITRE Corp.)
59. Taylor Stevens (George Mason University)
60. Igor Semyonov (George Mason University)

61. An Pham (Penn State University)
62. Cigole Thomas (George Mason University)
63. Justin Thorpe (George Mason University)
64. Diego Torrejon (BlackSky)
65. Deepanshu Verma (George Mason University)
66. Ryan Vogt (North Carolina State University/Argonne National Laboratory)
67. Tonatiuh Sanchez-Vizuet (Courant Institute, New York University)
68. David Walnut (George Mason University)
69. Jean-Paul Watson (Sandia National Laboratories)
70. Janxiang Wang (George Mason University)
71. Jie Xu (George Mason University)
72. Guan Yuan (George Mason University)
73. Hong Zhang (Louisiana State University)
74. Yingqiu Zhang (Virginia Tech)
75. Shana (Naval Postgraduate School)
76. Miao Zhang (Louisiana State University)