Solving Chance-Constrained Problems via a Smooth Sample-Based Nonlinear Approximation

Andreas Waechter, Northwestern University

We discuss a new approximation of chance constraints that results in differentiable functions which can be integrated in nonlinear optimization problems and solved with standard nonlinear programming techniques. For problems with joint chance constraints, our formulation can be used to develop a new trust-region sequential quadratic programming algorithm with provable convergence guarantees.

Our formulation is based on sample average approximation and considers a set of random realizations of the constraints. Often, a mixed-integer programming formulation is used in this setting to select which of the resulting constraints should be enforced to achieve the desired probability of constraint satisfaction. However, this approach typically results in large computation times, due to the implicit enumeration performed by the branch-and-bound algorithm. Instead, we propose a compact reformulation that combines all constraint scenarios in a single smooth constraint. This is achieved by means of a smoothed cumulative distribution function for the random constraint values. We will present theoretical convergence results, and numerical experiments for the solution of DC optimal power flow problems with joint chance constraints showcase the efficiency of this approach.

This is work in collaboration with Alejandra Pena-Ordieres at Northwestern University; James Luedtke and Line Roald at the University of Wisconsin-Madison; and Dan Molzahn at Georgia Tech.