CHANCE-CONSTRAINED OPTIMIZATION FOR RESILIENT CRITICAL INFRASTRUCTURE

SAND2018-2085C

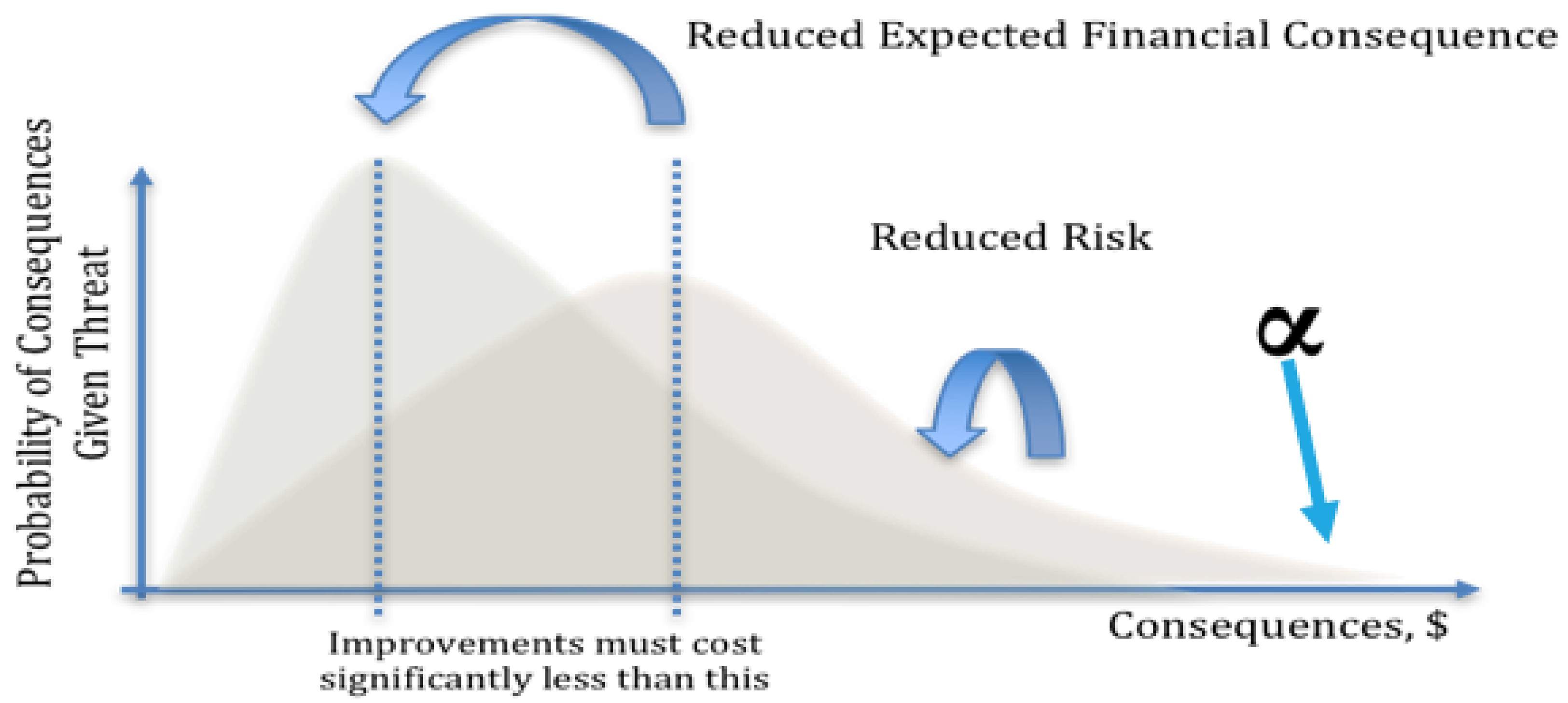
BISMARK SINGH, JEAN-PAUL WATSON
Discrete Math and Optimization Department, Center for Computing Research, Sandia National Laboratories

ABSTRACT

Chance-constrainted (CC) models involve a stochastic optimization model where highly reliable decisions need to be made, while acknowledging that we cannot safeguard ourselves against the entire set of possibilities of the future. Defending against all possible realizations is too expensive, and hence a cost-reliability tradeoff is considered. CC models answer the following question: how should we make decisions today to defend against most of tomorrow's unseen realizations? Thus, they serve a risky proposition—safeguarding against a future where high-risk low-likelihood failures could be catastrophic. CC optimization is a known NP-hard and computationally intractable problem. We discuss some applications and algorithms for solving this challenging problem.

KEY IDEAS

- Protecting against any future outcome costs infinite money. So, control for risk and allow failure in some scenarios. **A tradeoff in Risk versus Cost**
- Applications: A resilient electrical grid protected against,
  - extreme weather attacks
  - terrorist & nation-state attacks



Safeguarding against all possible scenarios can be expensive. Using CC program instead of a traditional stochastic program, we can ignore a small α fraction of scenarios

$$
\begin{aligned}
\text{minimize} \quad & c \cdot x + \textstyle\sum_{s \in \mathcal{S}} p_s (f_s \cdot y_s) \qquad \text{(E)}\\
\text{subject to:} \quad & (x, y_s) \in \mathcal{Q}_s, \quad \forall s \in \{\mathcal{S} : d_s = 1\}\\
& \textstyle\sum_{s \in \mathcal{S}} p_s \, d_s \geq (1 - \alpha)\\
& d_s \in \{0, 1\}, \quad \forall s \in \mathcal{S}
\end{aligned}
$$

CONTACT INFORMATION

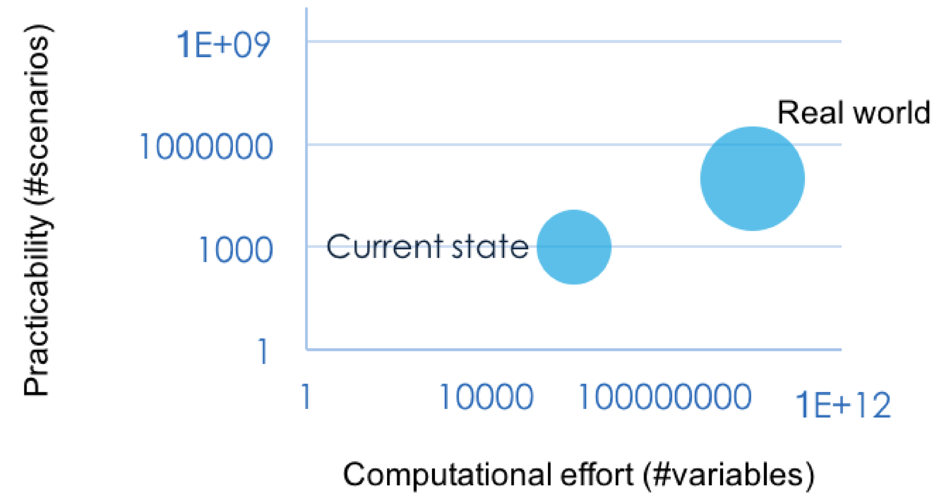
Bismark Singh, Postdoc, Discrete Math & Optimization, Sandia National Laboratories. **Email** bsingh@sandia.gov

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA-0003525.

CHALLENGES

Motivation: A natural and impactful modeling choice for securing infrastructure

- CC models: How to make highly reliable decisions under uncertainty, with controlled risk
- But ...CC models are computationally intractable
- Challenge: A known NP-hard problem
- Existing algorithms not scalable to practical sized problems



OUR RESEARCH

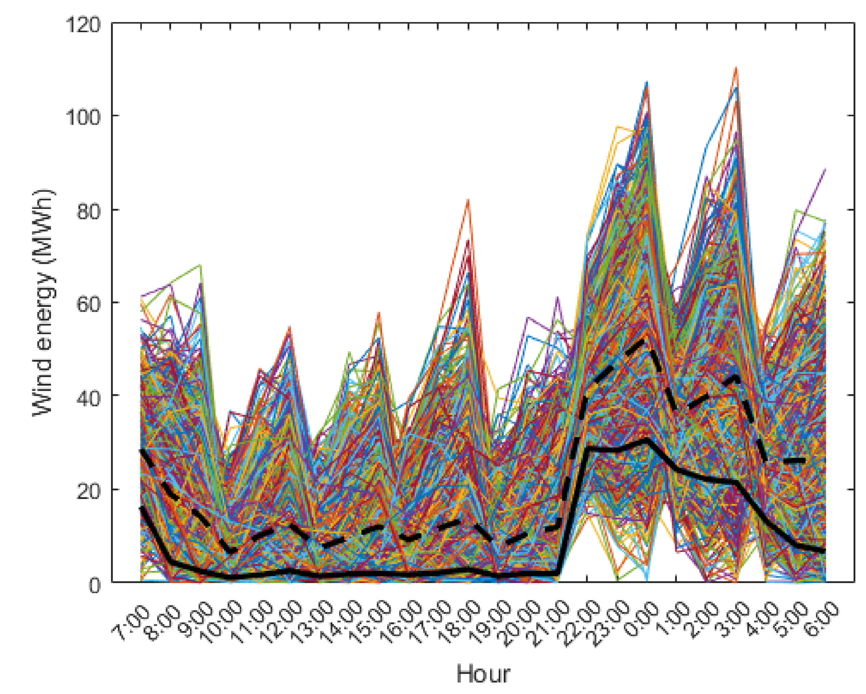
Aim: Design and implement a CC optimization algorithm to efficiently solve large scale practical problems. Test algorithm on large-scale power systems, focused on mitigating the impact of extreme weather attacks.

Our Existing Work: PhD dissertation at UT Austin, introducing a new algorithm to solve medium-sized CC problems very quickly. Start with few scenarios, use existing information to bias new solutions and gradually move to more scenarios

New ideas: Decomposition and Parallelization for scalability

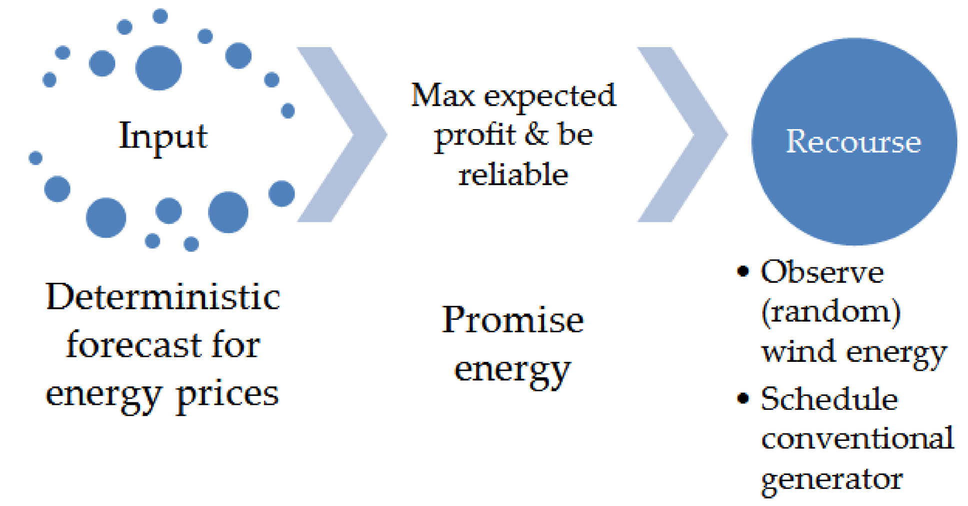
AN APPLICATION

A hybrid wind-diesel generator supplying reliably in the day-ahead market. Real-time dispatch decisions. Example: natural gas plant.



1500 hourly scenarios for wind energy generated using Monte Carlo sampling

Decisions for each hour: (i) how much energy to promise, and (ii) how much energy to schedule from conventional generator.



This problem is intractable!!

Scenarios	Reliability	Problem	Profit	Gap	Time
1500	95%	Naive	3422.3	67.4%	2100
1500	95%	Heuristic	6043.8	n/a	700

Below is a regularization algorithm, using which we can solve it efficiently:

Require: m scenarios, $\delta, \rho, time$, 1500 i.i.d. scenarios of w.
Ensure: $\hat{z}$: objective function value of original model with 1500 scenarios.
Generate m i.i.d. realizations of w, and solve the SAA of original model to obtain x_m^*. Let $\hat{x} \leftarrow x_m^*$.
while time $\leq time$ **do**
    Let $m \leftarrow \lceil m(1+\delta) \rceil$. (Increase number of scenarios)
    Generate m i.i.d. realizations of w, and solve the SAA of regularized model to obtain x_m^*. Let $\hat{x} \leftarrow x_m^*$.
    Solve original model with 1500 scenarios with x fixed to $\hat{x}$, and let $\hat{z}$ denote the objective function value.
    Update time to the cumulative wall-clock time consumed so far.
end while