REGROW: Renewable Energy Generation Risk from Outlier Weather

 $\begin{array}{cccc} \textbf{Giray Ogut}^1 & \mathsf{Bennet\ Meyers}^2 & \mathsf{David\ Chassin}^2 & \mathsf{Kirsten\ Perry}^3 & \mathsf{Stephen\ Boyd}^1 \end{array}$

¹Stanford University ²SLAC National Accelerator Laboratory ³National Renewable Energy Laboratory

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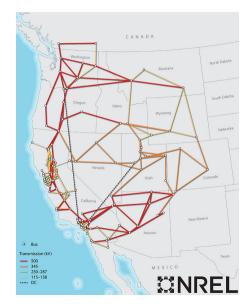
Overview

- motivation: 2020 CAISO blackouts caused by
 - extreme weather: very high energy demand
 - high renewable penetration: 'duck curve' effect
 - day-ahead electricity market: supply challenges

objectives:

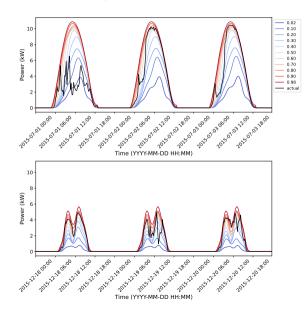
- estimation of correlated losses and fat tails
- robust model predictive control of the grid
- counterfactual reasoning for different scenarios
- model: white-box ML model based on convex optimization for
 - joint probability distribution of load and renewable generators
 - efficient, tractable and robust planning

Dataset curation and grid modeling



- curate datasets covering historical abnormal weather patterns
- obtain multidimensional data covering grid conditions, renewable generation, and weather
- example datasets
 - NREL PVFleets
 - NREL 144-bus model of WECC electrical grid
 - NOAA extreme weather

Risk modeling

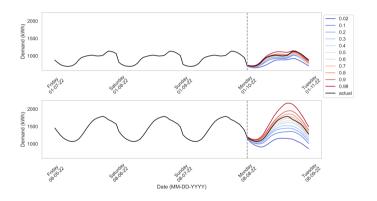


- develop risk models of renewable generator underperformance and outages
- capture correlations between generators and ambient meteorological conditions
- make a 'nightmare scenario generator'
- figure shows estimated quantiles for power generation of a residential PV system

Robust control

- model predictive control (MPC) consisting of
 - forecast: predict stochastic future values
 - plan: solve optimization problem assuming forecasts are correct
 - execute: take first action in plan
 - repeat
- works extremely well in practice (e.g. to land rockets)
- can be specified as a convex optimization problem
- tractable and can be solved efficiently and robustly

Multi-forecast MPC



- incorporate uncertainty and information patterns via multiple scenarios
- can be conditioned on historical and future information
- figure shows net load forecast for Rhode Island

Implementation

```
minimize -q_T + \kappa \|c\|_1 + \sum_{t=1}^T \phi(g_t)
subject to q_1 = Q^{init}
                  0 \prec r^{\text{curt}} \prec r.
                  c + r^{\text{curt}} + g = I.
                  0 \prec a \prec Q1.
                  0 \prec \varphi \prec G\mathbf{1}.
                   |c| \prec C1.
```

convex optimization problem that can be solved efficiently and robustly

```
import cvxpy as cp
                             c = cp.Variable(T)
                             q = cp.Variable(T + 1, nonneg=True)
                             r_curt = cp.Variable(T, nonneg=True)
                             g = cp.Variable(T, nonneg=True)
q_{t+1} = q_t + c_t, t = 1, ..., T, obj = -q[-1] + kappa*cp.norm1(c) +
                                     alpha*cp.sum(g) +
                                     beta*cp.sum_squares(g)
                             cons = [q[0] == Q_init.
                                     q[1:] == q[:-1] + c,
                                     r_curt <= r.
                                      c + r_curt + g == 1.
                                      q \leftarrow Q, g \leftarrow G, cp.abs(c) \leftarrow C
                             mpc = cp.Problem(cp.Minimize(obj), cons)
                             mpc.solve()
```

can be implemented in only a few lines of code

Impact

- current paradigm: we need fossil energy sources for grid resilience during extreme weather events
- ▶ hypothesis: extreme weather events are not a barrier to large-scale renewable integration provided that we have the right planning tools
- potential benefits: enable high-penetration of renewables and decarbonize the grid
- ► transfer of knowledge: use well-known techniques from finance and portfolio optimization to mitigate risks in the energy sector