Distributionally Robust Control of Energy Storage
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Motivation
Energy Storage is necessary to offset power fluctuations from renewable energy. Availability of wind energy is difficult to model and predict. We need to predict future wind production to optimally control the energy storage device. Previous work: \cite{1,2,3,4,5}

Solution: design a controller that is robust to errors in the model of the probability distribution.

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Ambiguity Set
Set of possible distributions of random variable $w$, based around observed historical data. Historical data shown by histogram

We assume true pdf lies within shaded region

Robustness: minimize cost of most expensive possible distribution.

\cite{6,7,8,9} \cite{Castillo, Gayme, 2014} \cite{Harsha, Dahleh, 2015} \cite{Lakshminarayana et al., 2016}

System Outline
Moment-based ambiguity set: \cite{6,7,8,9}
Assume true distribution has similar mean, variance as historical data

$$D_{\epsilon} := \left\{ \mu \in P(\mathbb{R}) \mid |\mu_t(W_t) - m_t| \leq \epsilon_t \right\}$$

$$E_{\mu_t}[|w_t - m_t|^2] \leq c_t \sigma^2$$

State of charge: $x_t \in X := [x_{\min}, x_{\max}]$
Control: amount battery is charged
System dynamics: $x_{t+1} = \eta(x_t + u_t)$
Cost function: mismatch between available wind energy and amount battery is charged

\cite{El Ghaoui et al, 2003}, \cite{Delage, Ye, 2010}, \cite{Zymler et al, 2013}, \cite{Wiesemann et al, 2014}

Dual Reformulation
Robust to incorrect distribution estimation: minimize worst case cost

This infinite program is hard to solve: reformulate as a semi-infinite minimization problem. Can be solved with convergent algorithms \cite{10,11,12,13}

Take Lagrangian dual of inner infinite dimensional maximization. A generalized Slater condition is satisfied \cite{14}

Performance analysis: \cite{15}: Compare performance of distributionally robust controller to standard stochastic controller. We use real-world historical data \cite{16} divided into training and testing data (below).

Simulation Results

Evaluate performance of distributionally robust controller to standard stochastic controller. We use real-world historical data \cite{16} divided into training and testing data (below).

Analysis: Distributionally robust controller shows superior performance when training data does not represent future data. It has a more conservative response to predictions of large wind values. Standard controller willing to incur a certain cost in the present to prevent a potential future cost, distributionally robust controller is not.

Future work: incorporate approximate dynamic programming methods and moment-based relaxation to alleviate dimensionality issues in storage networks.

\cite{15} \cite{http://www.pjm.com/markets-and-operations/ops-analysis.aspx}