Integrating Random Energy into the Smart Grid

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Collaborators

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... and thanks to many useful discussions with:
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Outline

The Smart Grid

The Smart Grid is a vision of the future electric energy system.

What's in it?

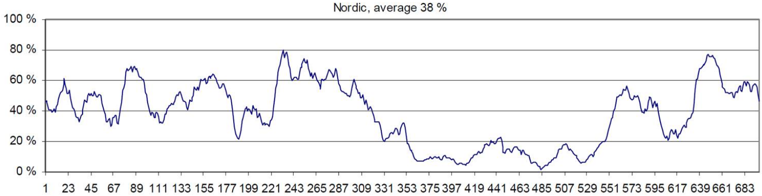
- demand response
- smart metering
- new materials
- communication
- cyber security
- PHEVs
- micro-grids
- renewables
- storage
- new market systems

Wind Power Variability

Wind is variable source of energy:

- Non-dispatchable - cannot be controlled on demand
- Intermittent - exhibit large fluctuations
- Uncertain - difficult to forecast

This is *the* problem! Especially large ramp events



Hourly wind power data from Nordic grid, Feb. 2000 – P. Norgard et al.,2004

Wind Energy: *Status Quo*

Current penetration is modest, but aggressive future targets

- Wind energy is 25% of added capacity worldwide in 2009 (40% in US) – surpassing all other energy sources
- Cumulative wind capacity has doubled in the last 3 years – growth rate in China $\approx$ 100%

Almost all wind sold today uses extra-market mechanisms

- Germany – Renewable Energy Source Act
  TSO must buy all offered production at fixed prices
- CA – PIRP program
  end-of-month imbalance accounting + 30% constr subsidy

Dealing with Variability

Today:

- All produced wind energy is taken, treated as negative load
- Variability absorbed by operating reserves
- Integration costs are socialized

Tomorrow:

- Deep penetration levels, diversity offers limited help
- Too expensive to take all wind, must curtail
- Too much reserve capacity $\implies$ lose GHG reduction benefits

Today's approach won't work tomorrow

Dealing with Variability Tomorrow

At high penetration ($> 20\%$), wind power producer (WPP) will have to assume integration costs

Consequences:

1. WPPs participating in conventional markets [ex: GB, Spain]
2. WPPs procuring own reserves [ex: BPA *self-supply* pilot]
3. Firming strategies to mitigate financial risk [ex: Iberdrola]
   - energy storage
   - co-located thermal generation
   - aggregation services
4. Novel market systems
   - Intra-day [recourse] markets
   - Novel instruments [ex: interruptible contracts]

Our Broader Research Agenda

Systems and control problems relevant to renewable integration and grid operations

- Novel market instruments
- Optimal operation of energy storage
- Control and communication architectures
- Statistical wind forecasting

These realize system flexibility for the Smart Grid

Problem Formulation

1. Wind Power Model
2. Market Model
3. Pricing Model
4. Contract Model
5. Contract Sizing Metrics

Wind Power Model

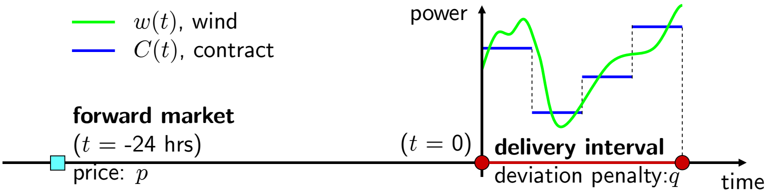
Wind power $w(t)$ is a stochastic process

- Marginal CDFs assumed known, $F(w,t) = \mathbb{P}\{w(t) \leq w\}$
- Normalized by nameplate capacity so $w(t) \in [0,1]$

Time-averaged distribution on interval $[t_0, t_f]$

$$F(w) \;=\; \frac{1}{T}\int_{t_0}^{t_f} F(w,t)dt$$

Market Model



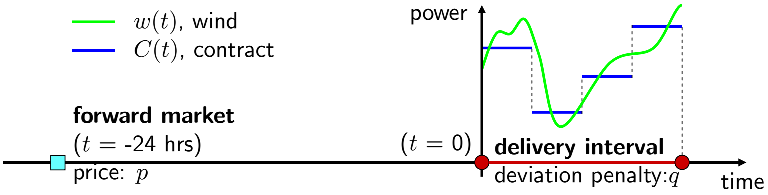
ex-ante: single forward market

ex-post: penalty for contract deviations

Remarks:

- Offered contracts are piecewise constant on 1 hr blocks
- No energy storage ⇒ no price arbitrage opportunities ⇒ contract sizing decouples between intervals

Pricing Model



Prices ($ per MW-hour)

p = clearing price in forward market

q = imbalance penalty price

Assumptions:

- Wind power producer (WPP) is a price taker
- Prices p and q are fixed and known

Metrics of Interest

For a contract C offered on the interval $[t_0, t_f]$, we have

$$\begin{aligned}
\text{profit acquired} \quad \Pi(C,w) &= \int_{t_0}^{t_f} pC - q\,[C - w(t)]^+\,dt \\
\text{energy shortfall} \quad \Sigma_-(C,w) &= \int_{t_0}^{t_f} [C - w(t)]^+\,dt \\
\text{energy curtailed} \quad \Sigma_+(C,w) &= \int_{t_0}^{t_f} [w(t) - C]^+\,dt
\end{aligned}$$

These are random variables.
So we're interested in their expected values.

Optimal Contracts

Taking expectation with respect to w,

$$\begin{aligned} J(C) &= \mathbb{E}\ \Pi(C,w) \\ S_-(C) &= \mathbb{E}\ \Sigma_-(C,w) \\ S_+(C) &= \mathbb{E}\ \Sigma_+(C,w) \end{aligned}$$

Optimal contract maximizes expected profit:

$$C^* = \arg\max_{C\geq 0} J(C)$$

Objectives

Theoretical

- Studying effect of wind uncertainty on profitability
- Understanding the role of p and q
- Utility of local generation and storage

Empirical

- Calculating marginal values of storage, local-generation

Bigger picture

- Using studies to *design* penalty mechanisms to incentivize WPP to limit injected variability
- Dealing with variability at the system level

Related Work

- Bathurtst et al (2002)
- Pinson et al (2007)
- Matevoysyan and Soder (2006)
- Botterud et al (2010)
- Morales et al (2010)
  - Incorporate risk of profit variability
  - Uncertainty in prices using ARIMA models
  - AR models and wind power curves for wind production
  - LP based solution using scenarios for uncertainties

Main Results

1. Optimal contracts in a single forward market
2. Role of forecasts
3. Role of local generation
4. Role of energy storage
5. Optimal contracts with recourse

Optimal Contracts: γ-quantile policy

Theorem

Define the time-averaged distribution

$$F(w) = \frac{1}{T}\int_{t_0}^{t_f} F(w,t)dt$$

The optimal contract C^* is given by

$$C^* = F^{-1}(\gamma) \qquad \textit{where} \quad \gamma = p/q$$

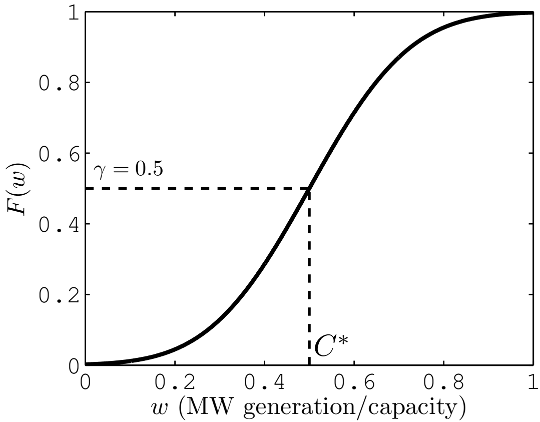
Optimal Contracts: Profit, Shortfall, & Curtailment

Theorem

The expected profit, shortfall, and curtailment corresponding to a contract C^* *are:*

$$
\begin{aligned}
J(C^*) &= J^* = & qT\int_0^{\gamma} F^{-1}(w)dw \\
S_-(C^*) &= S_-^* = & T\int_0^{\gamma}\left[C^* - F^{-1}(w)\right]dw \\
S_+(C^*) &= S_+^* = & T\int_{\gamma}^{1}\left[F^{-1}(w) - C^*\right]dw
\end{aligned}
$$

Graphical Interpretation of Optimal Policy



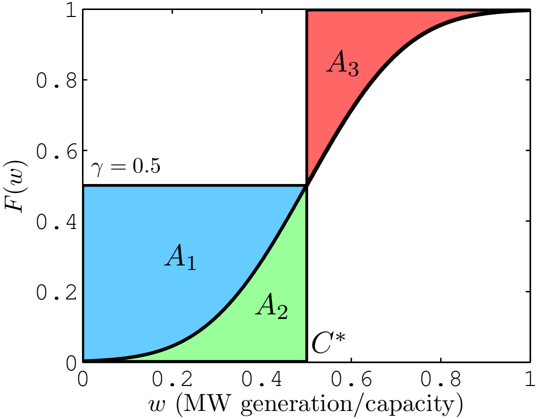
Price-Penalty Ratio

$$\gamma = \frac{p}{q}$$

Optimal Contract

$$C^* = F^{-1}(\gamma)$$

Graphical Interpretation of Optimal Policy



Profit:

$J^* = qT\ A_1$

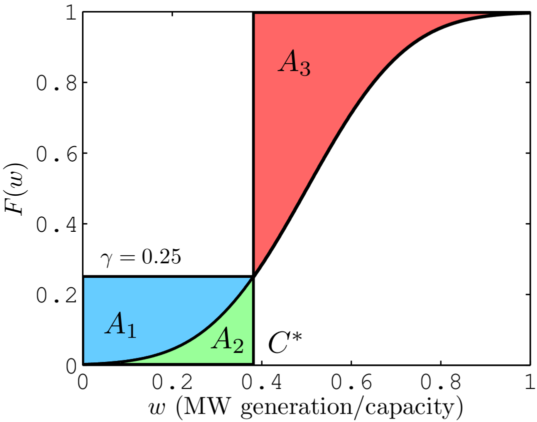
Shortfall:

$S_-^* = T\ A_2$

Curtailment:

$S_+^* = T\ A_3$

Graphical Interpretation of Optimal Policy



Profit:

$J^* = qT\ A_1$

Shortfall:

$S^*_- = T\ A_2$

Curtailment:

$S^*_+ = T\ A_3$

Some Intuition ...

Large penalty q, price/penalty ratio $\gamma \approx 0$

- optimal contract ≈ 0
- optimal expected profit ≈ 0
- sell no wind – too much financial risk for deviation

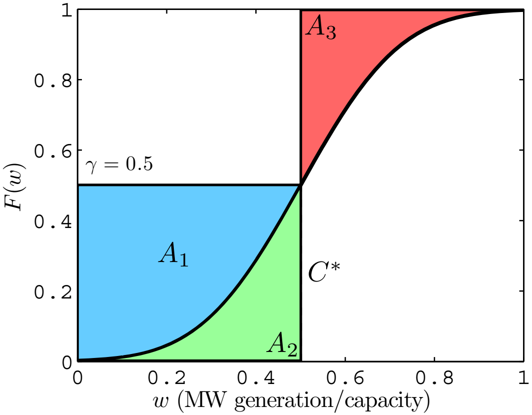
Small penalty q, price/penalty ratio $\gamma \approx 1$

- offered optimal contract $\approx 1 =$ nameplate
- optimal expected profit $= pT\mathbb{E}[W]$ [expected revenue]
- sell all wind – no financial risk for deviation

Price/penalty ratio γ controls prob of meeting contract, curtailment, variability taken

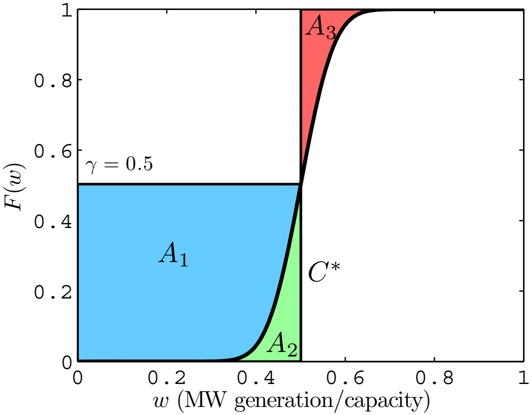
Result is simple application of Newsboy problem

The Role of Information



ex: 24 hour ahead forecast

The Role of Information



ex: 4 hour ahead forecast

Good Forecasts are Valuable

Better information ⇒ larger profit [want to formalize this]

EX: $W \sim$ uniform

$$J^* = \underbrace{pT\mathbb{E}[W]}_{\text{expected revenue}} - \underbrace{pT\sigma\sqrt{3}(1-\gamma)}_{\text{loss due to forecast errors}}$$

loss due to forecast errors is linear in standard deviation σ

General case:
Can quantify value of information using deviation measures

Result Generalizes...

Rockafellar et. al. (2002) provide an axiomatic formulation

Definition (General Deviation Measures)

A *deviation measure* is any functional $\mathcal{D} : \mathcal{L}^2 \to [0, \infty)$ satisfying

1. $\mathcal{D}(X + C) = \mathcal{D}(X)$ for constant C
2. $\mathcal{D}(\lambda X) = \lambda \mathcal{D}(X)$ for all $\lambda > 0$.
3. $\mathcal{D}(X + Y) \leq \mathcal{D}(X) + \mathcal{D}(Y)$
4. $\mathcal{D}(X) \geq 0$

for all $X, Y \in \mathcal{L}^2$.

Examples: standard dev., mean absolute dev.

Result Generalizes...

Optimal expected profit:

$$J^* = \underbrace{pT\mathbb{E}[W]}_{\text{expected revenue}} - \underbrace{pT\mathcal{D}_\gamma(W)}_{\text{loss due to forecast error}}$$

where

$$\mathcal{D}_\gamma(W) = \mathbb{E}[W] - \frac{1}{\gamma}\int_0^\gamma F^{-1}(w)dw$$

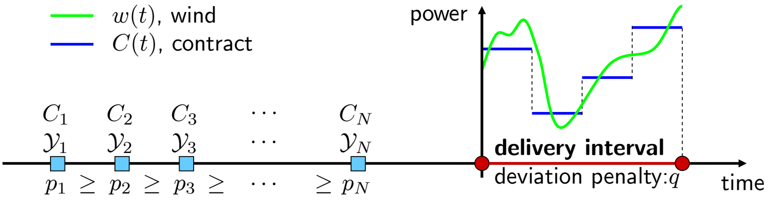
is the conditional value-at-risk (CVaR) deviation measure

Properties

1. $\mathcal{D}_\gamma(W)$ Monotone non-increasing in γ
2. $\lim_{\gamma\to 0} \mathcal{D}_\gamma(W) = \mathbb{E}[W], \qquad J^* \to 0$
3. $\lim_{\gamma\to 1} \mathcal{D}_\gamma(W) = 0, \qquad J^* \to pT\ \mathbb{E}[W]$

γ discounts the impact of uncertainty on profit J^*

Intra-day Markets



1. **ex-ante**: In market n, offer contract C_n at price p_n
2. **ex-post**: Imbalance deviation penalty from cumulative contract $C = \sum_{k=1}^{N} C_k$

Trade-off: decreasing prices , increasing information

Recourse Profit Criterion

Expected Profit Criterion:

$$J\left(C_{1:N}\right) = \mathbb{E} \int_{t_0}^{t_f} \sum_{n=1}^{N} \underbrace{p_n C_n\left(\mathcal{Y}_n\right)}_{\text{stage-n revenue}} - \underbrace{q\left[C\left(\mathcal{Y}_N\right) - w(t)\right]^+}_{\text{penalty on cumulative contract}} \, dt$$

Define a portfolio of profit maximizing contracts $\{C_n^*\}$ as

$$\{C_n^*\} = \arg \max_{\{C_n\} \geq 0} J\left(C_{1:N}\right)$$

Solution given by stochastic dynamic programming

Markets with Recourse

Theorem

The optimal contracts $\{C_n^*\}$ *are characterized by thresholds* $\{\varphi_n\}$

$$C_n^* = \left[\varphi_n - \sum_{k=1}^{n-1} C_k^*\right]^+$$

Threshold φ_n is a $\frac{p_n}{q}$-**quantile**, function of information $\mathcal{Y}_n$

Energy Storage

WPP has co-located energy storage facility

Questions:

- *ex ante* Optimal contract with local storage?
- *ex post* Optimal storage operation policy?
- Impact of storage capacity [capital cost] on profit?

Can be treated as:
finite-horizon constrained stochastic optimal control problem

Energy Storage Model

Model: $$\dot{e}(t) = \alpha e(t) + \eta_{\text{in}} P_{\text{in}}(t) - \frac{1}{\eta_{\text{ext}}} P_{\text{ext}}(t)$$

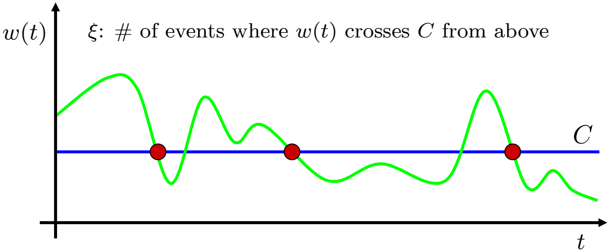
Constraints:

$$0 \leq e(t) \leq \overline{e}$$
$$0 \leq P_{\text{in}}(t) \leq \overline{P}_{\text{in}}$$
$$0 \leq P_{\text{ext}}(t) \leq \overline{P}_{\text{ext}}$$

Dynamics and constraints are linear

Marginal Value of Energy Storage (Intuition)

Consider storage system [small capacity ϵ, not lossy]



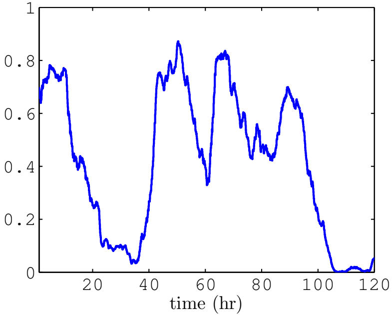
- ξ equivalent to number of energy arbitrage opportunities
- Each arbitrage opportunity gives savings $= q\epsilon$

$$\text{Marginal value of storage} = q\,\frac{\eta_{\text{in}}}{\eta_{\text{ext}}}\,\mathbb{E}[\xi]$$

Wind Power Data

Bonneville Power Authority [BPA]

- Measured aggregate wind power over BPA control area
- Wind sampled every 5 minutes for 639 days



Empirical Wind Power Model

Simplifying assumptions to estimate distributions.

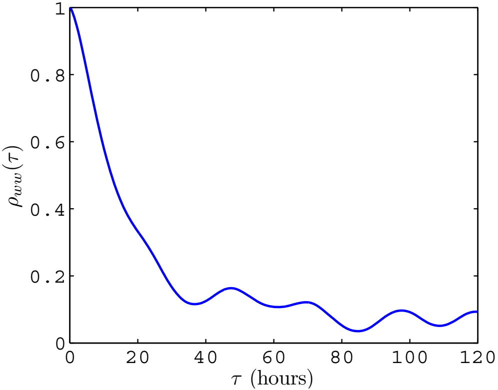
A1 The wind process $w(t)$ is assumed to be **first-order cyclostationary** in the strict sense with period $T_0 = 24$ hours,

$$F(w,t) = F(w, t + T_0) \quad \text{for all } t$$

A2 For a fixed time τ, the discrete time stochastic process $\{w(\tau + nT_0) \mid n \in \mathbb{N}\}$ is **independent** in time (n).

Empirical Wind Power Model

Autocorrelation $\rho_{ww}(\tau) = \mathbb{E}\ w(t)w(t+\tau)$



Empirical Wind Power Model

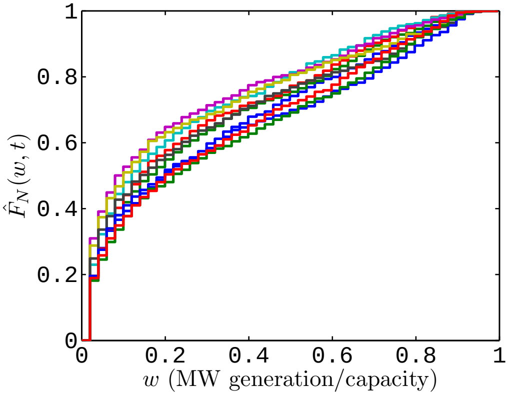
- Fix a time $\tau \in [0, T_0]$
- Consider a finite length sample realization of the discrete time process $z_\tau(n) := w(\tau + nT_0)$ for $n = 1, \cdots, N$.
- Compute the **empirical distribution** $\hat{F}_N(w, \tau)$

$$\hat{F}_N(w, \tau) = \frac{1}{N} \sum_{i=n}^{N} \mathbf{1}\left\{ z_\tau(n) \leq w \right\}$$

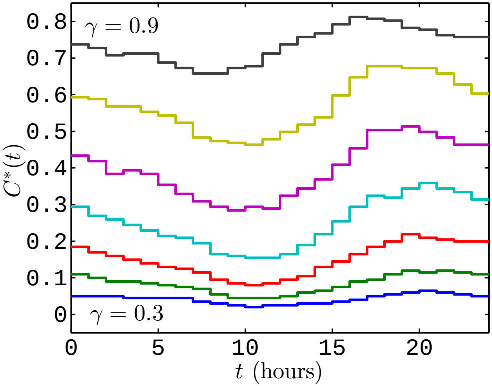
- $\hat{F}_N(w, \tau)$ is **consistent** with respect to $F(w, \tau)$ [A1, A2, LLN].

Empirical Distributions

Empirical CDFs for nine different hours



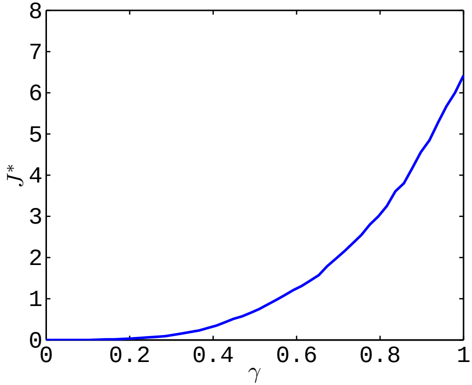
Optimal Forward Contracts



- Optimal contracts for $\gamma = [0.3 : 0.9]$
- Consistent with typical wind pattern
- Bigger penalty $\Longrightarrow$ smaller contract

Optimal Expected Profit - Empirical

Optimal expected profit J^* as a function of γ

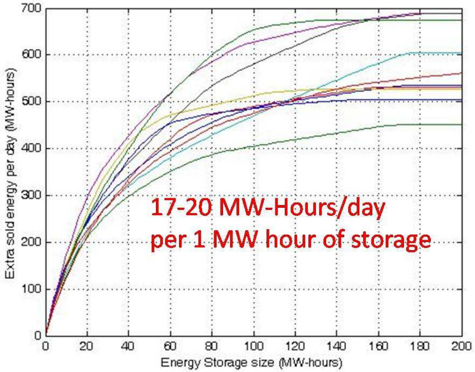


Typical numbers

- p=50 \$/MW-hour
- q=60 \$/MW-hour
- Capacity = 160 MW
- ex: $\gamma = 5/6$
  $J^* \approx$ \$ 28K per day

Marginal Value of Storage - Empirical

Useful in sizing storage



Recap

1. Optimal contracts in a single forward market
2. Optimal contracts with recourse
3. Role of forecasting
4. Role of local generation
5. Role of energy storage

Future Directions

- Alternative penalty mechanisms that support system flexibility
- Network aspects of wind integration
- Aggregation and profit sharing
- New markets systems: interruptible power contracts

Thank you. Questions?

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