On mitigating wind energy variability with storage

Vijay Arya, Partha Dutta, Shivkumar Kalyanaraman

IBM–Research India

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Introduction to wind power

- Wind is a major source of renewable energy worldwide. Used in grids, micro-grids, & distributed generation settings to power data centers, base stations, residential customers, etc.

- Characteristics of wind power
  - Variability
    function of wind-speed and air density
  - Uncertainty
  - Non-dispatchable & hard to integrate into grids & markets.
  - Requires complementary dispatchable generation/consumption: wind + dispatchable generation = load.
The need for mitigating variability

1. Variable wind power can increase the load-following variability negatively impacting the reliability and sustainability of energy
   - Higher costs of cycling power plants
   - Uneconomic dispatch of generation
   - Higher reserve requirements
   - Higher prices & CO$_2$ emissions
   - Blackouts

2. Variable wind power requires higher transmission capacity
   - expensive and inefficient utilization of transmission resources
   - Similar to higher bandwidth provisioning for VBR videos

3. Variable wind power is hard to integrate into electricity markets
   - Wind generators may not get the best economic value for their power.
This work: controlling variability using storage

- We present an optimization-based wind power smoothing system, which uses energy forecast and storage optimally to mitigate the variability of energy exported from a wind farm.

- The system determines an energy export curve that minimizes variability while maximizing the energy exported or revenue earned. It can be used in planning or invoked continuously for real-time operations.

- The optimization models a relaxed buffer system using only linear constraints and still yields optimal solutions.

- The system helps integrate more wind energy into the power system in a reliable and sustainable manner and enables wind power generators to get better economic benefits for their power.

- We highlight the connection to video smoothing problems.
Outline

- Mathematical models
- Minimize variability, maximize export
  - Extensions to micro-grid settings
  - Relationship to video smoothing
  - Online extension for real-time operation
  - Minimize variability, maximize revenue
- Experiments
Mathematical models

- We assume a discrete time system with wind energy forecast available for the next \( n \) time steps.

- **Cumulative models for (forecasted) generation, export, wastage**

  Cumulative: \( G(t), E(t), W(t) \).
  Instantaneous: \( \Delta G(t) = G(t) - G(t-1), \Delta E(t), \Delta W(t) \).

- **Buffer**: \( b(t) = \min \{ [b(t-1) + \Delta G(t) - \Delta E(t)]^+, B \} \)
  standard buffer model, but does not model wastage

- **Conservation**: \( G(t) = E(t) + b(t) + W(t), \forall t \)

- **Wastage**: charging/discharging losses + overflow

  \[
  \Delta W(t) \geq \omega |b(t) - b(t-1)| = \omega |\Delta b(t)|
  \]

  \( \omega \in (0,1) \): loss factor
Objective: Given a forecasted generation curve \( \{G(t)\}_t \), a buffer of size \( B \), to determine an export curve \( \{E(t)\}_t \) that has minimum variability, but maximizes the total energy exported.
Minimize variability, maximize export: LP (relaxed)

LP1 \hspace{1cm} \text{Objective:} \quad \max_{E(t), W(t), b(t)} \ E(n) - \nu \forall t

\hspace{1cm} \text{Variation penalty:} \quad \nu = \gamma \sum_{t=1}^{n} |\Delta E(t) - \Delta E(t-1)|

\hspace{1cm} \text{Cumulative:} \quad W(t) \geq W(t-1) \quad \forall t, \text{ etc.}

\hspace{1cm} \text{Others: conservation, wastage}

\hspace{1cm} \text{battery capacity, ramp rate, non-negative}

\hspace{1cm} \text{Input:} \quad G(t) \forall t, B, \gamma, \omega, r

\hspace{1cm} \text{Output:} \quad E(t), b(t), W(t) \forall t

- **LP1 models a buffer without overflow constraints (integer)**
  The buffer can discard energy even if it is not full.

**Claim** \hspace{1cm} \text{LP1 yields the optimal piece-wise linear export curve } E^*(t)

[see lemma 1 in paper]
Minimize variability, maximize export: LP solutions

<table>
<thead>
<tr>
<th>Time step</th>
<th>Solution 1</th>
<th>Solution 2</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>$\Delta G(t)$</td>
<td>$\Delta E(t)$</td>
</tr>
<tr>
<td>$i$</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>$i + 1$</td>
<td>30</td>
<td>10</td>
</tr>
<tr>
<td>$i + 2$</td>
<td>20</td>
<td>10</td>
</tr>
<tr>
<td>$i + 3$</td>
<td>15</td>
<td>10</td>
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<td>...</td>
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Solutions with the same $\{E(t)\}_t$ but different $\{b(t)\}_t$ and $\{W(t)\}_t$.

Buffer capacity $B = 20$, loss factor $\omega = 0.1$.

- $W(t)$ is non-decreasing, if $LP1$ assigns $W(t_i) = x$, then $\forall t > t_i$, it must assign $W(t) \geq x$. [see transform in paper]

- **Advantages**
  - Computationally efficient, can work in an online manner using successive forecasts available at each time step.
  - Wasted energy can be supplied to a secondary consumer at different times based on its value.
  - Delayed/lazy charging of battery is possible.
Extensions to micro-grid settings

- LP1 can be extended in micro-grid settings, to directly control the variability faced by non-wind generation.
- Let $L(t)$ be the cumulative load forecast, then

  \[
  \text{Residual load: } R(t) = L(t) - E(t)
  \]

  \[
  \text{Variation penalty: } v = \gamma \sum_{t=1}^{n} |\Delta R(t) - \Delta R(t - 1)|
  \]

- Helps control the efficiency of dispatchable generation leading to more reliable and sustainable micro-grids.
Relationship to a video smoothing problem

- A wind farm exports energy to a grid, buffer at the wind farm.
- \( G(t) - B \leq E(t) \leq G(t), \forall t \) allows overflow, models wastage.
- Total energy and variability are variables in optimization.
- Potentially related to live VBR video streaming problem.
- Uncertainty of generation

- Streaming server transmits a stored VBR video to a client over the network (with zero delay/loss), buffer at the client.
- \( G_v(t) \leq E_v(t) \leq G_v(t) + B_c, \forall t \) no overflow, no wastage.
- Total data is fixed, only variability needs to be minimized.
- Uncertainty of network channel conditions, live video.
Minimize variability, maximize revenue

Generators and retailers buy/sell energy in hourly day-ahead and real-time intra-hour markets. After markets close, participants are committed to supply/consume energy at location-based marginal prices for an upcoming time interval.

**Objective**: When energy prices vary across intervals, to determine an export curve that maximizes revenue by optimally meeting commitments and minimizing rate changes within each interval.

**LP2** Helps wind farm operators to deliver on committed energy and obtain better economic benefits for their power. [see paper]
Experiments

- We use historical 10-min wind energy and load time series from Alberta Electric System Operator (AESO), Canada (2011).
- Aggregate wind energy upto 8% of system load, average 2.3%.

(a) Comparison of variability: load has lower variability than wind energy.
(b) Operational impacts of injecting more 3 times the original wind energy
   - Ramp range rises from 2GWh to 3GWh, sharper peaks needs less baseload and more inefficient peaker generation.
   - Increased short term variability more reserves to match the short term random fluctuations of load.
Experiments

(a,b) Smoothing using LP1 for a sample day wind energy varies from 135 – 585 MWh. \( B = \sigma(\Delta G(t)) \) and \( \gamma = 1 \).

(c) Fraction of total energy exported as a function of buffer size \( B \) for different variation penalties \( \gamma \), could be used to size storage.
Conclusions

Summary

- Solutions to mitigate the variability of wind energy are essential to integrate it in a reliable and sustainable manner into grids/microgrids.

- We presented an optimization-based wind power smoothing system that uses storage to mitigate the variability of wind power. The system maximizes the energy exported or revenue earned. We presented a novel technique of modeling the buffer using only linear constraints that allows efficient computation of optimal smoothing solutions.

- We showed the connection to video smoothing problems.

Future

- Extension of battery model: varying loss rates, the number and depth of charging/discharging cycles, and battery lifetime.

- Stochastic forecasts

- Sizing of storage
Thank you
vijay.arya@in.ibm.com
Critique

- The LP1 formulation allows for changes in export rate between successive time steps, albeit minimal. Also, by having a limit on the amount of ramp between consecutive points allows for losses in energy when you have energy that can be exported but is being held back because of the constraint on the ramp rate.

- Different timescales are used (when maximizing revenue)- DA time quantum and RT time quantum. Not entirely clear from the description how. (Also, could be because of a lack of working knowledge beyond what is mentioned in the paper of how electricity markets work)

- Lastly, experimental results take historical data as forecast and evaluate against that. There's nothing mentioned in the paper as to how the system would react if the forecast does not match up to what's happening in reality. An intuition could help pave the way for more complex optimization formulations.