Dispatch of Storage for Adequacy Studies

Simon Tindemans
Delft University of Technology (TU Delft)

Michael Evans, David Angeli
Imperial College London

LOLE WG meeting - roundtable
NERC Atlanta office, 9 August 2019
Capacity Market

The Capacity Market (CM) is one of the key policies of the Electricity Market Reform programme. The CM aims to ensure the future security of our electricity supply at the lowest cost to consumers.
Storage as a ‘generator’ of last resort

From “Duration-Limited Storage De-Rating Factor Assessment – Final Report”

National Grid, December 2017
Relevant papers

Robustly Maximal Utilisation of Energy-Constrained Distributed Resources
Michael Evans, Simon Tindemans, David Angeli, 2018
PSCC 2018, Dublin. 10.23919/PSCC.2018.8443058 ; arXiv:1710.06302

A Graphical Measure of Aggregate Flexibility for Energy-Constrained Distributed Resources
Michael Evans, Simon Tindemans, David Angeli, 2019
Transactions on Smart Grid, in press. 10.1109/TSG.2019.2918058 ; arXiv:1805.09315

Minimising Unserved Energy Using Heterogeneous Storage Units
Michael Evans, Simon Tindemans, David Angeli, 2019
Transactions on Power Systems, in press. 10.1109/TPWRS.2019.2910388 ; arXiv:1807.09044

See also:
Optimal scheduling of energy storage resources
James Cruise, Stan Zachary
arXiv:1808.05901

A simple optimizing model for reservoir control
Technical report for the British Water Board
Problem definition
Assumptions

• Focus on security of supply
  – Cost of unserved energy $\gg$ cost of generation

• Discharging only
  – Focus on supply shortfall events
  – No cross-charging (energy scarcity)
  – Naturally applies to fuel-constrained generators
Definitions

set of devices $\mathcal{D} = \{D_1:n\}$
maximum power output $\bar{p}_i$
state of charge $E_i(t)$ (incorporates losses)
state $x_i(t) \equiv E_i(t)/\bar{p}_i$ [time-to-go]
control parameters $u_i(t)$ [power delivered by $D_i$]
state dynamics $\dot{x}_i(t) = -\frac{1}{\bar{p}_i}u_i(t)$
power reference $P^r(t)$ [power requested]
aim $\sum_i u_i(t) = P^r(t)$
Visual language

[time]

$x_1 \quad E_1 \quad \tilde{p}_1$

$x_2 \quad E_2 \quad \tilde{p}_2$

$x_3 \quad E_3 \quad \tilde{p}_3$

[power]

$p (\text{MW})$

$t (\text{h})$

$p^r$
Control strategy
Questions

For a given set of storage units $\mathcal{D}$:

1. Can we satisfy the power request $P^r(t)$?
2. What do we need to know about $P^r(t)$ to decide on an optimal action?

**Objective**: define a policy that maximises ability to satisfy a (partially) unknown request $P^r(t)$
Feedback policy (visual)

“Use batteries with largest time to go”

fleet state

reference power

power [kW]

power [kW]
Feedback policy (explicit)

- Order devices in groups of decreasing $x_i$
- Define:

$$r_i = \begin{cases} 
1, & \text{if } \sum_{j \leq i} 1^T \bar{U}_j \leq P^r \\
0, & \text{if } \sum_{j < i} 1^T \bar{U}_j \geq P^r \\
\frac{P^r - \sum_{j < i} 1^T \bar{U}_j}{1^T \bar{U}_i}, & \text{otherwise,}
\end{cases}$$

$$u^*(x, P^r) = \left[ r_1 \bar{U}_1^T \ldots r_q \bar{U}_q^T \right]^T.$$

- If $z^*(t)$ is state trajectory under algorithm, closed loop dynamics:

$$\dot{z}^*(t) = -P^{-1} u^*(z^*(t), P^r(t)).$$
Policy properties

- Equalises time-to-go between devices
- Maintains order of time-to-go between devices
- Maximises, at all times, instantaneous available power

\[
\bar{P}r(x) = \sum_i \bar{p}_i \mathbb{I}_{x_i > 0}
\]

- Greedily maximises the feasible set of signals
What if supply is infeasible?

- Define a policy for a feasible signal that is ‘close’.
- Define a **loss function** and find a policy that minimises it.
- Use **energy not served** (ENS – aka ‘unserved energy’):

\[
\Gamma(P^r, u) \equiv \int_0^\infty \max \left( P^r(t) - \sum_i u_i(t), 0 \right) dt
\]
ENS-minimising policy (identical!)

ENS is minimised
Discrete time policy

Policy is defined in continuous time. What about discrete time, e.g. for markets or simulations?

Define discretisation that **inherits optimality**

1. Determine *continuous* optimal response to piecewise constant request
2. Identify initial and final state for each interval
3. Determine a piecewise constant control signal with those initial/final states
4. Confirm that control is feasible (yes)
Algorithm 1 \[ u = \text{Constant input policy}(P^r, x, \bar{p}, \Delta t) \]

1: \[ y \leftarrow \text{unique sort-descending} \left[ x \max\{x - \Delta t 1, 0\} \right] \]
2: \[ \bar{E} \leftarrow 0 \quad \triangleright \text{Upper bound on energy in this iteration} \]
3: \[ i \leftarrow 0 \quad \triangleright \text{Counter} \]
4: do
5: \[ i \leftarrow i + 1 \]
6: \[ \bar{E} \leftarrow \bar{E} \quad \triangleright \text{Lower bound on energy in this iteration} \]
7: \[ \bar{E} \leftarrow \bar{p}^T \max\{\min\{x - y_i 1, \Delta t 1\}, 0\} \]
8: until \[ \bar{E} \geq P^r \Delta t \text{ or } i = \text{length}[y] \]
9: if \[ \bar{E} \leq P^r \Delta t \] then
10: \[ \hat{z} \leftarrow y_i \quad \triangleright \text{Upper bound equals energy requirement, or } P^r \text{ infeasible} \]
11: else
12: \[ \hat{z} \leftarrow y_{i-1} + \frac{P^r \Delta t - \bar{E}}{E - \bar{E}} (y_i - y_{i-1}) \quad \triangleright \text{Interpolation} \]
13: end if
14: \[ u \leftarrow \bar{p} \circ \max\{\min\{\frac{x - \hat{z} 1}{\Delta t}, 1\}, 0\} \]
Application: GB adequacy study

Estimate risks by (brute force) MC sampling of 10,000 years:

- **LOLE**: loss-of-load expectation (hours/year) [baseline: 2.9h/year]
- **EENS**: expected energy

Simulation details

- Heuristic recharging policy (inverse of discharging policy)
- Annual net demand traces by independent sampling of
  - 10 years of demand traces (2006-2015)
  - 30 years of wind power traces (1985-2014; synthesised from MERRA data using assumed 10GW installed capacity)
- Conventional generation portfolio of 63GW
  - Capacities 20x1200MW, 40x600MW, 40x250MW, 20x120MW, 20x60MW, 40x20MW, 60X10MW
  - Availability 90%; Poisson process with MTBF 2000h
- Battery capacity: 3x portfolio of Feb 2018 T-4 capacity auction
  (3x27 units; energy capacity inferred from derating factors)
Study results

<table>
<thead>
<tr>
<th>Policy</th>
<th>LOLE (h/y)</th>
<th>EENS (MWh/y)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Optimal Policy</td>
<td>1.74 ± 0.09</td>
<td>2431 ± 165</td>
</tr>
<tr>
<td>Lowest Power First</td>
<td>1.74 ± 0.09</td>
<td>2443 ± 165</td>
</tr>
<tr>
<td>Proportion of Power</td>
<td>1.74 ± 0.09</td>
<td>2435 ± 165</td>
</tr>
<tr>
<td>Proportional Discharge</td>
<td>1.85 ± 0.09</td>
<td>2438 ± 165</td>
</tr>
<tr>
<td>No Storage</td>
<td>2.98 ± 0.12</td>
<td>3810 ± 208</td>
</tr>
</tbody>
</table>

Optimal policy minimises EENS

Batteries improve security of supply

**Note**: despite large confidence intervals, results are comparable, because traces are identical between runs.
Summary and next steps
Summary and conclusion

• Myopic policy that
  – maximises instantaneous available power
  – maximises time-to-infeasibility
  – maximises future flexibility
  – minimises unserved energy
• Discrete time algorithm for simulations and dispatch
• [not shown] Aggregate representation of fleet capability

Next steps
• Recharging, including cross-charging
• Efficient computation schemes
• Generalised representations of flexibility
Capacity Value of Interconnection Between Two Systems

Simon H. Tindemans
Department of Electrical Sustainable Energy
Delft University of Technology
The Netherlands
s.h.tindemans@tudelft.nl

Matthew Woolf and Goran Strbac
Department of Electrical and Electronic Engineering
Imperial College London
United Kingdom
{mattwoolf, g.strbac}@imperial.ac.uk

Relates to work presented at LOLE WG 2016, Boston
Bonus slides
Comparison with alternative policies

Random request (pw constant)

Three policies
• OP: optimal policy
• LPF: lowest power first
• PoP: proportion of power

Results
• Largest time to infeasibility
• Largest available power
Discrete time algorithm (visual)

Goal: deliver $P^r \Delta t$ in $\Delta t$
## Example

### Graphical Representation

- The graph shows a time series for power consumption (`p`) over time (`t` in hours).
- The shaded area represents an energy consumption of 5 kWh.

### Table

<table>
<thead>
<tr>
<th>variable</th>
<th>unit</th>
<th>limit</th>
<th>time step</th>
</tr>
</thead>
<tbody>
<tr>
<td>(P^r)</td>
<td>[kW]</td>
<td>4</td>
<td>18 12 1</td>
</tr>
<tr>
<td>(x_1)</td>
<td>[h]</td>
<td>4</td>
<td>3 2 1</td>
</tr>
<tr>
<td>(x_2)</td>
<td>[h]</td>
<td>3</td>
<td>2.5 1.5 0.5</td>
</tr>
<tr>
<td>(x_3)</td>
<td>[h]</td>
<td>2</td>
<td>2 1 0</td>
</tr>
<tr>
<td>(x_4)</td>
<td>[h]</td>
<td>1</td>
<td>1 0 0</td>
</tr>
<tr>
<td>(z)</td>
<td>[h]</td>
<td>2.5</td>
<td>0 0 0.5</td>
</tr>
<tr>
<td>(u_1)</td>
<td>[kW]</td>
<td>2</td>
<td>2 2 2 1</td>
</tr>
<tr>
<td>(u_2)</td>
<td>[kW]</td>
<td>4</td>
<td>2 4 4 0</td>
</tr>
<tr>
<td>(u_3)</td>
<td>[kW]</td>
<td>3</td>
<td>0 3 3 0</td>
</tr>
<tr>
<td>(u_4)</td>
<td>[kW]</td>
<td>7</td>
<td>0 7 0 0</td>
</tr>
<tr>
<td>ENS</td>
<td>[kWh]</td>
<td>0</td>
<td>2 3 0</td>
</tr>
</tbody>
</table>
Table 8 – CM De-Rating Factors Proposed for Duration-Limited Storage Class in the 2018/19 T-1 and the 2021/22 T-4 Auctions

<table>
<thead>
<tr>
<th>Final De-Ratings Per Duration in Hours</th>
<th>&quot;2018/19&quot;</th>
<th>&quot;2021/22&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>Storage Duration: 0.5h</td>
<td>21.34%</td>
<td>17.89%</td>
</tr>
<tr>
<td>Storage Duration: 1h</td>
<td>40.41%</td>
<td>36.44%</td>
</tr>
<tr>
<td>Storage Duration: 1.5h</td>
<td>55.95%</td>
<td>52.28%</td>
</tr>
<tr>
<td>Storage Duration: 2h</td>
<td>68.05%</td>
<td>64.79%</td>
</tr>
<tr>
<td>Storage Duration: 2.5h</td>
<td>77.27%</td>
<td>75.47%</td>
</tr>
<tr>
<td>Storage Duration: 3h</td>
<td>82.63%</td>
<td>82.03%</td>
</tr>
<tr>
<td>Storage Duration: 3.5h</td>
<td>85.74%</td>
<td>85.74%</td>
</tr>
<tr>
<td>Storage Duration: 4h +</td>
<td>96.11%</td>
<td>96.11%</td>
</tr>
</tbody>
</table>
The E-p transform
The E-p transform

**Observation**: if $P^r(t)$ is feasible, all time-permuted variations are also feasible.

**Idea**: characterise feasible set in a representation that is insensitive to permutation of signals

**Definition**: 

$$E_{p^r}(p) \equiv \int_0^\infty \max(P^r(t) - p, 0) \, dt$$
Constructing the E-p diagram

\[ E_{Pr}(p) \equiv \int_0^\infty \max(P^r(t) - p, 0) \, dt \]
How to describe the system?

Consider a *just feasible* signal, the worst-case reference

\[ R(t) \doteq \sum_{i=1}^{n} \bar{p}_i [H(t) - H(t - x_i)], \]

Define its E-p transform

\[ \Omega_{\bar{p},x}(p) \equiv E_R(p) \]
E-p diagram of the worst-case reference
How to describe the system?

Consider a *just feasible* signal, the worst-case reference

\[
R(t) = \sum_{i=1}^{n} \bar{p}_i [H(t) - H(t - x_i)],
\]

Define its E-p transform

\[
\Omega_{\bar{p},x}(p) \equiv E_R(p)
\]

Theorem

\[
E_{pr}(p) \leq \Omega_{\bar{p},x}(p), \forall p \iff Pr(\cdot) \in F_{\bar{p},x}
\]

*dominance feasibility*
Graphical feasibility test

$p \ [\text{MW}]$

$E \ [\text{MWh}]$

$p_t$

$X \quad \text{infeasible}$
The power of the E-p diagram

- The max energy gap in the E-p diagram is equal to ENS!
Summary: E-p representation

- Necessary and sufficient for feasibility
  - Summarises fleet capability
  - Summarises power profile properties
- Convex and monotone

Applications
- Instant feasibility check
- Visualises effect of heterogeneity ("flexibility gap")
- Instant determination of minimum ENS