Stochastic programming of energy system operations considering terminal energy storage levels

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Introduction

- Energy storage units provide vital balancing power for energy systems.

- When trading electricity in the day-ahead market, the optimization of energy system operations follows a repeating pattern.

- If the end-effect is not handled, the energy storage is drained empty at the end of each optimization horizon.
Outline

- Overview of methods to mitigate the end-effect
- Proposed approach: electricity price-based valuation of terminal storage level
- Case studies
  - Energy storage arbitrage
  - Hybrid energy system of photovoltaic power and energy storage
A brief overview

Methods to mitigate the end-effect in the literature of energy systems

<table>
<thead>
<tr>
<th>Method</th>
<th>Example references</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rolling horizon</td>
<td>Mauch et al. (2012); Cao et al. (2019); Ding et al. (2015)</td>
</tr>
<tr>
<td>Starting and terminal energy levels enforced to be <strong>equal</strong></td>
<td>García-González et al. (2008); He et al. (2015); Wang et al. (2017); Han and Lee (2021)</td>
</tr>
<tr>
<td>Starting and terminal energy levels enforced to be <strong>within a given tolerance</strong></td>
<td>Ding et al. (2012); Krishnamurthy et al. (2017)</td>
</tr>
<tr>
<td>Value function approximation</td>
<td>Shin et al. (2017)</td>
</tr>
<tr>
<td>Terminal energy level valuation</td>
<td>Kahvecioğlu et al. (2022)</td>
</tr>
</tbody>
</table>
End-effect mitigation via the objective function

- No mitigation

\[
\max \sum_{t \in H} P_t, \quad |H| = |T|
\]

- Rolling horizon

\[
\max \sum_{t \in H} P_t, \quad |H| > |T|
\]

- Terminal energy level valuation

\[
\max \sum_{t \in H} P_t + V E_{|T|}, \quad |H| = |T|
\]

Indices
- \(t\): A time slot

Sets
- \(T\): Time slots of the day ahead
- \(H\): Time slots of the optimization horizon

Parameters
- \(V\): Value of the stored energy at the end of the horizon

Variables
- \(P_t\): Profit of time slot \(t\)
- \(E_t\): Stored energy level at the end of time slot \(t\)
## Proposed end-effect mitigation

|                         | horizon length $|H|$ | terminal level valuation $V$ |
|-------------------------|-----------------|-------------------------------|
| **proposed methods**    |                 |                               |
| min price-based valuation | 24              | predicted **minimum** electricity price during the next period |
| mean price-based valuation | 24              | predicted **mean** electricity price during the next period |
| **reference methods**   |                 |                               |
| no mitigation           | 24              | 0                             |
| equal start and terminal levels$^1$ | 24              | 0                             |
| rolling horizon         | 48, 72          | 0                             |
| perfect foresight$^2$   | 24, 48, 72      | 0                             |

$^1$ Enforced by an additional constraint.

$^2$ Actual price and variable renewable energy (VRE) information.
Multi-day-ahead electricity price forecasting

▶ We forecast electricity prices using the Lasso Estimated AutoRegressive model (Uniejewski et al., 2016)
▶ An open-source implementation for day-ahead prices is available at github.com/jeslago/epftoolbox (Lago et al., 2021)
▶ We have extended the forecast horizon to multiple days
▶ The following features are used:
  ▶ Past electricity prices
  ▶ Forecasted electricity demand
  ▶ Aggregated wind and solar forecast
  ▶ Day of week using a binary representation (e.g., Tuesday is [0, 1, 0, 0, 0, 0, 0])
Multi-day-ahead electricity price forecasting

- Prediction accuracy in the German day-ahead market during April 1 - July 31, 2022

<table>
<thead>
<tr>
<th>N-days-ahead</th>
<th>Mean absolute error [EUR/MWh]</th>
<th>$R^2$ [-]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>33.65</td>
<td>0.821</td>
</tr>
<tr>
<td>2</td>
<td>50.25</td>
<td>0.608</td>
</tr>
<tr>
<td>3</td>
<td>58.12</td>
<td>0.503</td>
</tr>
</tbody>
</table>
Case study 1: energy storage arbitrage

\[
\text{max } \tau \sum_{t \in T} \left[ \pi_t (p_i^d - p_i^c) - C_c p_i^c - C_d p_i^d \right] + V E_{|T|}
\]

s.t. bounds on charging,
\[
\text{ bounds on discharging,}
\]
conservation of energy, and
\[
\text{bounds on energy storage.}
\]

Parameters

\[\pi_t\] Electricity price at \(t\)
\[\tau\] Length of time slot
\[V\] Value of the stored energy
\[C_c\] Cost of charging
\[C_d\] Cost of discharging
\[E_0\] Initial stored energy

Variables

\[p_t^c\] Charging power at \(t\)
\[p_t^d\] Discharging power at \(t\)
\[p_t^{\text{da}}\] Traded power at \(t\)
\[E_t\] Stored energy level at the end of time slot \(t\)
Case study 1: energy storage arbitrage

\[
\begin{align*}
\text{max } & \tau \sum_{t \in T} \left[ \pi_t (p_t^d - p_t^c) - C_c p_t^c - C_d p_t^d \right] + V E_{|T|} \\
\text{s.t.} & \quad 0 \leq p_t^c \leq C_{\text{max}}, \quad t \in T \\
& \quad 0 \leq p_t^d \leq D_{\text{max}}, \quad t \in T \\
& \quad E_t = E_{t-1} + \eta_c \tau p_t^c - \frac{\tau}{\eta_d} p_t^d, \quad t \in T \\
& \quad E_{\text{min}} \leq E_t \leq E_{\text{max}}, \quad t \in T
\end{align*}
\]

Parameters
- \(\pi_t\): Electricity price at \(t\)
- \(\tau\): Length of time slot
- \(V\): Value of the stored energy
- \(C_c\): Cost of charging
- \(C_d\): Cost of discharging
- \(E_0\): Initial stored energy

Variables
- \(p_t^c\): Charging power at \(t\)
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- \(p_t^{\text{da}}\): Traded power at \(t\)
- \(E_t\): Stored energy level at the end of time slot \(t\)
Case study 2: photovoltaic power & energy storage

New set
\[ \Omega \text{ Scenarios} \]
New parameters
\[ \gamma^+, \gamma^- \text{ Pos./Neg. deviation penalty coefficient} \]
\[ \rho_\omega \text{ Probability of scenario } \omega \]
New Variables
\[ \Delta^+_t, \Delta^-_t \text{ Pos./Neg. deviation at } t \text{ in } \omega \]
\[ p^s_{t,\omega}, p^d_{t,\omega} \text{ Photovoltaic power at } t \text{ in } \omega \]

\[
\max \sum_{\omega \in \Omega} \rho_\omega \left\{ \tau \sum_{t \in T} \left[ \pi_t (p^s_{t,\omega} + p^d_{t,\omega} - p^c_{t,\omega}) - C_c p^c_{t,\omega} - C_d p^d_{t,\omega} - \gamma^+ \pi_t \Delta^+_t - \gamma^- \pi_t \Delta^-_t \right] + V_E |T|_\omega \right\}
\]

s.t. bounds on charging,
bounds on discharging,
conservation of energy, and
bounds on energy storage.

bounds on photovoltaic power,
positive deviation from the day-ahead bidding,
negative deviation from the day-ahead bidding,
Case study 2: photovoltaic power & energy storage

New set
\[ \Omega \quad \text{Scenarios} \]
New parameters
\[ \gamma^+, \gamma^- \quad \text{Pos./Neg. deviation penalty coefficient} \]
\[ \rho_\omega \quad \text{Probability of scenario } \omega \]
New Variables
\[ \Delta^+_t, \Delta^-_t \quad \text{Pos./Neg. deviation at } t \text{ in } \omega \]
\[ p^s_{t,\omega} \quad \text{Photovoltaic power at } t \text{ in } \omega \]

\[
\max \sum_{\omega \in \Omega} \rho_\omega \left\{ \tau \sum_{t \in T} \left[ \pi_t \left( p^s_{t,\omega} + p^d_{t,\omega} - p^c_{t,\omega} \right) - C_c p^c_{t,\omega} - C_d p^d_{t,\omega} - \gamma^+ \pi_t \Delta^+_t, \omega - \gamma^- \pi_t \Delta^-_t, \omega \right] + VE_{|T|, \omega} \right\}
\]

s.t. \[ 0 \leq p^c_{t,\omega} \leq C_{\text{max}}, \quad t \in T, \omega \in \Omega \]
\[ 0 \leq p^d_{t,\omega} \leq D_{\text{max}}, \quad t \in T, \omega \in \Omega \]
\[ 0 \leq p^s_{t,\omega} \leq S_{t,\omega}, \quad t \in T, \omega \in \Omega \]
\[ \Delta^+_t, \omega \geq p^s_{t,\omega} + p^d_{t,\omega} - p^c_{t,\omega} - p^d_{t,\omega}, \quad t \in T, \omega \in \Omega \]
\[ \Delta^-_t, \omega \geq -(p^s_{t,\omega} + p^d_{t,\omega} - p^c_{t,\omega} - p^d_{t,\omega}), \quad t \in T, \omega \in \Omega \]

\[ E_{t,\omega} = E_{t-1,\omega} + \eta_c \tau p^c_{t,\omega} - \left( \tau / \eta_d \right) p^d_{t,\omega}, \quad t \in T, \omega \in \Omega \]
\[ E_{t,\omega} \leq E_{t,\omega} \leq E_{\text{max}}, \quad t \in T, \omega \in \Omega \]
Solar irradiance scenarios

- Probabilistic predictions and past of data Global Horizontal Irradiance (GHI) are obtained from Solcast (2019)

- We use a variation of the statistical method by Pinson et al. (2009) to generate scenarios
Energy system and the data

- **Energy system**
  - Energy storage unit is a lithium ion-battery with the maximum discharge/charge power is 4 MW and the total capacity is 16 MWh
  - Photovoltaic power plant with the maximum power of 10 MW (only Case Study 2)
  - Located in Bavaria, Germany
  - Evaluation period of August 1 - October 28, 2022

- **Electricity market data**
  - German Federal Network Agency (https://www.smard.de/en)
  - Transmission system operator Tennet (https://netztransparenz.tennet.eu/)
  - ENTSO-E transparency platform (https://transparency.entsoe.eu/)

- **Solar irradiance data**
  - Predictions and actual values are obtained by Solcast (2019)
Case study 1: Average daily profits

► Min price-based valuation and no mitigation have the same average daily profit with a gap of 7.3% to perfect foresight with $|T| = 72$
► Perfect foresight with $|T| = 24$ is only 0.4% worse than with $|T| = 72$
► Draining the storage empty is beneficial in this case
Case study 2: Average daily profits

- The average profits are expressed relative to the perfect foresight.
Case study 2: cost breakdown

- Min price-based valuation has 1.6 to 38.8% smaller operating costs and 2.4 to 67.4% smaller penalties than no mitigation.
- In comparison to rolling horizon ($|T| = 48$), the corresponding differences are -0.4 to 22.1% and -5.2 to 25.3%.
Case study 2: Demonstration with $\gamma^+, \gamma^- = 2$

- GHI scenarios
  - stored energy
    - no mitigation
  - stored energy
    - min price-based valuation
Case study 2: Demonstration with $\gamma^+, \gamma^- = 2$

- GHI scenarios
- stored energy
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Case study 2: Demonstration with $\gamma^+, \gamma^- = 2$

- GHI scenarios

- stored energy
  - no mitigation

- stored energy
  - min price-based valuation
Conclusions

▶ We propose the **minimum price-based valuation** method for optimization of energy system operations with energy storage
  ▶ 0.0 to 14.0% greater profits than with no mitigation
  ▶ 0.0 to 3.4% greater profits than with rolling horizon + shorter time horizons!

▶ The method has also **desirable operation characteristics**
  ▶ Reduced cycling of the energy storage → extended life
  ▶ Smaller deviations from the day-ahead bidding

▶ Additional remarks
  ▶ The method of **enforcing start and end storage levels to be equal** is often used in the literature but yields a low profit on the studied energy systems
  ▶ Energy storage arbitrage: draining the storage empty at the end of the horizon is often a part of the optimal operation strategy, if an optimization period starts with cheap electricity prices
References


References (cont.)


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