Aging-aware NaS battery model in a stochastic wind-storage simulation framework

Pierre Haessig, Bernard Multon, Hamid Ben Ahmed, Stéphane Lascaud, and Lionel Jamy

EDF R&D LME, ENS Cachan SATIE
contact: pierre.haessig@ens-cachan.fr

PowerTech 2013, Grenoble, June 17th 2013

session Energy storage systems for power grids 1
Outline of the presentation

1. Introduction
   - Industrial context
   - Simulation objectives

2. Model description
   - Storage management to fulfill a commitment
   - Forecast error model
   - NaS battery model

3. Simulation results
   - Observation of stochastic trajectories
   - Parametric study of the performance

4. Conclusion and perspectives
Outline of the presentation

1. Introduction
   - Industrial context
   - Simulation objectives

2. Model description

3. Simulation results

4. Conclusion and perspectives
Wind Power Production with an Energy Storage System
an industrial application

The French Commission for the Regulation of Energy (CRE) launched a call for tender for wind farms “with services” targeting French islands.

**Key requirement**

*commitment* on a day-ahead production plan, hour by hour.
Wind Power Production with an Energy Storage System

system overview

Storage Control
to fulfill a production commitment
NaS battery testing

In parallel to the “wind-storage” call for tenders, the French utility EDF is testing a **1 MW/7 MWh** Sodium-Sulfur (NaS) battery in La Réunion.

![Map of La Réunion](image)

**NaS battery**

**La Réunion**

- population: ~1 M
- peak power: ~500 MW

*map source: Google Maps*
Objective

We study the *sizing* and the *control* (energy management policy) of an Energy Storage System (ESS) to fulfill the day-ahead production commitment of a wind farm.

The specific storage technology being investigated here is NaS since it is currently tested on field.

For this purpose, we build a **simulation model** of a wind-storage system that should:

- *Assess the performance* of an Energy Storage System (NaS battery) to fulfill a day-ahead production commitment
- Run without need of wind power forecast data (limited availability).
Outline of the presentation

1. Introduction

2. Model description
   - Storage management to fulfill a commitment
   - Forecast error model
   - NaS battery model

3. Simulation results

4. Conclusion and perspectives
The wind operator should keep the production $P_{grid}$ close to its commitment $P^*_grid$. We thus define the commitment deviation:

$$P_{dev} = P_{grid} - P^*_grid$$

...which should be kept “small” at all times.
To perfectly fulfill the commitment \((P_{dev} = 0)\), the ESS should absorb the “ideal storage request”:

\[
P_{sto}^* = P_{prod} - P_{grid}^*
\]

Energy management policy

Store \(P_{sto} = P_{sto}^*\), whenever the ESS is neither full nor empty.
Ideal storage request

This ideal request $P_{sto}^*$ is equal to the *forecast error* (assuming the commitment is taken equal to the forecast)

... thus the interest of studying and *modeling* forecast errors.
A look at wind power forecasting

One week of a wind farm production and forecast/commitment:

We focus on the difference between production and forecast because $P_{sto}^*$ is the input of the storage control.
Modeling forecast errors

One week of forecast errors (i.e. $P_{st}^*$):

Available time series are not long enough (~few months), we need a forecast error simulation model (a “noise generator”).
Autoregressive modeling of forecast errors

An AR(1) model captures the *autocorrelation* of forecast errors:

\[ P_{sto}^*(k + 1) = \phi P_{sto}^*(k) + \sigma_P \sqrt{1 - \phi^2} \varepsilon(k + 1) \]
NaS battery modeling

Sodium-Sulfur (NaS) batteries are designed for stationnary grid-scale storage of electricity (manufactured by NGK, Japan).

![Diagram of NaS Storage module and Electrical model of a NaS cell]

EDF commissioned a 7.2 MWh battery \( (N = 20 \text{ modules}) \). But the model is fully sizable in terms of rated energy (by setting \( N \) to an arbitrary number).
NaS battery modeling
requirements of the model

Because NaS batteries are \textit{hot} (operating at 300 – 350 °C), the \textit{thermal modeling} is important. Temperature impacts the cell resistance, thus efficiency.

Losses of electrical energy need to be computed to evaluate their cost.
NaS battery model: power flows

Power flows in the NaS battery model
(flows represented during charging)

AC Power Grid

Power absorbed by the inverter

Power absorbed by the battery

Power actually stored

Joule losses in the battery

Inverter losses

Electrochemical energy

Electrochemical energy

Thermal energy

Sensible heat

Latent heat

Thermal losses

Heating power

AC Power Grid

Electrochemical energy

Thermal energy

Latent heat

Thermal losses

Power flows in the NaS battery model
(flows represented during charging)
# Outline of the presentation

<table>
<thead>
<tr>
<th>1</th>
<th>Introduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>Model description</td>
</tr>
<tr>
<td>3</td>
<td>Simulation results</td>
</tr>
<tr>
<td></td>
<td>- Observation of stochastic trajectories</td>
</tr>
<tr>
<td></td>
<td>- Parametric study of the performance</td>
</tr>
<tr>
<td>4</td>
<td>Conclusion and perspectives</td>
</tr>
</tbody>
</table>
Combining the forecast and ESS models

For given model parameters, the wind-storage simulation generates stochastic trajectories.

Model parameters are:

- for the forecast error: RMS error $\sigma_P$ and correlation $\phi$
- for the NaS battery: the rated energy $E_{\text{rated}}$
Case study
a typical wind farm in La Réunion island

We consider a wind farm with a rated power $P_{nom} = 10$ MW. For the forecast error model, we consider:

- an RMS forecast error of 10 %: $\sigma_P = 1$ MW
- an inter-hour correlation of 80 %: $\phi = 0.8$

Before looking at the performance statistics, we first observe the trajectories (samples of stochastic time series).

We will look at the effect of increasing the storage capacity $E_{rated}$ from 5 to 20 MWh. Rated power rises accordingly since the “E/P ratio” is fixed with the NaS technology at 7.2 hours.
Stochastic trajectories from the simulation

Behavior of a 5.0 MWh battery

Power flows (storage nominal power: 0.6 MW)

Deviation from commitment

Power losses
Stochastic trajectories from the simulation

- **Behavior of a 7.0 MWh battery**
- **Power flows (storage nominal power: 0.9 MW)**
  - Storage request $P_{sto}^*$
  - Stored power $P_{sto}$
- **Deviation from commitment**
  - $P_{dev} = P_{sto}^* - P_{sto}$
- **Power losses**
  - $P_{losses}$
  - $P_{heater}$
Stochastic trajectories from the simulation

Behavior of a 10.0 MWh battery

Power flows (storage nominal power: 1.3 MW)

Deviation from commitment

Power losses
Stochastic trajectories from the simulation

Behavior of a 15.0 MWh battery

Power flows (storage nominal power: 1.9 MW)

Deviation from commitment

Power losses

SoE

Power [MW]

Power [MW]

Power [MW]

Power [MW]

Deviation from commitment

Power losses

time [days]
Stochastic trajectories from the simulation

Behavior of a 20.0 MWh battery

Power flows (storage nominal power: 2.6 MW)

Deviation from commitment

Power losses

P_{dev} = P_{sto}^{*} - P_{sto}

P_{losses} P_{heater}
Observations:
- a bigger battery “absorbs” better the forecast error
- a smaller battery consumes less heating power.

We want now to compute *quantitative* performance indices...
The stochastic simulations are repeated to collect many (1000) trajectories on which to compute statistics of performance indices like losses and commitment deviation.
Parametric study of the performance by varying the ESS capacity (0–50 MWh)

Performance metrics computed from 1000 trajectories of 30 days

Filled color intervals show the standard deviation among the different trajectories (i.e. *inter-month variability*).
Study of a cost model

We put a monetary weight (cost) on each performance metrics (commitment deviation, losses, aging), to find an optimal storage capacity.

\[
\tilde{C}_{tot} = \frac{1}{P_{prod}} \left( c_{batt} \left( \frac{P_{sto}}{2N_{life}} + \frac{E_{rated}}{t_{life}} \right) \text{ cycling and calendar aging} \\
+ c_{elec} (\bar{P}_{losses} + \bar{P}_{heat}) \text{ lost electricity} \\
+ c_{dev} |P_{dev}| \text{ commitment deviation} \right)
\]

Cost in €/MWh of produced wind energy.

Here, commitment deviation is penalized as Mean Absolute Deviation, but other choices are possible.
A look at the optimal capacity

With a penalty of 150 €/MWh$_{\text{dev}}$, the optimal capacity is 8.5 MWh, with an optimal cost of 50 €/MWh$_{\text{prod}}$ (30 for penalties, 20 for storage costs).

Dashed lines show the sensitivity to ± 30 % variations of the deviation penalty.
Outline of the presentation

1. Introduction
2. Model description
3. Simulation results
4. Conclusion and perspectives
From our simulations, we observe that:

- An Energy Storage System can indeed mitigate forecast errors to fulfill a day-ahead commitment.
- Battery cycling is kept below the allowed limit of 5000 cycles in 15 years.
- Variability of forecast errors generates a significant variability of performance metrics, like monthly penalty averages. This could impact day-to-day operation.
Conclusion

From our simulations, we observe that:

- An Energy Storage System can indeed mitigate forecast errors to fulfill a day-ahead commitment.
- Battery cycling is kept below the allowed limit of 5000 cycles in 15 years.
- Variability of forecast errors generates a significant variability of performance metrics, like monthly penalty averages. This could impact day-to-day operation.

The case for Energy Storage (for day-ahead commitment):

- the cost function is quite “flat”: not such a clear case for storage (high sensitivity to storage cost and penalty fee).
- but other penalty criterions may make the case clearer (like adding a tolerance deviation band).
Possible extensions

Additional degrees of freedom that should be taken into account to get a better performing system:

- *bidding strategy*: commitment power not necessarily equal to forecast power.
- *curtailment*: ability to lower the production level
- *energy management*: optimized control of storage power (→ stochastic dynamic optimization)