Firming Wind Power Dispatch with Battery Energy Storage

Virtual Trials in South Australia

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South Australia

World-leading jurisdiction for penetration of VRE generation and storage

- In fiscal year 2016–17, 48.4% of the electricity generated in SA came from variable renewable energy (VRE) sources

Energy source	Registered capacity MW	Registered capacity % of total	Electricity generated GWh	Electricity generated % of total
Gas	2,668	49.1	5,596	50.5
Wind	1,698	31.2	4,343	39.2
Rooftop PV	781	14.4	1,016	9.2
Other	289	5.3	122	1.1
Coal	0	0.0	0	0.0
Total	5,436	100.0	11,077	100.0

Source: Australian Energy Market Operator

- Largest battery in the world is coupled to the Hornsdale wind farm in the state's mid-north
- SA government has announced a policy to create the world's largest virtual power plant — 50,000 households equipped with solar panels and a battery

South Australia

High wholesale electricity prices

- In fiscal year 2016–17 wholesale electricity prices in SA averaged \$123/MWh — the highest price among the five regions of the National Electricity Market
- In July 2016 wholesale electricity prices averaged \$229/MWh, with the Grattan Institute† attributing the soaring prices to:
  - High penetration of VRE generation
  - Limited connectivity with other regions in the NEM
  - Historically high wholesale gas prices
- During the 06:30 trading interval on 13 July 2016, wholesale electricity prices in SA spiked to \$7,068/MWh
  - Australian Energy Regulator identified wind forecast error as the major contributing factor to the price spike
  - Half-an-hour ahead of the trading interval semi-scheduled wind power in SA was forecast to be 820MW, but actual output was only 600MW

† T. Wood and D. Blowers (Sep. 2016). Keeping the lights on: Lessons from South Australia's power shock. Grattan Institute.

Firming wind power dispatch with battery energy storage

- Conjecture that if wind farms were to dependably supply power scheduled during pre-dispatch, then wholesale electricity prices would be less volatile and, on average, lower
- Examine the use of battery energy storage to firm wind power dispatch
- Coupling a utility-scale battery to a wind farm would serve to address recommendations in the Finkel Report[‡]
    - "Require new generators to have fast frequency response capability"
    - "The Generator Reliability Obligation should include undertaking a forward looking reliability assessment, . . . , to inform requirements on new generators to ensure adequate dispatchable capacity is present in each region"

[‡] Dr Alan Finkel, Chief Scientist, Chair of the Expert Panel, Ms Karen Moses, Ms Chloe Munro, Mr Terry Effeney, Professor Mary O'Kane (June 2017). Independent review into the future security of the National Electricity Market: Blueprint for the future.

State-space model predictive control (MPC)

Wind power dispatch with battery energy storage

State-space model describes process outputs as a function of state variables, which depend on control signals

- State of charge (SOC) of the battery:

$$e(t+1) = e(t) + \delta\eta p_{b+}(t) - \frac{\delta}{\eta} p_{b-}(t),$$

- Power dispatched to the grid:

$$p_d(t+1) = p_{b-}(t) - p_{b+}(t) + p_w(t),$$

where $p_{b+}(t) \geq 0$ is the battery charge control signal,
$p_{b-}(t) \geq 0$ battery discharge control signal,
$p_w(t) \geq 0$ wind power control signal,
$\eta \in (0, 1]$ one-way charge/discharge efficiency of the battery, and
$\delta > 0$ conversion factor from MW to MWh for the dispatch interval

Incremental state-space model

Single-period setting

Incremental formulation of the state-space model allows the MPC controller to penalise control effort

$$\underbrace{\begin{bmatrix} e(t+1) \\ p_{b+}(t) \\ p_{b-}(t) \\ p_w(t) \end{bmatrix}}_{\boldsymbol{z}(t+1)} = \underbrace{\begin{bmatrix} 1 & \delta\eta & -\delta/\eta & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}}_{A} \underbrace{\begin{bmatrix} e(t) \\ p_{b+}(t-1) \\ p_{b-}(t-1) \\ p_w(t-1) \end{bmatrix}}_{\boldsymbol{z}(t)} + \underbrace{\begin{bmatrix} \delta\eta & -\delta/\eta & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{B} \underbrace{\begin{bmatrix} \Delta p_{b+}(t) \\ \Delta p_{b-}(t) \\ \Delta p_w(t) \end{bmatrix}}_{\boldsymbol{\Delta u}(t)},$$

$$\underbrace{\begin{bmatrix} e(t+1) \\ p_d(t+1) \end{bmatrix}}_{\boldsymbol{y}(t+1)} = \underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 1 \end{bmatrix}}_{C} \underbrace{\begin{bmatrix} e(t+1) \\ p_{b+}(t) \\ p_{b-}(t) \\ p_w(t) \end{bmatrix}}_{\boldsymbol{z}(t+1)}$$

Incremental state-space model

Multi-period prediction and control horizons

- Set receding prediction and control horizons to n dispatch intervals, and let

$$\vec{\boldsymbol{y}}_{t+1} = \begin{bmatrix} \boldsymbol{y}(t+1)^T & \boldsymbol{y}(t+2)^T & \dots & \boldsymbol{y}(t+n)^T \end{bmatrix}^T,$$
$$\overrightarrow{\boldsymbol{\Delta u}}_t = \begin{bmatrix} \boldsymbol{\Delta u}(t)^T & \boldsymbol{\Delta u}(t+1)^T \dots \boldsymbol{\Delta u}(t+n-1)^T \end{bmatrix}^T$$

- Recursively applying the single-period state-space model

$$\boldsymbol{y}(t+1) = CA\boldsymbol{z}(t) + CB\boldsymbol{\Delta u}(t)$$

over the n-period horizon yields

$$\vec{\boldsymbol{y}}_{t+1} = K\boldsymbol{z}(t) + L\overrightarrow{\boldsymbol{\Delta u}}_t,$$

where

$$K = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^n \end{bmatrix} \text{ and } L = \begin{bmatrix} CB & 0 & 0 & \dots & 0 \\ CAB & CB & 0 & \dots & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ CA^{n-1}B & CA^{n-2}B & \dots & CAB & CB \end{bmatrix}$$

MPC controller

Multi-period performance index

- MPC controller determines control increments by optimising performance index f, which penalises tracking error and control effort:

$$f = \left\| \sqrt{\Omega}\, (\vec{\boldsymbol{r}}_{t+1} - \vec{\boldsymbol{y}}_{t+1}) \right\|_2^2 + \lambda \left\| \sqrt{\Psi}\, \overrightarrow{\boldsymbol{\Delta u}}_t \right\|_2^2 ,$$

  where $\vec{\boldsymbol{r}}_{t+1} = \begin{bmatrix} \boldsymbol{r}(t+1)^T & \boldsymbol{r}(t+2)^T & \ldots & \boldsymbol{r}(t+n)^T \end{bmatrix}^T$ is the set point vector, Ω and Ψ are positive semidefinite diagonal weighting matrices, and $\lambda \geq 0$ is a scalar weighting coefficient
- Optimisation of the performance index is subject to process constraints, which take the form of bounds on observable and internal state variables, the latter expressed in terms of control increments:
  - Wind power is set to unconstrained intermittent generation forecasts
  - Upper and lower bounds on SOC of the battery
  - Charge/discharge rates cannot exceed rated power (continuous) of the battery
  - Linear complementarity of battery charge and discharge control signals

MPC controller

Mixed integer quadratic programming

- Expanding the performance index, dropping the constant terms and imposing process constraints, the quadratic program is written in standard form:

$$\begin{aligned} \underset{\overrightarrow{\boldsymbol{\Delta u}}_t}{\operatorname{argmin}} \quad & \frac{1}{2}\overrightarrow{\boldsymbol{\Delta u}}_t^T \left(L^T \Omega L + \lambda \Psi\right) \overrightarrow{\boldsymbol{\Delta u}}_t + \left(K\boldsymbol{z}(t) - \vec{\boldsymbol{r}}_{t+1}\right)^T \Omega L \overrightarrow{\boldsymbol{\Delta u}}_t \\ \text{subject to} \quad & \underline{\boldsymbol{x}} \preceq \boldsymbol{x}(t+k) \preceq \overline{\boldsymbol{x}}, \\ & \underline{\boldsymbol{\Delta u}} \preceq \boldsymbol{\Delta u}(t+k-1) \preceq \overline{\boldsymbol{\Delta u}}, \\ & k = 1, \ldots, n, \end{aligned}$$

  where the $\preceq$ operator represents component-wise inequality between vectors
- Introducing a binary variable to ensure linear complementarity of battery charge and discharge control signals transforms the optimisation problem into a mixed integer quadratic program (MIQP)

Virtual trials

Wind farm and utility-scale battery data

- Perform virtual trials on the 99MW Snowtown (Stage 1) wind farm
  - 5-minute dispatch intervals from 2017-04-01 00:00:00 to 2018-03-31 23:55:00
  - 30-minute prediction and control horizons comprising $n = 6$ five-minute dispatch intervals
  - Predicted process outputs and their set points over prediction horizon are derived from 5-minute pre-dispatch unconstrained intermittent generation forecasts (UIGF)
  - Normalised mean absolute error (NMAE) is calculated using measured (SCADA) wind power
- Suppose that a utility-scale battery is coupled to the Snowtown wind farm in order to firm wind power dispatch
  - Simulations run for a range of battery sizes (power rating and energy capacity)
  - Assumptions about battery characteristics
    - One-hour discharge rate
    - Round-trip efficiency, $\eta^2 = 80\%$
    - Upper (87.5%) and lower (12.5%) bounds on SOC of the battery
  - Depending on SOC of the battery, scheduled power (i.e., set point for power dispatched to the grid) at the end of the prediction horizon is set to the corresponding UIGF forecast, or limited below that available capacity

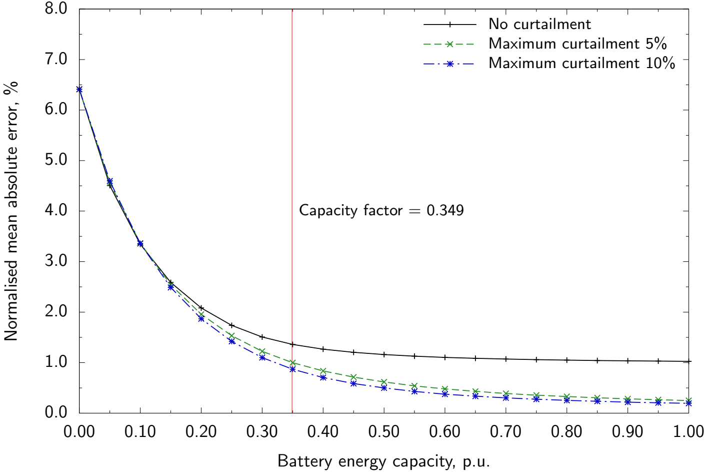
Virtual trials

Power system quantities

- Report power system quantities on a per unit (p.u.) basis
  - Per-unit system expresses quantities in SI units as a ratio relative to base quantities
  - Choose 99MW (nominal capacity of the Snowtown wind farm) as the base quantity for power
  - For simplicity choose 99MWh as the base quantity for energy

Snowtown wind farm (1.0 p.u.) coupled with a utility-scale battery

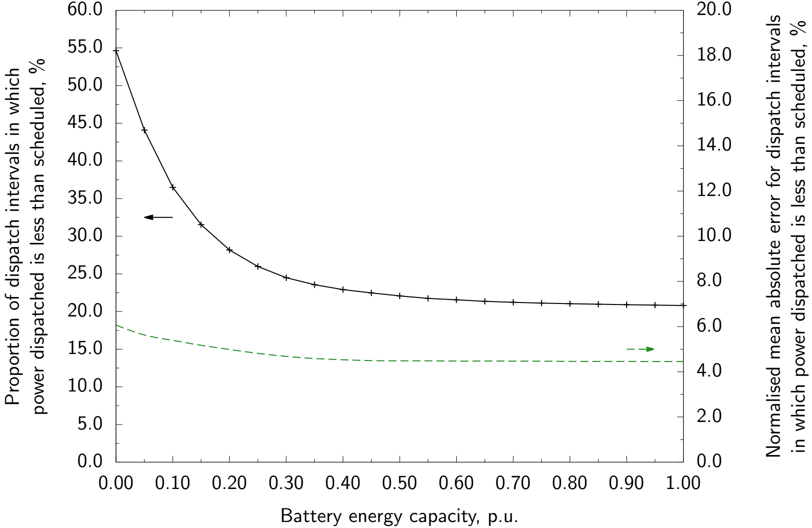
Curtailment of scheduled power depends on energy capacity and state of charge of the battery



Normalised mean absolute error (NMAE) is calculated as the absolute difference between wind power forecast and actual output divided by the nominal capacity of the wind farm

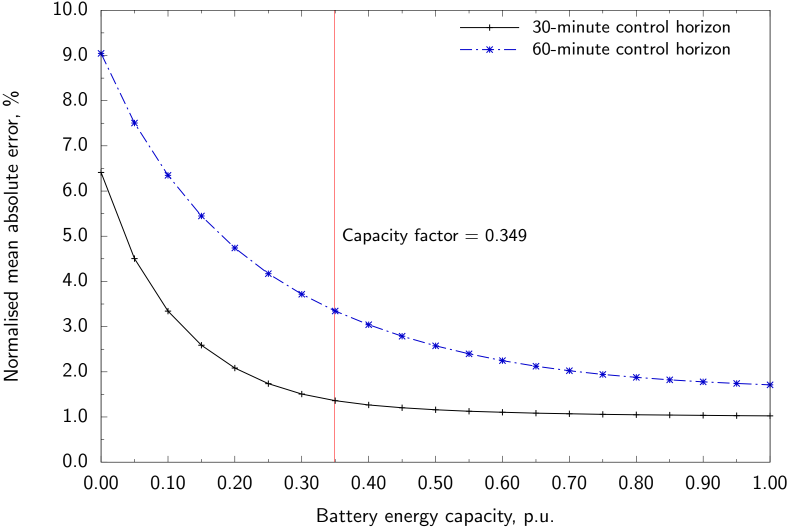
Snowtown wind farm (1.0 p.u.) coupled with a utility-scale battery

Dispatch intervals in which power dispatched to the grid is less than scheduled power



Snowtown wind farm (1.0 p.u.) coupled with a utility-scale battery

Varying prediction and control horizons of MPC controller



Direction of future research