## Wind Power Dispatch with Battery Energy Storage

Virtual Trials in South Australia

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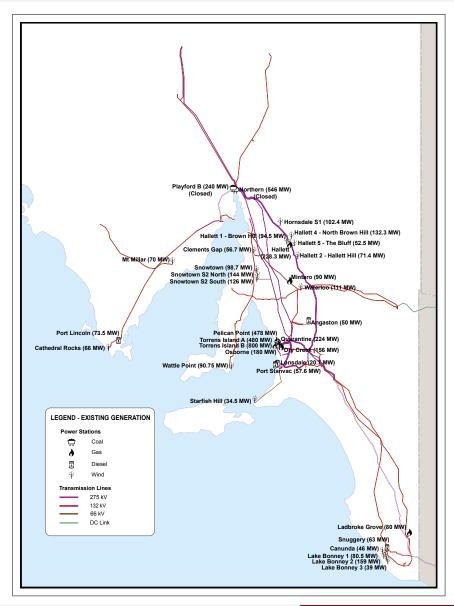
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MATHEMATICAL AND STATISTICAL FRONTIERS



#### Registered capacity and electricity generated in SA (2015–16)

High penetration of intermittent renewable energy



Energy source	Registe MW	ered capacity % of total	Electrici GWh	ty generated % of total
Gas	2,668	44.6	4,538	36.4
Wind	1,576	26.3	4,322	34.7
Coal	770	12.9	2,601	20.9
Rooftop PV	679	11.4	938	7.5
Other	289	4.8	60	0.5
Total	5,982	100.0	12,459	100.0

Source: Australian Energy Market Operator

Following the closure of the last coal-fired power plant in SA, from 10 May 2016 to 31 July 2016, 51% of electricity generated in the state came from wind and rooftop PV

# Market and technical challenges faced by SA

- Dependable supply of scheduled (baseload) power:
  - High penetration of intermittent renewable energy
  - Limited connectivity with other regions in the NEM
- High and volatile wholesale electricity prices:
  - Variability in wind and solar power generation
  - Difficulty in making wind and solar forecasts, especially about the future
  - Balance of generation is gas-fired
- Secure operation of the power system:
  - Ancillary services historically provided by conventional generators
  - Renewable energy generation is displacing conventional generation as SA transitions to a low-carbon economy
  - Tight availability of locally provisioned ancillary services when islanded

## Wind power dispatch with battery energy storage

State-space model predictive control (MPC)

- Suppose that a utility-scale battery has been coupled to an SA wind farm, enabling time shifting of wind power dispatched to the grid
- Represent the process of wind power dispatch with battery energy storage as a state-space model
- MPC controller computes battery charge/discharge control signals by minimising tracking error of power dispatched to the grid relative to a set point — target baseload power
- Virtual trials computer simulations using publicly available dispatch data
   measure the improvement in dispatchability of wind power with battery energy storage

## Modelling contributions to the literature

Proper accounting of battery charge/discharge efficiency

Time evolution of state of charge (SOC) of the battery,

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

properly accounts for battery charge/discharge efficiency, and power dispatched to the grid is given by

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

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

### Modelling contributions to the literature

Incremental state-space model

Incremental formulation of the state-space model for wind power dispatch with battery energy storage allows the MPC controller to penalise control effort

$$\begin{bmatrix} e(t+1) \\ p_{b+}(t) \\ p_{b-}(t) \\ p_{w}(t) \end{bmatrix} = \begin{bmatrix} 1 & \delta \eta & -\delta/\eta & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} e(t) \\ p_{b+}(t-1) \\ p_{b-}(t-1) \\ p_{w}(t-1) \end{bmatrix} + \begin{bmatrix} \delta \eta & -\delta/\eta & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \Delta p_{b+}(t) \\ \Delta p_{b-}(t) \\ \Delta p_{w}(t) \end{bmatrix},$$

$$\mathbf{z}(t+1) \quad \mathbf{z}(t) \quad \mathbf{z}(t) \quad \mathbf{z}(t)$$

$$\begin{bmatrix} e(t+1) \\ p_d(t+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -1 & 1 & 1 \end{bmatrix} \begin{bmatrix} e(t+1) \\ p_{b+}(t) \\ p_{b-}(t) \\ p_w(t) \end{bmatrix}$$

$$\mathbf{z}(t+1)$$

## Optimisation of the performance index

MPC controller determines control increments by optimising a performance index that penalises tracking error and control effort

Let  $r(t) \in \mathbb{R}^m$  be a set-point vector, and define the quadratic cost function

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

where  $\lambda \geq 0$  is a scalar weighting coefficient, and  $\Omega \in \mathbb{R}^{m \times m}$  and  $\Psi \in \mathbb{R}^{q \times q}$  are positive semidefinite diagonal weighting matrices

- Process constraints take the form of bounds on observable and internal state variables, the latter expressed in terms of control increments
- Quadratic optimisation problem is written in standard form:

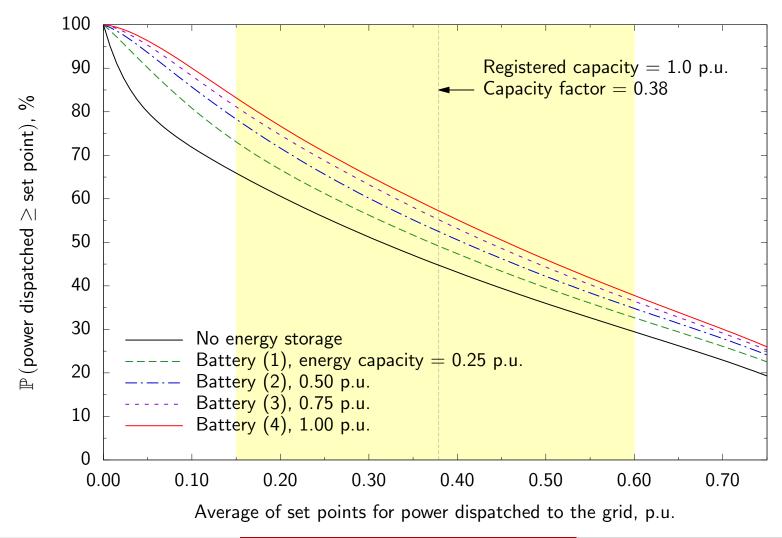
argmin 
$$\frac{1}{2} \Delta \boldsymbol{u}(t)^T \left( B^T C^T \Omega C B + \lambda \Psi \right) \Delta \boldsymbol{u}(t)$$
  
  $+ \left( C A \boldsymbol{z}(t) - \boldsymbol{r}(t+1) \right)^T \Omega C B \Delta \boldsymbol{u}(t)$   
subject to  $\underline{\boldsymbol{x}} \preceq \boldsymbol{x}(t+1) \preceq \overline{\boldsymbol{x}},$   
 $\underline{\Delta \boldsymbol{u}} \preceq \Delta \boldsymbol{u}(t) \preceq \overline{\Delta \boldsymbol{u}}$ 

#### Virtual trials in South Australia

- Implement a naïve, single-period dispatch strategy:
  - Charge battery with surplus wind power whenever available capacity for dispatch exceeds the set point
  - Discharge battery to supplement wind power whenever available capacity for dispatch is less than the set point
- Virtual trials perform computer simulations using real-world data:
  - Optimise control increments for 5-minute dispatch intervals from 1 April 2015 to 31 March 2016 using publicly available dispatch data
  - For different set points representing target baseload power
  - For different size utility-scale batteries
- Some observations:
  - Probability of power dispatched to the grid supplying a target baseload power is moderately higher with battery energy storage
  - Not very sensitive to shape of the load profile or battery charge/discharge efficiency due to autocorrelation of wind power over dispatch intervals
  - Even on today's utility scale, battery power can only substitute for a fraction of the registered capacity of a commercial wind farm for a limited time

#### Improvement in Wind Power Dispatch with Battery Energy Storage

Number of 5-minute dispatch intervals over one full year where power dispatched to the grid equals or exceeds the set point is 10-28% higher with utility-scale battery than no energy storage



#### Direction of future research

- Soaring wholesale electricity prices in SA during July 2016:
  - During the month RRP averaged \$229/MWh, more than three times the average price of any other region in the NEM
  - On 13 July 2016 electricity traded at \$7,068 during the 06:30 trading interval
  - AER reported "[t]he major contributing factor to the high price was wind forecast error"
- Conjecture that if wind farms were to dependably supply power scheduled during pre-dispatch, wholesale electricity prices would be less volatile and, on average, lower
- Ongoing research proposal:
  - Extend incremental state-space model to a multi-period setting
  - Use pre-dispatch unconstrained intermittent generation forecasts (UIGF) produced by the Australian Wind Energy Forecasting System (AWEFS)
  - Empirically examine the dependability of supply of wind power scheduled during pre-dispatch up to 40 hours ahead of dispatch using battery energy storage to enable time shifting