

## Abstract

The ecological transition to cleaner energy production is a fundamental part in facing the challenge of climate change. Many renewables, such as solar and wind powers, have an intermittent nature as their outputs strongly depend on factors like the weather, time of the day, season etc. This may create issues to the stability of the power grid, in particular it may accentuate frequency fluctuations. A possible solution to this problem is the introduction of energy storage systems in the grid, such as batteries. In this study we propose two different algorithms for battery operations: one is based on an optimisation technique called model predictive control which aims at smoothing power from renewables, and another which acts as an additional primary and secondary control.

## Model ingredients

- Conventional power plant: swing equation, primary and secondary control
- Fluctuating demand (actual data from Gran Canaria (Spain) + correlated noise)
- Wind generation  $W$  (actual data from Gran Canaria (Spain))
- Energy storage system

**Conventional power plant**

generator inertia Reference frequency Generator power Demand

$$\frac{d\omega}{dt} = \frac{\omega_R^2}{2HP_G(\omega + \omega_R)} (P_m + P_w - P_l)$$

Deviation from reference frequency

$$\frac{dP_m}{dt} = \frac{1}{\tau} \left( P_s - P_m - \frac{P_r \omega}{R \omega_R} \right)$$

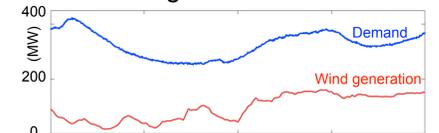
Mechanical power (primary control)

$$\frac{dP_s}{dt} = -\frac{k}{\omega_R} \omega$$

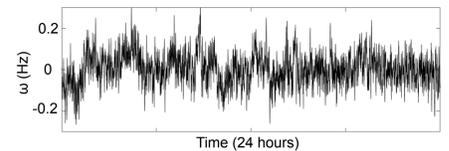
Spinning reserve (secondary control)

primary control response time secondary control response time

Demand and wind generation in Gran Canaria for 24 hours starting at 20:00 on June 30th 2020.



Frequency dynamics obtained integrating the model with data above.



## Battery with model predictive control

Aimed at smoothing real wind power  $W$  by solving an optimisation problem. The output  $P_w$  goes in the swing equation instead of  $W$ .

Model:

- error between real wind power  $W$  and smoothed wind power  $P_w$
- battery state of charge  $Q$

$$e(t + \Delta t) = W(t) - P_w(t)$$

$$Q(t + \Delta t) = e(t)\Delta t + Q(t)$$

Optimisation problem:

- quadratic cost function: minimise the error and keep the battery around a reference value
- constraints

$$\min_{P_w} J = \sum_{t=0}^{M-1} (W(t) - P_w(t))^2 + \gamma(Q(t) - Q_r)^2$$

$$0 \leq P_w(t) \leq c_1$$

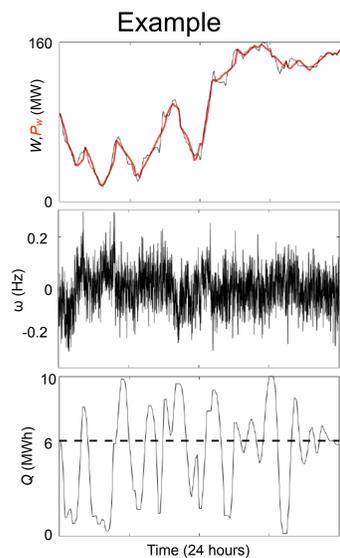
Wind turbine nominal power

$$|P_w(t+1) - P_w(t)| \leq c_2$$

Limit on smooth wind rate of change

$$0 \leq Q(t) \leq Q_{max}$$

Battery capacity



## Battery as primary and secondary control

Responds to both wind power fluctuations and fast demand fluctuations.

Two equations corresponding to additional primary ( $P_b$ ) and secondary ( $P_s$ ) control. Last equation for the dynamics of the battery state of charge ( $Q$ )

$$\frac{dP_b}{dt} = \frac{1}{\tau_1} (P_c - P_b - \alpha\omega)$$

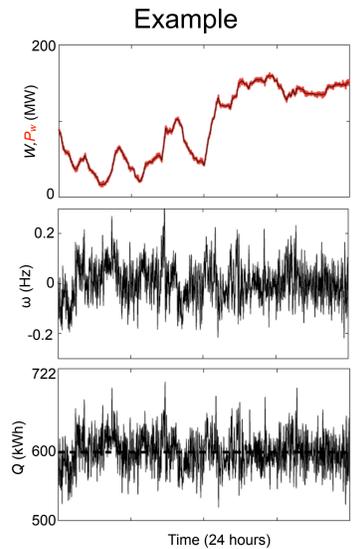
Battery response time: faster than conventional primary control

$$\frac{dP_c}{dt} = -\beta\omega + \gamma(Q - Q_r)$$

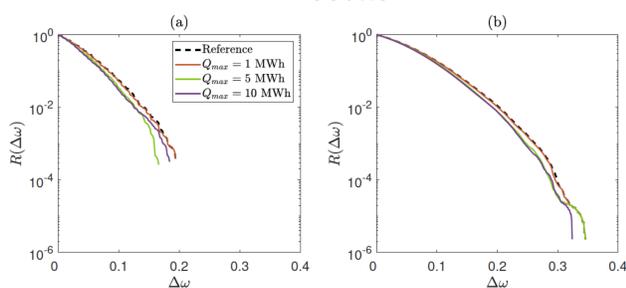
Term that prevents the battery from discharging too fast

$$\frac{dQ}{dt} = -P_b$$

When we couple these equations with the model of the conventional power plant we set  $P_w = W + P_b$



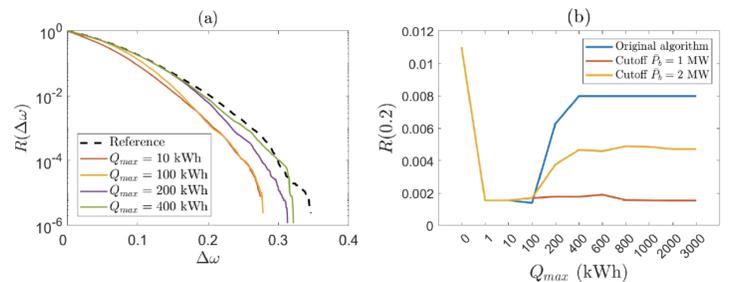
## Results



- (a) Actual demand data with no noise. Cumulative probability ranks (10 days of data) for frequency fluctuations. Comparison between the reference case with no battery and different battery sizes.
- (b) Same as panel (a) but with correlated noise added to the demand.

The effect of this method is more visible in the case with no noise. This is due to the fact that the optimisation problem only takes into account wind fluctuations. This model requires batteries that are big enough to ensure the convergence of the algorithm used to solve the optimisation problem.

## Results



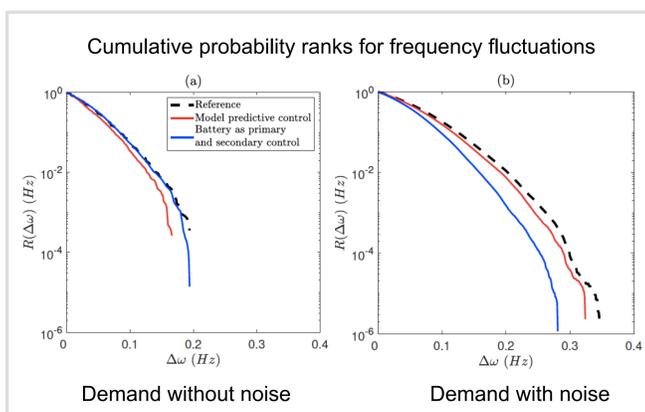
- (a) Cumulative probability ranks (10 days of data, demand with added noise) for frequency fluctuations. Comparison between the reference case with no battery and different battery sizes.
- (b) Cumulative probability rank of a fluctuation of amplitude 0.2 Hz as a function of battery size. Lines of different colours correspond to different limits on the battery power.

Counterintuitive effect: small batteries work better than bigger ones. Solution: set a cutoff for the battery power.

The cutoff improves the performance of the battery in reducing frequency fluctuations.

## Discussion

- Both methods can be used to reduce frequency fluctuations.
- In general, to implement the model predictive control algorithm, a battery of bigger capacity is needed. Thus may increase the operation costs.
- To compare the two methods we consider the cumulative probability ranks obtained with and without noise added to actual demand data for 10 days in Gran Canaria. We used a battery of 10 MWh and a cutoff of 1 MW on the battery power for the additional primary and secondary control.
- The model predictive control algorithm performs better without noise in the demand (a). The other battery usage mode does not reduce the fluctuations, which in this case are caused only by the variability of wind generation.
- The battery as an additional primary and secondary control outperforms the model predictive control algorithm the case of noisy demand (b), even though the latter can still cause a small reduction of frequency fluctuations.



## References

- [1] H. Saadat, McGraw - Hill (1999)
- [2] M. Khalid and A. V. Savkin, Renewable Energy, 25, 1520-1526 (2010)
- [3] E. B. Tchawou Tchuisseu et al., Physical Review E, 96, 2, 022302 (2017)

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