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# Dispatch and clustering of ancillary services from distributed storage

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# Outline

1. Mainstream trends for the integration of battery storage systems in electrical grids.

2. Dispatch of stochastic generation and distribution systems with batteries and downstream flexibility.

3. Practices for modelling and control of grid-connected battery systems in energy management applications.

# 1

# Mainstream trends for the integration of battery storage systems in electrical grids.

# Battery storage integration in the electrical grid

Two operational perspectives for the integration of batteries in the grid:

- Improving performance at the system level and increasing social benefit, e.g. reducing reserve, meeting reliability levels, reducing costs, relieving congestions in transmission systems, reducing $CO_2$ emissions (?)*.

- Enabling a larger installed capacity of distributed renewable generation in distribution systems (e.g. voltage control, congestion management, peak shaving).

* Storage might lead to increased $CO_2$ levels due to displacing gas in favor of coal generation, see e.g. [Lueken and Apt, 2014], [Preskill and Callaway, 2018].

# Storage applications at the system level

"Classical" market-driven applications:

- Energy arbitrage: buying cheap electricity and reselling at higher price (economic advantage does not scale with the number of batteries).
- Reserve provision, i.e. use batteries to provide reserve capacity instead of conventional generation units.
- Primary frequency control.

# Storage integration at system level – Tracking capability

**AGC signal-tracking capability**: coal-fired generation plant *vs.* battery [AEMO, 2018].

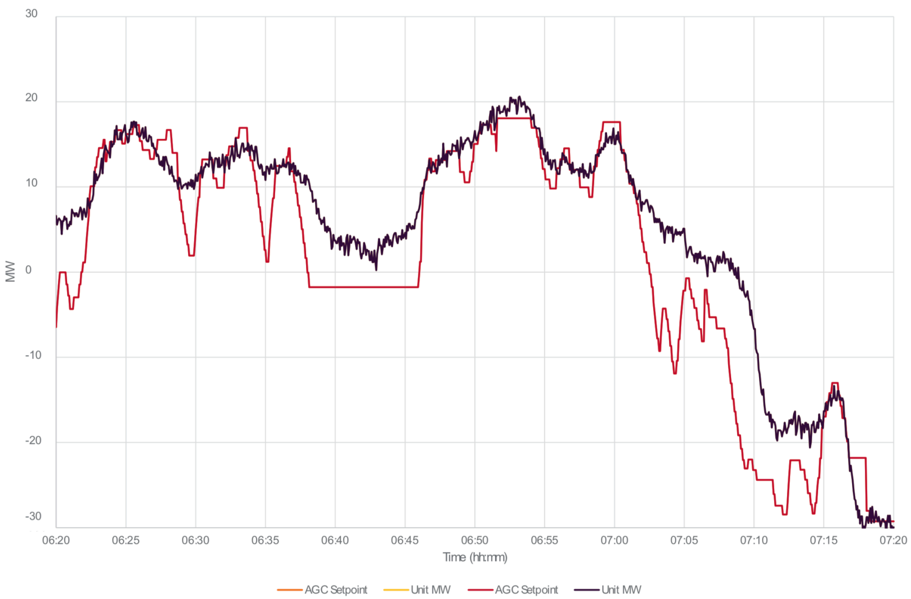



**Fig.:** Large coal power plant.

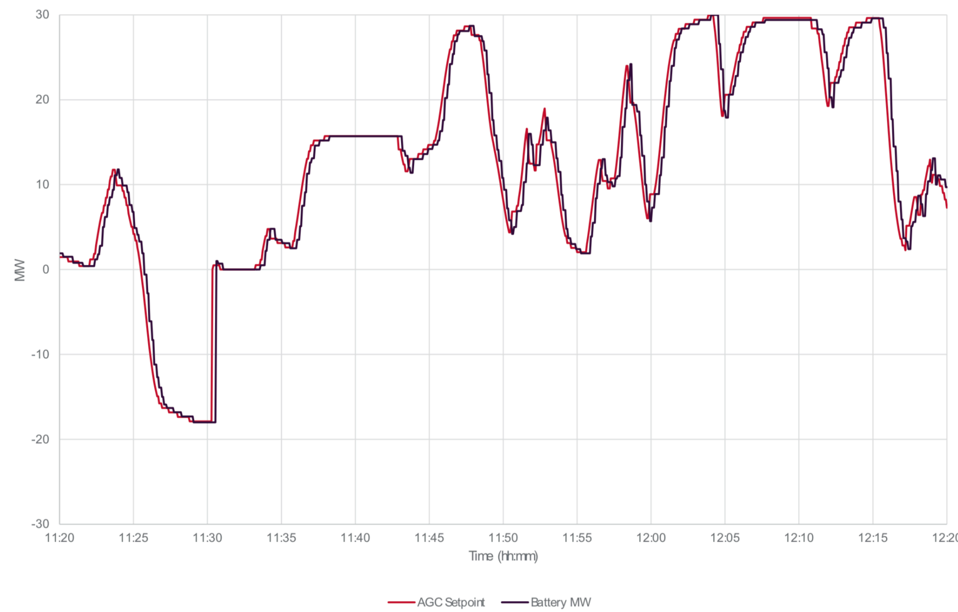



**Fig.:** *Hornsdale power reserve*
100/80 MW, 129 MWh grid-connected battery
(New South Wales, Australia, in operation since Dec 2017, connected to 275 kV HV).

# Storage integration at system level – Empirical evidence

**Ramping rate** of *Hornsdale power reserve* during a contingency (18 Dec 2016, loss of 690 MW generating capacity) [AEMO, 2018]:

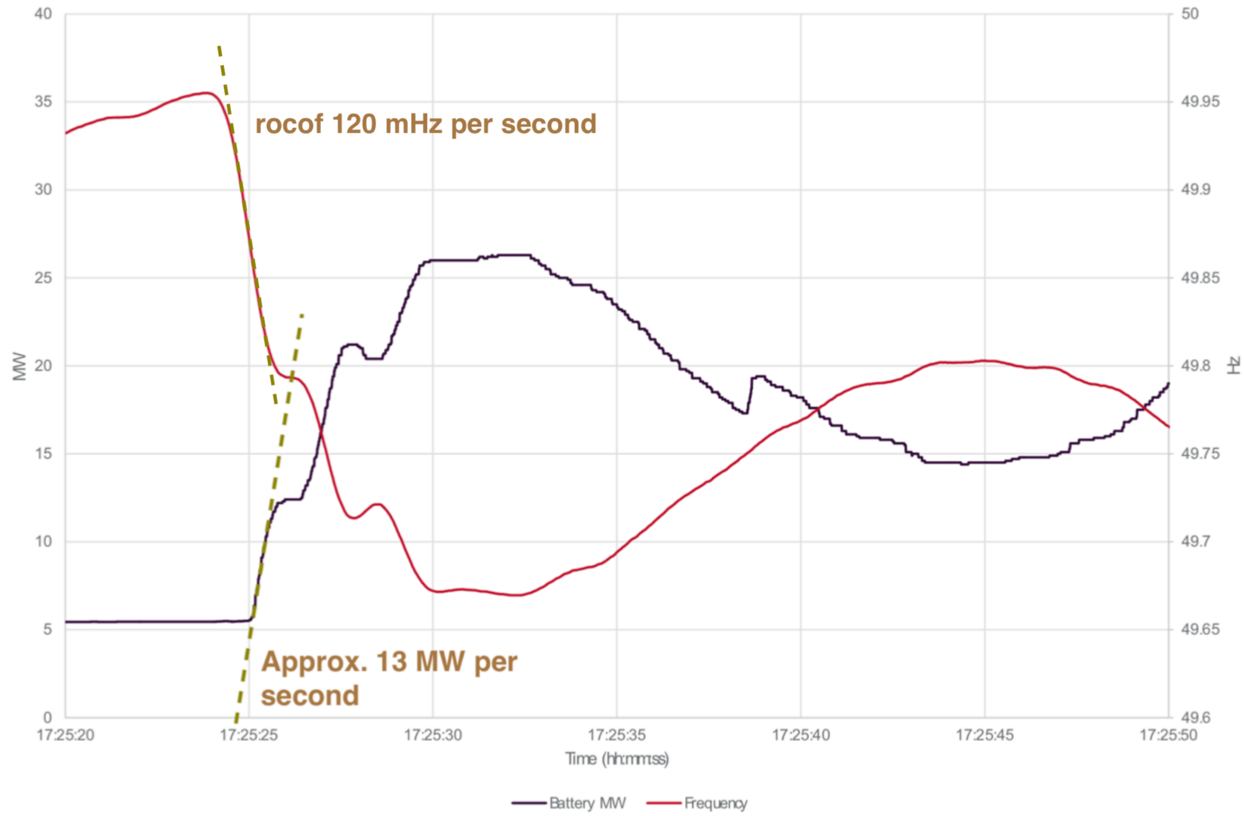



**Fig.:** *Hornsdale power reserve*'s power delivery after a frequency drop. Estimated ramping rate is 13 MW/s, approx. 780% of nominal capacity per minute vs. 5, 15, 20% of coal, hydro, and gas.

# Storage integration at system level – Empirical evidence, cont'd

**2016 South Australia blackout.** Grid with low meshing factor. 48% wind, 34% import, 18% gas. Faults on 5 transmission lines, 500 MW generation loss from wind farms due to storm conditions, activation of a loss-of-synchronism protection and tripping of 1 of the 2 line importing power.

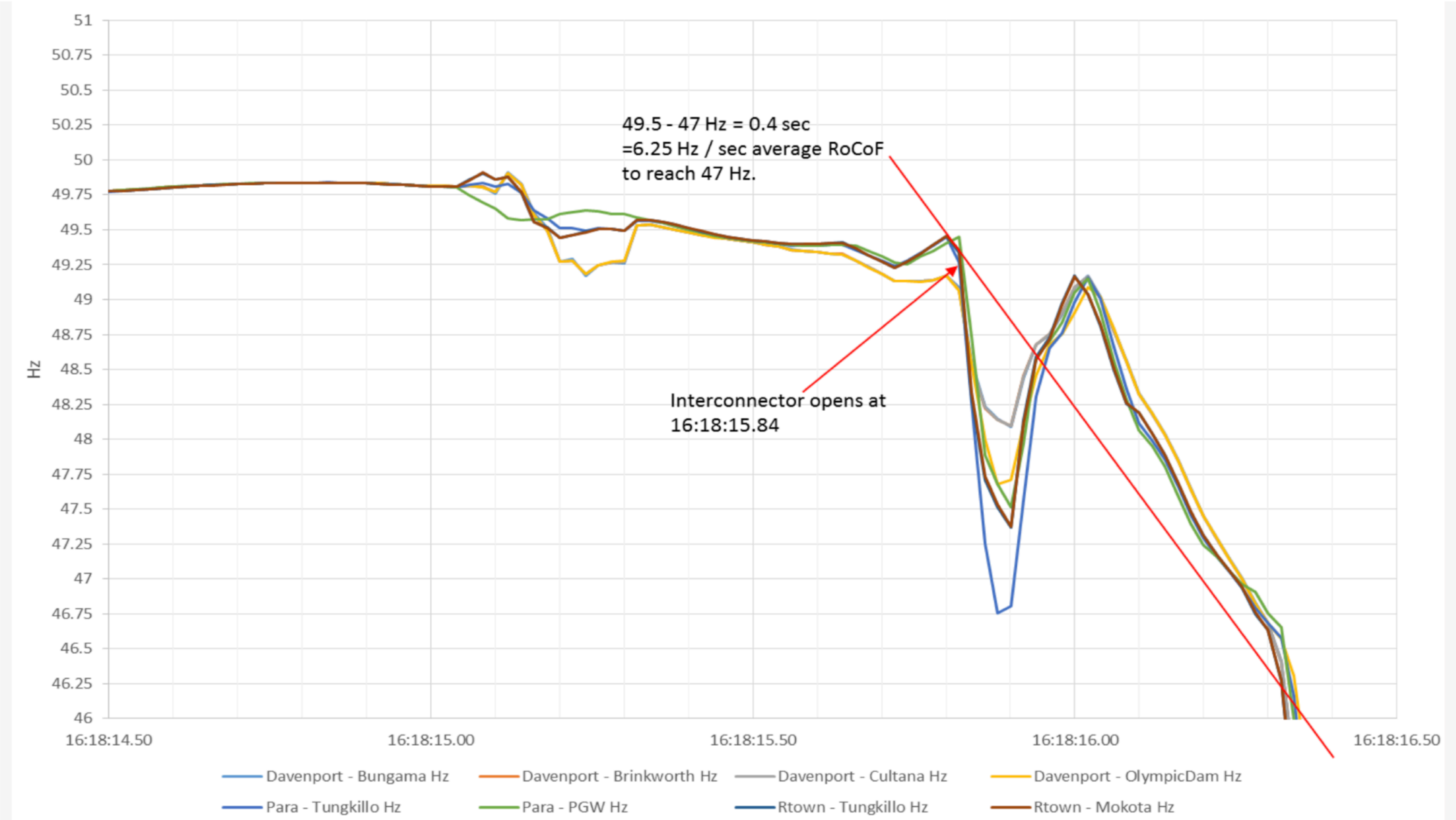



**Fig.:** Grid frequency before power blackout in South Australia on Sept. 26th [AEMO, 2017].

# Applications of storage in distribution systems

Applications of storage in distribution systems have been proposed for:

- Peak-shaving, PV self-consumption.

- Mitigation of violations of nodal voltage and line current constraints, normally including a network model, where power flow equations are linearized (e.g. [Christakou et al., 2013], [Bolognani and Dorfler, 2015], [Bernstein and Dall'Anese, 2017], [Fortenbacher et al., 2017]) or convex relaxation (e.g. [Gan et al., 2015], [Nick et al., 2018]) to achieve tractable formulations.

# Battery storage applications

General consensus on:

- operational value of distributed storage;
- delivering multiple services with batteries leads to better exploitation of storage capacity and shortens payback times;
- importance of storage will increase for increasing installed capacity of distributed generation (e.g. increased ramping duties of low-inertia power systems, grid control in LV/MV systems);
- specific policies and market regulations will play a crucial role in storage deployment.

# 2

## Dispatch of stochastic generation and distribution systems with batteries and downstream flexibility.

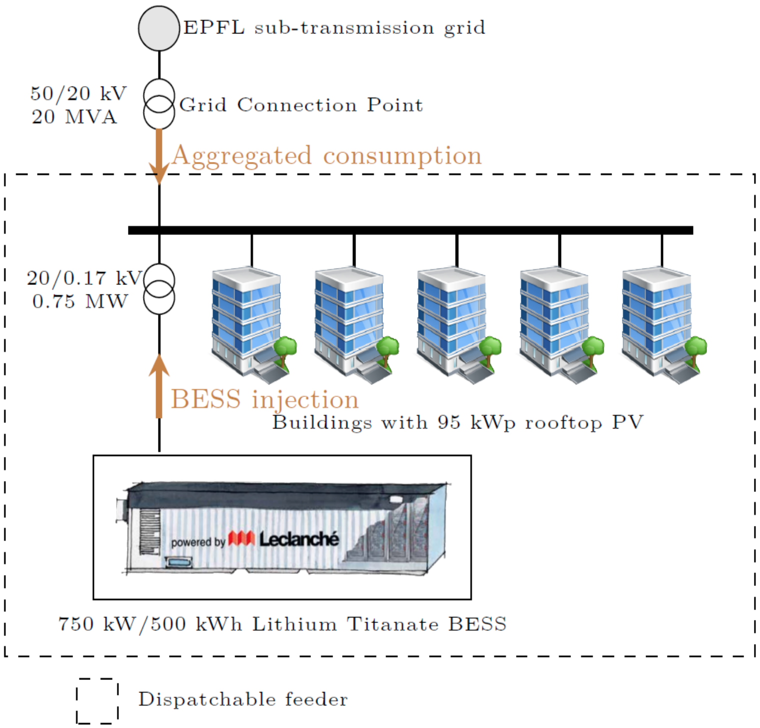
# Dispatching stochastic resources

Dispatching stochastic resources, such as:

- PV plants [Marinelli et al., 2014], [Conte et al., 2017].
- wind farms [Abu Abdullah et al., 2015], and
- heterogeneous resources [Sossan et al., 2016], [Appino et al., 2018],

by leveraging forecasts and exploiting local flexibility is often advocated to reduce the amount of reserve requirements required to operate the grid.

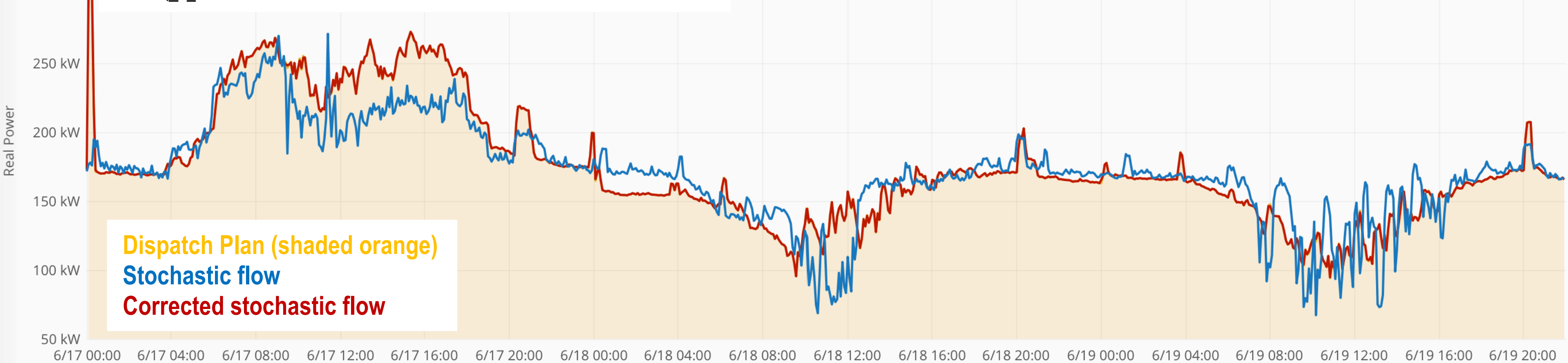
# Dispatching heterogeneous resources [Sossan et al., 2016]



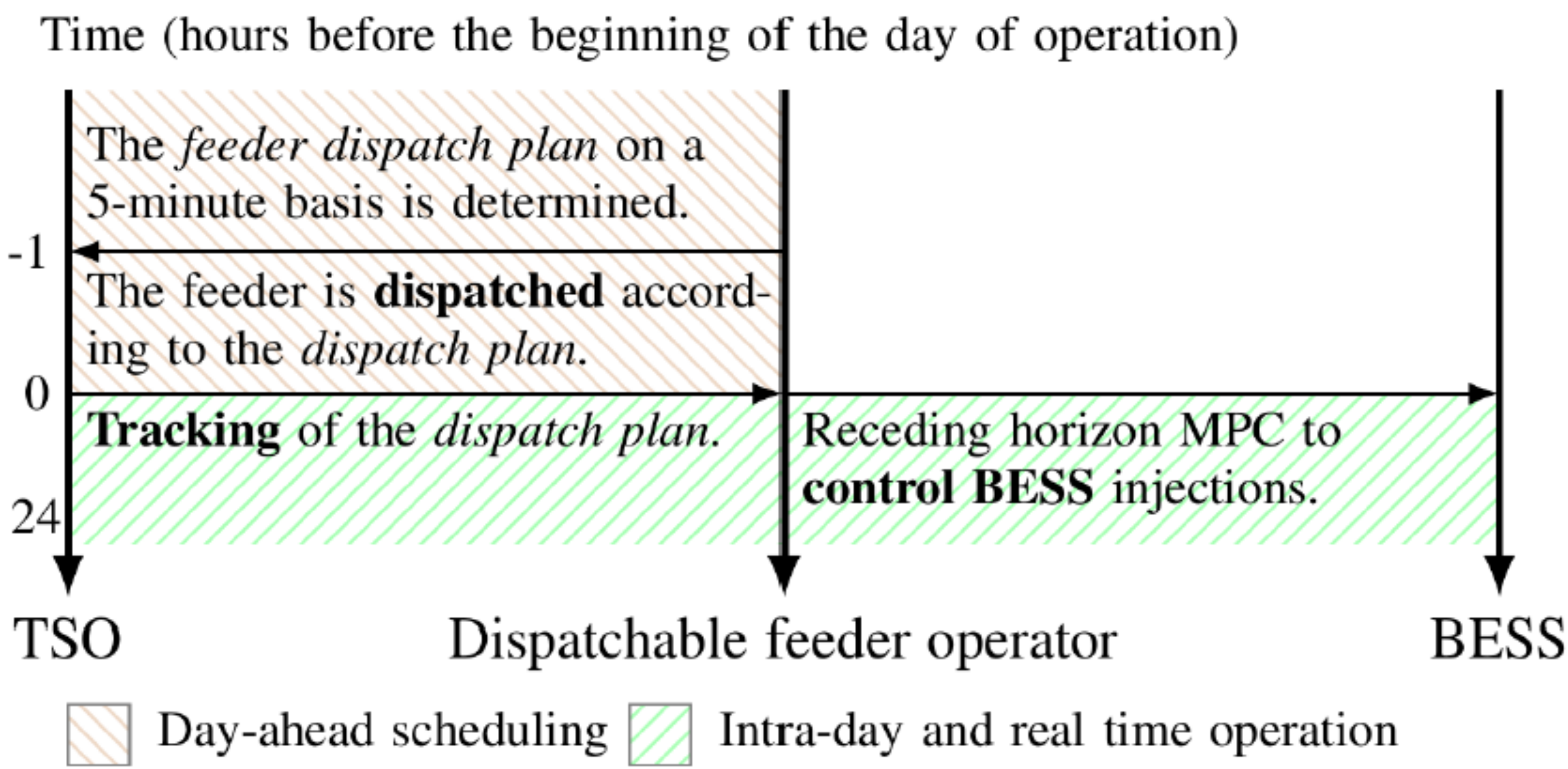

## Problem Statement

- Compute a **dispatch plan** for a set of heterogeneous resources at the grid connection point (GCP) accounting for local grid constraints and local storage capacity (see also [Stai et al., 2017]).

- Control storage devices in real-time to track the dispatch plan.



# Dispatch of stochastic resources – A two stage process



# Dispatch of stochastic resources – Dispatch plan

The **dispatch plan** is a 1-day long sequence at 5 minute resolution of the scheduled power flow at the GCP:

$$\widehat{P}_t = \widehat{L}_t + F_t \qquad t = 1, \dots, N$$

**Prosumption point prediction at the GCP**

**Offset profile**

It restores an adequate battery state-of-energy to ensure that enough up/down-flexibility is available during operation to compensate for the mismatch between prosumption and realization.

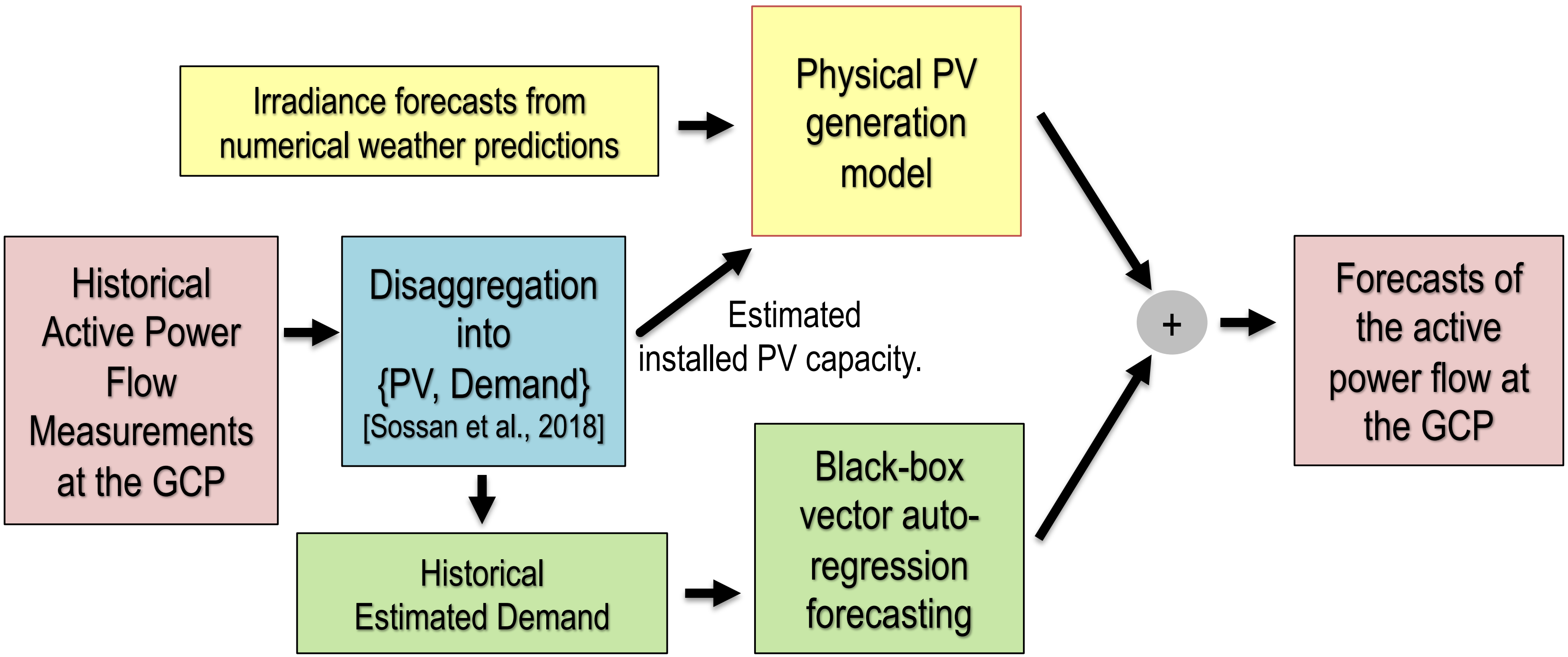
# Dispatch of [..] resources – Day-ahead forecasts

$$\widehat{P}_t = \widehat{L}_t + F_t$$

**Objective**: forecasting the aggregated active power flow at the GCP of the set of heterogeneous resources for the next day.

Broad topic, generally. **Challenging and novel** due to the **low level of aggregation** (volatile series, very dependent on the mix of the underlying demand → whenever possible, tendency to adopt physical models to explain power flow patterns).

**Procedure for hybrid black-box/physical forecasting with demand and PV:**



# Dispatch of stochastic resources – Offset profile

$$\widehat{P}_t = \widehat{L}_t + \boxed{F_t}$$

During operation, at time $i$, the battery compensates for the mismatch between the dispatch plan and the realization $L_i$. The battery's power injection is:

$$B_i = \widehat{P}_i - L_i = F_i + \underline{\widehat{L}_i - L_i}$$

from the previous definition of the dispatch plan

Let $L_i^{\uparrow}, L_i^{\downarrow}$ the largest and smallest deviation of the prosumption's realization from its expected value (based on scenarios).

E.g., the battery's lowest injection at time $i$ is

$$B_i^{\downarrow} = F_i + L_i^{\downarrow}$$

We seek for a solution $\boldsymbol{F}=[F_1, .., F_N]$ so that the battery's state-of-energy and power injection are within limits.

$$\boldsymbol{F}^o = \underset{\boldsymbol{F}\in\mathbb{R}^N}{\arg\min} \left\{ \sum_{i=1}^{N} F_i^2 \right\}$$

Offset with least norm-2 (arbitrary standard choice, it could be just a feasibility problem)

subject to (for $i = 0, \ldots, N-1$):

$$F_i + L_i^{\downarrow} \geq B_{\min}$$
$$F_i + L_i^{\uparrow} \leq B_{\max}$$

Battery's injection within converter limit (only active power)

Worst case lowest state-of-energy must be higher than minimum allowed

$$\mathrm{SOE}_{i+1}^{\downarrow} = \mathrm{SOE}_i^{\downarrow} + \eta \left[F_i + L_i^{\downarrow}\right]^+ + 1/\eta \left[F_i + L_i^{\downarrow}\right]^-$$
$$\mathrm{SOE}_{i+1}^{\downarrow} \geq \mathrm{SOE}_{\min}$$

Charging efficiency

Worst case highest state-of-energy must be higher than minimum allowed

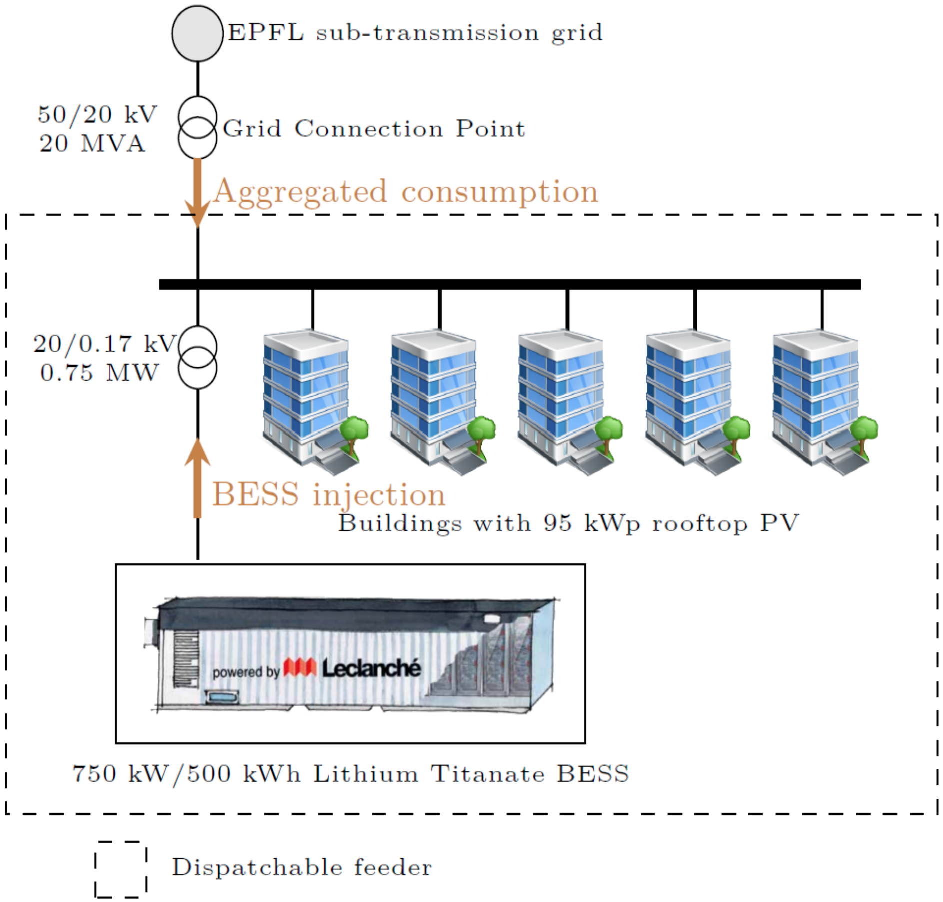
$$\mathrm{SOE}_{i+1}^{\uparrow} = \mathrm{SOE}_i^{\uparrow} + \eta \left[F_i + L_i^{\uparrow}\right]^+ + 1/\eta \left[F_i + L_i^{\uparrow}\right]^-$$
$$\mathrm{SOE}_{i+1}^{\uparrow} \leq \mathrm{SOE}_{\max}$$

(nonconvex due to the sign operators, convexified in [Sossan et al., 2016])

$$\widehat{P}_i \leq P_{\max}$$

Flow constraint at the GCP (assuming 1 pf)

# Experimental validation: setup at EPFL, CH






- Single measurement point at the GCP.
- 350 kW peak demand during winter.
- 95 kWp roof-top PV installation.

# Experimental validation: results

Dispatched operation -- 14 Jan 2016
https://snapshot.raintank.io/dashboard/snapshot/PuW1Rf5d470Q0gsT7UNponM25bGDNTRA

Dispatched operation -- 13 Jan 2016
https://snapshot.raintank.io/dashboard/snapshot/cDS4IDniZjRiePXvusnmQXOmMwpGLnR6

Dispatched operation + Peak Shaving -- 22/06/2016
https://snapshot.raintank.io/dashboard/snapshot/LSF3bPxtWYDjHVu6siEr1VPb92EXNkd6

Dispatched Operation + Load Levelling -- 14/03/2016
https://snapshot.raintank.io/dashboard/snapshot/4ztn800czpAzEFRzbGOmWc1A2pKeC9ab

Dispatched operation (continuos operation) -- 16 to 19/03/2016
https://snapshot.raintank.io/dashboard/snapshot/TNbEgP7j1AWhaW7cEK1ZiK3tY1Or7P4U

# Provision of multiple ancillary services with same battery

Single service applications lead to poor exploitation of battery's power and energy ratings.

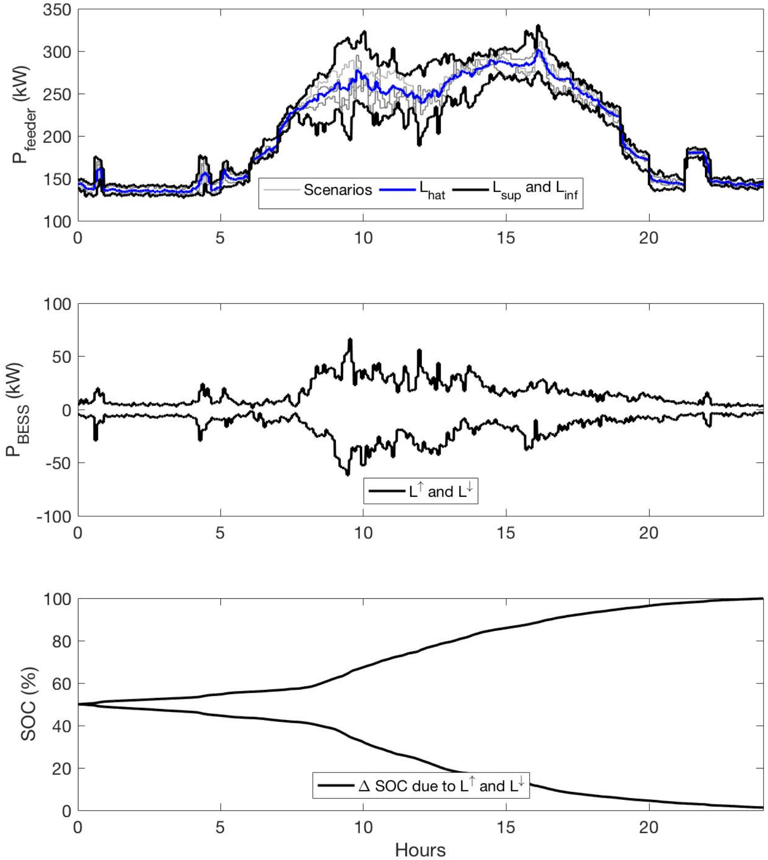



**Fig.:** Dispatch planning with **higher** uncertainty.

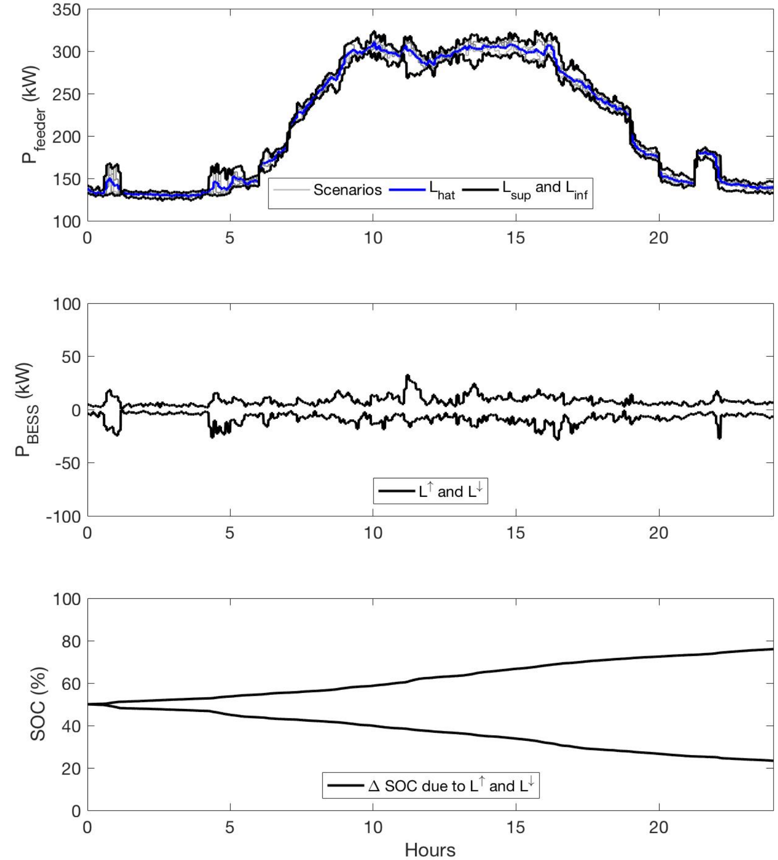
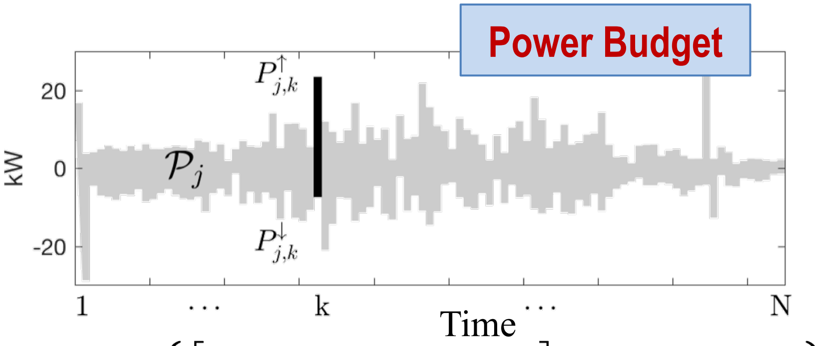



**Fig.:** Dispatch planning with **lower** uncertainty.

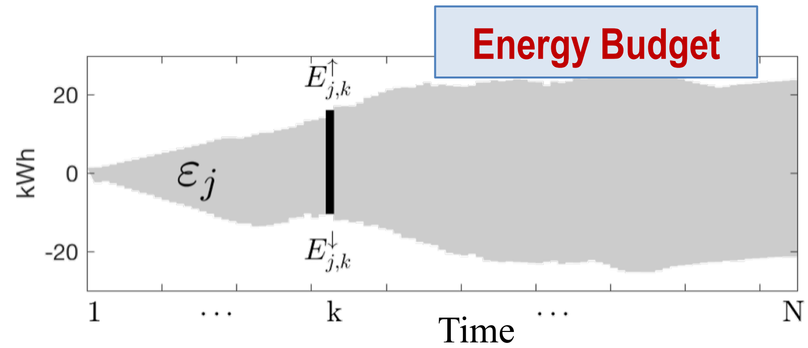
Residual power/energy capacity can be used to **provide multiple ancillary services simultaneously**.

# Stacking of ancillary services [Namor et al., 2018]

We have multiple services to provide. We define for each grid ancillary service $j$ the:




$$\mathcal{P}_j = \left\{ \left[ P^{\downarrow}_{j,k}(x,\theta), P^{\uparrow}_{j,k}(x,\theta) \right], k = 1, \ldots, N \right\}$$




$$\mathcal{E}_j = \left\{ \left[ E^{\downarrow}_{j,k}(x,\theta), E^{\uparrow}_{j,k}(x,\theta) \right], k = 1, \ldots, N \right\}$$

parametrized over vector of controller's parameters $x$ and forecast of the unitary budgets $\theta$.

Operator to determine width of envelopes: $w(\mathcal{E}_j(x,\theta)) \triangleq \{E^{\uparrow}_{j,k}(x,\theta) - E^{\downarrow}_{j,k}(x,\theta), k = 1, \ldots, N\}$

We seek to find the controllers' parameters which maximize the exploitation of the battery energy capacity subject to the battery's power and energy constraints.

$$\arg\max_x \left\| w\left(\sum_j \mathcal{E}_j(x,\theta)\right) \right\|_1$$

subject to:

$$E_{init} + \sum_j \mathcal{E}_j(x,\theta) \in [E_{min}, E_{max}]$$

$$\sum_j \mathcal{P}_j(x,\theta) \in [-P_{max}, P_{max}]$$

# Stacking of ancillary services: Results [Namor et al., 2018]

## Dispatch + primary frequency regulation (PFR)

| | Dispatch | PFR |
|---|---|---|
| Power Budget | Worst case high and worst case low power deviation from the dispatch plan. | Drop coefficient (**unknown, to determine**) time worst case frequency deviation (200 mHz). |
| Energy Budget | Integral of worst case deviations. | 5-95% quantiles of the distribution of the accumulated frequency deviation in 1 day over a 2-year period. |

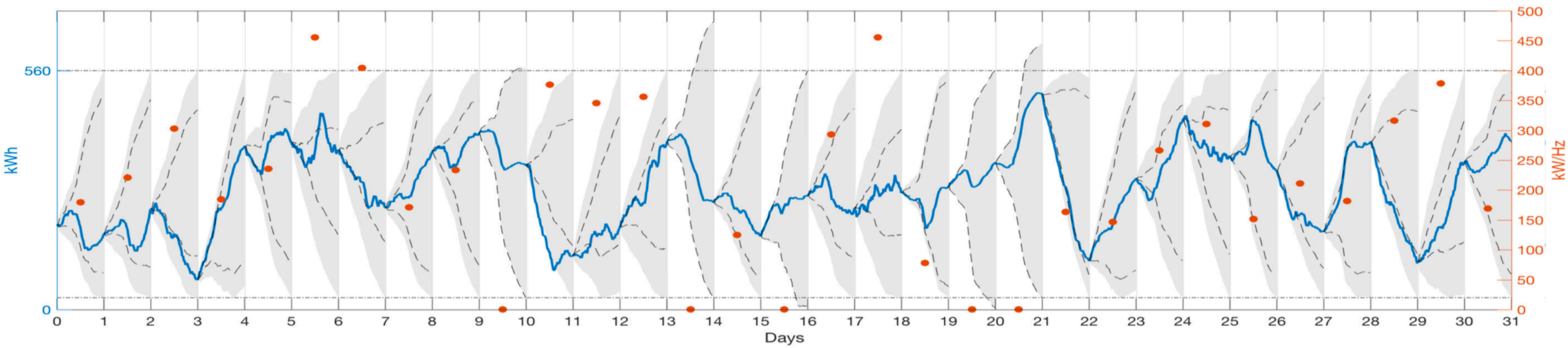



**Fig.:** Battery's state of energy (SOE): realization (**thick** blue line), worse cases for dispatch (dashed black line), worse cases for dispatch + PFR (shaded grey), and allocated drop coefficient (orange dots).

Link to results

# Dispatch: extension to multiple controllable resources

With multiple flexible element in the mix (e.g. **battery +** building with controllable **electric space heating**), the problem can be extended by (in brief):

- Compute one dispatch plan per each element in the mix [Fabietti et al., 2018].
- The aggregated dispatch plan is the algebraic sum of the individuals dispatch plans.
- The real-time control problem with multiple controllable elements is distributable (tractable) [Fabietti et al., 2017] [Gupta et al., 2018].

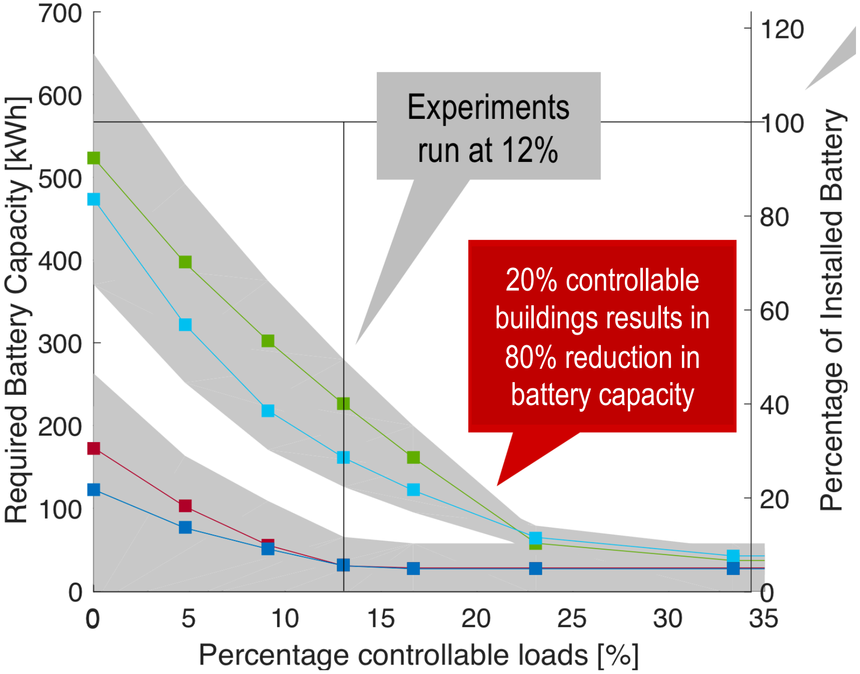


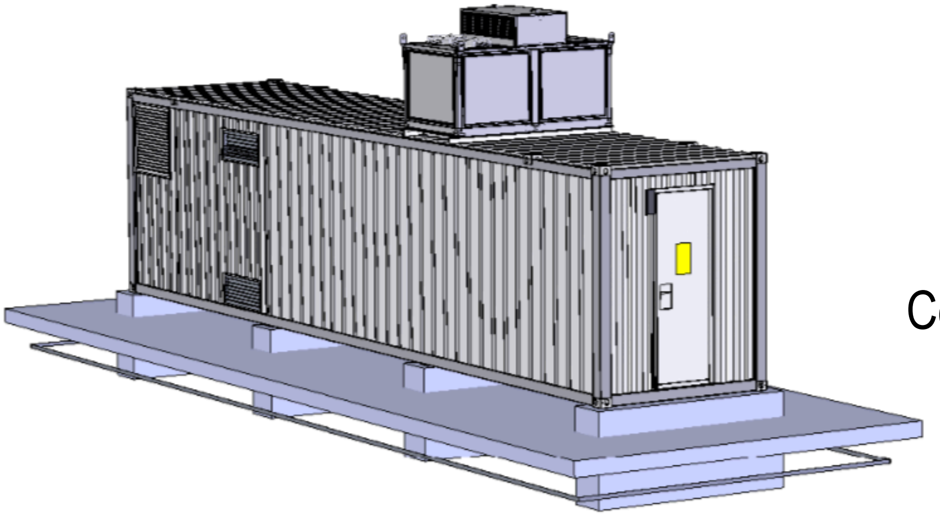

**Fig.:** Dispatch with batteries and flexible demand. Battery capacity to achieve control targets decreases for larger penetration of controllable loads [Fabietti et al., 2017].

# 3

## Practices for modelling and control of grid-connected battery systems in energy management applications.

# Anatomy of a grid-connected battery system

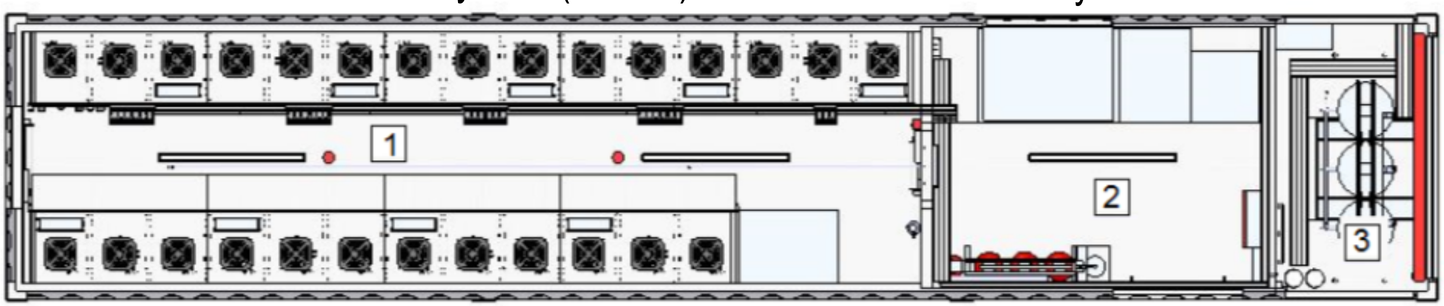
**720 kVA, 560 kWh battery system**



Container, 12 x 3 x 2 m, approx. 20 tons

Air conditioning (7 kW) and
ventilation system (0.5 kW)

Fire extinguishing
system




Battery stack

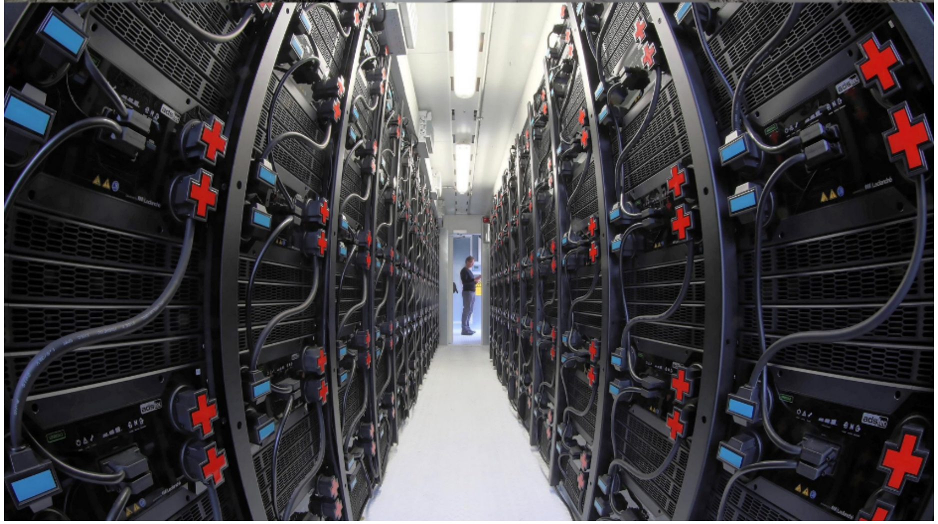
DC/AC Power
Converter

Step-up
transformer

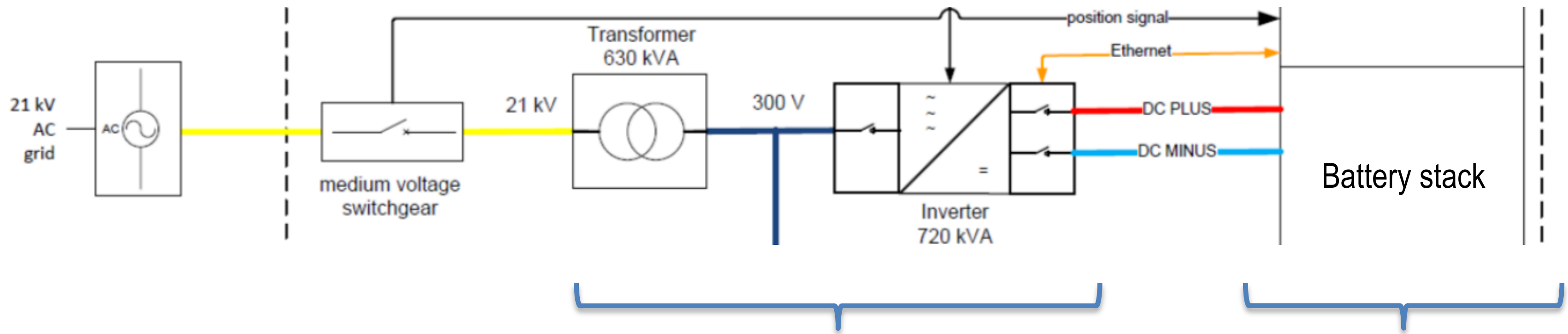
Courtesy of *Leclanché*.

# Example of utility-scale grid-connected battery

| Parameter | Value |
|---|---|
| Nominal Capacity | 720 kVA/560 kWh |
| GCP Voltage | 20 kV |
| DC Bus Voltage Range | 600/800 V |
| Cell Technology (Anode/Cathode) | Lithium Titanate Oxide (LTO)<br>Nichel Cobalt Alumnium Oxide (NCA) |
| Number of racks | 9 in parallel |
| Number of modules per rack | 15 in series |
| Cells configuration per module | 20s3p |
| Total number of cells | 8100 |
| Cell nominal voltage | 2.3 V (limits 1.7 to 2.7 V) |
| Cell nominal capacity | 30 Ah (69 Wh) |
| Round-trip efficiency (AC side) | 94-96% |
| Round-trip efficiency (DC side) | 97-99% |

# Grid-connected batteries: modelling requirements




**Models discussed in the next section, with focus on time constants for energy management applications:**

Converter

Lumped model of the cells' stack

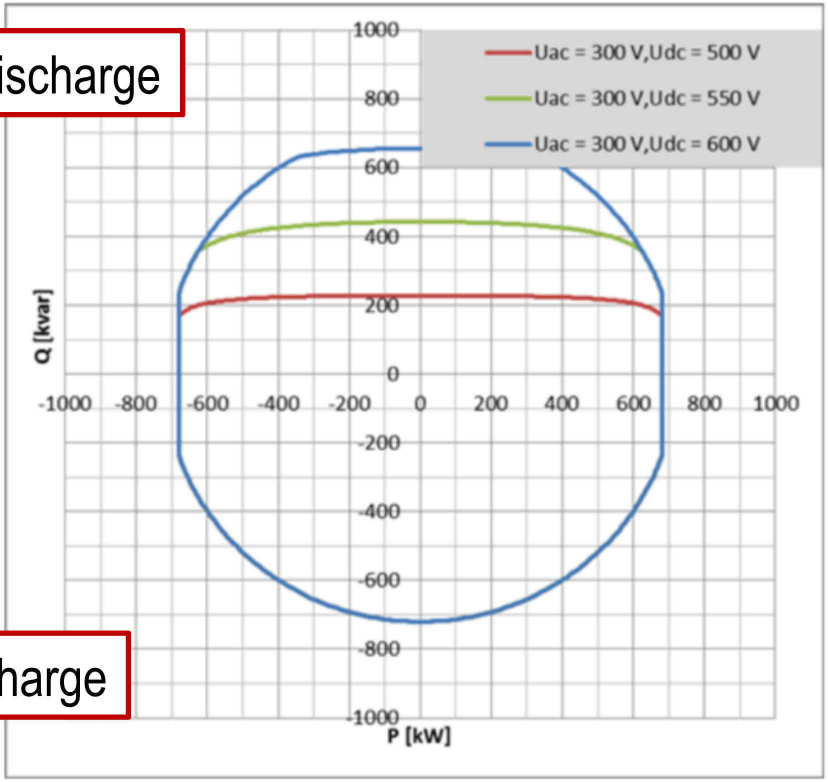
**Fig.:** Components of a grid-connected battery energy storage systems.

# Modelling for energy management – Power converter

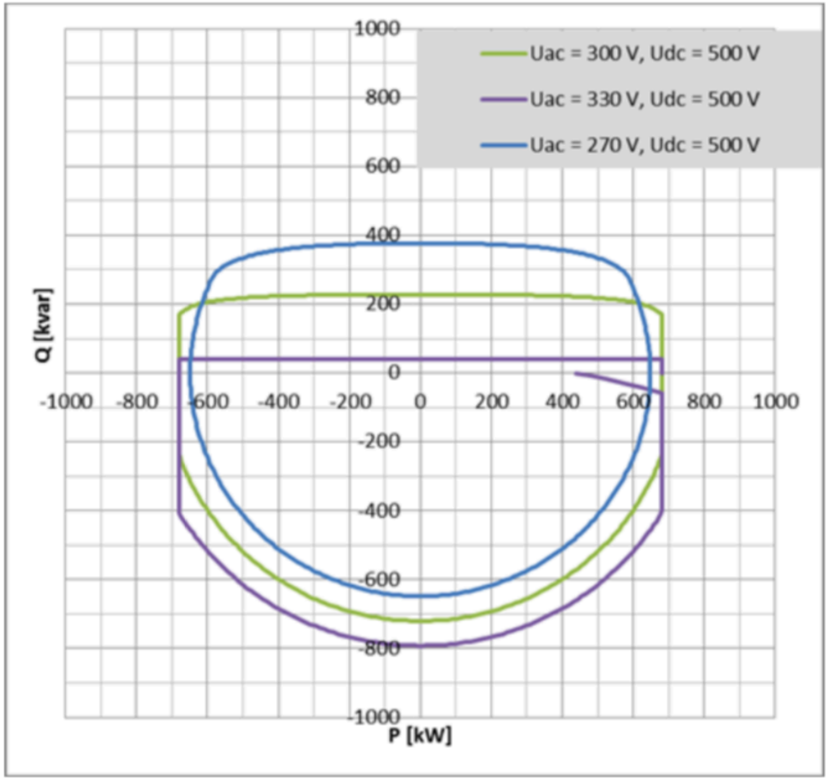
Converter's real capability curves (or PQ characteristics):

Discharge

Charge




Voltage constant on grid side (Uac), variable on DC bus (Udc)




Voltage constant on DC bus (Udc), variable on grid side(Uac)

Converter's capability modelled with a static circular PQ characteristic (convex), piecewise linearized, see e.g. [Nick et al., 2014]. Converter + transformer losses modelled with a constant coefficient (fraction of cell stack's losses).

# Modelling the Battery's state of charge (SOC)

1. Integral of the power over the energy capacity (brutal, especially for inefficient storage).

$$\mathrm{SOC}_{t+1} = \mathrm{SOC}_t + \frac{1}{T}\frac{1}{E_{\mathrm{nom}}}P_t$$

2. Constant efficiency. It can be rendered convex by expressing the power as the sum of 2 mutually exclusive (to be verified a-posteriori!) variables [Kraning et al., 2011]:

$$\mathrm{SOC}_{t+1} = \mathrm{SOC}_t + \frac{1}{T}\frac{1}{E_{\mathrm{nom}}}\left(\eta[P_t]^+ - \frac{1}{\eta}[P_t]^-\right)$$

3. When the problem is coupled to a load flow, the battery's series resistance is a new line in an augmented load flow [Stai et al., 2017] (little additional complexity!).
4. Second order model to capture rate capacity effect or charge relaxation effect, see e.g. application in [Fortenbacher et al., 2017].

# Modelling requirements – Battery's voltage dynamics

Two time constant (TTC) models widely adopted to describe **lumped** voltage dynamics on the DC bus as a function of the DC current.

| Pros | Cons |
|---|---|
| Capture dynamics quite accurately.<br><br>Tractable (linear).<br><br>Few parameters to identify.<br><br>It can be estimated from measurements.<br><br>Easy to apply (one variable to observe). | Parameters depend on:<br>• State of charge<br>• Charge/Discharge rate<br>• Temperature<br><br>Gives no insight into underlying electrochemical processes.<br><br>Fails to capture ageing mechanism. |

# Data-driven identification of TTC models

**Steps:**

1. Perform experiments with pseudo random binary signal (PRBS) and collect voltage and current measurements on the DC bus.
2. Model formulation.
3. Parameter identification.
4. Validation (and cross-validation).
5. If performance is not acceptable. Change model and repeat.

See e.g. [Namor et al., 2018b].

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# Data-driven identification of TTC models – PRBS

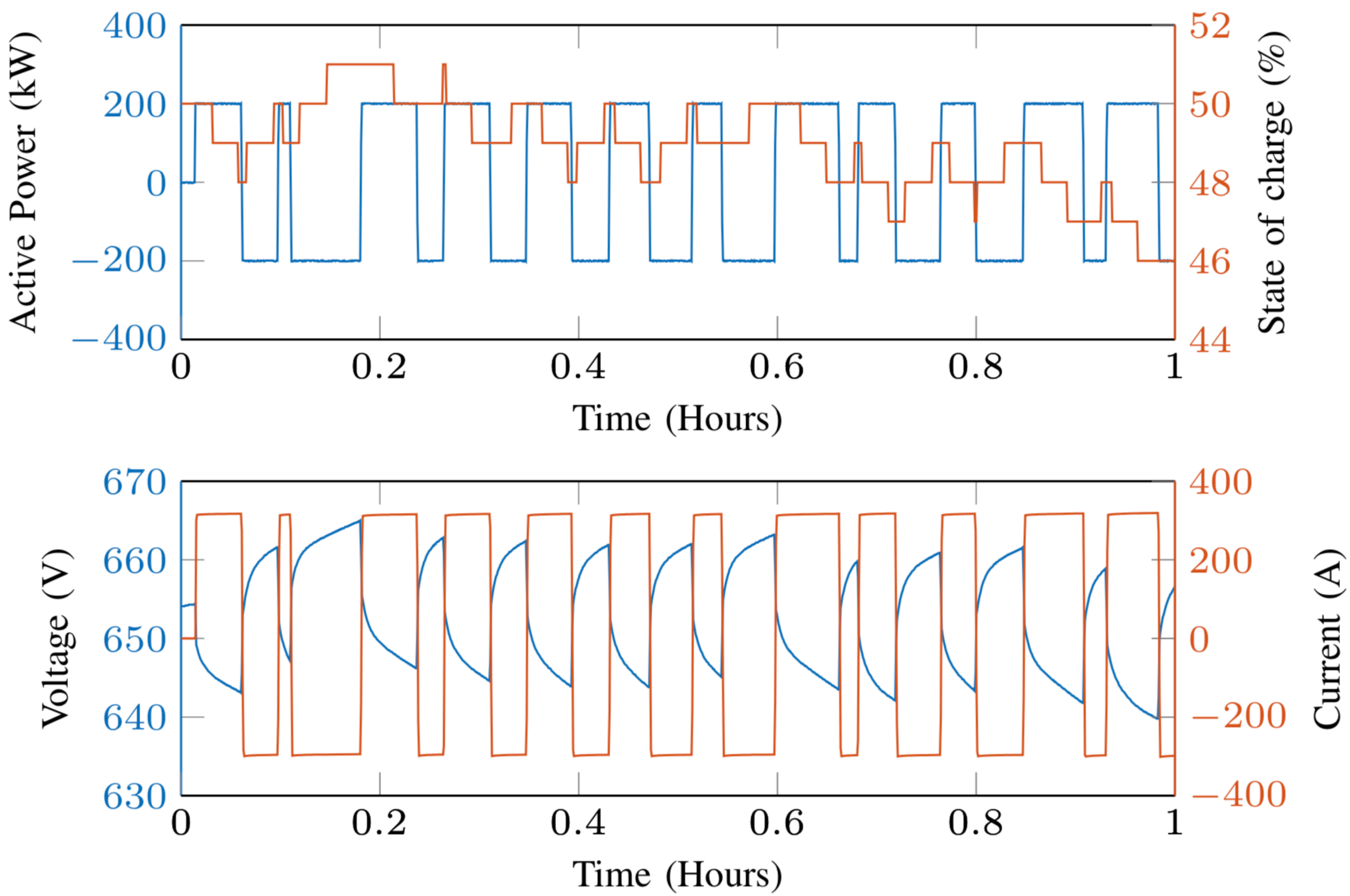
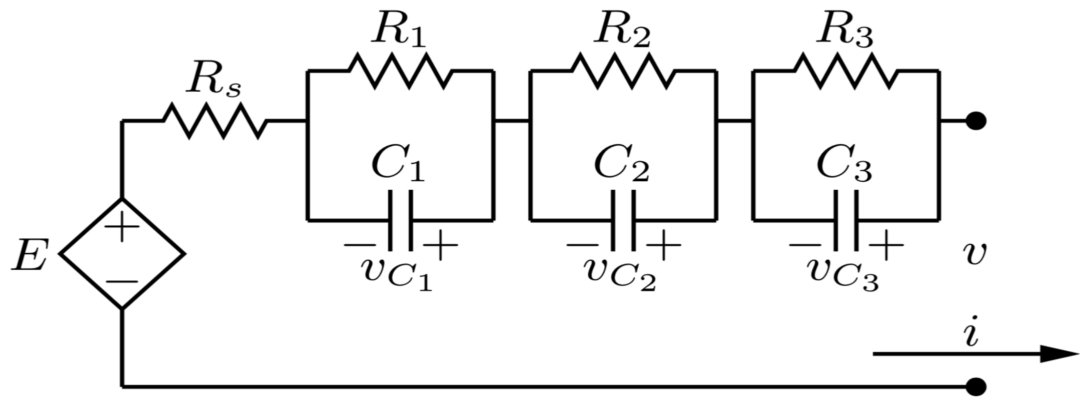



**Fig.:** Example of zero-mean PRBS signal.

# Identification of TTC models – Model formulation




3rd state normally needed to capture time dynamics in the scale of few seconds.

2 or 3 states vs 1 output. State estimation required to apply the model in practice.

**Fig.:** Three time constant model with parameters Rx Cx and $E = \alpha + \beta z$ .

## Stochastic state-space model:

$$dx = \mathcal{A}_c(\theta)xdt + \mathcal{B}_c(\theta)u(t)dt + \mathcal{K}_c(\theta)d\omega$$
$$v_k = \mathcal{C}x_k + \mathcal{D}(\theta)u_k + \mathcal{G}(\theta)g_k,$$

**State vector and input** (for two time constants, the additional state is the battery's state-of-charge).

$$x = \begin{bmatrix} v_{C_1} & v_{C_2} & z \end{bmatrix}^T$$
$$u_{tk} = \begin{bmatrix} i_{tk} & 1 \end{bmatrix}^T .$$

## State-space matrices:

$$\mathcal{A}_c = -\mathrm{diag}\left(\frac{1}{R_1C_1}, \frac{1}{R_2C_2}, 0\right)$$
$$\mathcal{B}_c = \begin{bmatrix} \frac{1}{C_1} & 0 \\ \frac{1}{C_2} & 0 \\ \frac{1}{Q} & 0 \end{bmatrix}$$
$$\mathcal{K}_c = \mathrm{diag}(k_1, k_2, k_3)$$
$$\mathcal{C} = \begin{bmatrix} 1 & 1 & \beta \end{bmatrix}$$
$$\mathcal{D} = \begin{bmatrix} R_s & \alpha \end{bmatrix}$$
$$\mathcal{G} = \sigma_g.$$

# Identification of TTC models – Model validation

## Residual analysis

**One-step ahead prediction error:** $e_{k|k-1} = \widehat{v}_{k|k-1} - v_k$

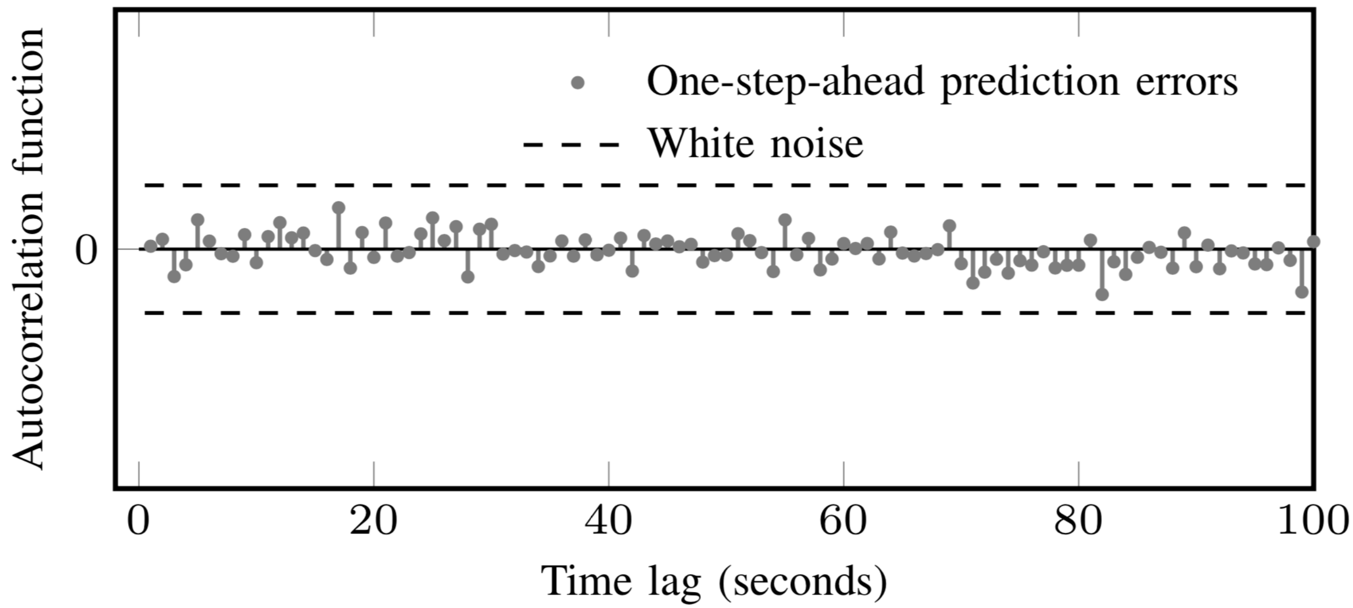



**Fig.:** Autocorrelation of the one-step ahead prediction errors vs white noise to check residual structure in the series.

# Example: energy model predictive control (MPC) of a battery

*Let $e_k$ be the* energy throughput's set-point for a battery. The problem is determining a power trajectory to achieve $e_k$ while respecting battery's voltage and current constraints. [Sossan et al., 2016].

**Two possible decision variables:**

- Battery's power output. Linear (integral) objective, nonlinear and nonconvex current and voltage constraints.

- Battery's current. Linear voltage and current constraints, cost function

$$\left(E_{\overline{k}|k}(\boldsymbol{i}_{\overline{k}|k}) - e_k\right)^2.$$

Battery energy throughput as a function of the battery DC current (convex under certain conditions see next)

Set-point

in the form $h(g(x))$, convex if $g(x)$ is convex and $h$ convex non-decreasing, thus nonconvex. Convex formulation.

# Energy MPC – Battery's energy is quadratic in the current

The battery's energy throughput is the sum over time of the battery's power output, i.e. product of battery's DC current, DC voltage and converter efficiency alpha:

Battery AC energy throughput

$$E_{\overline{k}|k}(\cdot) = \alpha \boldsymbol{v}_{\overline{k}|k}^T \boldsymbol{i}_{\overline{k}|k}$$

Battery DC voltage sequence

Battery DC current sequence

Battery's DC voltage as a function of the current is from the linear TTC model:

$$\boldsymbol{v}_{\overline{k}|k} = \phi^v x_k + \psi_i^v \boldsymbol{i}_{\overline{k}|k} + \psi_1^v \mathbf{1}$$

Phi, gamma from battery state-space matrices

Battery system state (Kalman-estimated)

Replacing the second into the first yields:

$$E_{\overline{k}|k}(\cdot) = \alpha \left( x_k^T {\phi^v}^T \boldsymbol{i}_{\overline{k}|k} + \boldsymbol{i}_{\overline{k}|k}^T {\psi_i^v}^T \boldsymbol{i}_{\overline{k}|k} + \mathbf{1}^T {\psi_1^v}^T \boldsymbol{i}_{\overline{k}|k} \right)$$

i.e., sum of two linear terms and a quadratic term in the current. <u>Convex if $\psi$ is SDP.</u>

# Energy MPC for a battery – A convex formulation

We use the previous result to formulate a convex problem of the energy tracking point. It maximizes the current (i.e. linear cost function) subject to the energy throughput being less or equal to the target energy throughput $e_k$ (i.e. convex inequality).

$$\boldsymbol{i}^o_{\overline{k}|k} = \underset{\boldsymbol{i}\in\mathbb{R}^{(k-\overline{k}+1)}}{\arg\max} \left\{ \mathbf{1}^T \boldsymbol{i}_{\overline{k}|k} \right\}$$

subject to :

$$\alpha \left( x_k^T {\phi^v}^T \boldsymbol{i}_{\overline{k}|k} + \boldsymbol{i}_{N|t}^T {\psi_i^v}^T \boldsymbol{i}_{\overline{k}|k} + \mathbf{1}^T {\psi_r^v}^T \boldsymbol{i}_{\overline{k}|k} \right) \leq e_k \quad \text{(BESS energy througput, convex if } \psi_i^v \text{ is SDP)}$$

$$\mathbf{1} \cdot i_{\min} \preccurlyeq \boldsymbol{i}_{\overline{k}|k} \preccurlyeq \mathbf{1} \cdot i_{\max} \qquad \text{(Current constraints)}$$

$$\mathbf{1} \cdot \Delta_{i,\min} \preccurlyeq H \boldsymbol{i}_{\overline{k}|k} \preccurlyeq \mathbf{1} \cdot \Delta_{i,\max} \qquad \text{(Current ramping constraints)}$$

$$\boldsymbol{v}_{\overline{k}|k} = \phi^v v_k + \psi_i^v \boldsymbol{i}_{\overline{k}|k} + \psi_1^v \mathbf{1} \qquad \text{(Voltage model)}$$

$$\mathbf{1} \cdot v_{\min} \preccurlyeq \boldsymbol{v}_{\overline{k}|k} \preccurlyeq \mathbf{1} \cdot v_{\max} \qquad \text{(Voltage constraints)}$$

$$\mathbf{SOC}_{\overline{k}|k} = \phi^{\text{SOC}} \text{SOC}_k + \psi_i^{\text{SOC}} \boldsymbol{i}_{\overline{k}|k} \qquad \text{(SOC model)}$$

$$\mathbf{1} \cdot \text{SOC}_{\min} \preccurlyeq \mathbf{SOC}_{\overline{k}|k} \preccurlyeq \mathbf{1} \cdot \text{SOC}_{\max} \qquad \text{(SOC constraints)}$$

# Energy MPC for a battery – Experimental results

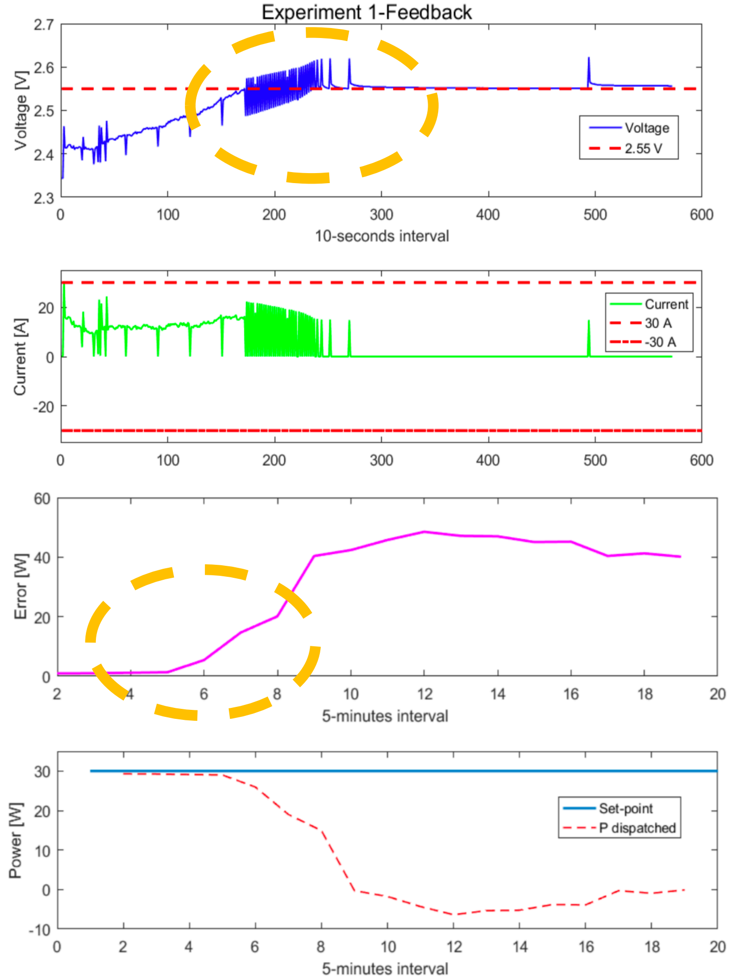



**Fig.:** Single battery cell with integral feedback control loop. Voltage constraints violations.

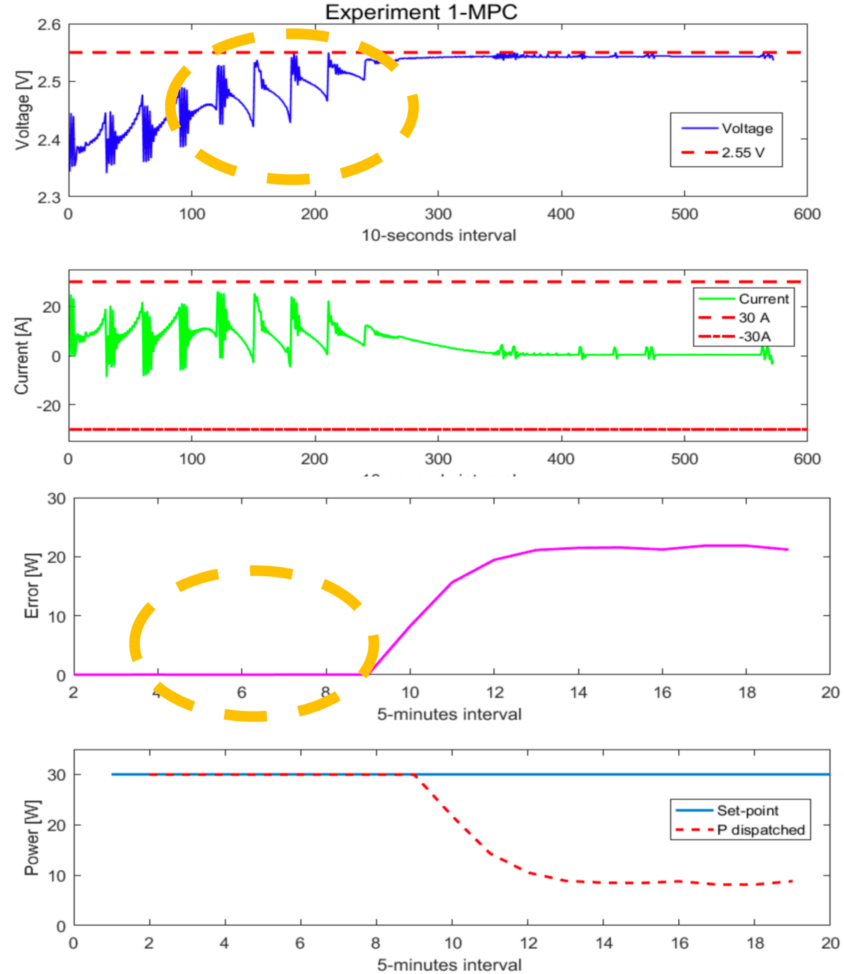



**Fig.:** Single battery cell with energy MPC. Better tracking performance with no violations.

# A side note about ageing and ageing-aware control

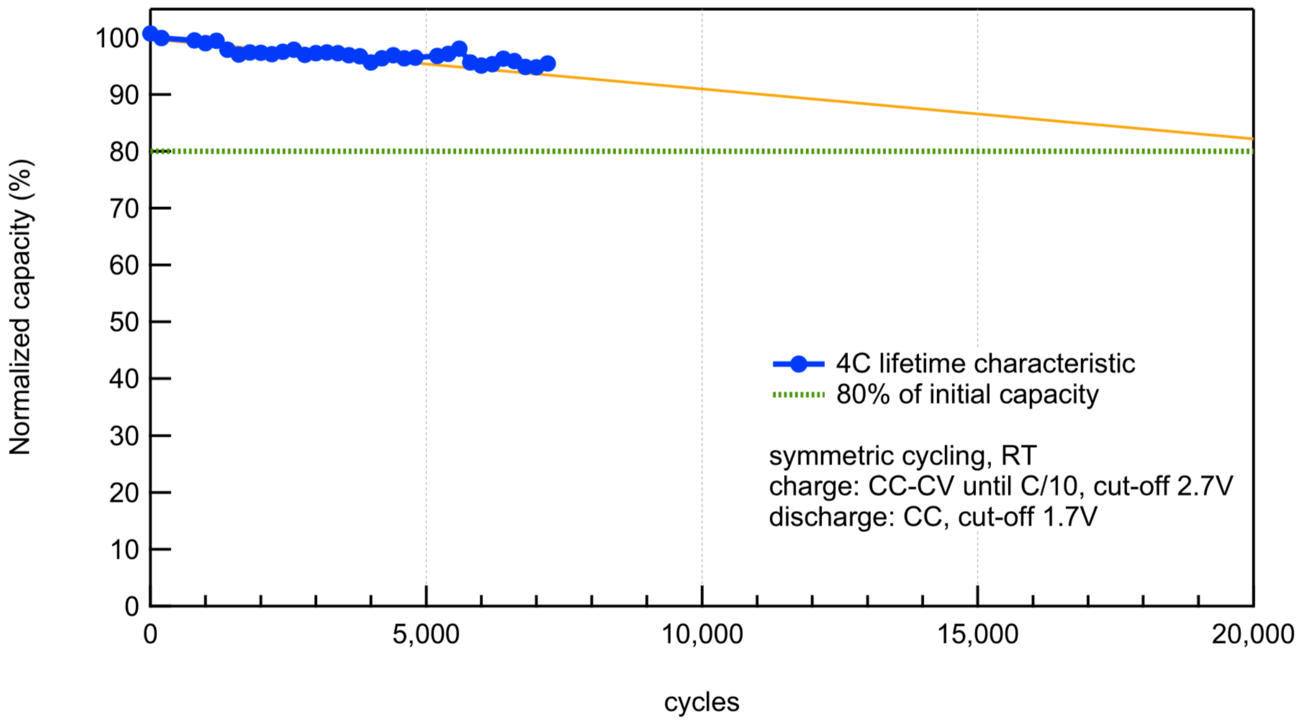



**Fig.:** Empirical assessment of battery ageing of a LTO cell based on laboratory tests. Courtesy of *Leclanché*.

Rule-of-thumb estimates (wo including path dependent aging):
- Expected life due to cycling: **55 years at 1 cycle per day**
- Expected calendar life: **15 years**

Ageing-aware control policies should be designed according to the available technology.

# Summary

1. Integration of battery storage in electrical grids. Two perspectives: increasing the performance at the system level, and enabling safe integration of renewable energies in distribution systems.

2. A framework to dispatch heterogeneous resources as a control paradigm for controlling battery systems and downstream flexibility → towards self-dispatching distribution systems?

3. Anatomy of a real-life grid-connected battery storage system – mainstream modelling practices for power converters, battery voltage dynamics, and state-of-charge.

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