

Some Aspects of Optimized Energy Dispatching and Trading

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Overview

1. Energy dispatch heuristics

- Dantzig-Wolfe decomposition

2. Cyclic battery aging

- Linear approximation
- Model predictive control

3. Optimized bidding

- Interleaved electricity markets

Part 1: Dispatching

Which component produces how much energy in the next time step?

- Satisfy requested loads
- Minimize fuel consumption, ...
- Balance power in/between nodes
- Secure against short term load variations, failures, ...

System simulation...

- Covers years
- Produces input for dispatcher
- Digests output of dispatcher
- Implements component behavior

... with dispatch optimization

- Called in every simulated time interval
- Component/network model
- Also useful in operation of network

Computation time

- One year simulation should be completed within minutes
- Computation time per problem should only take **milliseconds**
- Many different configurations are investigated for a **business plan**

Dispatch heuristics

From MILPs...

- linear approximation of relevant physical/economical aspects
- ideal for developing new features!

... to heuristics

- consistent with MILP model
- faster than MILP solver!

... via

- enumeration of next on/off/... decisions (fixing binary variables)
- => small number of LPs (rather than single MILP)
- decomposition of system/component equations (Danzig-Wolfe)

Dantzig-Wolfe decomposition (1960)

Linear problem

$$\sum_i c_i x_i$$

Subject to hard constraints

- bus power balances
- operation reserve inequalities
- ...

$$\sum_j A_{k,i} x_i = a_k$$

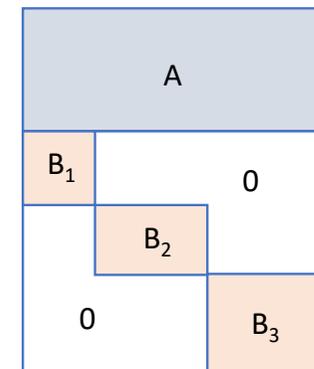
... and "easy" constraints

- component models
- matrix B is block diagonal

$$\sum_n B_{n,i} x_i = b_n$$

Idea:

- Represent $\{ Bx = b \}$ by its extremal vertices v_1, v_2, \dots, v_m
- and x as convex combination of v_1, v_2, \dots, v_m
- New variables $\alpha_1, \alpha_2, \dots, \alpha_m \geq 0, \alpha_1 + \alpha_2 + \dots + \alpha_m = 1$
- Solution is convex combination of subproblem vertices



Block angular
constraint matrix

$$x = \sum_h \alpha_h v_h$$

Dantzig-Wolfe decomposition (continued)

"Master problem": minimize $\sum_h c^T v_h \alpha_h$

subject to

$$\alpha_h \geq 0 \quad \sum_h \alpha_h = 1 \quad \sum_h (A_{k,h} v_h) \alpha_h = a_k$$

Solution method

- Simplex algorithm
- Set of vertices $V = (v_1, v_2, \dots, v_{k+1})$ for α -values in current basis
- Maintain inverse of current basis B^{-1}
- Compute dual variables y
- Compute dual costs C $y^T = c^T V B^{-1}$
- Use dual costs to check optimality or determine leaving vertex
- Use dual costs to calculate new entering vertex
- ... by solving independent "easy" independent sub-problems
- Update V and B^{-1} and repeat until optimality is reached

Slim Simplex Algorithm

Used in dispatch heuristic for

- solving master problem
- some component subproblems

Simplex method

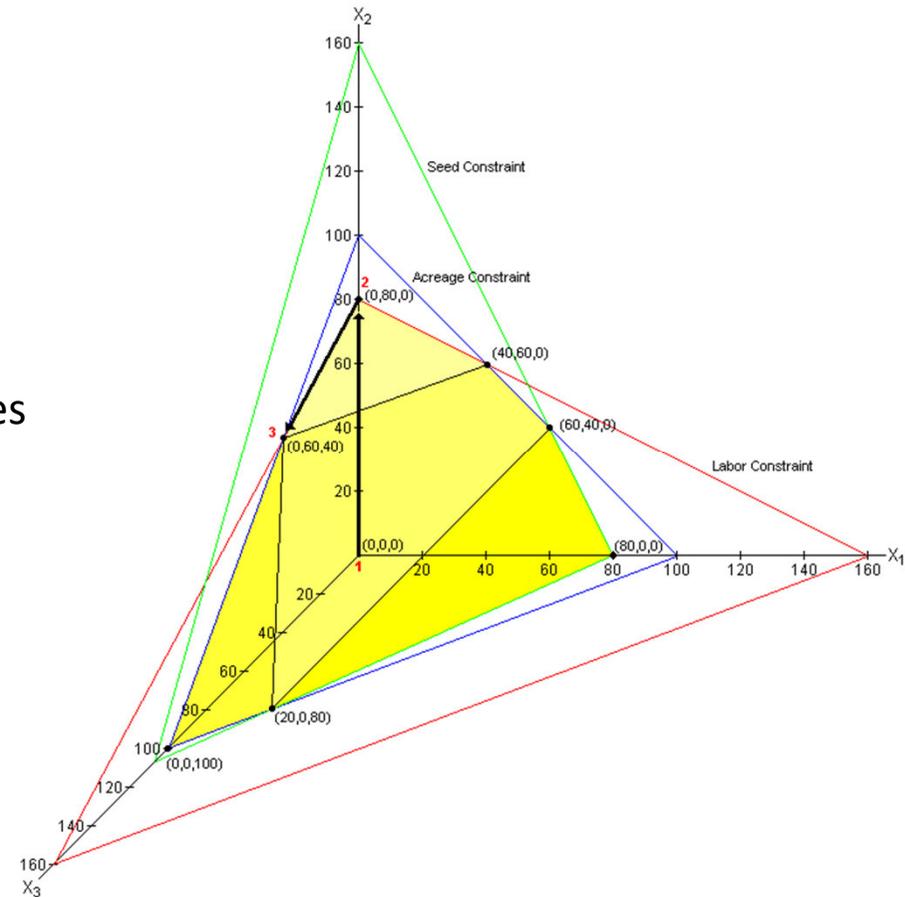
- Linear equations define polytope
- Simplex algorithm walks through vertices
- Until cost function is minimized

Slim implementation

- Avoid solver interfaces
- Explicit basis inverse

Two solution phases

1. Establish feasibility
2. Minimize cost



Conclusions Part 1:

Dispatch heuristic

- Selection of subsequent states
- Decomposed into small linear programs
- Solved by handcoded simplex

Results

- Quite fast (if network is not too complex)
- Quite successful in early planning stages
- Quite difficult to adapt to model changes

Compare [Altay and Delic \(ISGT Europe 2014\)](#)

Part 2: Cyclic battery aging

Storages can decouple production and consumption

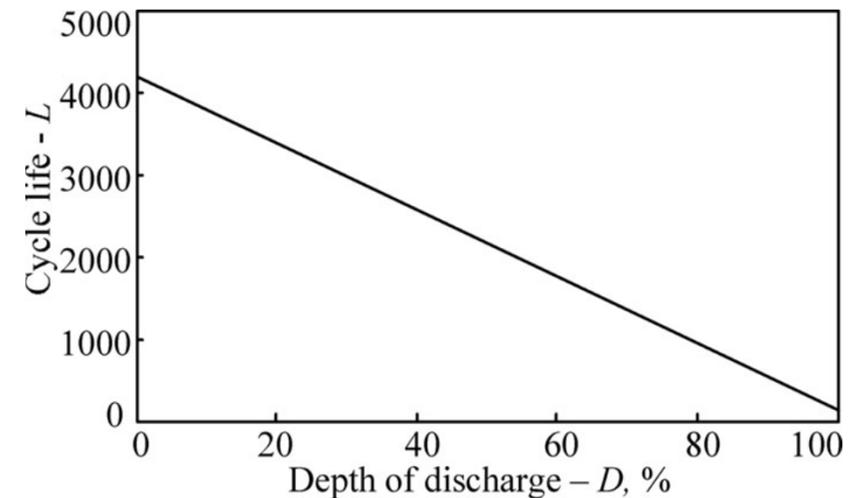
- Charge when energy is cheap
- Discharge when energy is expensive

Batteries are expensive

- Chemical processes reduce capacity
- Cyclic and calendaric aging
- Wear-out => replacement
- Profitable only, if earnings exceed aging costs!

Here we focus on cyclic aging depending on

- Temperature
- Energy throughput



Zhou, Qian, Allan, Zhou (2011)

Battery operation... (toy model)

Mixed-Integer Linear Program (MILP)

- Real, integer and binary variables
- Linear objective function and constraints

$$\begin{aligned} &\text{minimize} && \sum_{n=1}^N (C_n^+ \delta_n P_n^+ - C_n^- \delta_n P_n^-) \\ &\text{subject to} && E_n - E_{n-1} = \eta^+ \delta_n P_n^+ - \frac{1}{\eta^-} \delta_n P_n^-, \\ &&& E_{\min} \leq E_n \leq E_{\max}, \\ &&& 0 \leq P_n^+ \leq P_{\max}^+ I_n^+, \\ &&& 0 \leq P_n^- \leq P_{\max}^- (1 - I_n^+), \\ &&& I_n^+ \in \{0, 1\} \quad \text{for } n = 1, \dots, N \end{aligned}$$

Parameters

- N time intervals
- δ_n length of time interval n in [h]
- $C_n^{+/-}$ price for buying/selling energy in interval n
- $P_{\max}^{+/-}$ maximum charging/discharging power in [kW]
- $E_{\min/\max}$ min/max allowed energy in battery in [kWh]
- $\eta^{+/-}$ charging/discharging efficiency
- E_0 initial energy content of battery in [kWh]

Variables for time interval n

- E_n Energy content at end of time interval in [kWh]
- $P_n^{+/-}$ charging/discharging power in [kW]
- I_n^+ (binary) indicator; 1=charging, 0=discharging

Aging cost is missing in objective function!

... enhanced with simple temperature model

Temperatures are needed to estimate aging costs...

Update equation
$$T_n = \alpha_n T_{n-1} + \beta_n T_n^{\text{amb}} + (1 - \eta^+) \gamma_n P_n^+ + \left(\frac{1}{\eta^-} - 1 \right) \gamma_n P_n^-$$

Coefficients

$$\alpha_n = \exp(-D\delta_n)$$

$$\beta_n = (1 - \alpha_n)$$

$$\gamma_n = \frac{1}{HD} (1 - \alpha_n)$$

Represents solution of **differential equation**

$$\frac{dT(t)}{dt} = \frac{1}{H} P_{\text{heat}}(t) - D (T(t) - T_{\text{amb}}(t))$$

when P_{heat} and T_{amb} are constant on n-th time step.

$$P_{\text{heat}} = (1 - \eta^+) P_n^+ + \left(\frac{1}{\eta^-} - 1 \right) P_n^-$$

Parameters

- H heat capacity [kWh/K]
- D heat dissipation in [1/h]
- T_n^{amb} ambient temperature interval n in [K]
- T_0 initial temperature in [K]

Variables

- $P_n^{+/-}$ charging/discharging power in [kW]
- T_n temperature at end of interval n in [K]

Temperature dependence

Arrhenius Law

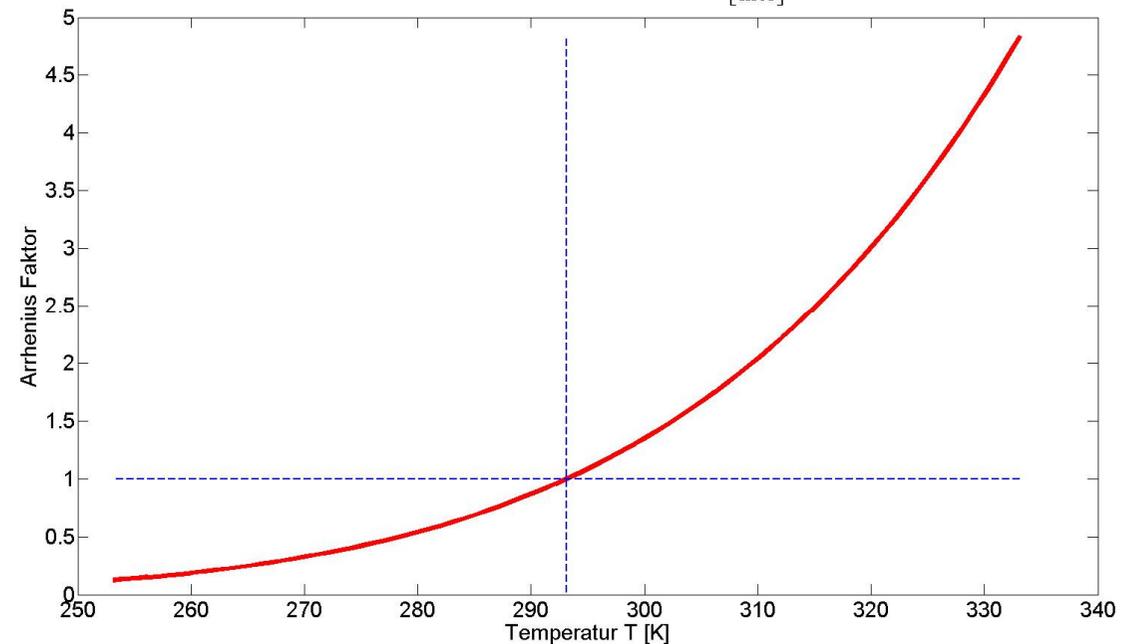
Compared to an absolute temperature T_{ref} the aging at temperature T is $f(T) / f(T_{\text{ref}})$ faster, where

$$f(T) := \exp\left(-\frac{E_a}{RT}\right)$$

Here

- E_a is the activation energy in [J/mol]
- R the universal gas constant (8.314 [J/mol/K])
- T the absolute temperature in [K]

Normiertes Arrhenius-Gesetz $e^{-\frac{E_a}{R}\left(\frac{1}{T} - \frac{1}{T_{\text{ref}}}\right)}$ mit Aktivierungsenergie $E_a = 32000 \left[\frac{\text{J}}{\text{mol}}\right]$ und Referenztemperatur $T_{\text{ref}} = 293.15[\text{K}]$



Non-linear cycle aging cost

Cost per energy throughput

$$C_E := C_B / E_{\text{tot}}$$

- C_B cost of battery
- E_{tot} is throughput until battery must be replaced
- Throughput in n-th time interval is $\delta_n (P_n^+ + P_n^-)$

Non-linear cycle aging costs

$$C_{\text{cyc}} = C_E \sum_{n=1}^N \frac{f(T_n)}{f(T_{\text{ref}})} \delta_n (P_n^+ + P_n^-)$$

Linear approximation of cycle aging cost

Blue surface shows behavior of term

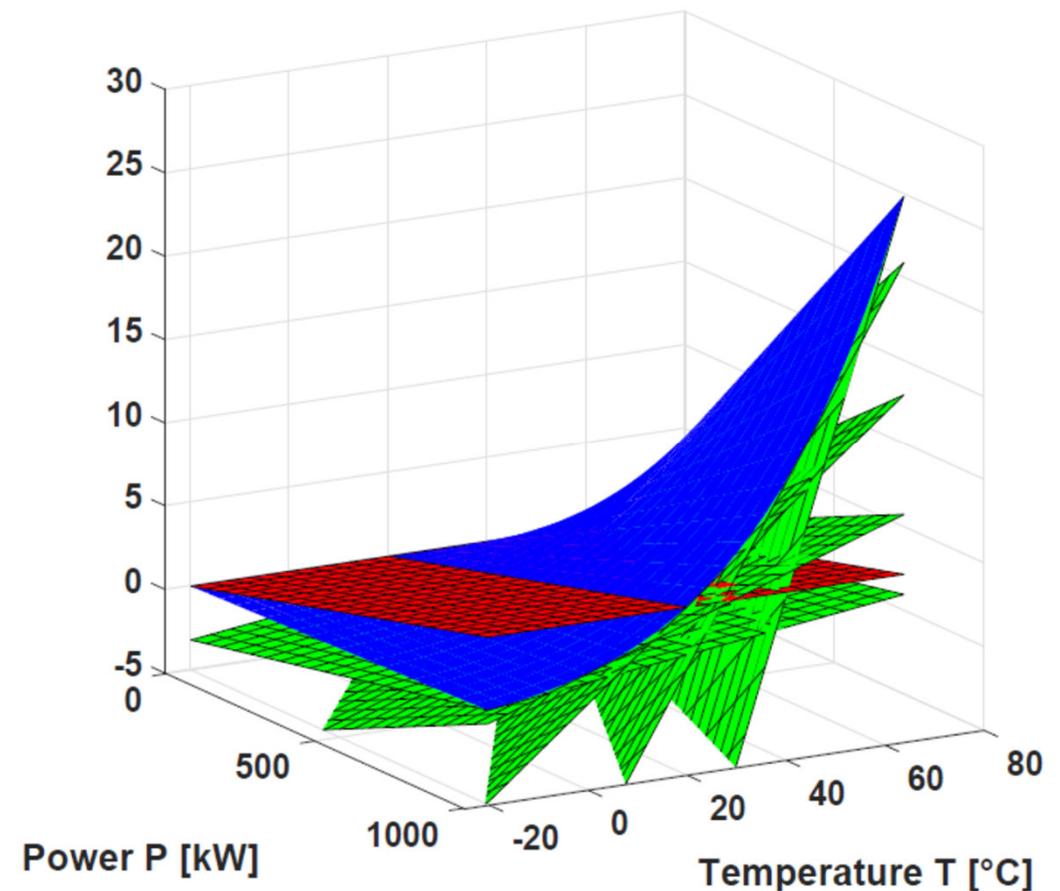
$$C_E \frac{f(T)}{f(T_{\text{ref}})} P$$

in cyclic aging cost sum as function of

- power and
- temperature

Plane approximation

- with red base plane
- and green tangent planes



Linear cycle aging cost

Aging cost in time interval n

$$C_n^{\text{cyc}} \geq a_{n,k} + b_{n,k}T_n + c_{n,k}(P_n^+ + P_n^-)$$

- $k = 0, \dots, K$ number of planes in linear approximation (e.g. $K = 4$)
- $a_{n,k}, b_{n,k}, c_{n,k}$ coefficients for planes (resulting from tangent equations)

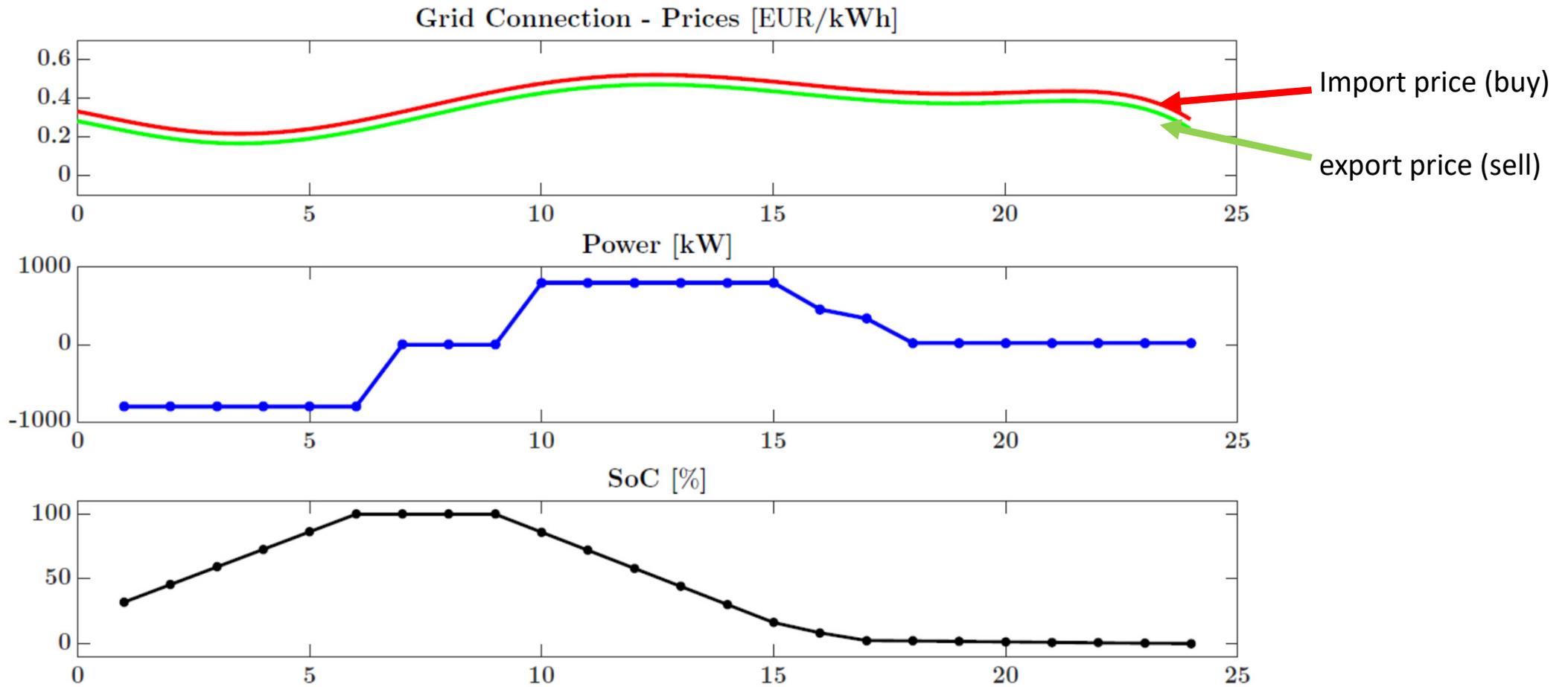
New cost function

$$\text{minimize} \quad \sum_{n=1}^N (C_n^+ \delta_n P_n^+ - C_n^- \delta_n P_n^- + \delta_n C_n^{\text{cyc}})$$

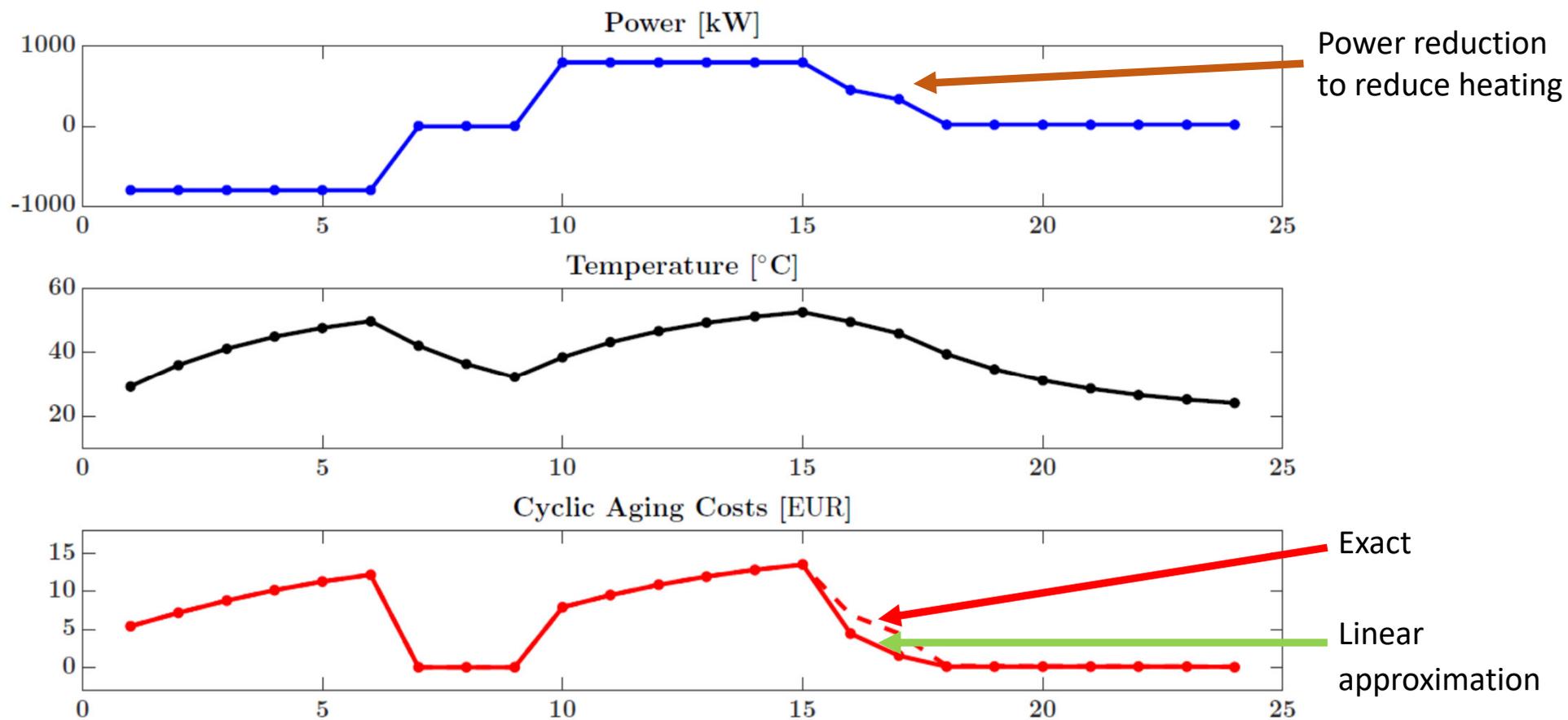
- Takes temperature and throughput into account

Example for cycle aging cost

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Example for cycle aging cost (continued)



Conclusions Part 2

Battery aging

- Temperature dependence: Arrhenius equation
- Aging implies replacement costs

Solution

- Linear approximation of aging
- Temporary reduction of charging/discharging power to reduce heating

Compare [Seydenschwanz, M., Gottschalk and Fink \(ISGT Europe 2019\)](#)

Part 3: Bidding of a VPP in electricity markets

Electricity markets

- Many periodic and overlapping sessions each day
 - Closed sessions => deliver traded power
 - Open sessions => optimize traded power
- Distinction between energy and reserve markets

Model predictive control

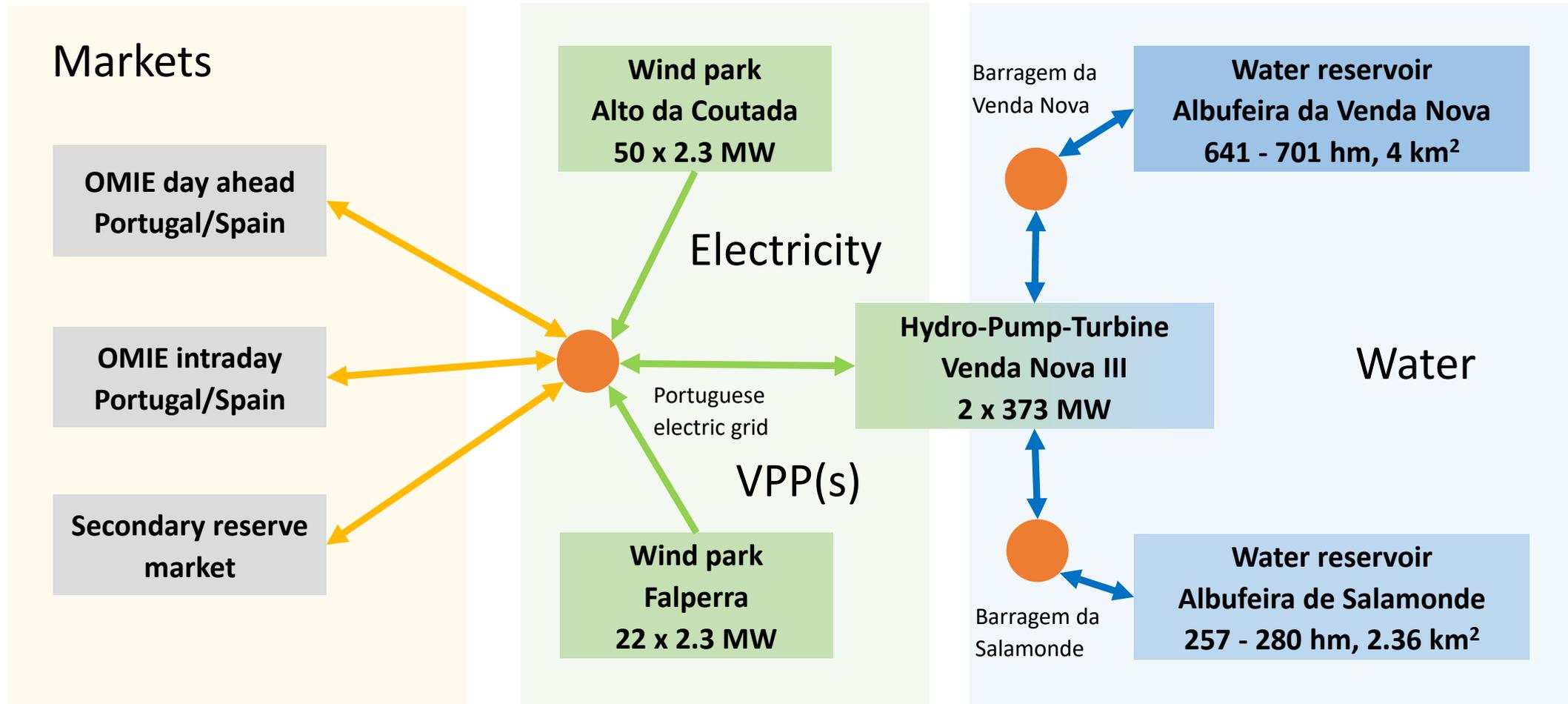
- Optimization horizon must cover
 - time from last known state of system
 - to end of bidding period + x
- With $x \approx 1$ day?

Forecasts needed

- Weather (for renewables) and prices
- => Stochastic/robust optimization

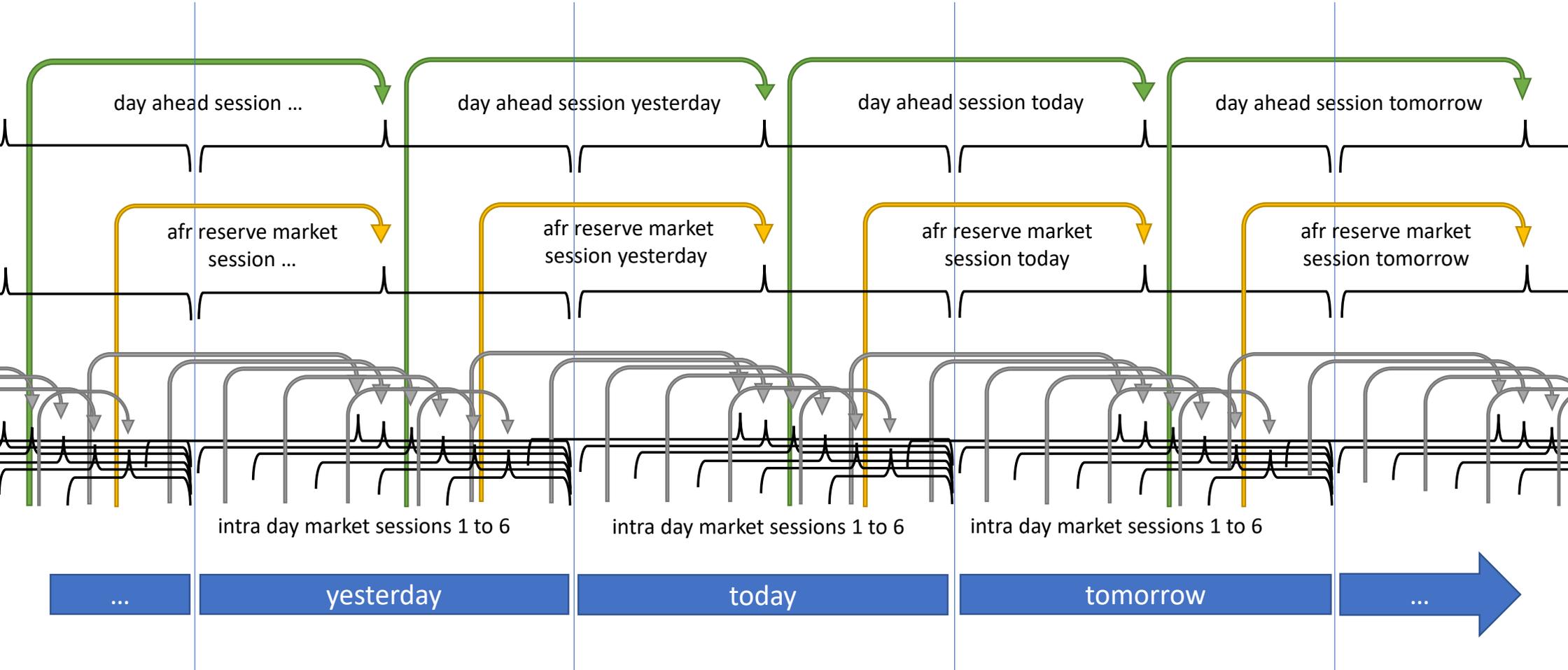
Example Topology (from SysFlex EU project)

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Market Timing

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MILP Approach

Current state

- Price, weather forecasts => optimized set-points
- MILP formulation
- Multiple scenarios to guard against volatility

Problems

- Also optimize prices of bids
- Bids might not be accepted
- Creation of scenarios

Conclusions Part 3

Bidding of VPPs in multiple markets

- Multiple components form a VPP
- Interleaving market sessions
- Predictive decision making under uncertainty
- Plenty of room for further research

Compare [Wozabal and Rameseder \(EJOR 2020\)](#)
and [Wang, Tang, Yang, Sun and Zhao \(Energy 2020\)](#)