How to design economic mechanisms for efficient operation of low-inertia power grids

TRANSIT

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3 topics covered

1. **Unlocking the support from DER** via risk-constrained optimization

2. From **low-level control** instructions to **system-level optimization** via data-driven methods

3. **Who should pay** for frequency-containment services?

Paper:

Q. Chen, L. Badesa et al., "Adaptive Droop Gain Control for Optimal Kinetic Energy Extraction From Wind Turbines to Support System Frequency," ***IEEE Access***, 2024

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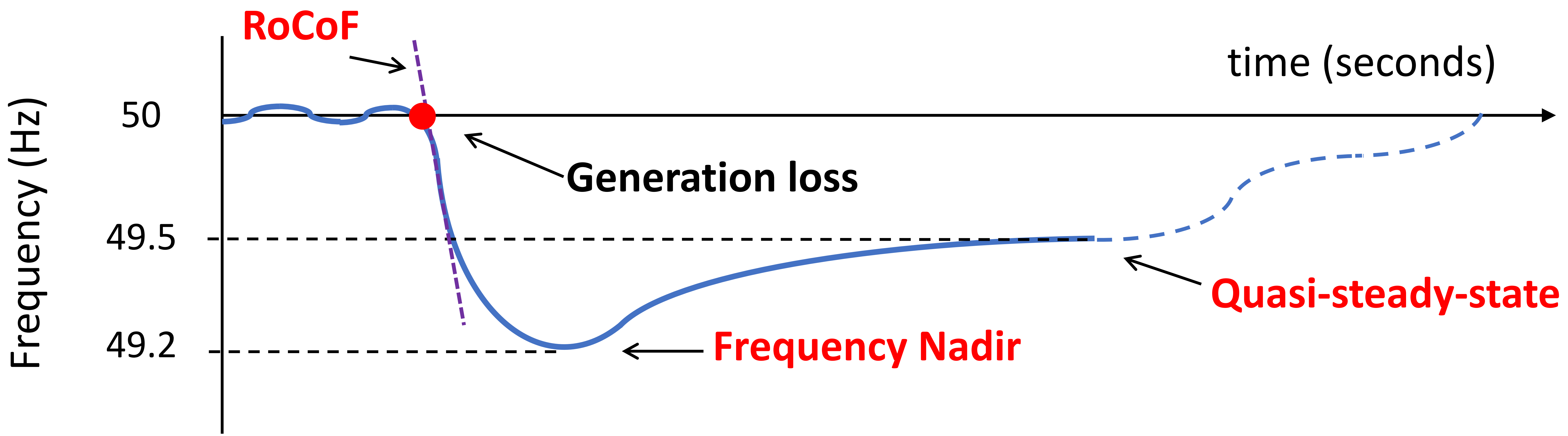
Frequency stability



Key to keep frequency within safe limits to **avoid demand disconnection!**

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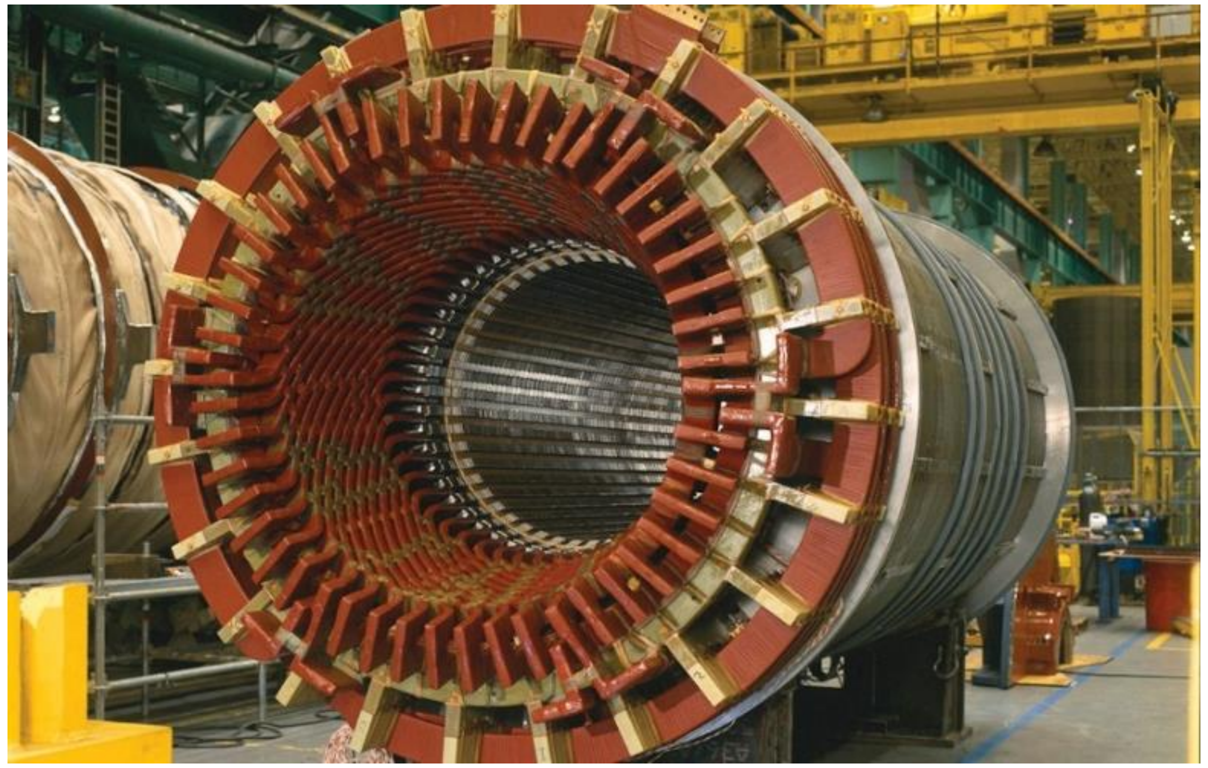
Lower inertia on the road to lower emissions

Thermal generators (nuclear, gas, coal…):



Decarbonization

Most renewables: ***no inertia***

The **risk of instability has increased!**

Inertia <u>stores kinetic energy</u>:

this energy gave us time to contain a sudden generation-demand imbalance

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Research question

How to **translate** the **system** optimal **dispatch**
into **specific control gains** for devices?

(not possible with fully analytical methods)

Goal:

Optimal kinetic energy extraction from wind turbines depending on **overall system dispatch**

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Approach we used

Data-driven methods allow to compute explicit control instructions

But, **how to choose the classifier?**

- We opt for an **Optimal Classification Tree** (OCT): **simple** structure and **tractable** for incorporating into optimization

Other options:

- Logistic regression and SVM: limited by hyperplane separation (although kernels could be used)
- Neural Networks: problems with tractability due to binary variables

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Adaptive Droop Gain (ADG)

$$\mathrm{ADG}(v_w, \boldsymbol{P_G}, L_D, pl,\ \Delta P_L, \omega_r) = \widetilde{K}_{\mathrm{sys}} \cdot \underbrace{(\omega_r{}^2 - \omega_{r,min}{}^2)}_{\text{deter over-deceleration}}$$

System operating condition

$$\widetilde{K}_{\mathrm{sys}} = f(v_w, \boldsymbol{P_G}, L_D, pl,\ \Delta P_L)$$

An **Optimal Classification Tree** (OCT) is used to encode frequency-stability conditions within a system-wide economic dispatch

- The **ADG** is **explicitly incorporated** into the OCT

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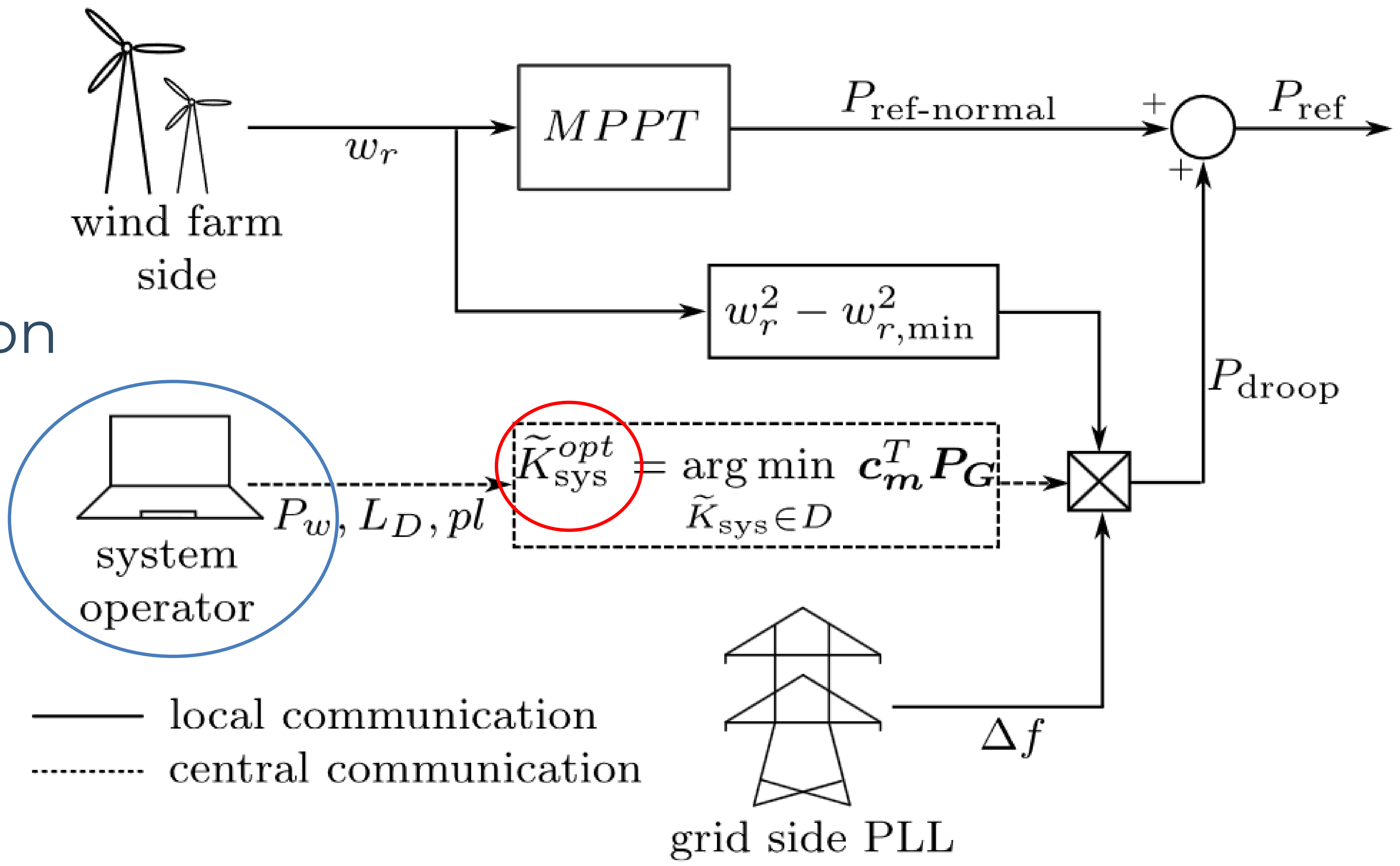
Communication requirements

Hourly communication with system operator (rest is local)



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Optimal Classification Tree

Offline training
(outside the Unit Commitment / OPF)

Minimize classification error

Penalize tree depth

$$\min \frac{1}{\hat{\mathcal{L}}} \sum_{t \in \Omega^{\mathcal{T}}} l_t + \alpha \sum_{m \in \Omega^{B}} d_m$$

$$\text{s.t. } l_t \geq \omega \cdot n_{0t} - \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \Omega^{\mathcal{T}}$$

$$l_t \leq \omega \cdot n_{0t} + \mathcal{M} \cdot c_t \quad \forall t \in \Omega^{\mathcal{T}}$$

$$l_t \geq n_{1t} - \mathcal{M} \cdot c_t \quad \forall t \in \Omega^{\mathcal{T}}$$

$$l_t \leq n_{1t} + \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \Omega^{\mathcal{T}}$$

$$n_{1t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} \cdot Y_i \quad \forall t \in \Omega^{\mathcal{T}}$$

$$n_{0t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} - n_{1t} \quad \forall t \in \Omega^{\mathcal{T}}$$

Classification boundaries (linearized via big-M)

Penalize 'false safe' predictions (adjustable parameter)

'Safe' classifications

'Unsafe' classifications

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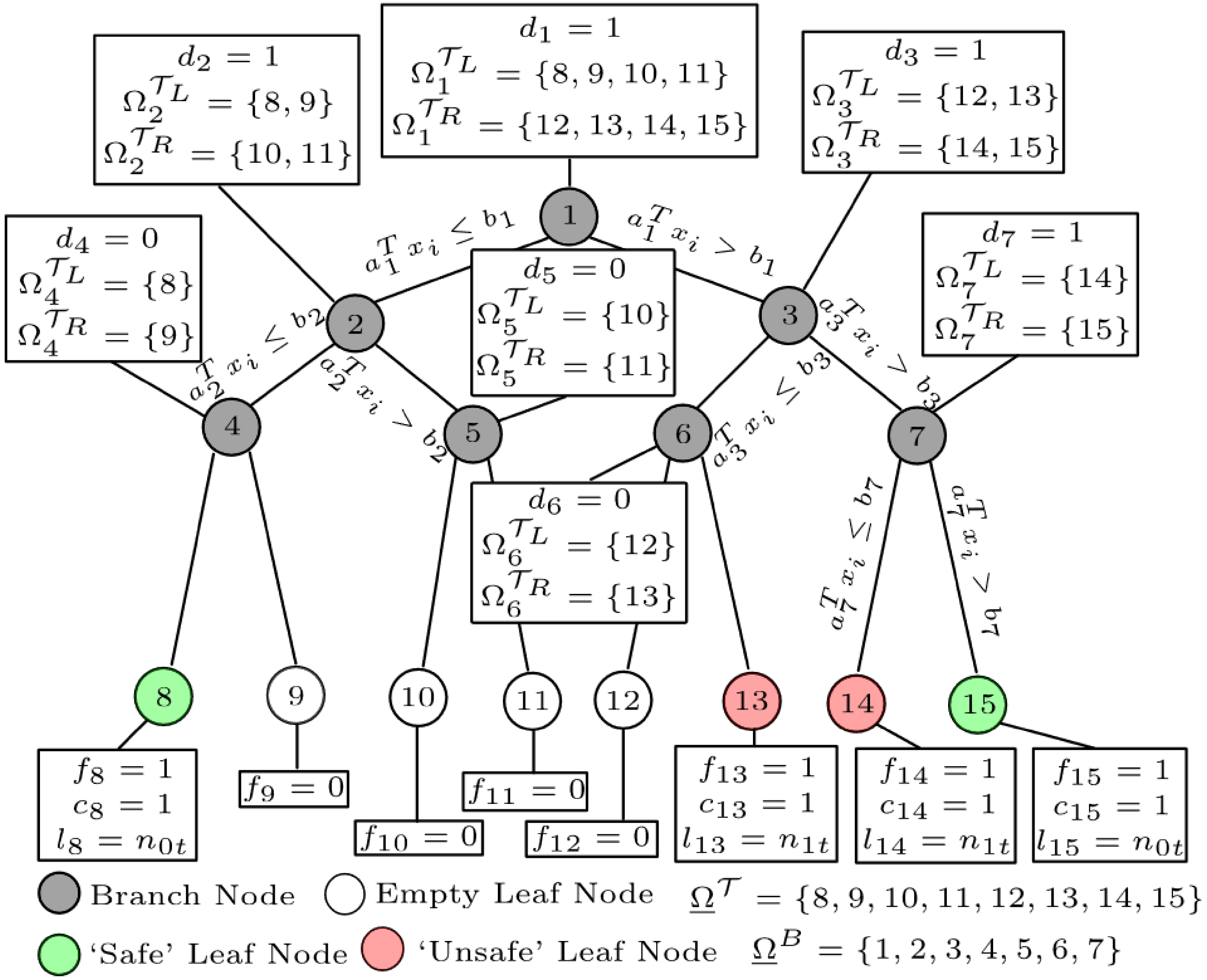
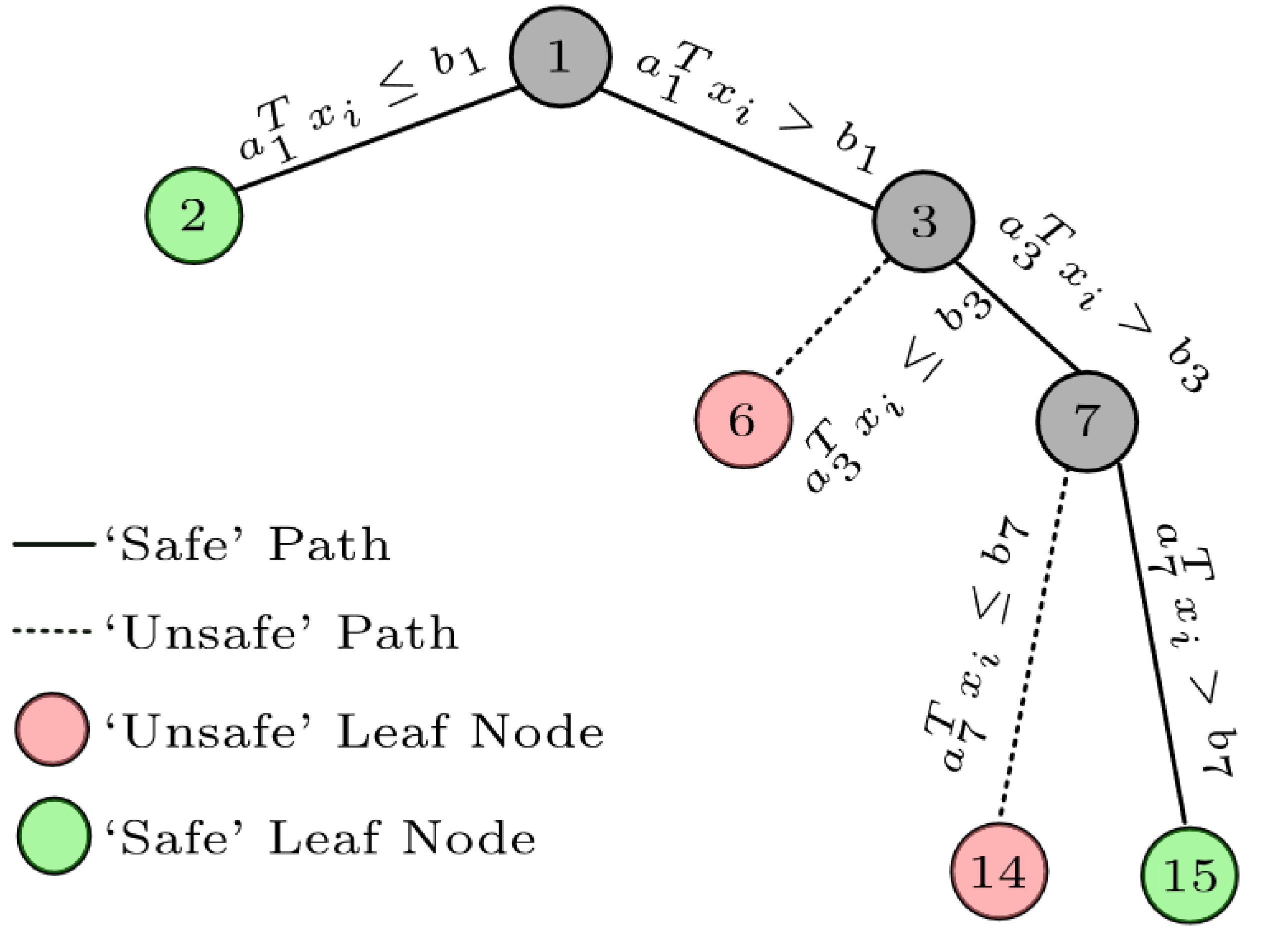
Optimal Classification Tree



Pruning redundancies



This OCT is **integrated into the OPF** as a set of constraints

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Case studies

- **Frequency-secured OPF** run for an IEEE 14-bus network

- 1,500 **labelled samples** from **dynamic simulations** in Simulink
  - ~2 days computing time (on standard laptop)
  - 70% for training, 20% for validation, 10% for testing

- **Training OCT** offline (solving MILP): ~30 min
  - Could be retrained, *e.g.*, daily, using new datasets with updated wind and load forecasts (reduces conservativeness)

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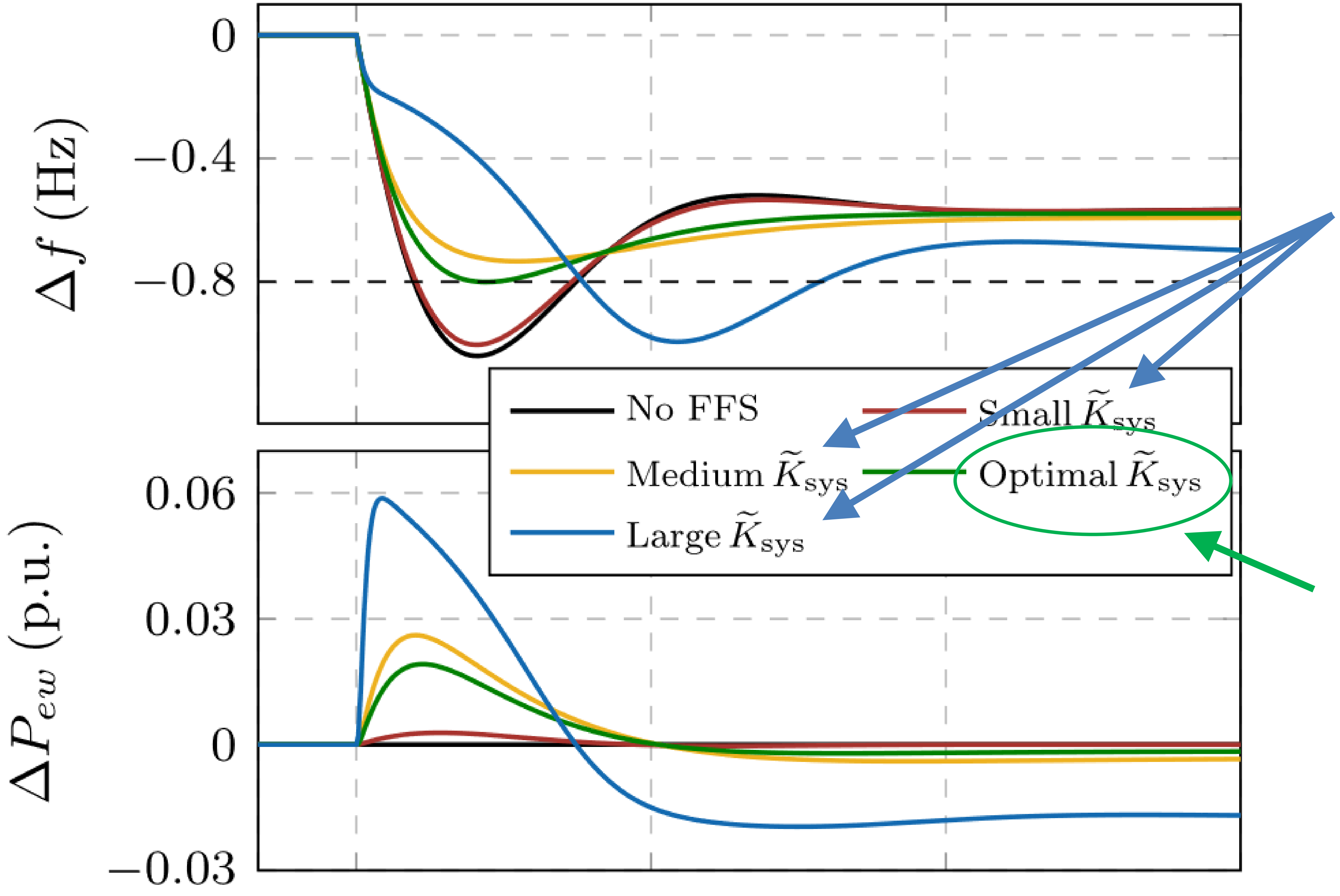
Results



Fixed *a priori*

Optimized for current **operating condition** via the classification tree

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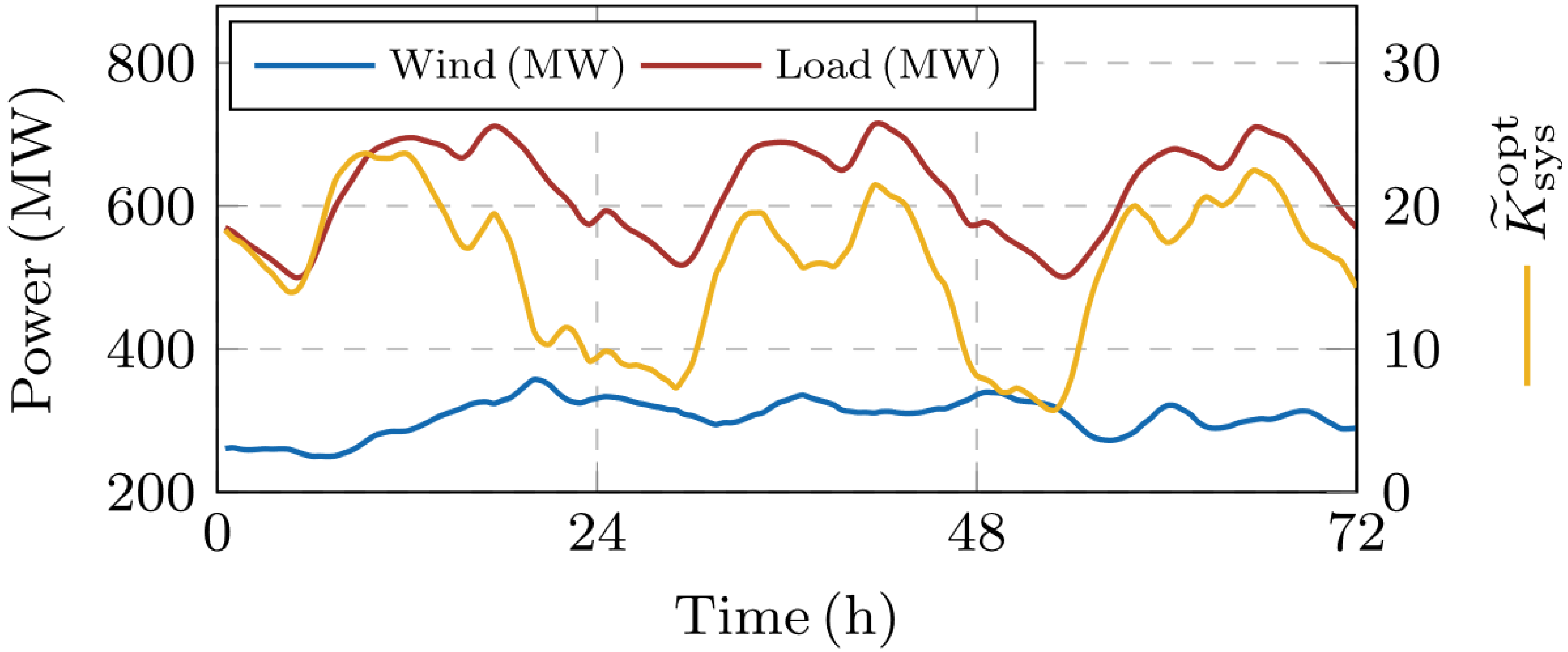
Dispatch solutions

The **optimal** droop gain $\boldsymbol{K_{sys}}$ **fluctuates** with the system dispatch: roughly inversely proportional to wind power



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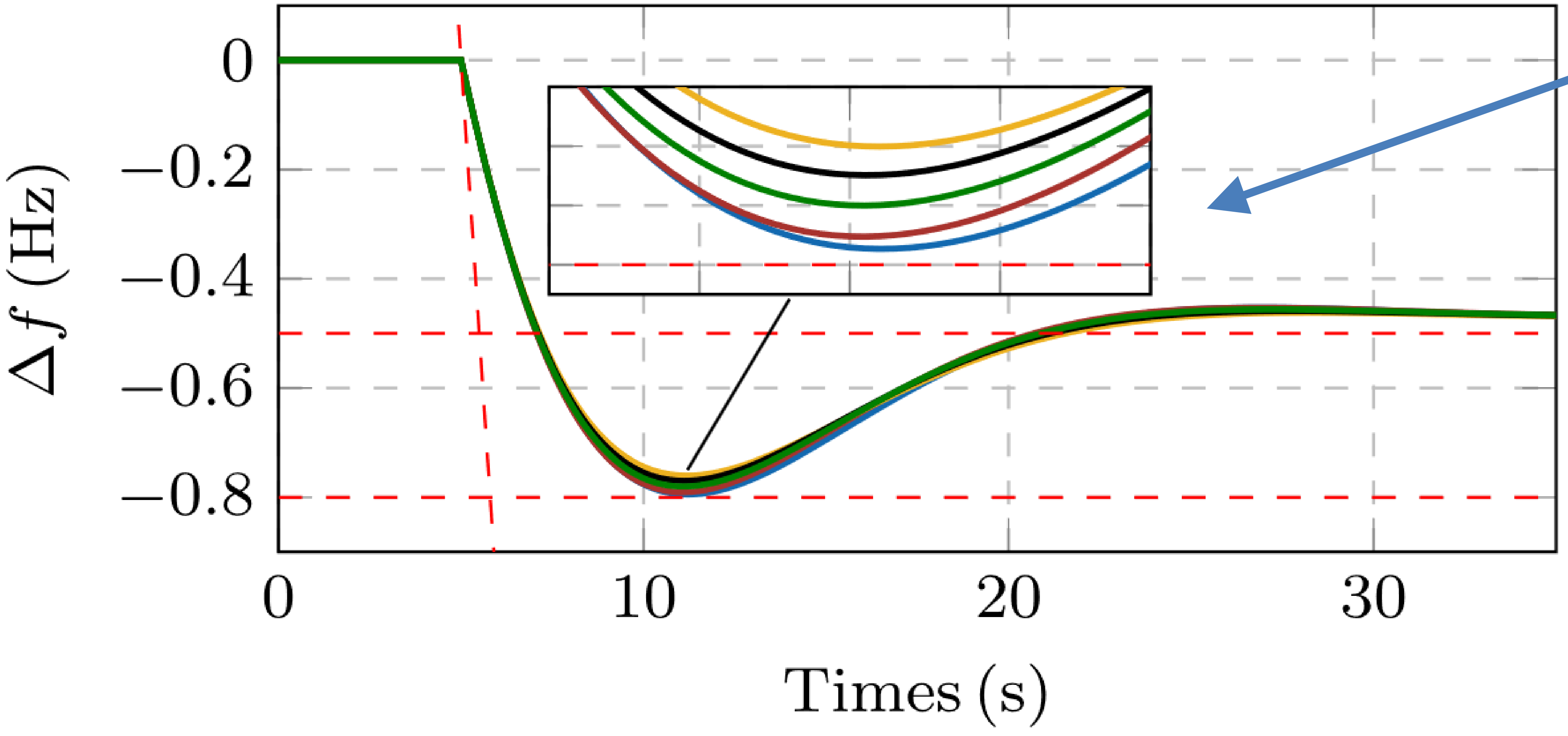
Security boundary

Slight underestimation of nadir due to **conservativeness** in **OCT**



5 different OPF solutions, arbitrarily chosen

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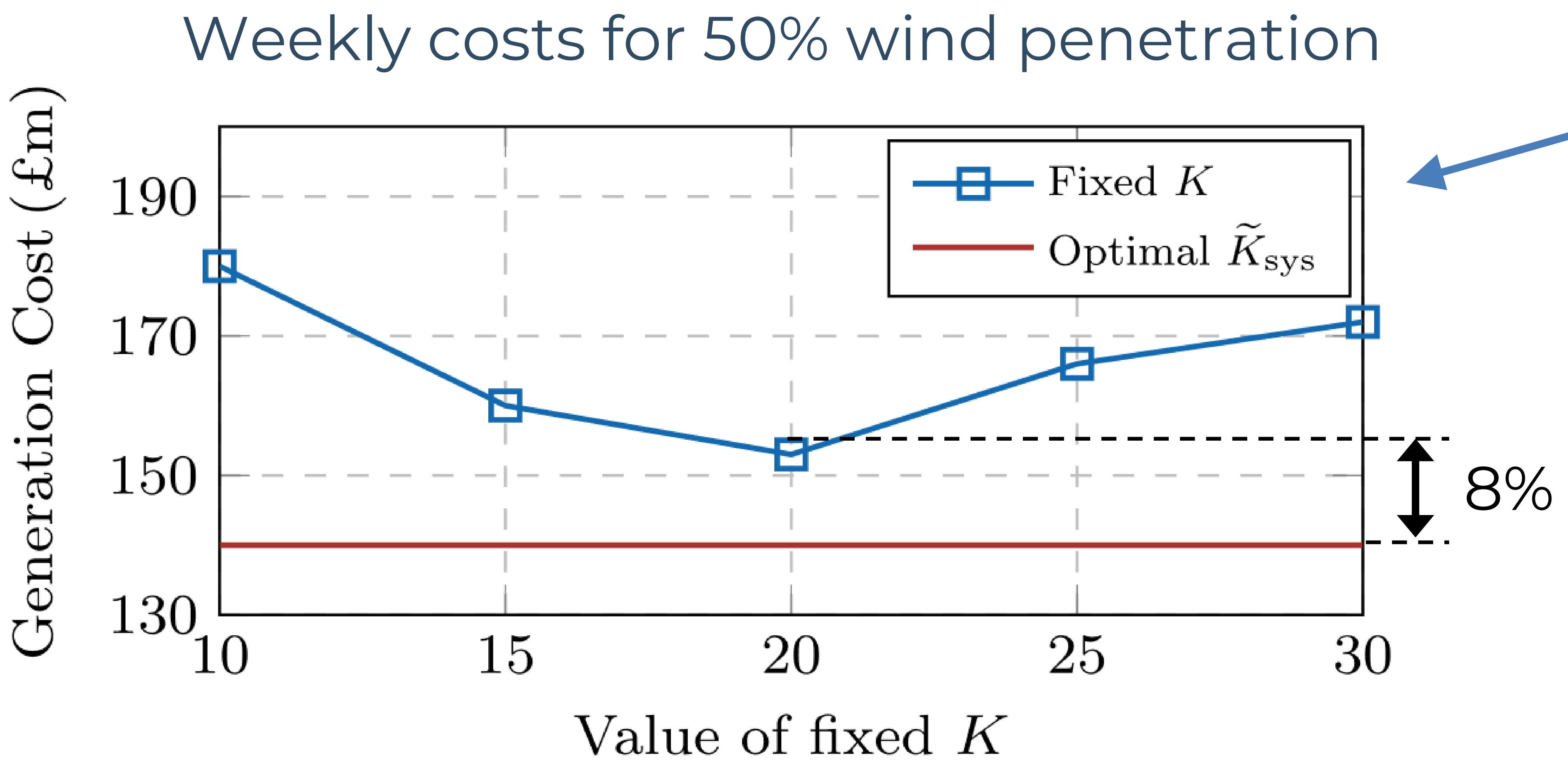
Cost savings

System **savings of** at least **8%** compared to system-unaware controller



Note that the optimal value of fixed gain (K = 20) can only be computed by system optimization (through the OCT)

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Thank you for your attention!

All papers and some related code on my website:

https://badber.github.io/

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