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

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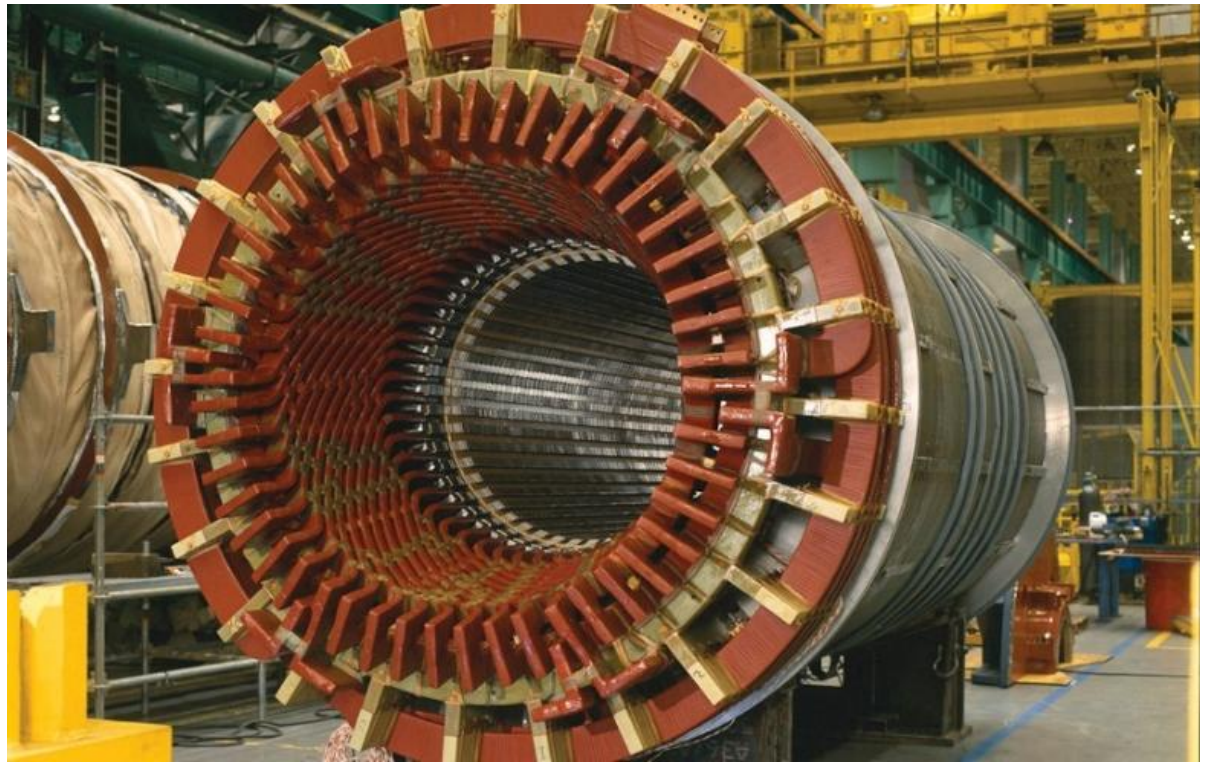
Paper:

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

Paper available here

Lower inertia on the road to **lower emissions**

Thermal generators
(nuclear, gas, coal...)



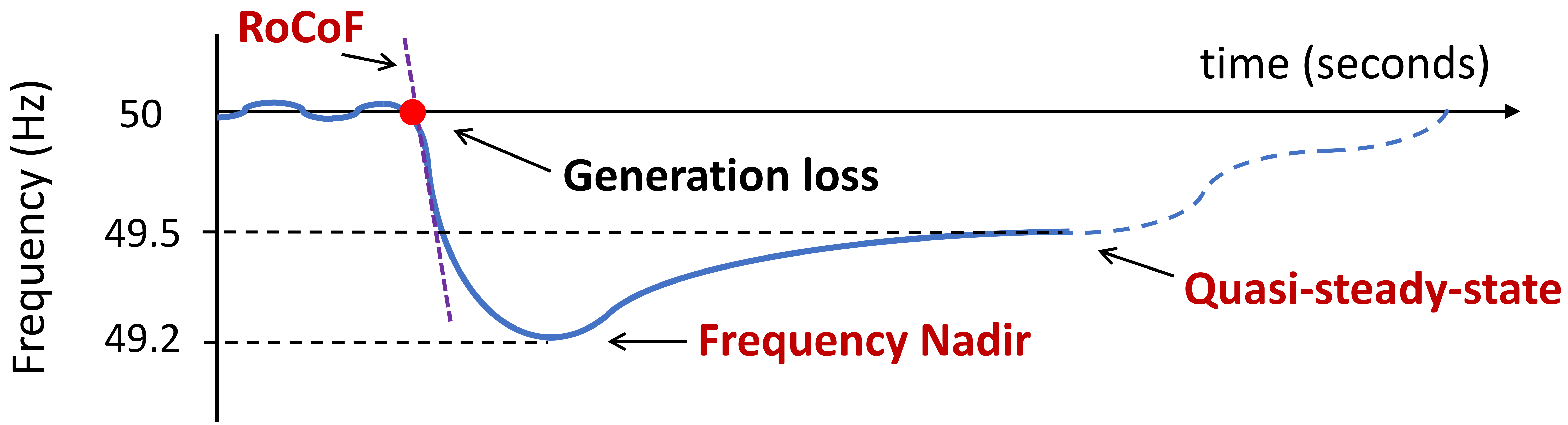
Decarbonization

Most **renewables**:
no inertia

The **risk of instability has increased!**

Inertia stores kinetic energy:
this energy gave us time to contain a sudden generation-demand imbalance

Frequency stability



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

Research question

How to **translate** the **system** optimal **dispatch**

into **specific control gains** for devices?

(not possible with fully analytical methods as the one shown earlier)

Goal:

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

Approach we used

$\boxed{\textbf{Data-driven methods}}$ 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

Adaptive Droop Gain (ADG)

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

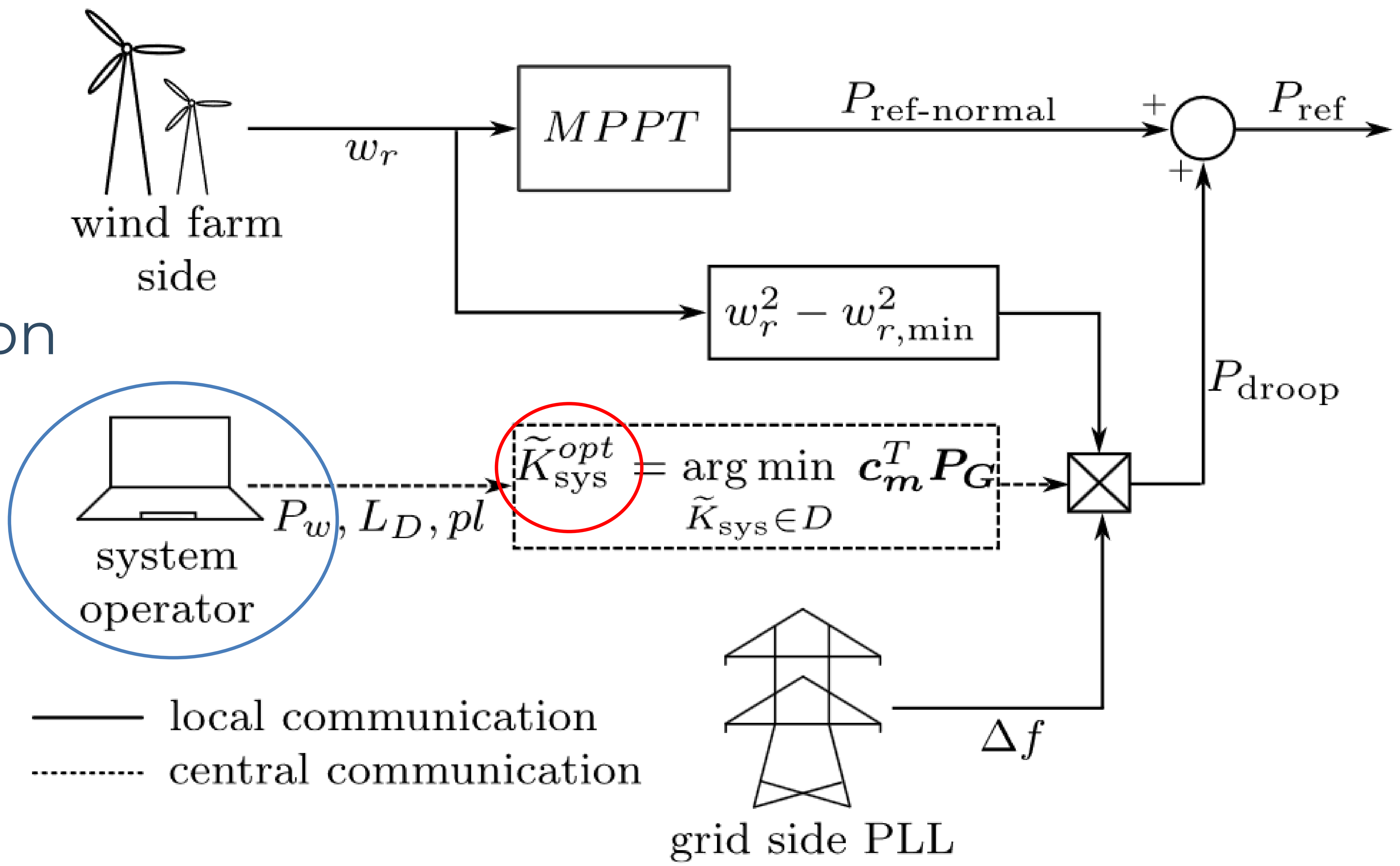
$$\widetilde{K}_{\mathrm{sys}} = f(v_w, \boldsymbol{P_G}, L_D, pl, \Delta P_L)$$

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

Communication requirements

Hourly communication with system operator (rest is local)



Optimal Classification Tree

Offline training

(outside the Unit Commitment / OPF)

Minimize classification error

Penalize tree depth

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

$$\begin{aligned}
\text{s.t. } l_t &\geq \omega \cdot n_{0t} - \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
l_t &\leq \omega \cdot n_{0t} + \mathcal{M} \cdot c_t \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
l_t &\geq n_{1t} - \mathcal{M} \cdot c_t \quad \forall t \in \underline{\Omega}^{\mathcal{T}} \\
l_t &\leq n_{1t} + \mathcal{M} \cdot (1 - c_t) \quad \forall t \in \underline{\Omega}^{\mathcal{T}}
\end{aligned}$$

Classification boundaries (linearized via big-M)

Penalize ‘false safe’ predictions (adjustable parameter)

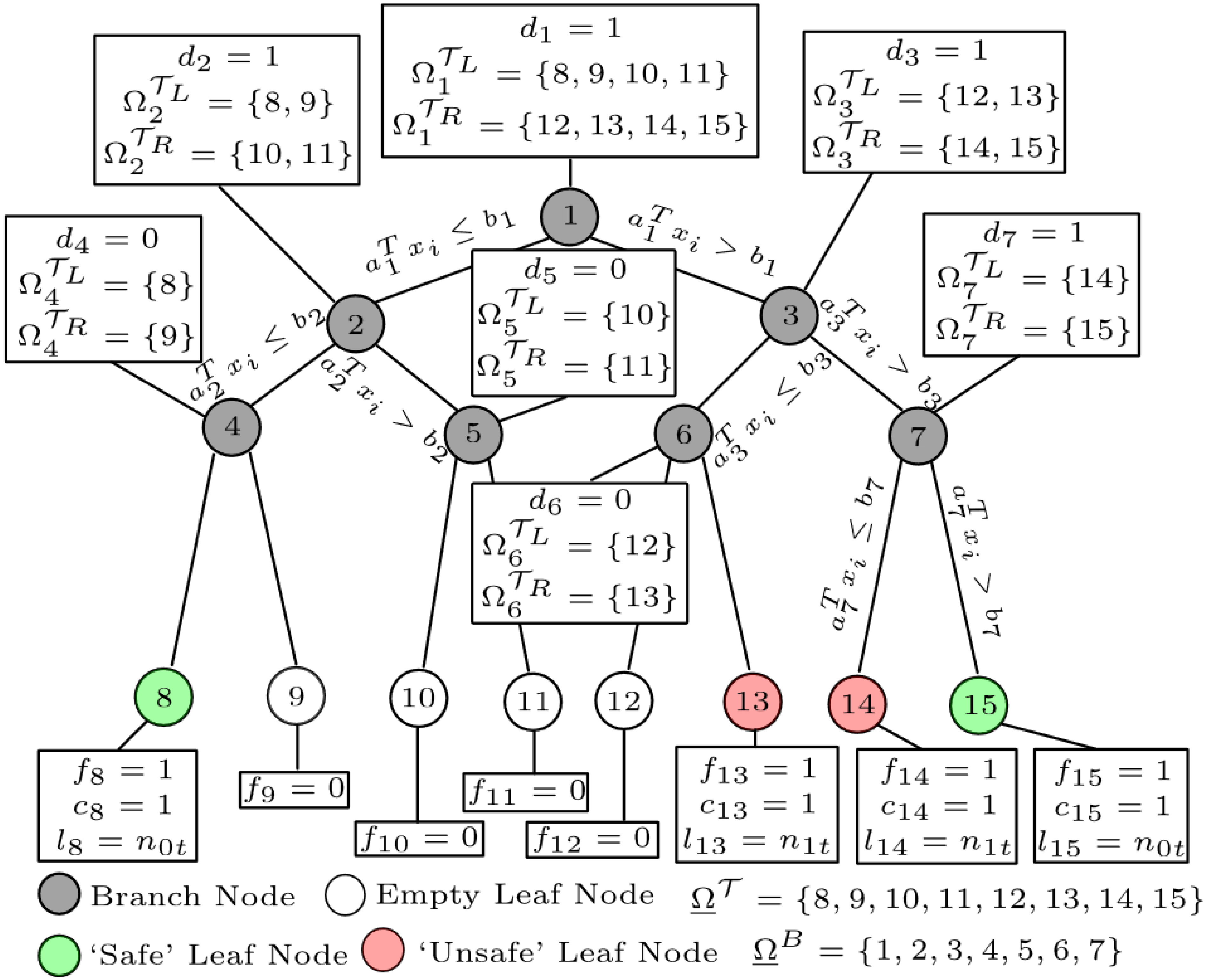
$$n_{1t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} \cdot Y_i \quad \forall t \in \underline{\Omega}^{\mathcal{T}}$$

‘Safe’ classifications

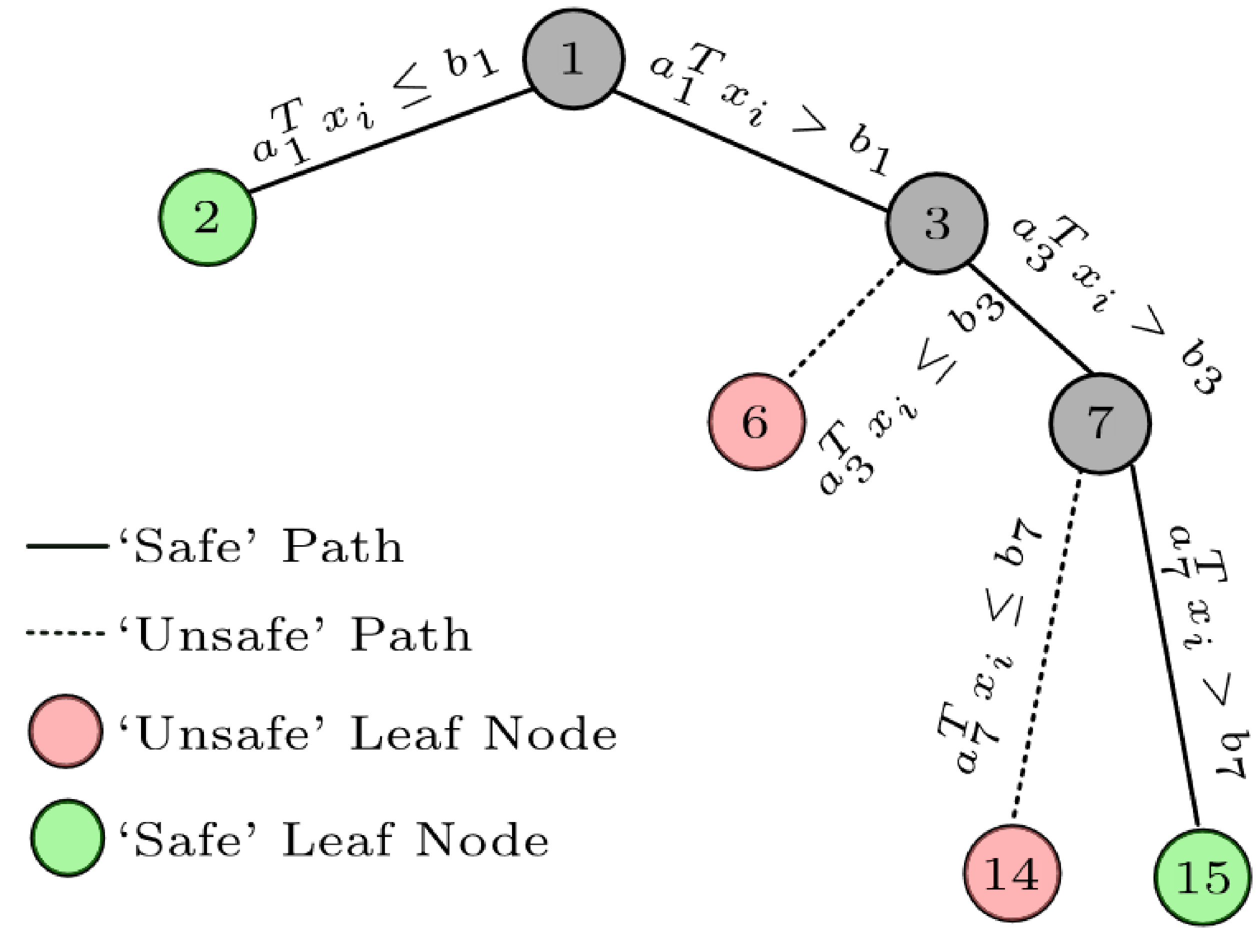
$$n_{0t} = \sum_{i \in \Omega^{\mathcal{N}}} z_{it} - n_{1t} \quad \forall t \in \underline{\Omega}^{\mathcal{T}}$$

‘Unsafe’ classifications

Optimal Classification Tree



Pruning redundancies

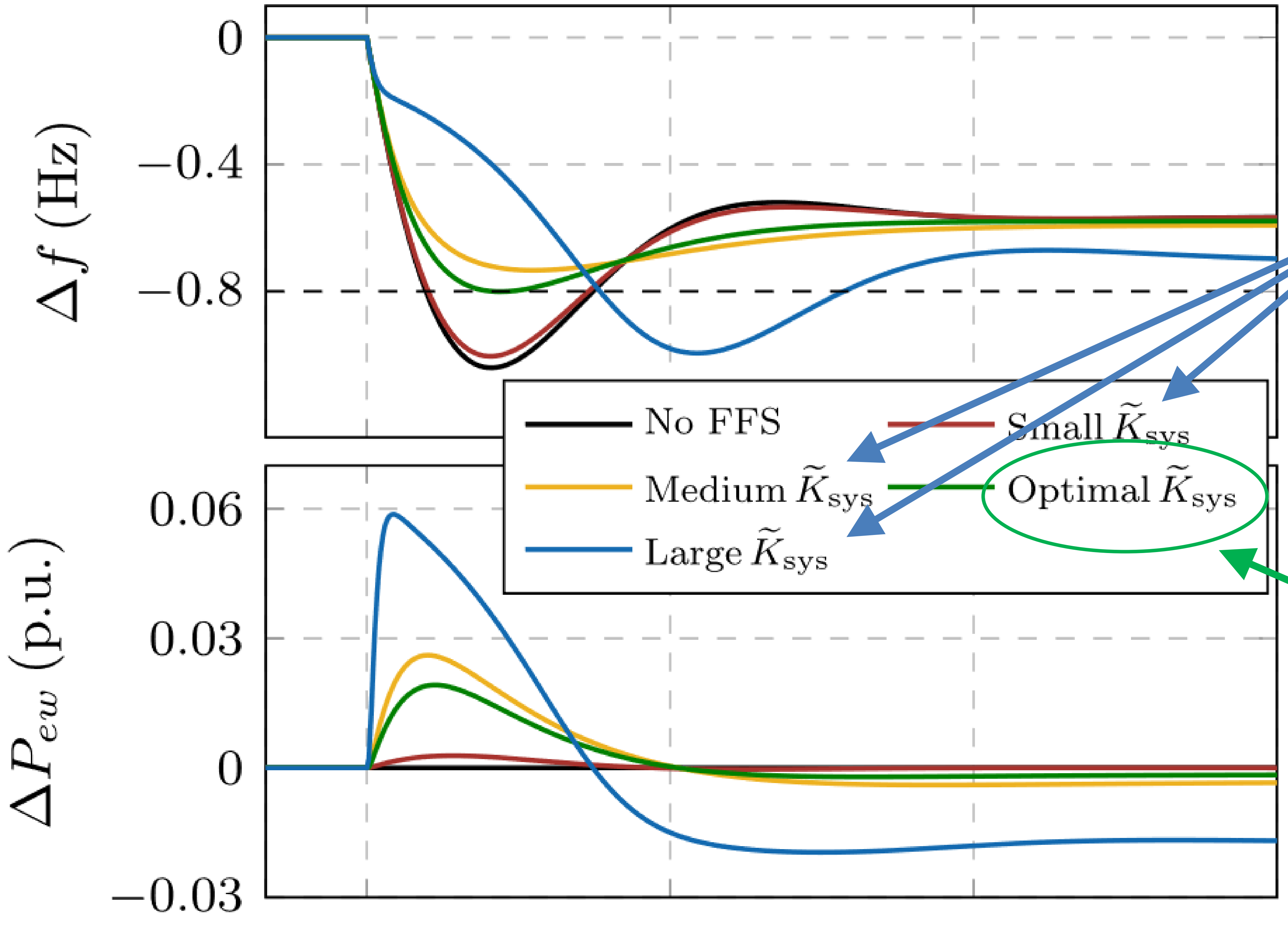


This OCT is **integrated into the OPF** as a set of constraints

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)

Results



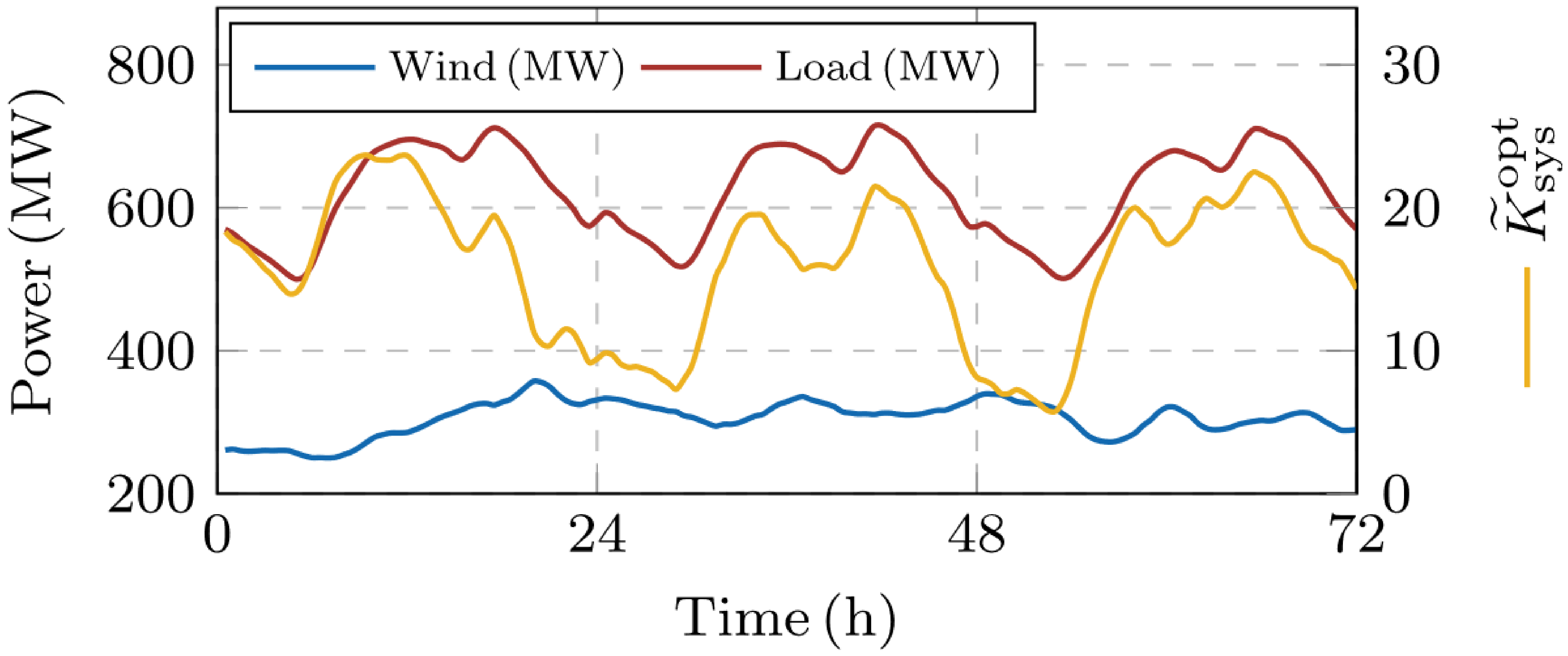
Fixed *a priori*

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

Dispatch solutions

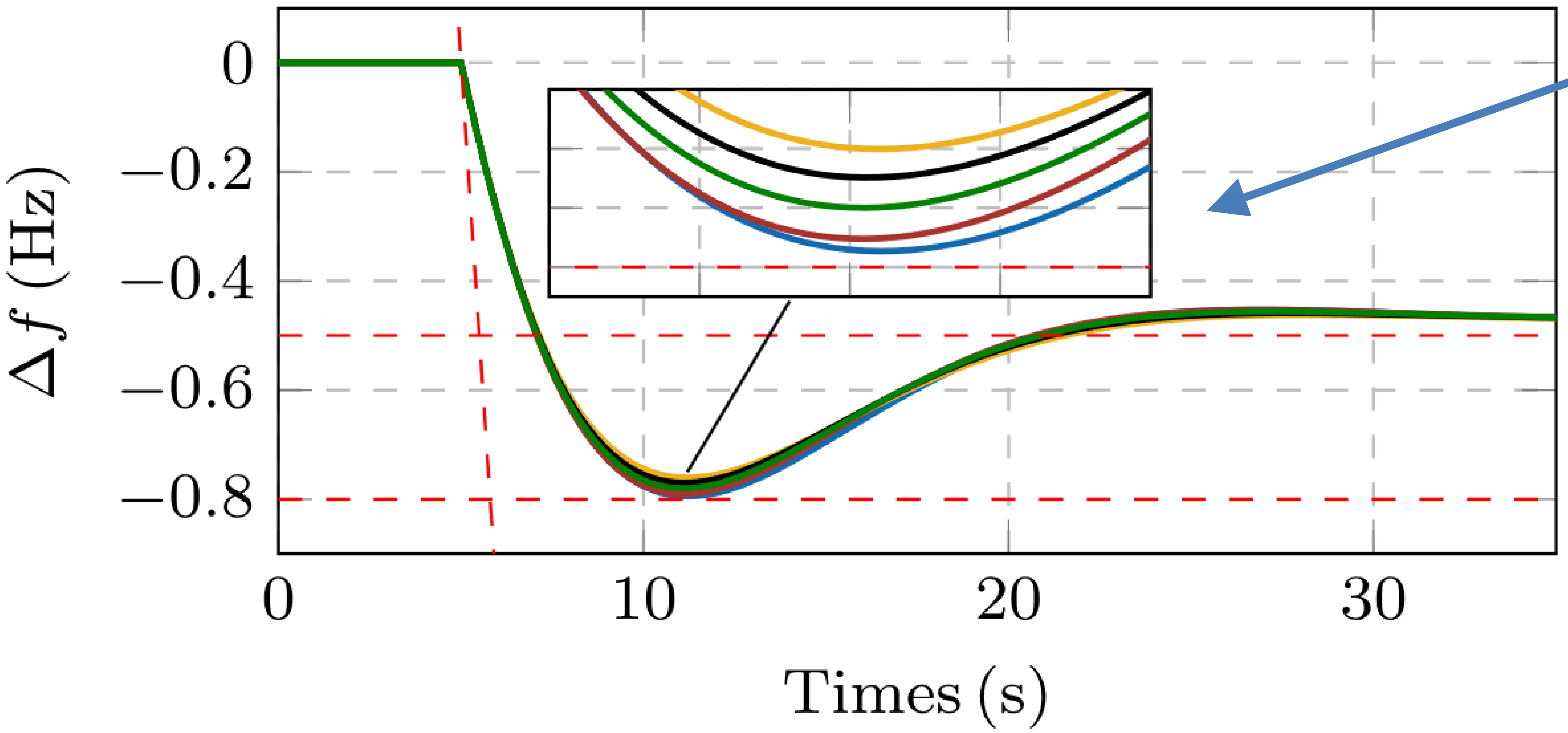
The **optimal** droop gain $\boldsymbol{K_{sys}}$ **fluctuates** with the system dispatch:

roughly inversely proportional to wind power



Security boundary

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

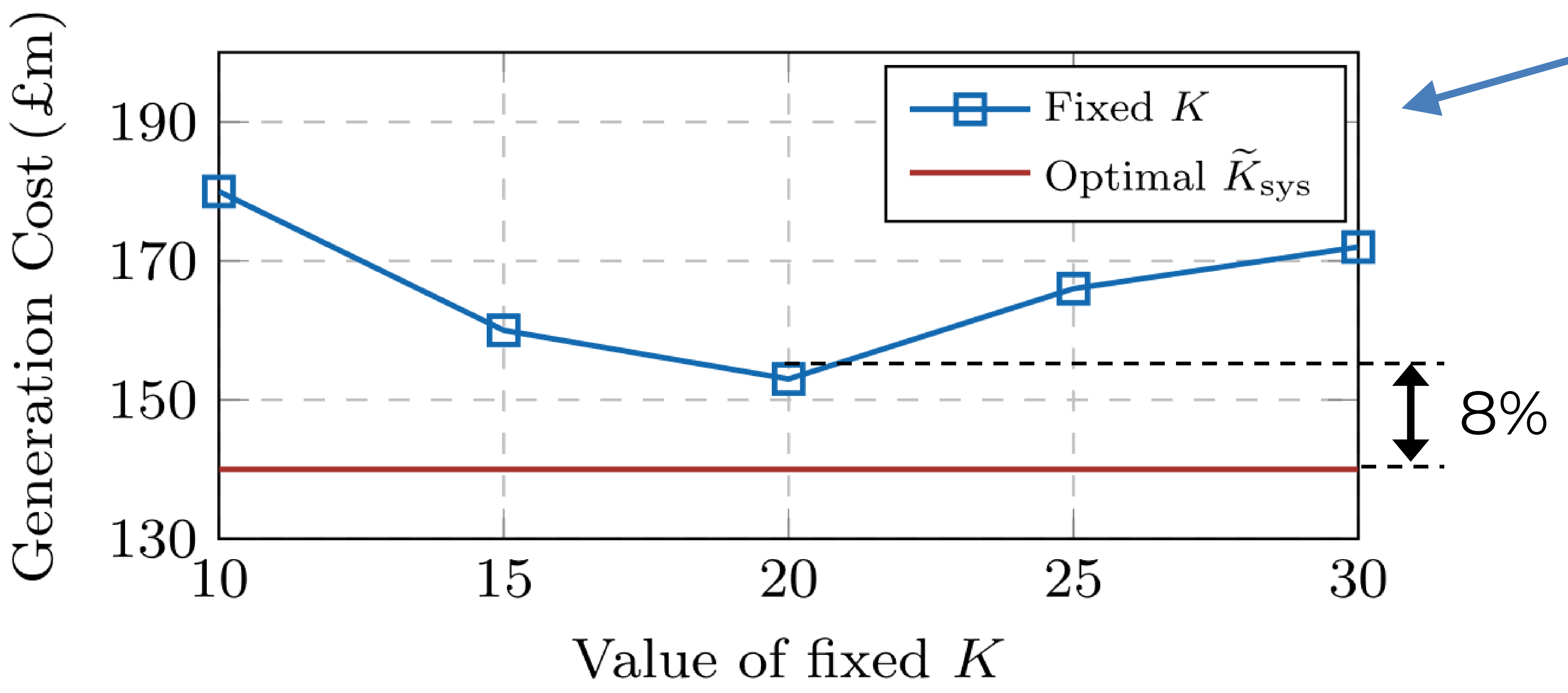


5 different
OPF solutions,
arbitrarily chosen

Cost savings

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

Weekly costs for 50% wind penetration



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

Thank you for your attention!

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