

# A hierarchical supervisory wind power plant controller

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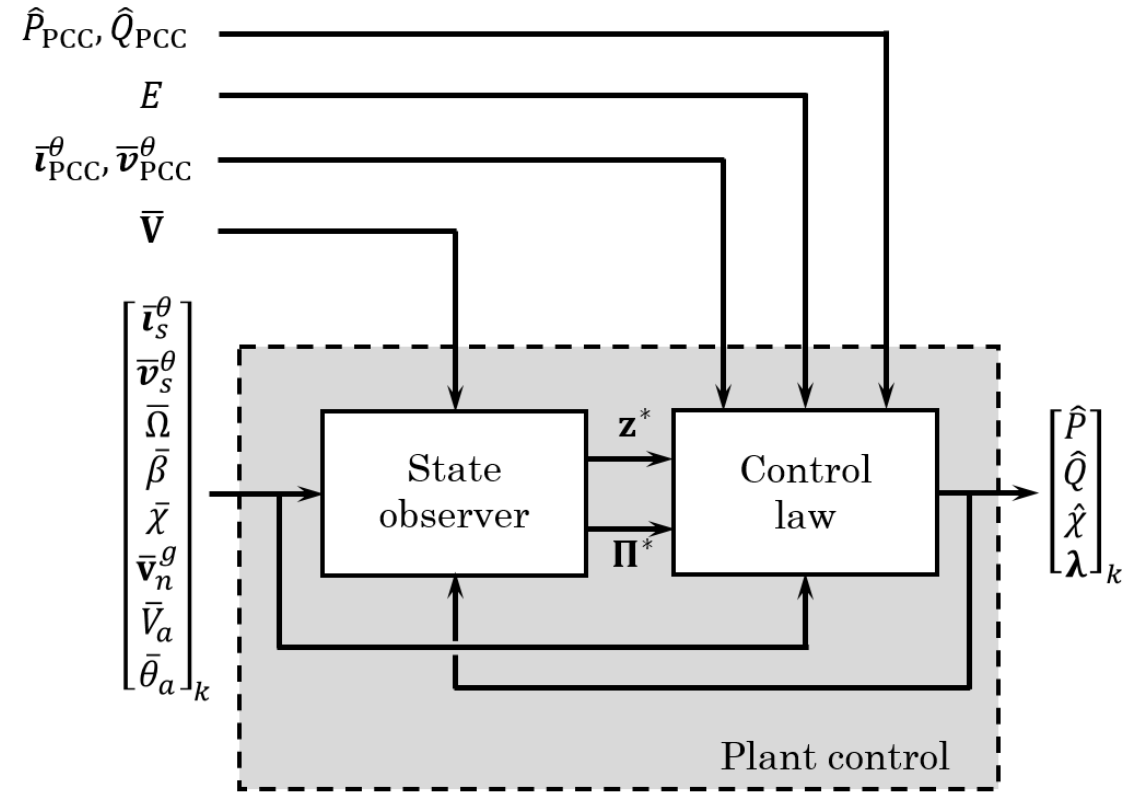
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## Background

When a wind power plant is operating with a reserve, whether curtailed or overplanted, there is a margin of flexibility in the operation of each wind turbine. This flexibility can be used beneficially, for instance to reject fluctuating loads.

The objective is to develop a plant control algorithm that

- is straightforward to understand and implement, using only basic sensor measurements;
- respects the hierarchy in which the turbine-level controller takes precedence, interacting only via power set-point commands to each turbine;
- tracks an operator power command at the plant level; and,
- rejects low-frequency loading due to turbulent winds.



$\hat{P}_{PCC}, \hat{Q}_{PCC}$  Power commands       $\bar{v}_a, \bar{\theta}_a$  Anemometer sp. and dir.

$\bar{i}_{PCC}^\theta, \bar{v}_{PCC}^\theta$  Meas. d-q current, voltage at PCC       $\mathbf{z}^*$  Observed outputs

$\bar{i}_s^\theta, \bar{v}_s^\theta$  Meas. d-q current, voltage at turbines       $\mathbf{\Pi}^*$  Observed spectral outputs

$\bar{\Omega}$  Meas. rotor speed       $\hat{P}, \hat{Q}$  Turbine power commands

$\bar{\beta}$  Meas. blade pitch      (Not used by the present algorithm):

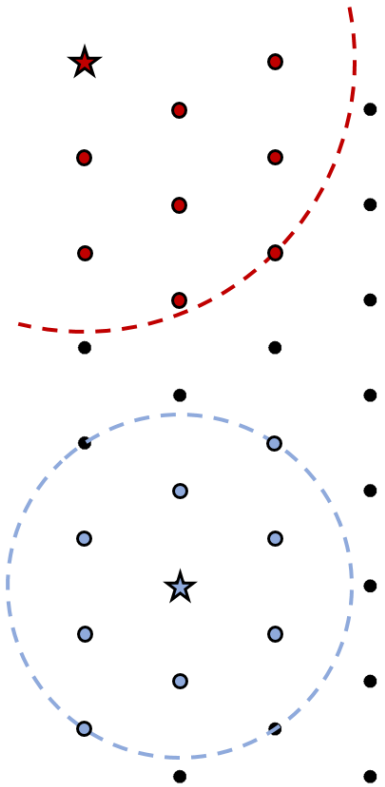
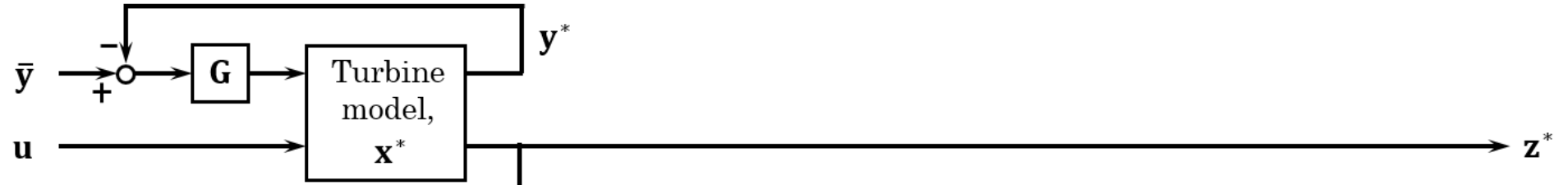
$\bar{\chi}$  Meas. nacelle yaw       $E$  Energy price metric

$\bar{v}_n^g$  Meas. nacelle velocity       $\bar{\mathbf{V}}$  Meas. wind field (lidar)

$\hat{\chi}$  Nacelle yaw command

## Observer architecture

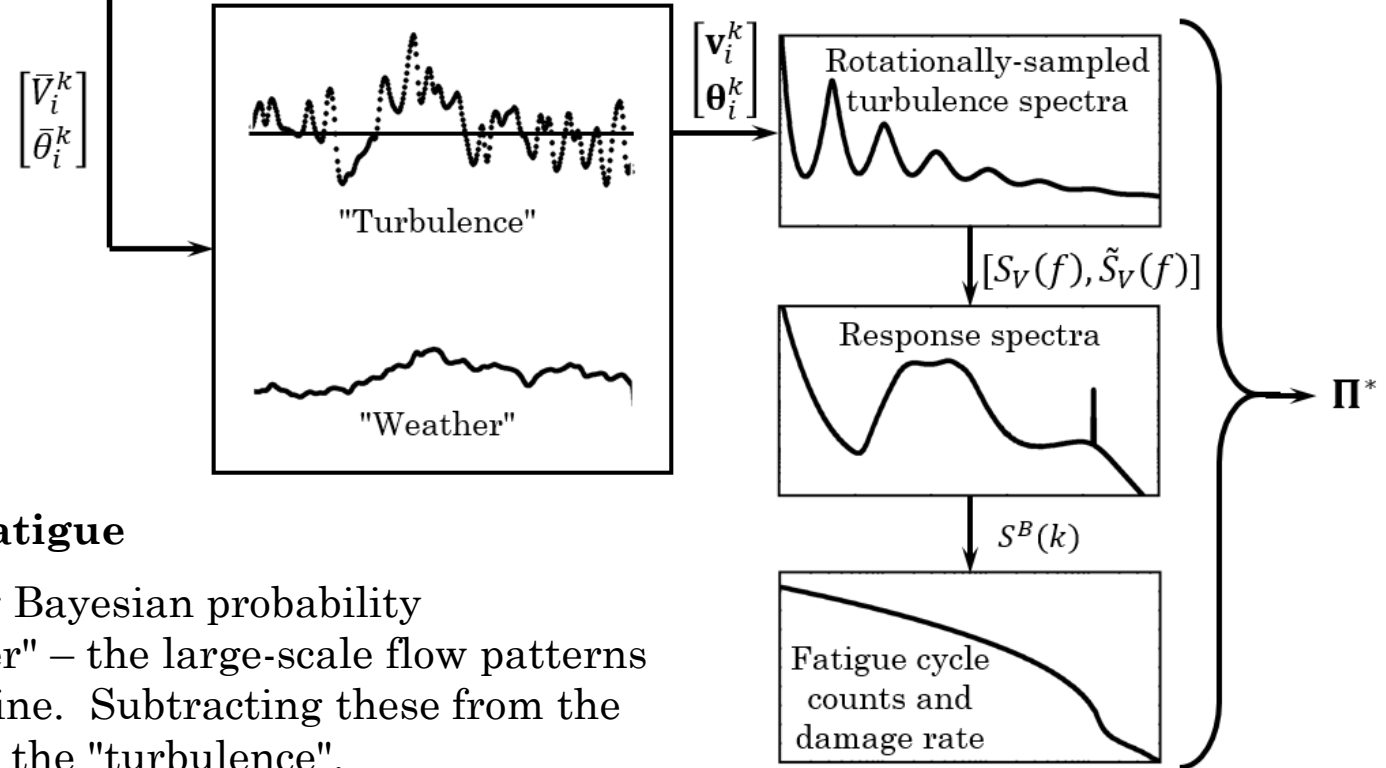
The observer is constructed around a state-space model of the wind turbine. It outputs quantities of interest  $\mathbf{z}^*$ , among which are the observed wind speed and direction. These are fed to a registry containing the last several minutes of timesteps.

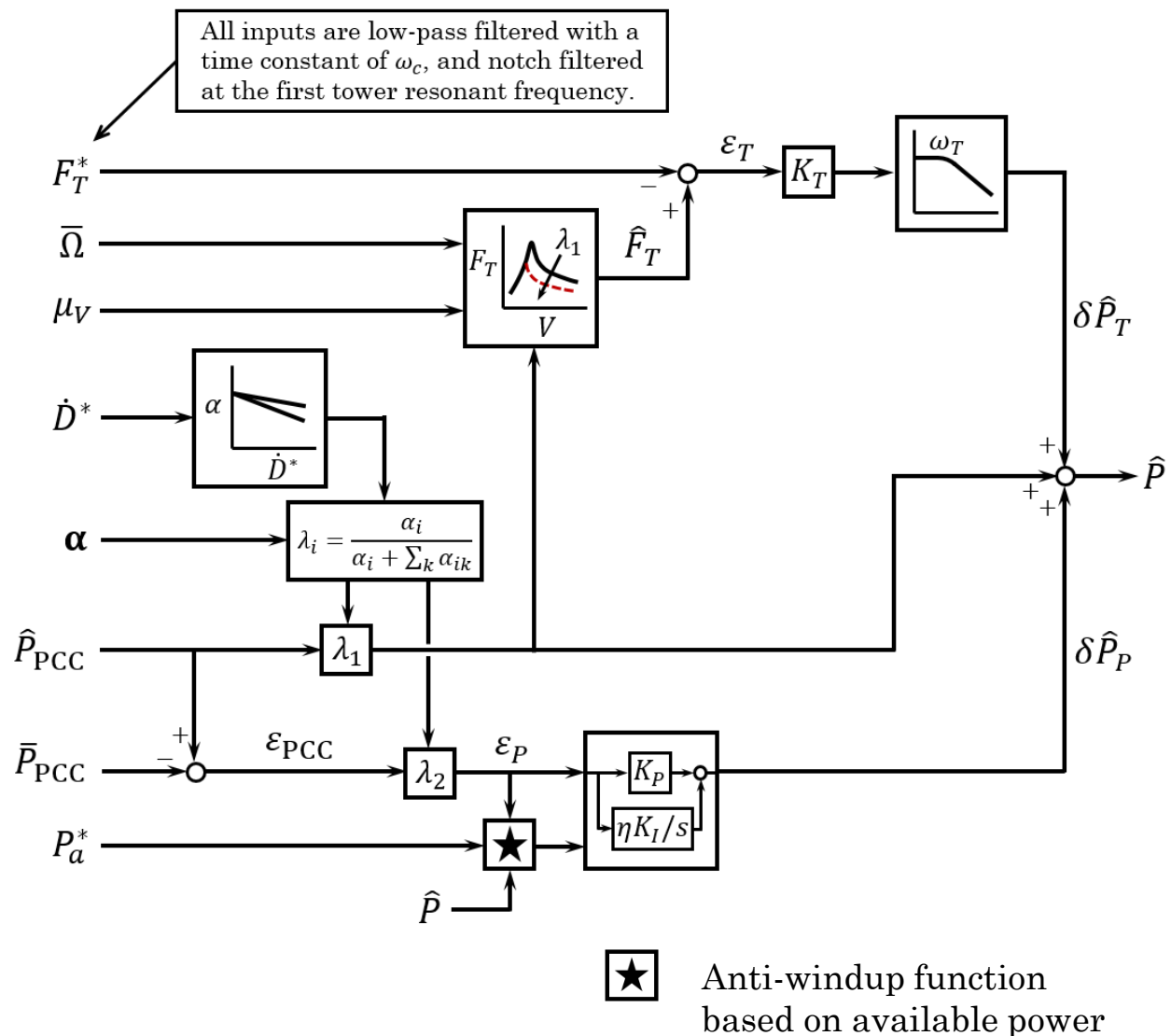


## Clustering and spectral fatigue

A clustering algorithm using Bayesian probability establishes the local "weather" – the large-scale flow patterns – in the vicinity of each turbine. Subtracting these from the locally observed values gives the "turbulence".

The cluster-average wind speed is used to set the target thrust, such that the controller rejects the turbulent fluctuations. The time series of turbulence is used together with an analytical method to estimate the loads on the rotating blades and the fatigue rates of turbine components.



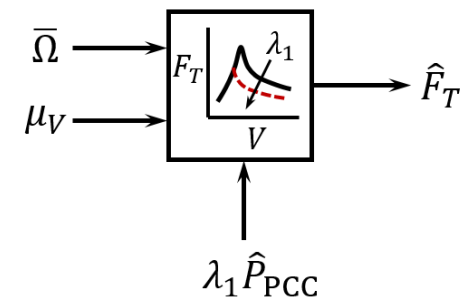


### Control architecture

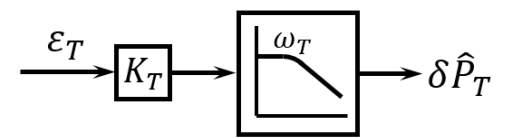
The thrust-hold and power-tracking branches may "duel", but the integral action of the power tracking will always win. Higher-damage-rate turbines are responsible for less power tracking, allowing for more effective thrust-hold.

### Target thrust

$\mu_V$  Cluster wind speed (weather)  
 $\lambda_1 \hat{P}_{PCC}$  Turbine's share of the total WPP power

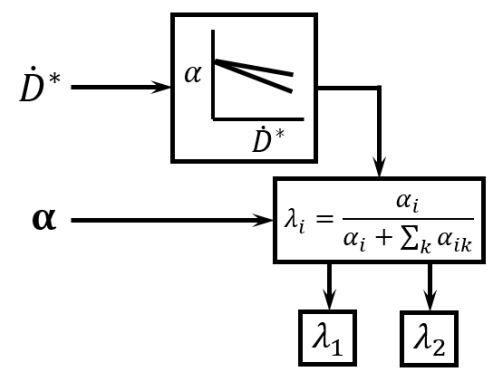


### High-gain LP filter

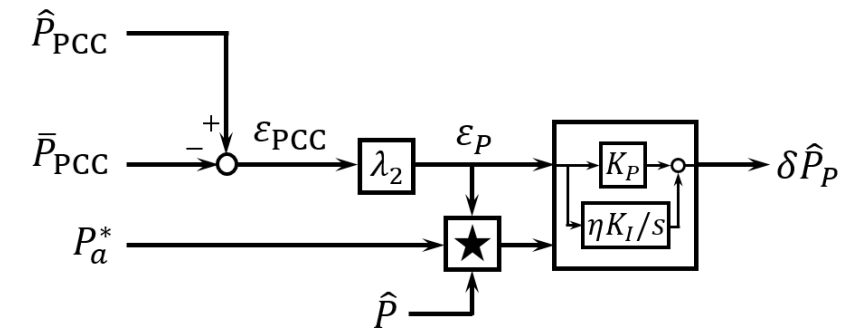


### Gain scheduling

$\alpha$  Penalty functions based on fatigue damage rate  $\dot{D}^*$   
 $\alpha$  Values from all other turbines



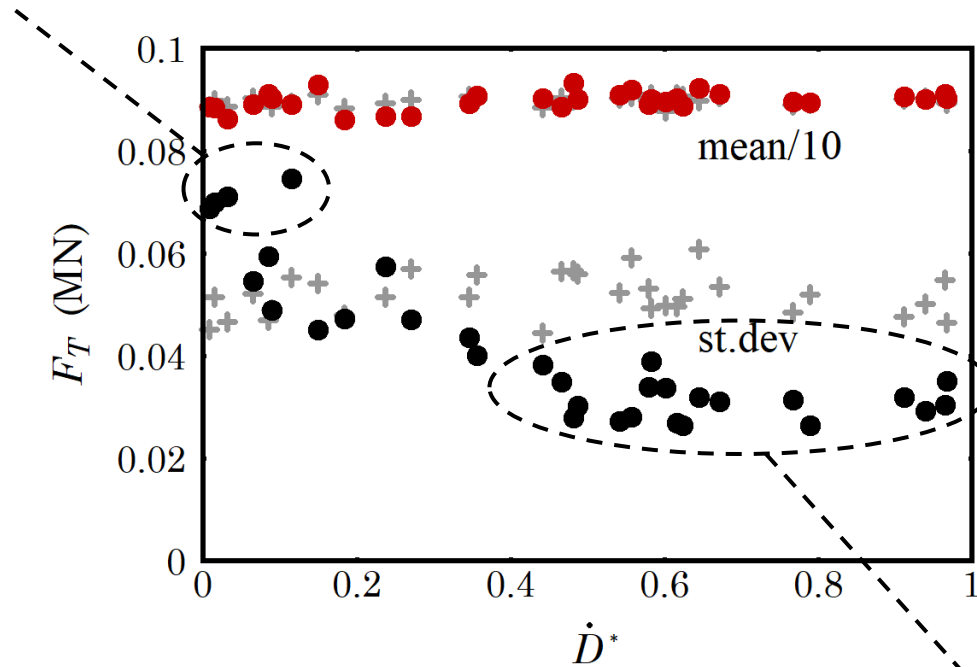
### PI for power command tracking



## Case study and performance

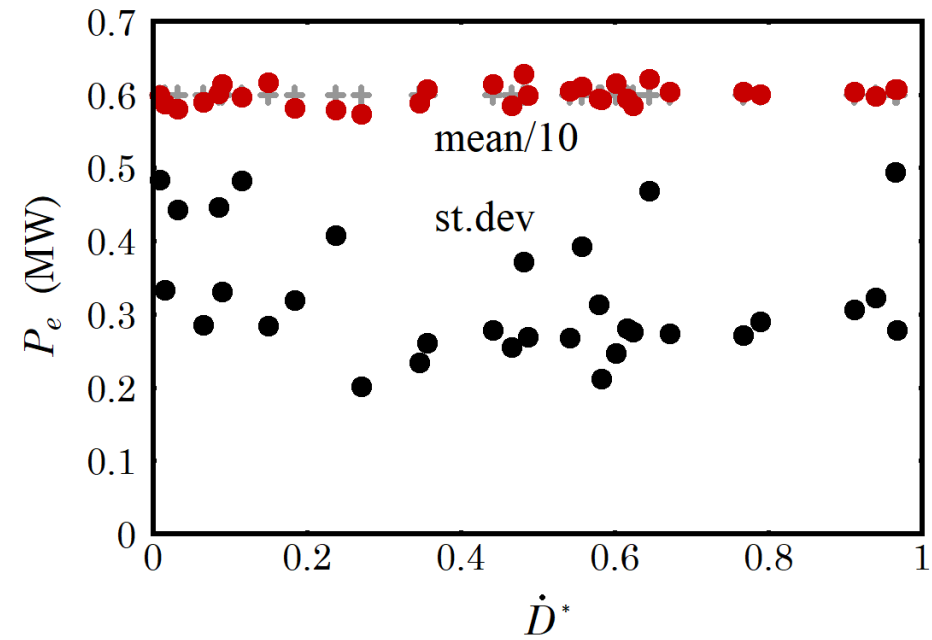
The control algorithm was tested and tuned in a simplified turbulent flow field, representative of normal operation. The TotalControl Reference Wind Power Plant (32 turbines) under 20% curtailment was used as a case.

These turbines, experiencing low levels of turbulent loading, are taking additional responsibility for power tracking



Note that the standard deviation of thrust is limited to the low-frequency component, and, as seen in the plot, it does not directly correspond to the component damage metric.

The results demonstrate that there is a synergy effect in coordinating the operation of the turbines.



These turbines, experiencing high levels of turbulent loading, are rejecting part of the low-frequency thrust fluctuations

## Outlook

Tuning of the observer was performed using linear theory. It remains to schedule the pointwise linear models to obtain a full nonlinear controller. There are two candidate approaches:

1. Linear parameter varying systems using either a global model reduction technique (one reduced basis across all models) or a multiple-model interpolation (fuzzy set) approach.
2. Nonlinear system identification / surrogate modelling using machine-learning techniques.

The methods will be compared for performance, robustness, and ease-of-use.

The "synergy effect" needs to be demonstrated in dynamic LES/CFD simulations that properly account for the atmospheric flow through a large wind power plant.

A full report and references to the wider literature can be found in Merz KO *et al.* (2020). *Hierarchical Wind Power Plant Supervisory Controller*. Deliverable D4-2, TotalControl. Available for download at <https://www.totalcontrolproject.eu/dissemination-activities/public-deliverables>