Nutzung der Rotationsenergie von Windenergieanlagen zur Reduktion von Kurzzeit-Leistungsfluktuationen erneuerbarer Energien

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Content

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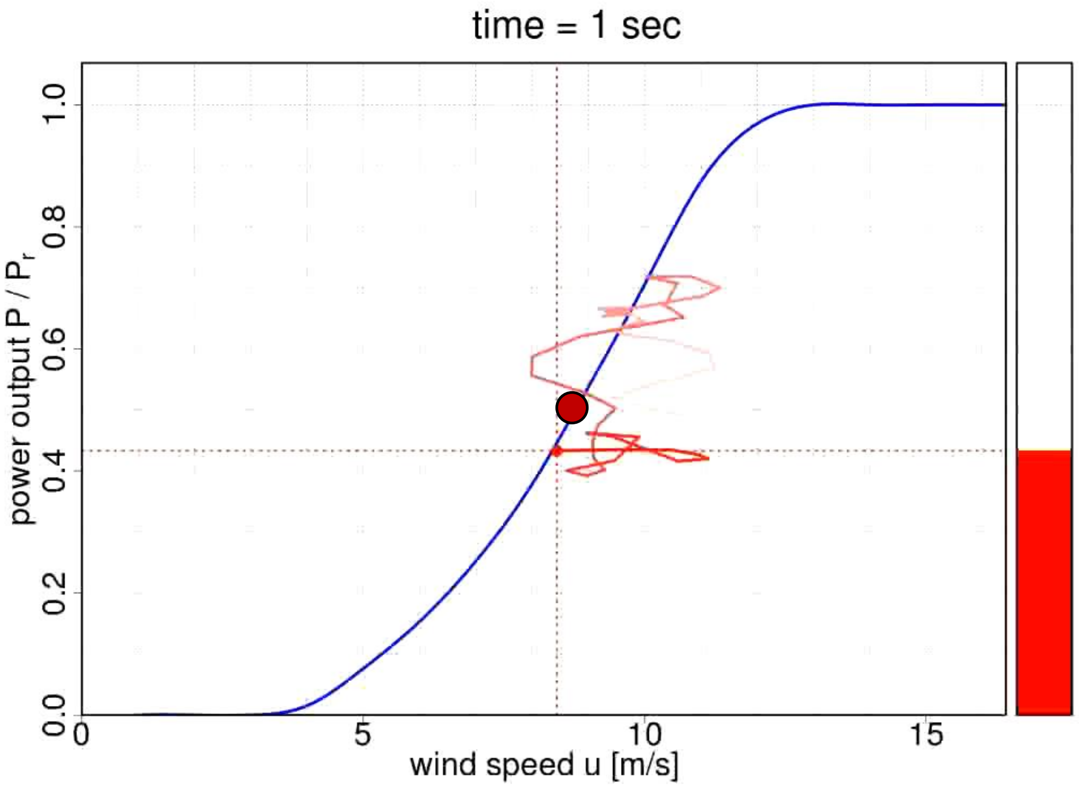
Motivation

Challenge of an increasing share of renewables in the power grid:

Electric power from renewables has intermittent, super-Gaussian fluctuations



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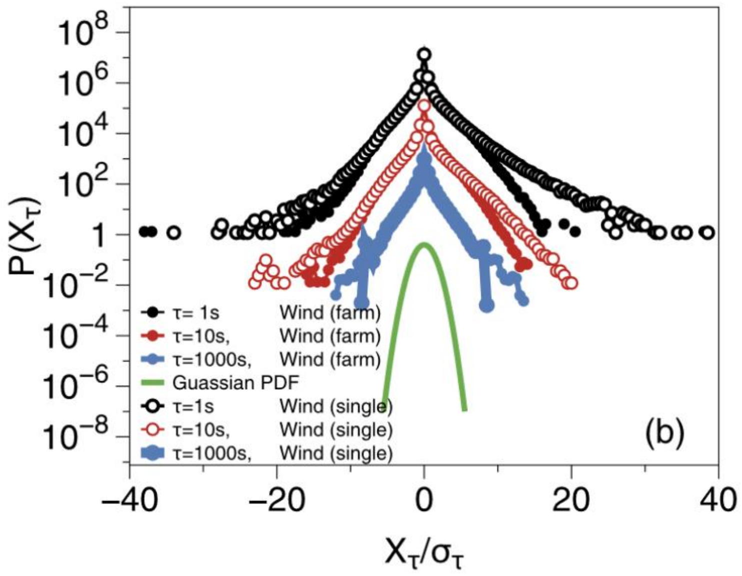
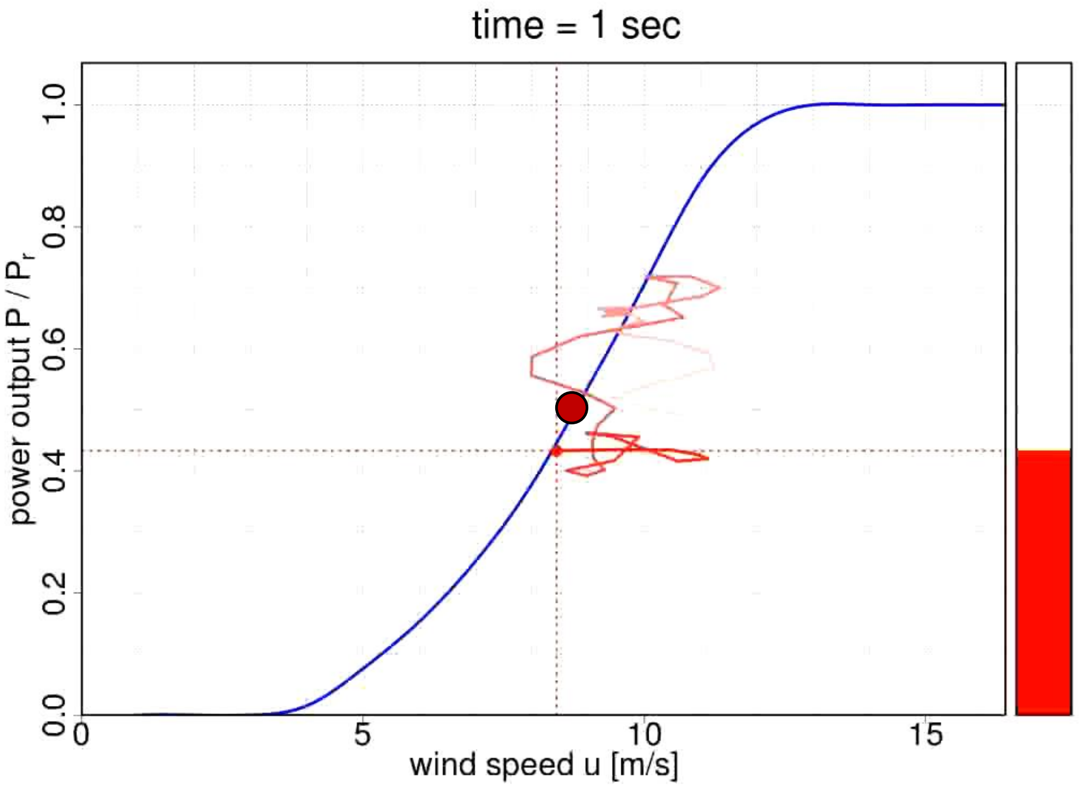


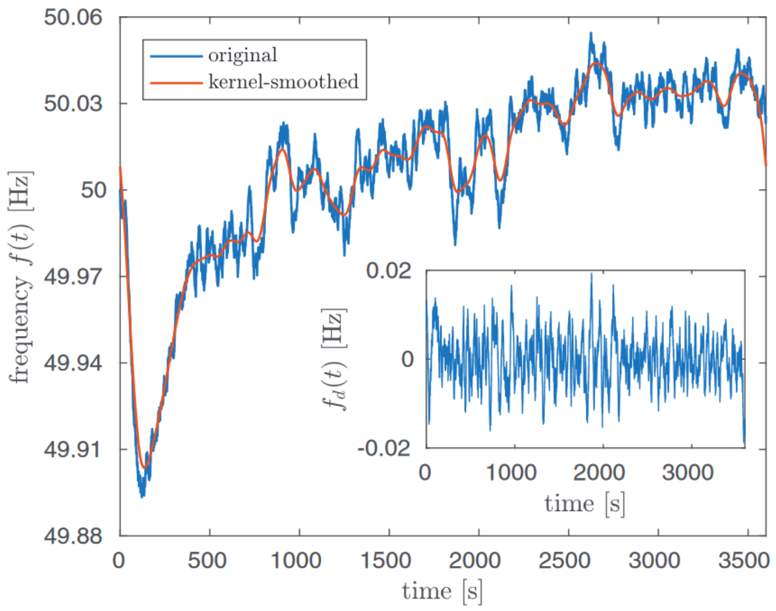
Anvari, *New J. Phys.*, 2016

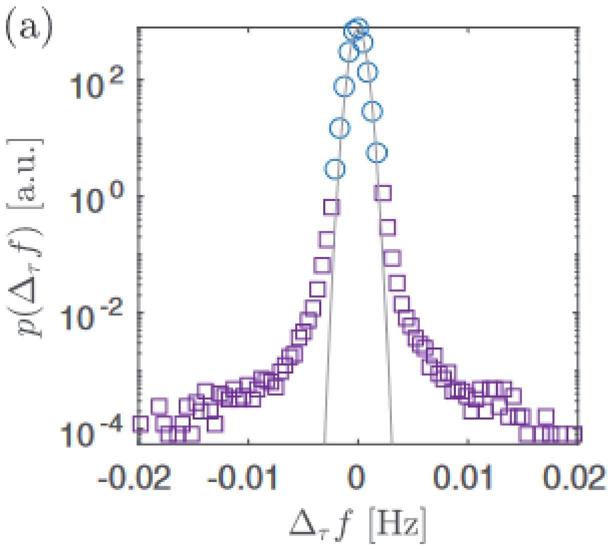


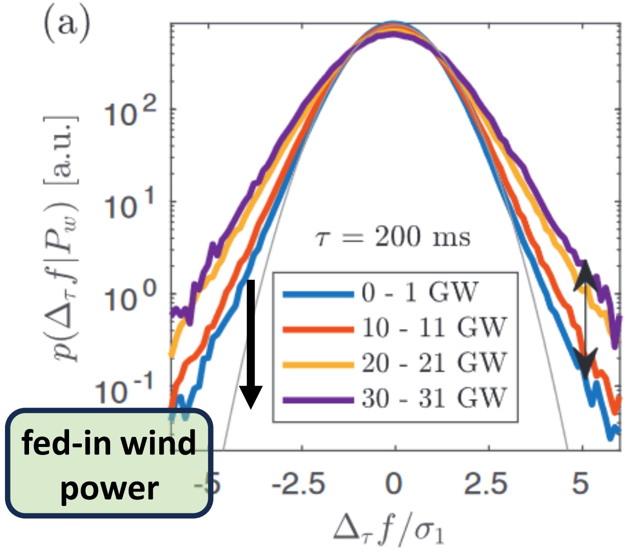
Motivation

In <u>grid frequency</u> measurements:

Also intermittency observed







Haehne, *EPL.*, 2018

Motivation

Intermittency exists on all scales and does not average out

➢ traditionally: no problem due to enough rotating masses

In a future with more renewable production, we need flexible battery storage:

- electric batteries

- rotating masses of wind turbines

  ➢ rotational energy can be accessed using control of wind turbines

Stromnetz

Abgeschaltetes Atomkraftwerk stabilisiert jetzt Stromnetz

29.02.2012 · Redakteur: Stéphane Itasse ·

Der Übertragungsnetzbetreiber Amprion und RWE Power haben vereinbart, den Generator von Block A im nicht-nuklearen Teil des abgeschalteten Atomkraftwerks Biblis für die Netzdienstleistung „Phaseschieberbetrieb“ umzurüsten. Damit wollen die Unternehmen zur Stabilisierung des Stromnetzes im Süden Deutschlands beitragen, wie Amprion mitteilt.

https://www.maschinenmarkt.vogel.de/abgeschaltetes-atomkraftwerk-stabilisiert-jetzt-stromnetz-a-355143/, accessed on 14 October 2024

Content

1. Motivation

    - Intermittency exists on all scales and is relevant for power grid

2. Power Conversion of Wind Turbines

3. Stochastic Langevin Model

4. Accessing Rotational Energy in Langevin Model

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    - Intermittency exists on all scales and is relevant for power grid
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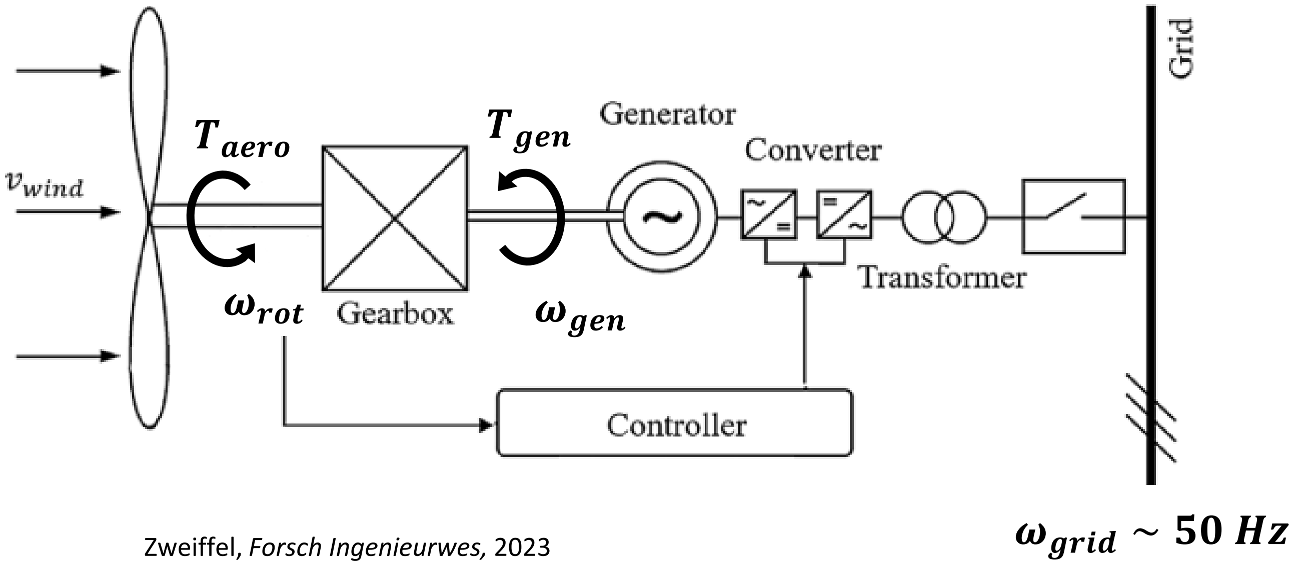
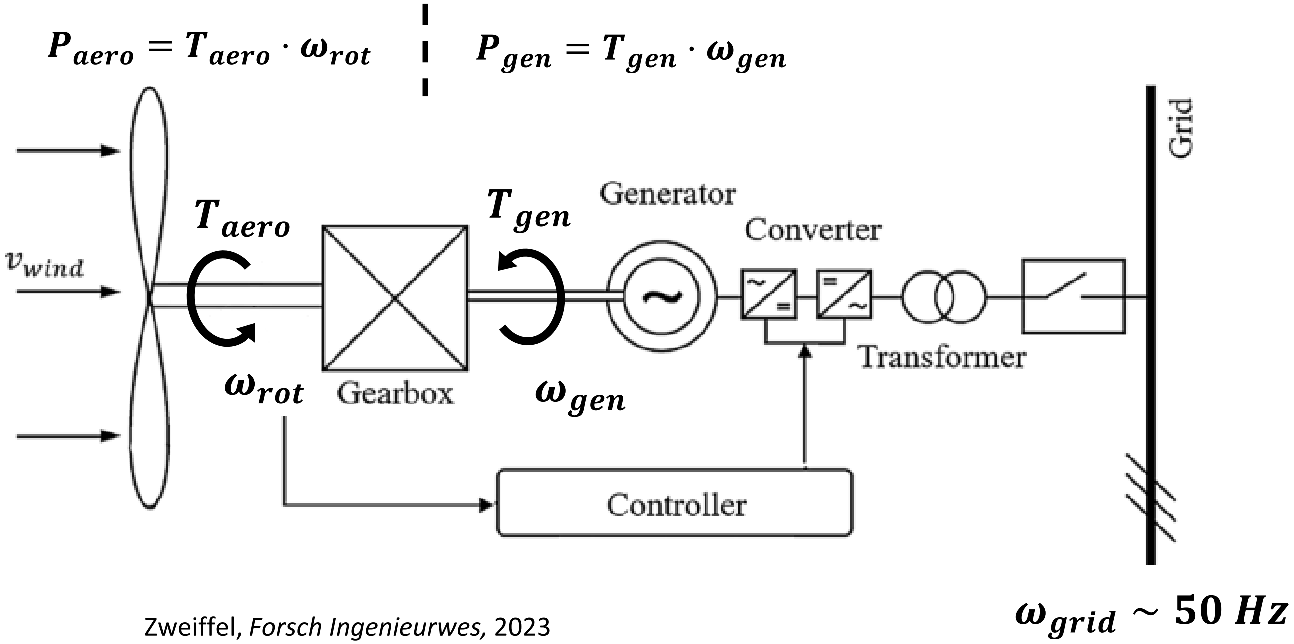
Schematic of power conversion of a wind turbine



Zweiffel, *Forsch Ingenieurwes*, 2023

Schematic of power conversion of a wind turbine



Zweiffel, *Forsch Ingenieurwes*, 2023

Drive train dynamics:

$$\frac{d\omega_{gen}}{dt} = \frac{1}{J}\left(kT_{aero}(v_{wind}, \omega_{rot}, \alpha, \dots) - T_{gen}(\omega_{gen})\right)$$

Gearbox with ratio $k < 1$:

$$\omega_{rot} = k \cdot \omega_{gen}$$

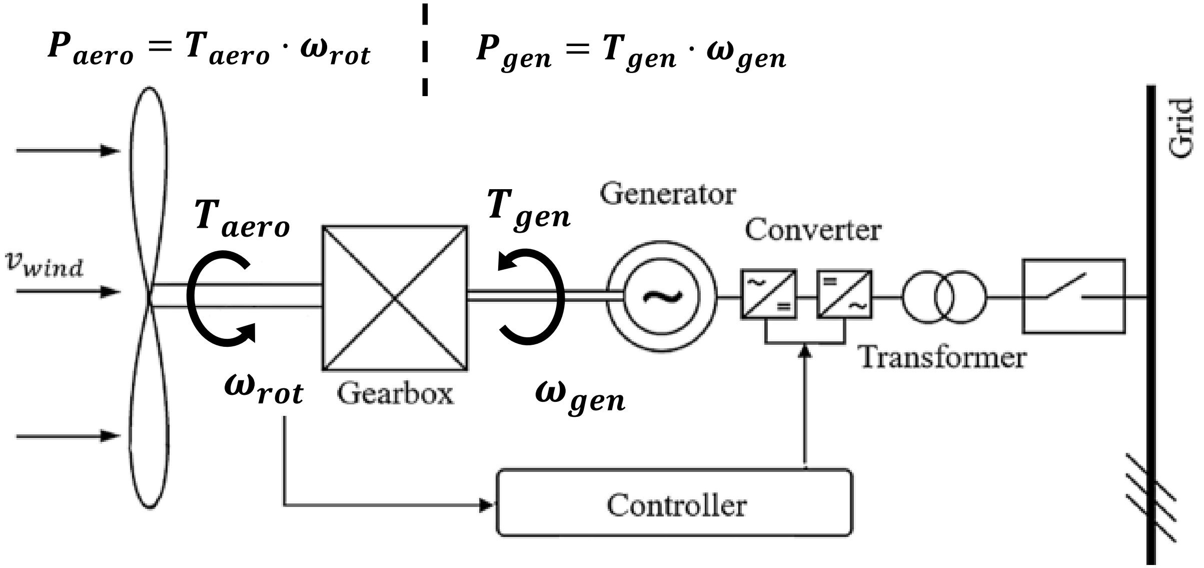
Aerodynamic power:

$$P_{aero} = T_{aero} \cdot \omega_{rot}$$

Electric power:

$$P_{gen} = T_{gen} \cdot \omega_{gen}$$

Schematic of power conversion of a wind turbine

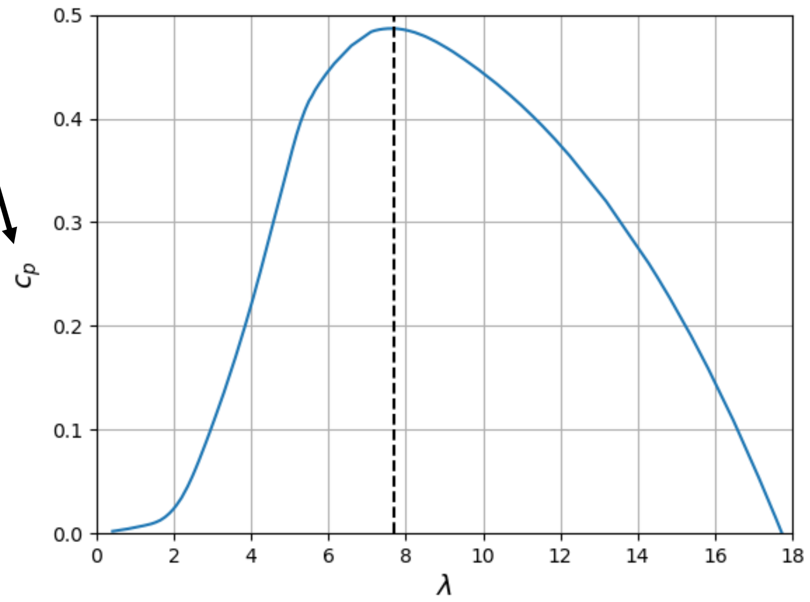


Zweiffel, *Forsch Ingenieurwes*, 2023

$\omega_{grid} \sim 50\ Hz$

Power coefficient

$c_p \sim P_{aero}$

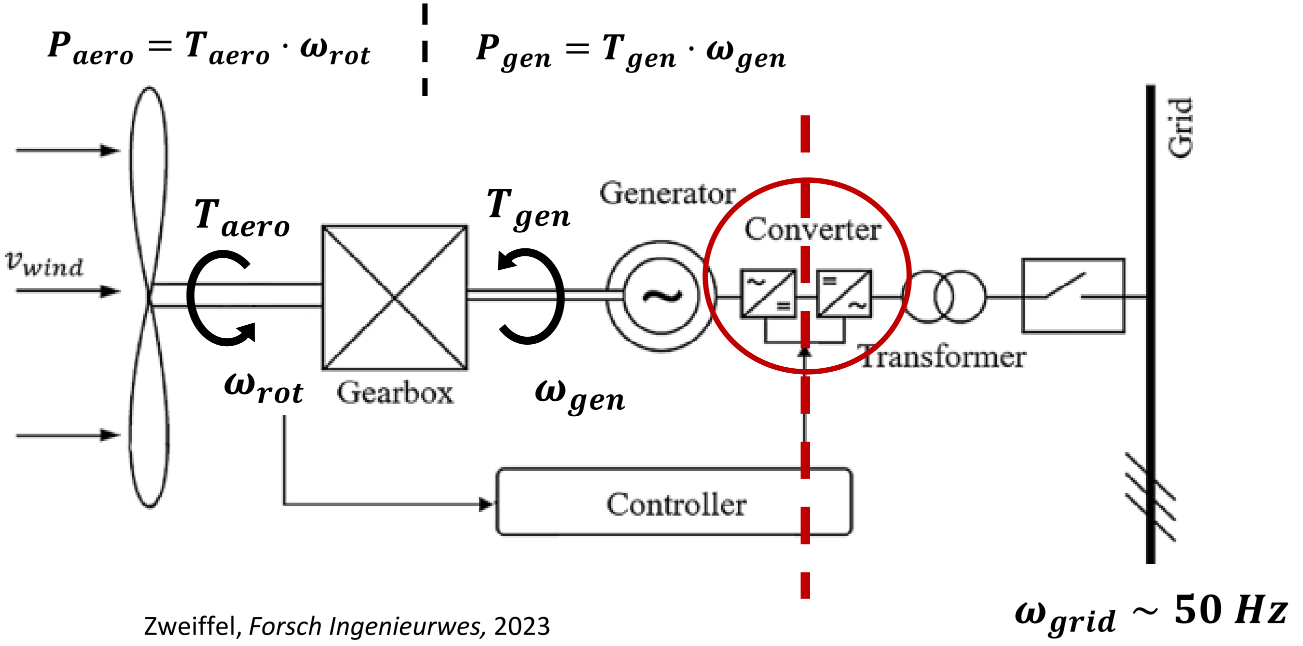


Tip speed ratio $\lambda = \frac{\omega_{rot} R}{v_{wind}}$

P_{aero} is maximal for a certain ratio between ω_{rot} and v_{wind}

➢ beneficial to change ω_{rot} and ω_{gen} independently of grid frequency ω_{grid}

Variable speed wind turbines



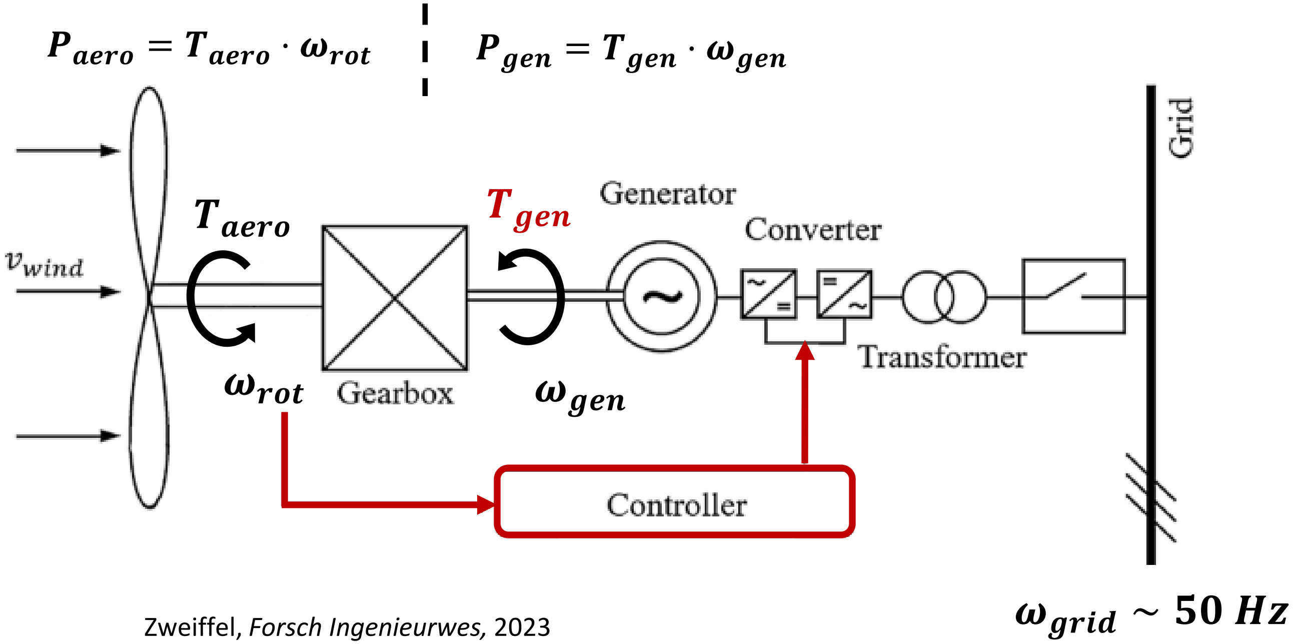
Zweiffel, *Forsch Ingenieurwes*, 2023

$$\omega_{gen} = \frac{\omega_{rot}}{k} \neq \omega_{grid}$$

Due to AC-DC-AC converter: Rotational frequency of turbine (ω_{gen} and ω_{rot}) is independent of grid frequency ω_{grid}

- also decouples rotating mass from the grid

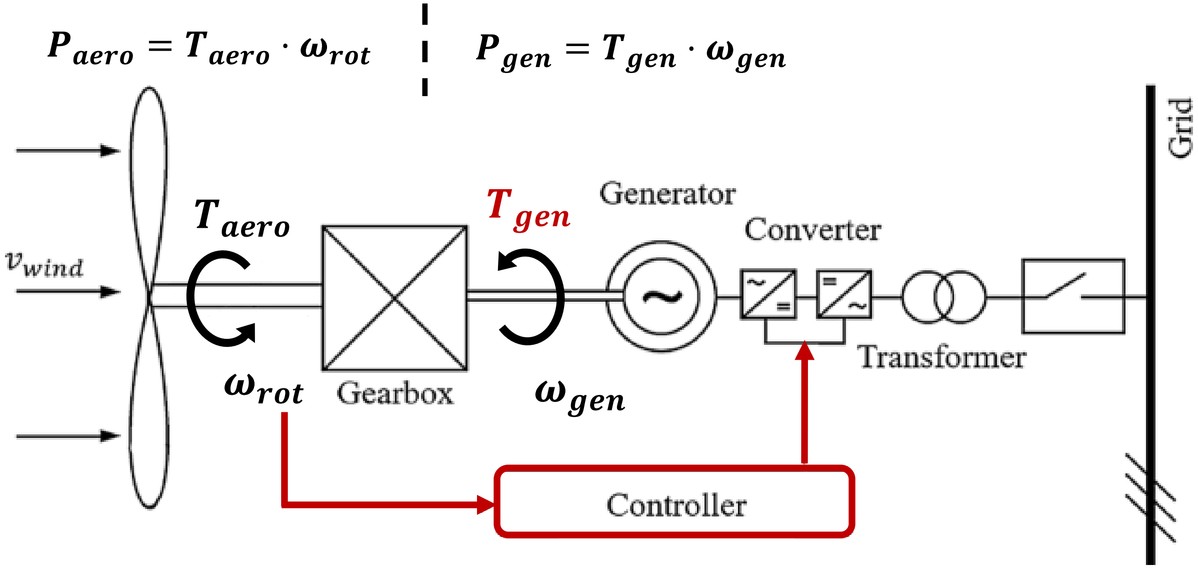
Torque control of variable speed wind turbines



Zweiffel, *Forsch Ingenieurwes*, 2023

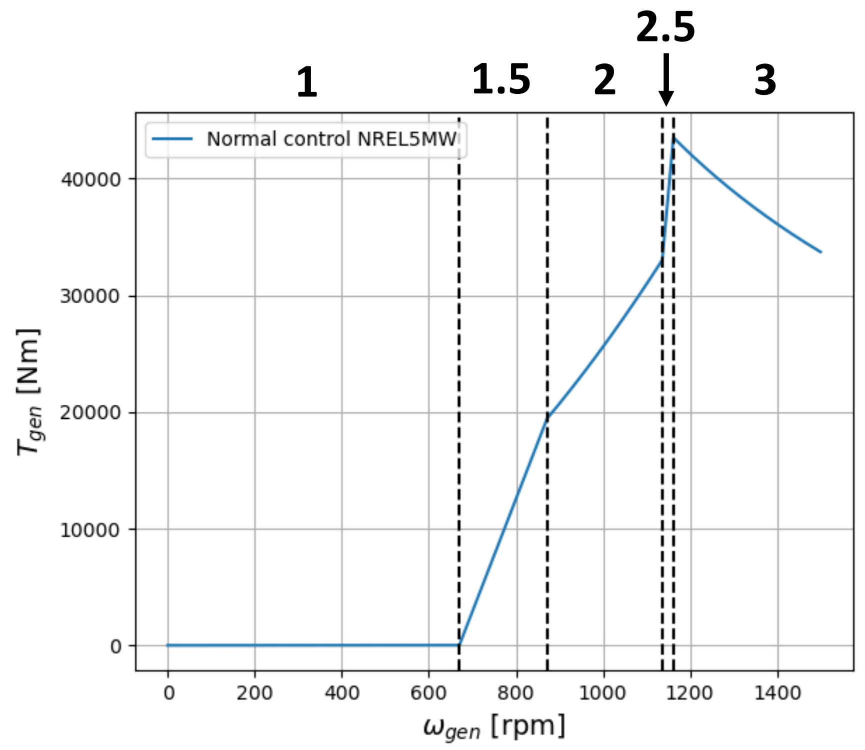
Parameter to control ω_{gen} and ω_{rot}: Electric torque T_{gen} on generator

Torque control of variable speed wind turbines



Zweiffel, *Forsch Ingenieurwes*, 2023

$\omega_{grid} \sim 50\ Hz$

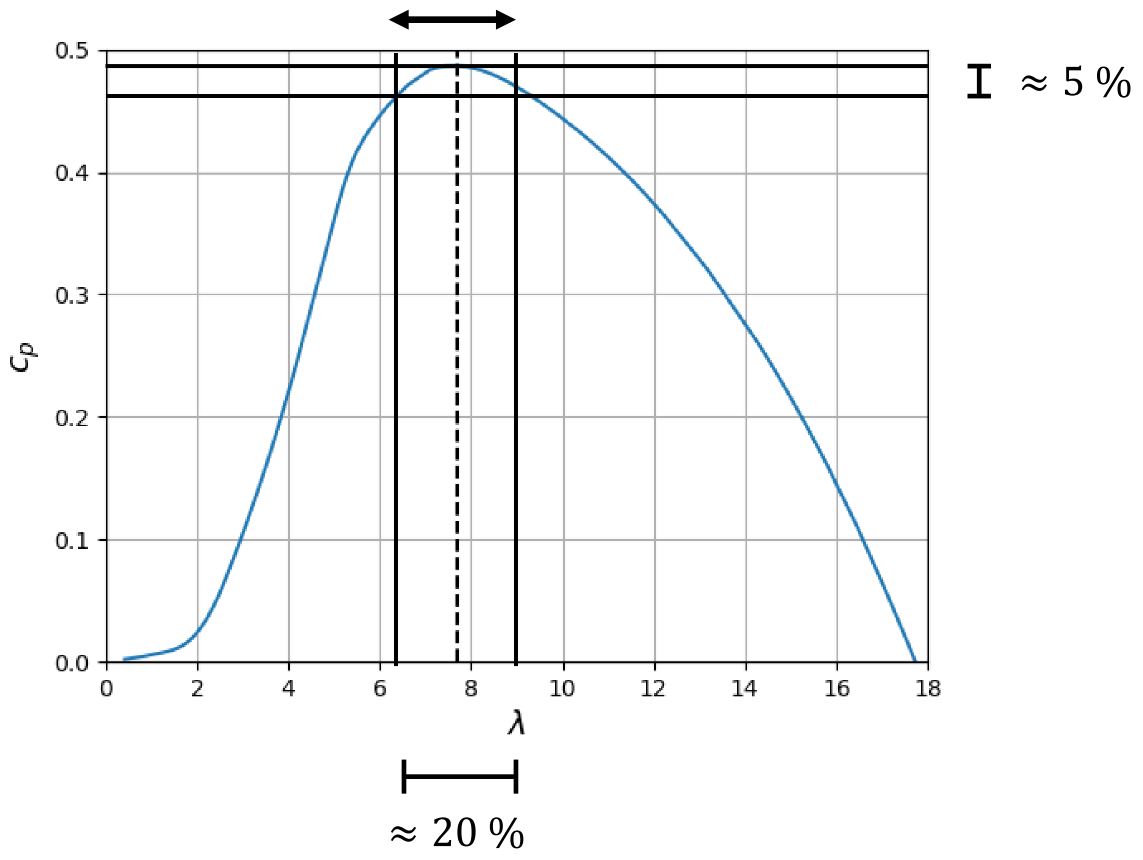


Parameter to control ω_{gen} and ω_{rot}: Electric torque T_{gen} on generator

➢ control law typically depends on ω_{gen} itself: $T_{gen}(\omega_{gen})$

Accessing the rotating masses

Rotational speed can be chosen using the generator torque

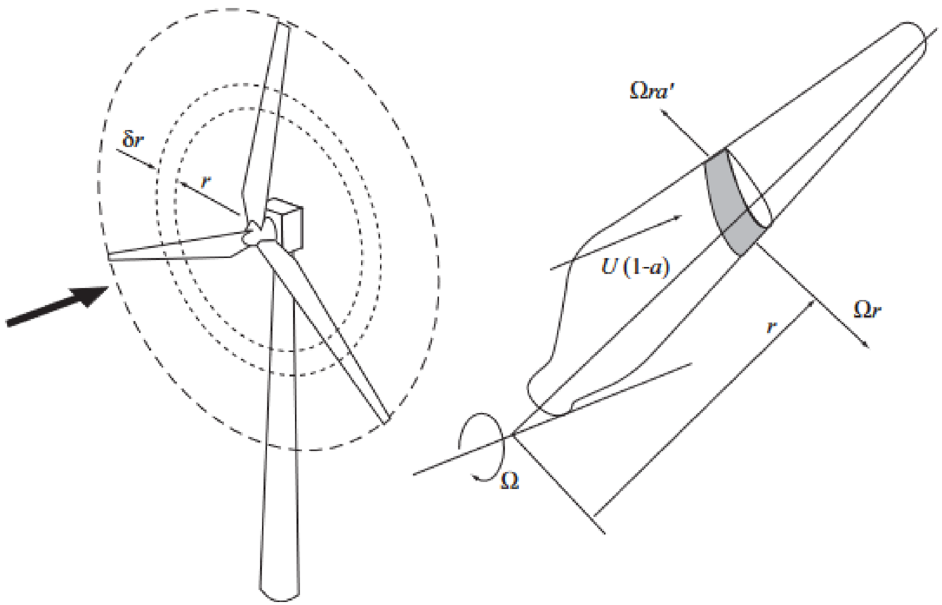


- ➢ access rotational energy **dynamically**, at the cost of only a small power loss

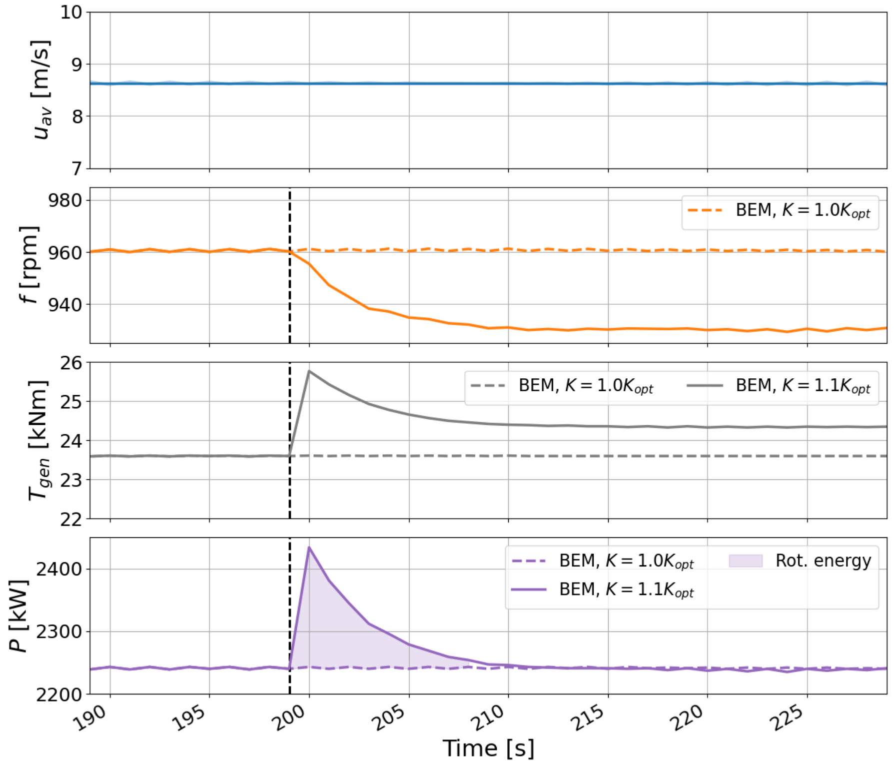
Accessing the rotating masses

Example from BEM (Blade Element Model), *NREL5MW* turbine with laminar inflow:

Increase Generator Torque at $t = 200$ s



Burton, *Wind Energy Handbook*, 60



- here: rotational energy provided for ≈ 10 s

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2. Power Conversion of Wind Turbines
   - A torque balance between rotor and generator dominates the drive train dynamics
   - Variable speed wind turbines are state of the art
     - **Advantage:** Maximization of power production
     - **Disadvantage:** Removal of grid inertia
   - Using the generator torque, rotational energy can be accessed at minimal power loss

3. Stochastic Langevin Model

4. Accessing Rotational Energy in Langevin Model

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3. Stochastic Langevin Model

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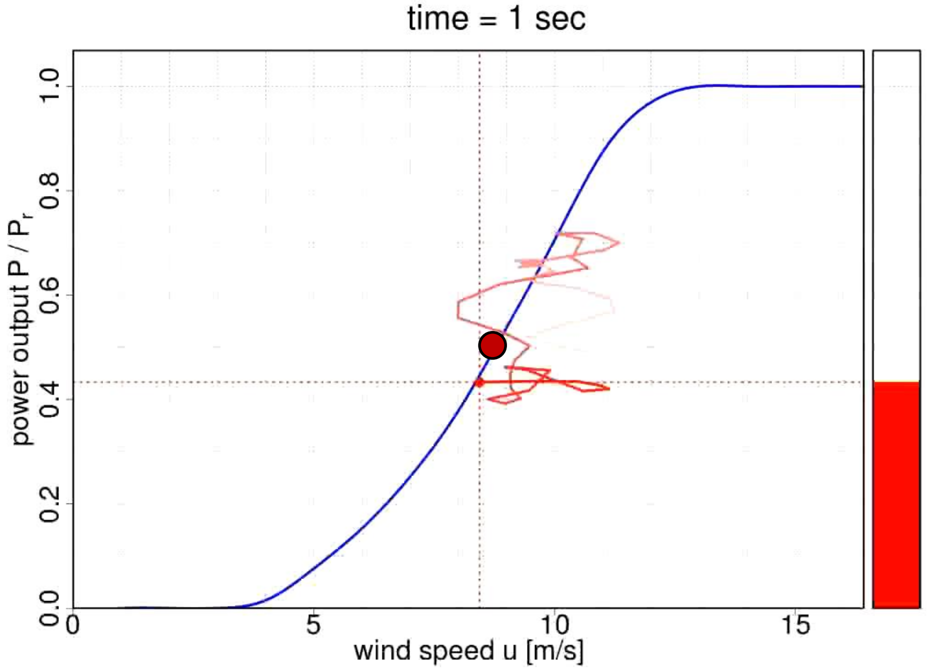
Stochastic Langevin model

In summary, we need a model to quantify…

1) the short-time dynamics of the noisy power conversion process

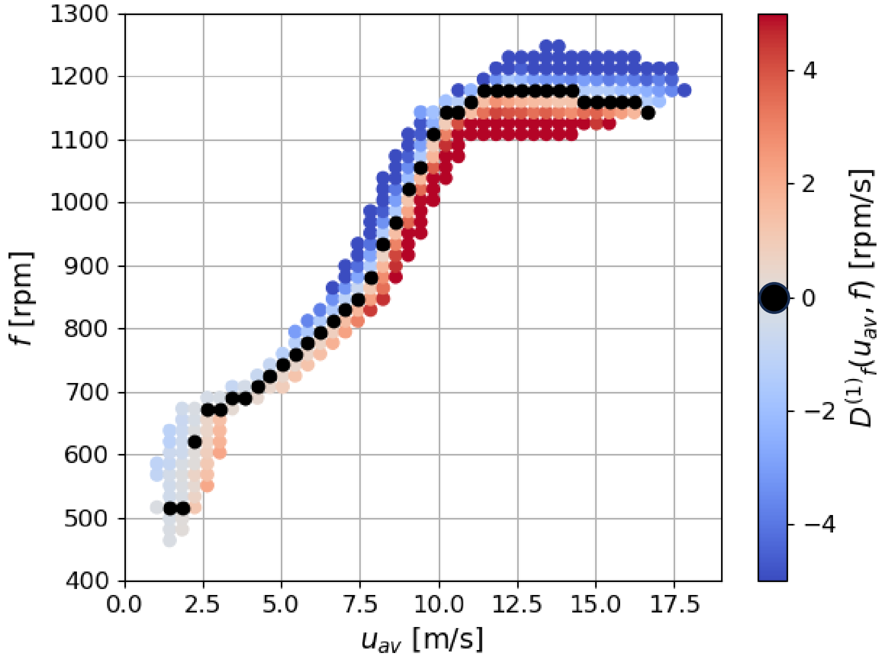
2) the power conversion of multiple turbines

- our approach: **stochastic Langevin model** (data-based and computationally inexpensive)

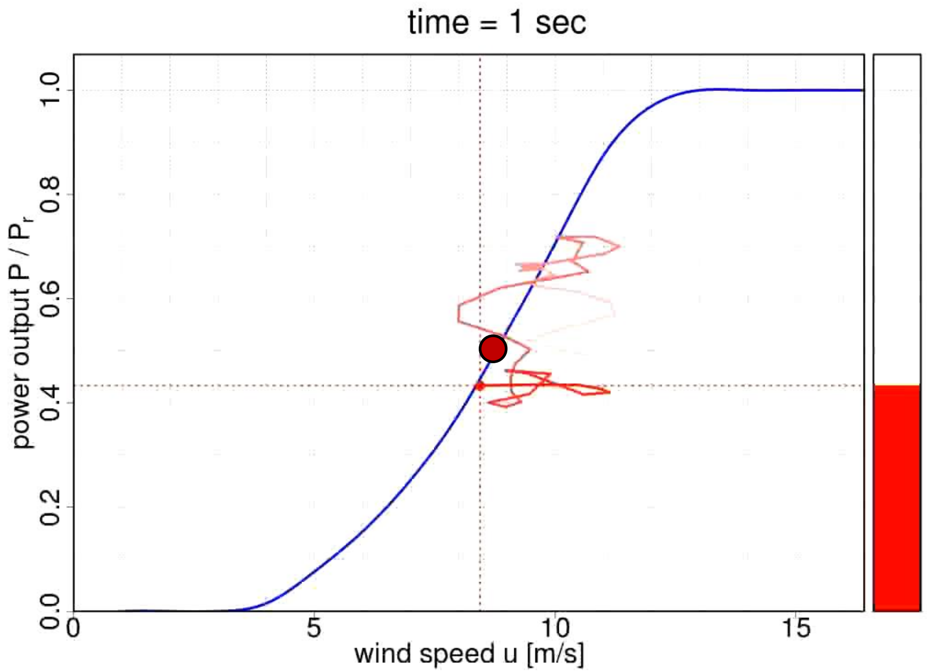


Stochastic Langevin model

Dynamic description:

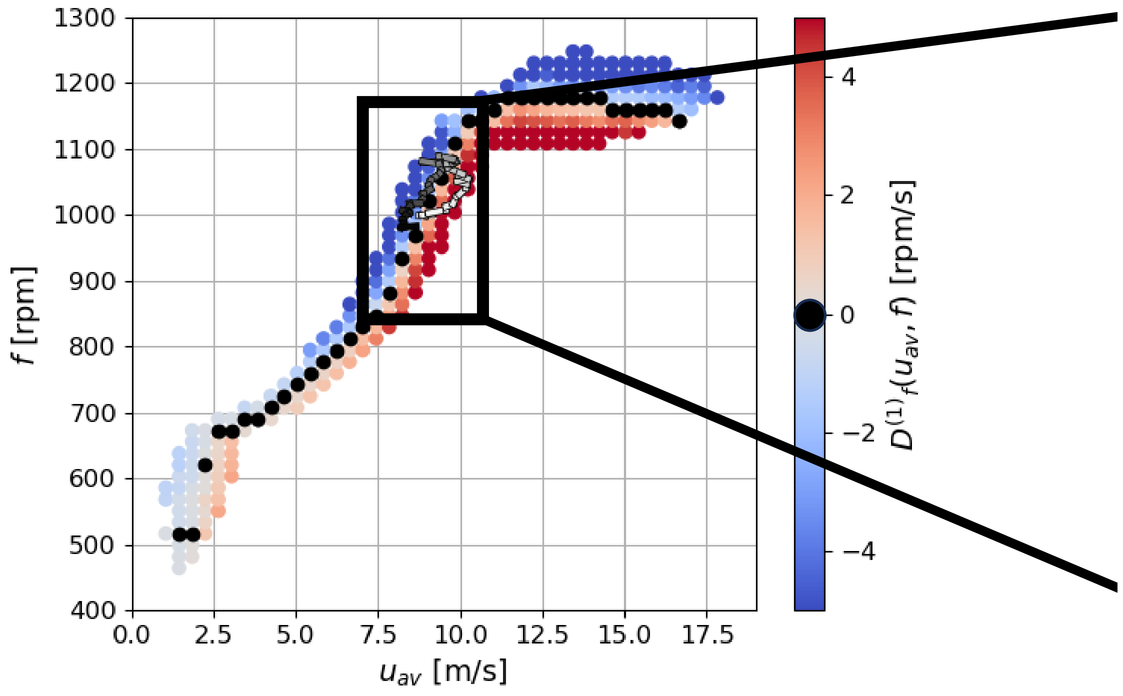


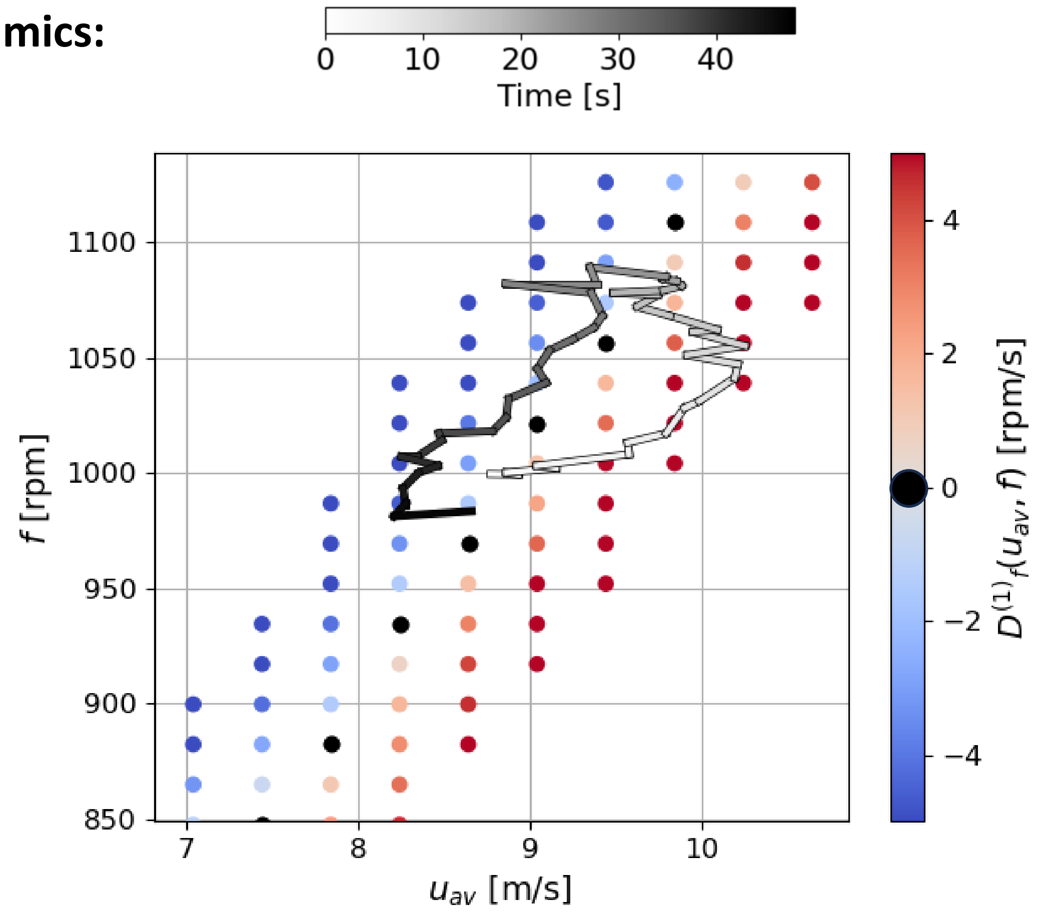
Static description (+ dynamic behaviour):



Stochastic Langevin model

Dynamic description allows us to extract deterministic dynamics:





Stochastic Langevin model

- target parameter to model: Rotational speed ω_{gen}
- in the following, use instead for reasons of clarity: $f := \frac{\omega_{gen}}{2\pi}$
- model is applied in phase space of (rotor-averaged) wind speed u_{av} and f

Central equation:

$$\frac{d}{dt} f(t) = D_f{}^{(1)}(f, u_{av}) + \sqrt{D_f{}^{(2)}(f, u_{av})} \cdot \Gamma(t)$$

f: generator frequency

u_{av}: rotor averaged wind speed

$\Gamma(t)$: Gaussian white noise

Stochastic Langevin model

$$\frac{d}{dt}f(t) = D_f{}^{(1)}(f,u) + \sqrt{D_f{}^{(2)}(f,u)} \cdot \Gamma(t)$$

f: generator frequency u: wind speed

$\Gamma(t)$: Gaussian white noise

Anahua et al., 2008, Wind Energy

$D_f{}^{(1)}(f,u)$ and $D_f{}^{(2)}(f,u)$ estimated from highly resolved ($1\ Hz$) „training data“ (*OpenFAST*, *NREL 5MW* turbine):

Risken, *The Fokker-Planck equation*, 48

$$M_f^{(n)}(f_i, u_{av,j}, \tau) = \langle (f(t+\tau) - f(t))^n \mid f(t) = f_i, u_{av}(t) = u_{av,j} \rangle$$

$$D_f{}^{(n)}(f_i, u_{av,j}) = \frac{1}{n!} \lim_{\tau \to 0} \frac{1}{\tau} M_f^{(n)}(f_i, u_{av,j}, \tau)$$

Drift coefficient $D_f{}^{(1)}(f,u)$: “At a certain point (f, u_{av}) in phase space, what is the average change of f in the next τ seconds?”

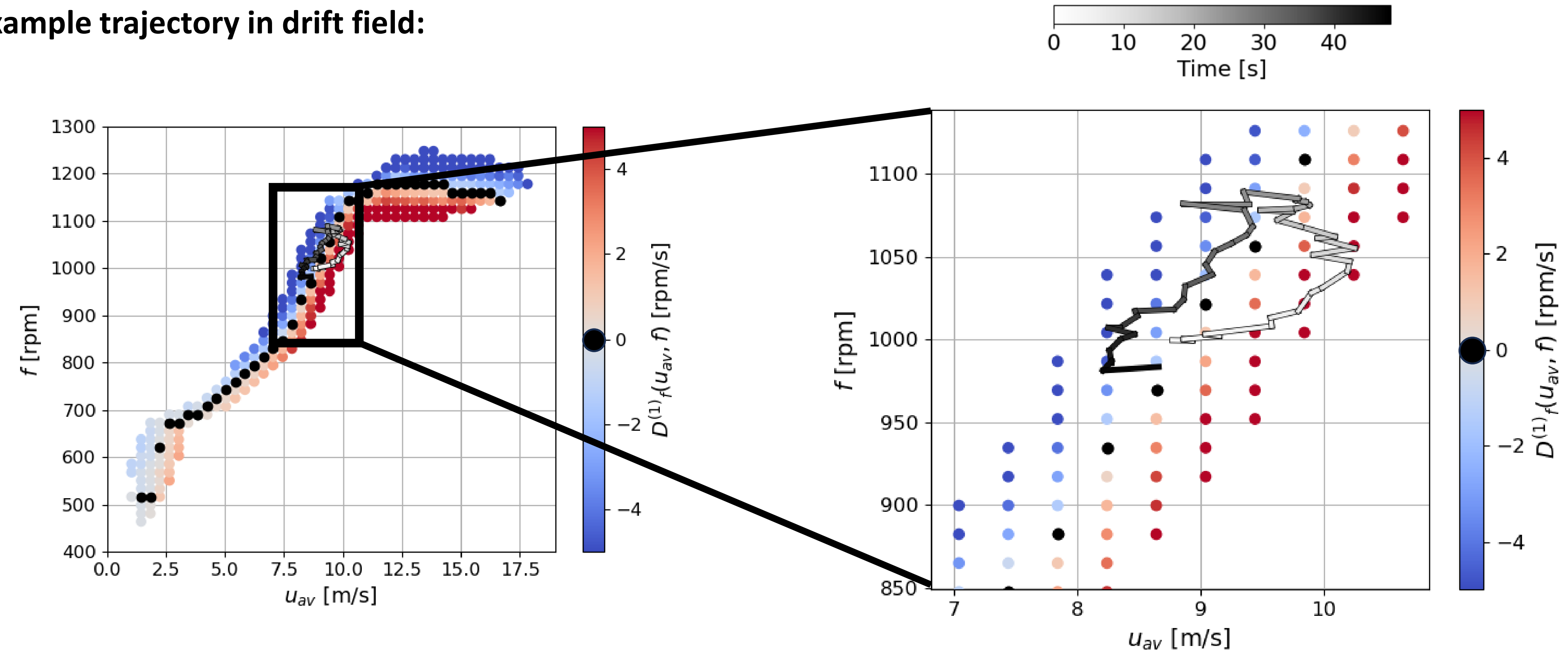
- ➢ **linear, deterministic dynamics**

Diffusion coefficient $D_f{}^{(2)}(f,u)$: “At a certain point (f, u_{av}) in phase space, what is average squared change of f (“variance of change”) in the next τ seconds?”

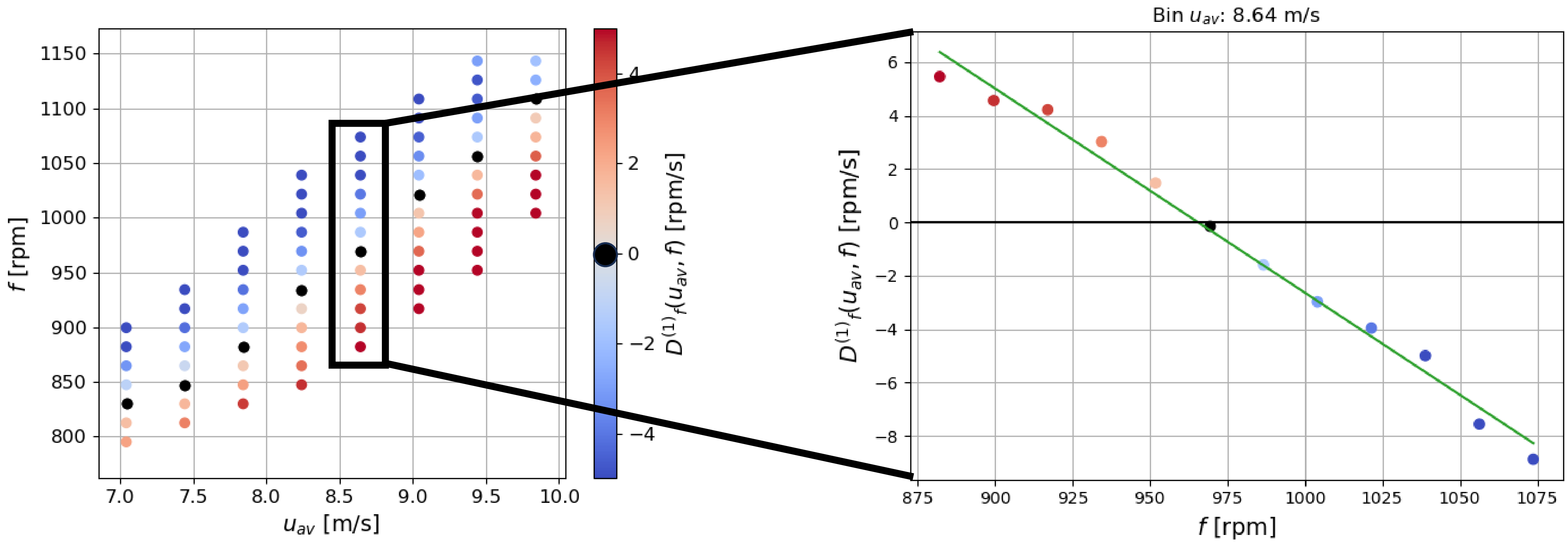
- ➢ **together with $\Gamma(t)$: random dynamics**

Stochastic Langevin model

Example trajectory in drift field:



Parametrization of drift coefficients



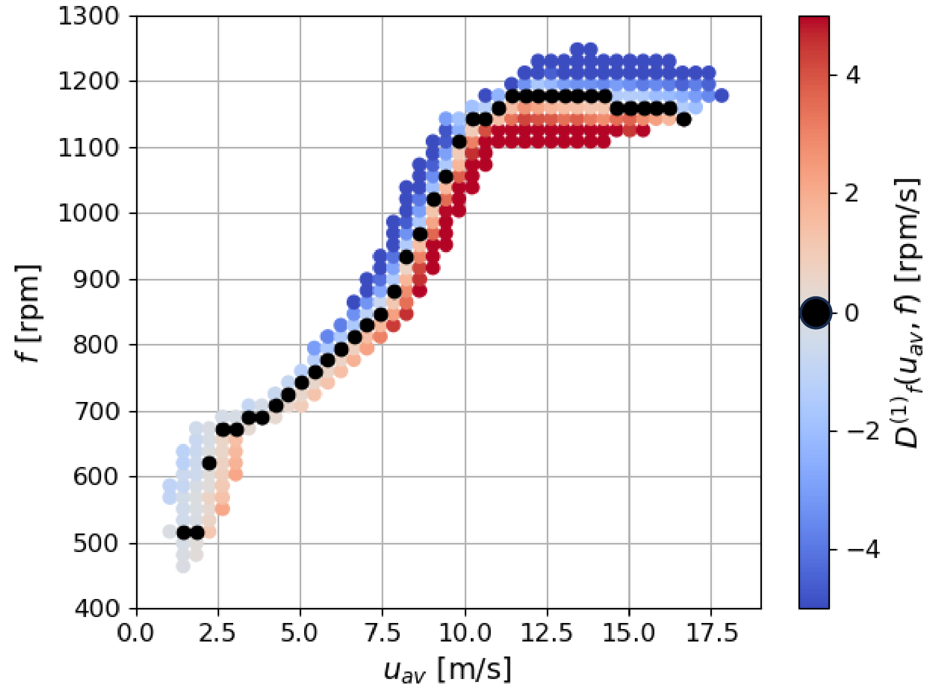
- approximately linear dependency also for other bins $u_{av,i}$
- fit linear parametrization $D_f^{(1)}(f|u_{av,i}) = a \cdot f + b$ to drift values in every bin $u_{av,i}$

Stochastic Langevin model

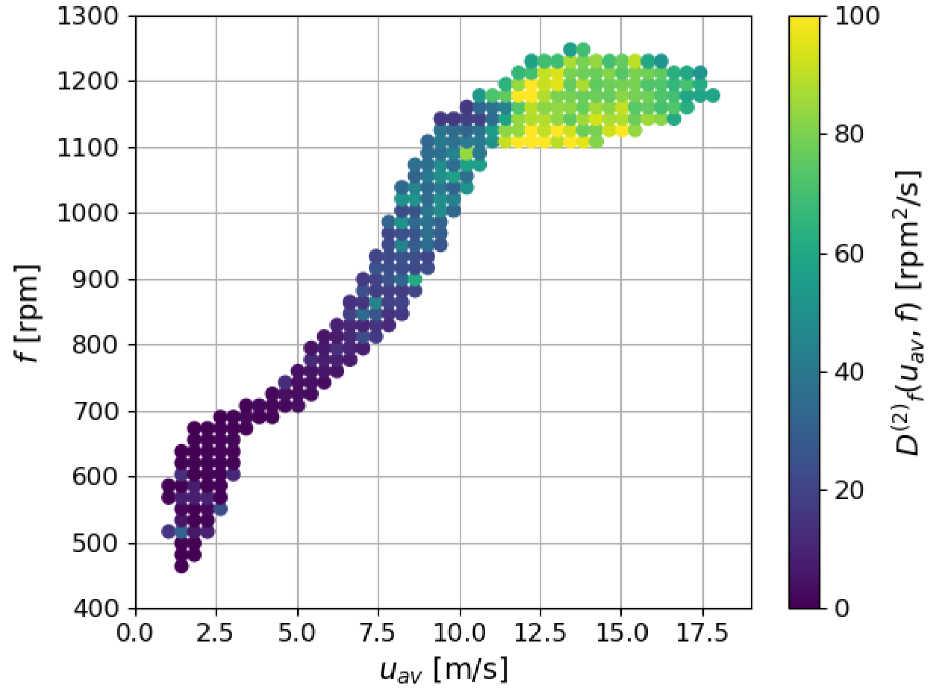
Estimation results:

$$\frac{d}{dt} f(t) = D_f{}^{(1)}(f,u) + \sqrt{D_f{}^{(2)}(f,u)} \cdot \Gamma(t)$$

$D_f{}^{(1)}(f,u)$ ("drift field")



$D_f{}^{(2)}(f,u)$ ("diffusion field")

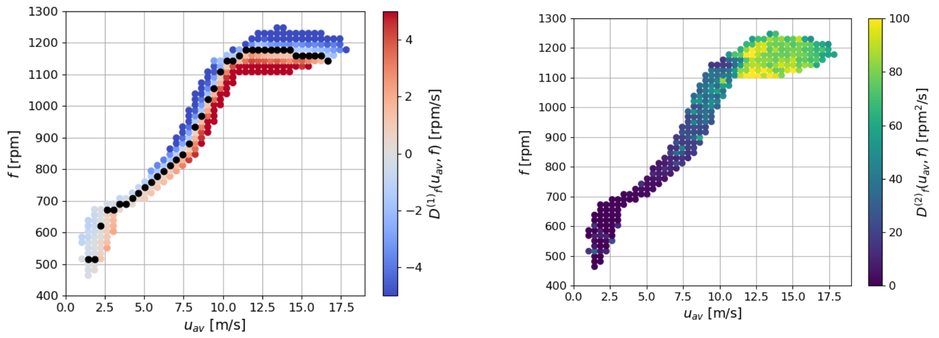


Recursive stochastic model via integration

$$\frac{d}{dt} f(t) = D_f{}^{(1)}(f,u) + \sqrt{D_f{}^{(2)}(f,u)} \cdot \Gamma(t)$$

Step 1) "Training" data set:

Estimate drift $D_f{}^{(1)}$ and diffusion $D_f{}^{(2)}$



Step 2) "Test" wind speed data set:

Reconstruct $f(t)$ by integration of

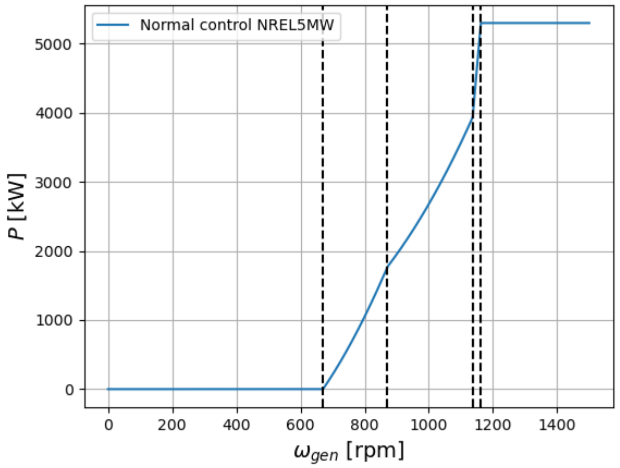
Langevin equation

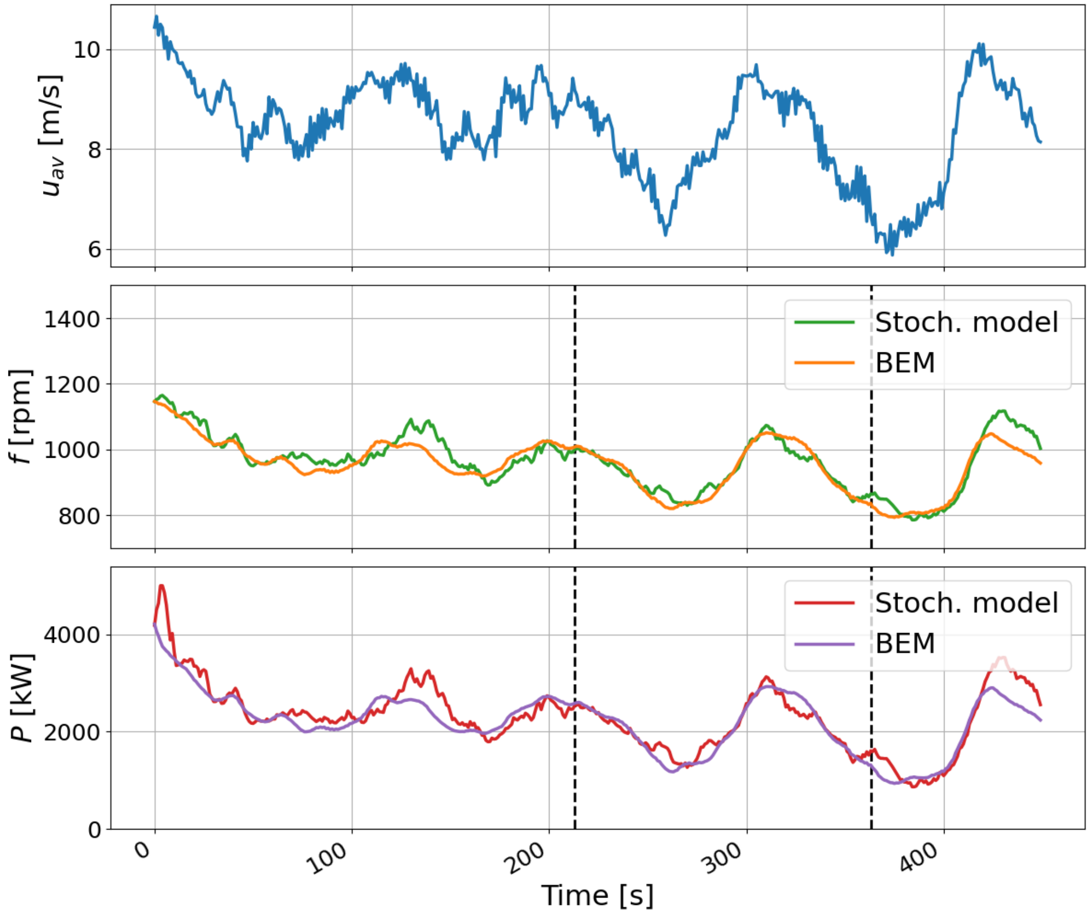
$$f(t + \Delta t) = f(t) + D_f{}^{(1)}(f,u)\Delta t + \sqrt{D_f{}^{(2)}(f,u)\Delta t} \cdot \Gamma(t)$$

➢ **stochastic model**

Stochastic Langevin model

Example for modelled time series
(mean wind speed 8.5 m/s, turbulence class B)

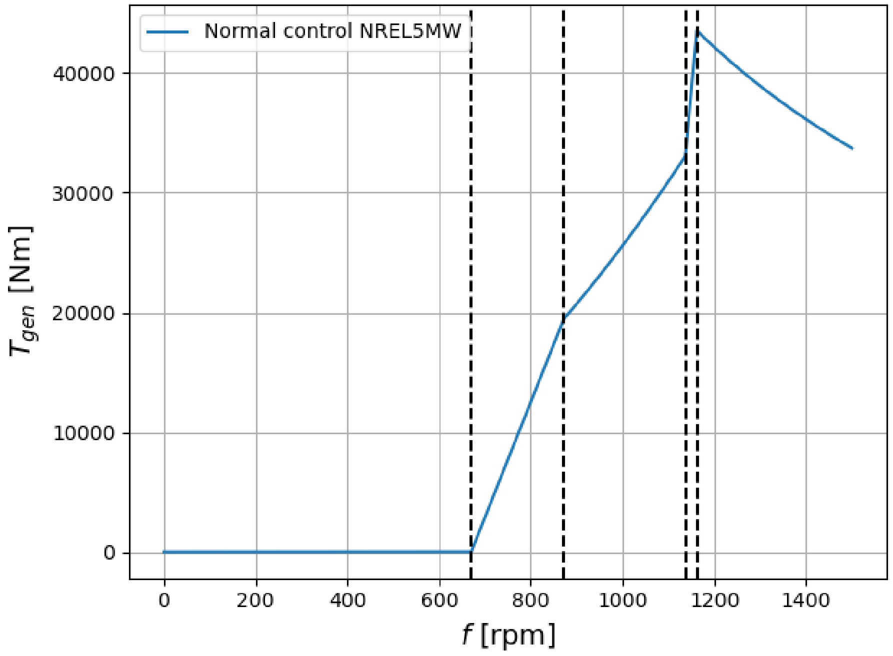


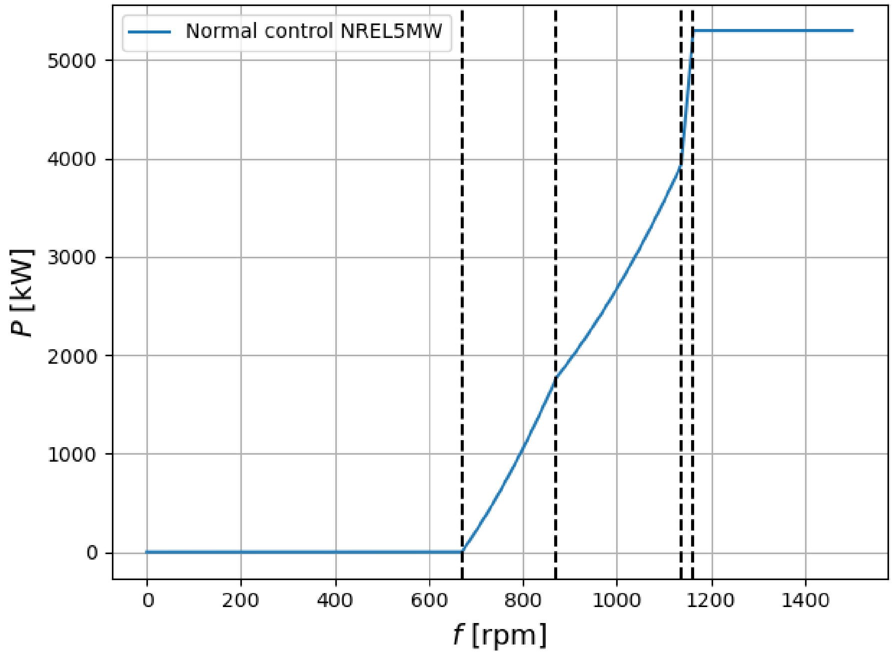


Obtain power via parametrization

How to obtain power time series from stochastically modeled time series $f(t)$?

➢ Parametrization via $P = T_{gen} \cdot \omega_{gen} = T_{gen} \cdot 2\pi f$





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2. Power Conversion of Wind Turbines

3. Stochastic Langevin Model

   - dynamical description of the wind turbine power conversion using stochastic approach
   - extraction of the deterministic dynamics from a noisy system is successful
   - gives a recursive model that agrees well with engineering model data

4. Accessing Rotational Energy in Langevin Model

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   - extraction of the deterministic dynamics is successful
   - gives a recursive model that agrees well with engineering model data

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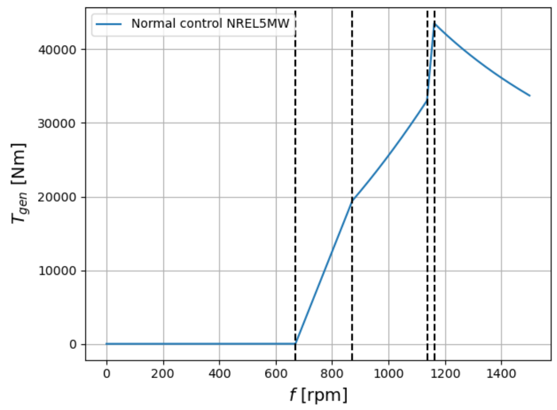
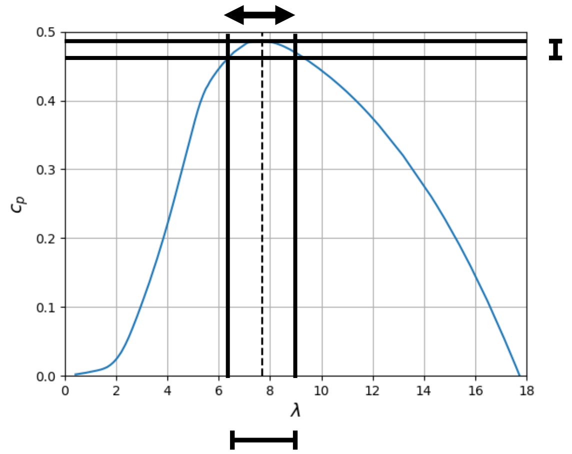
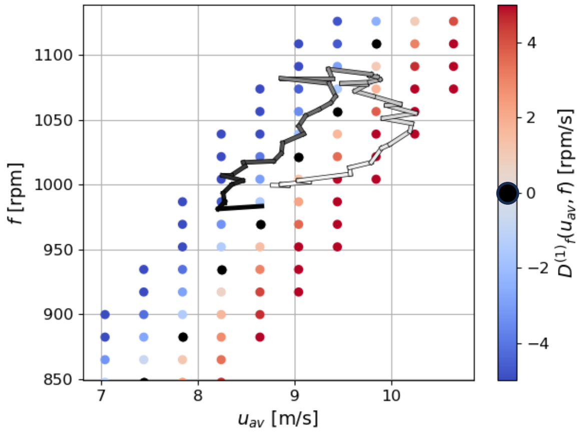
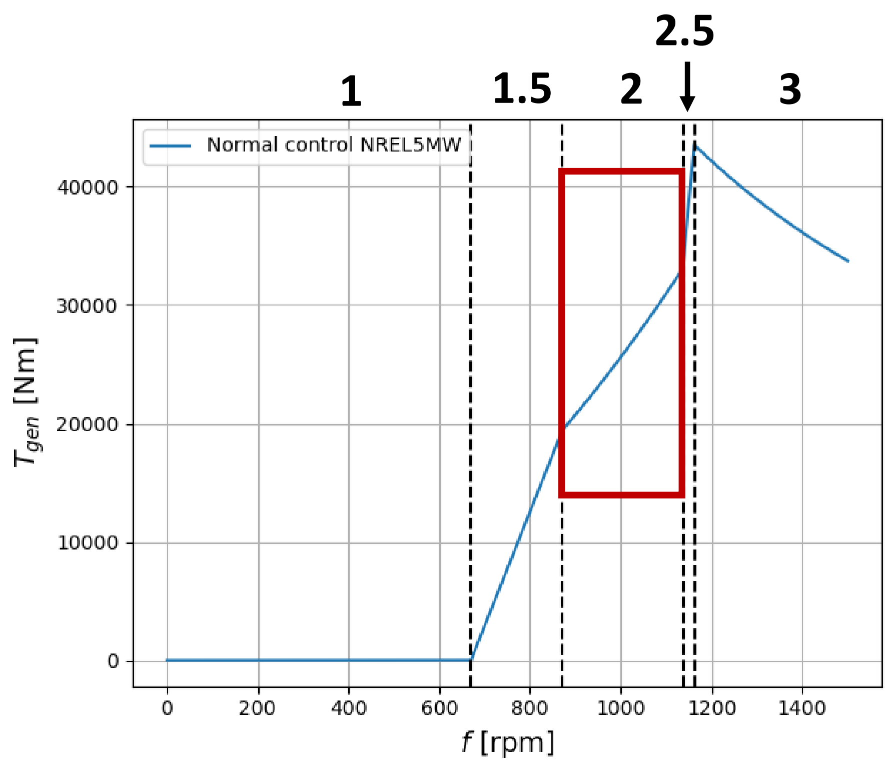


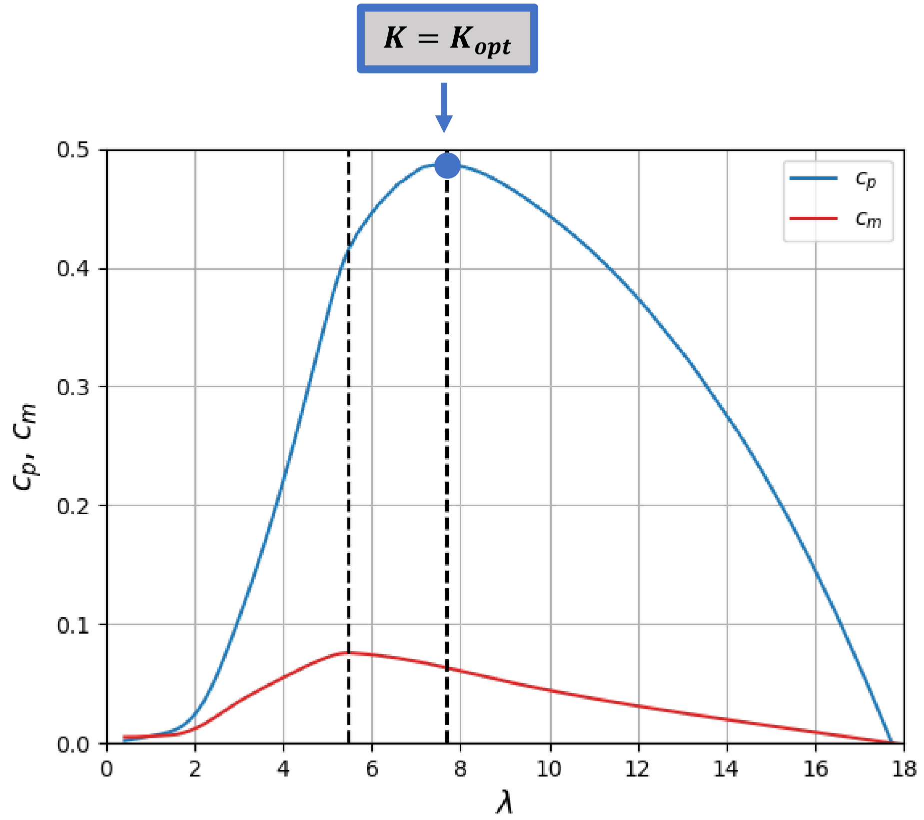




Torque control in stochastic Langevin model

Use the following torque control:





Focus on region 2, where: $T_{gen} = Kf^2 \rightarrow P = 2\pi K f^3$

Torque control in stochastic Langevin model

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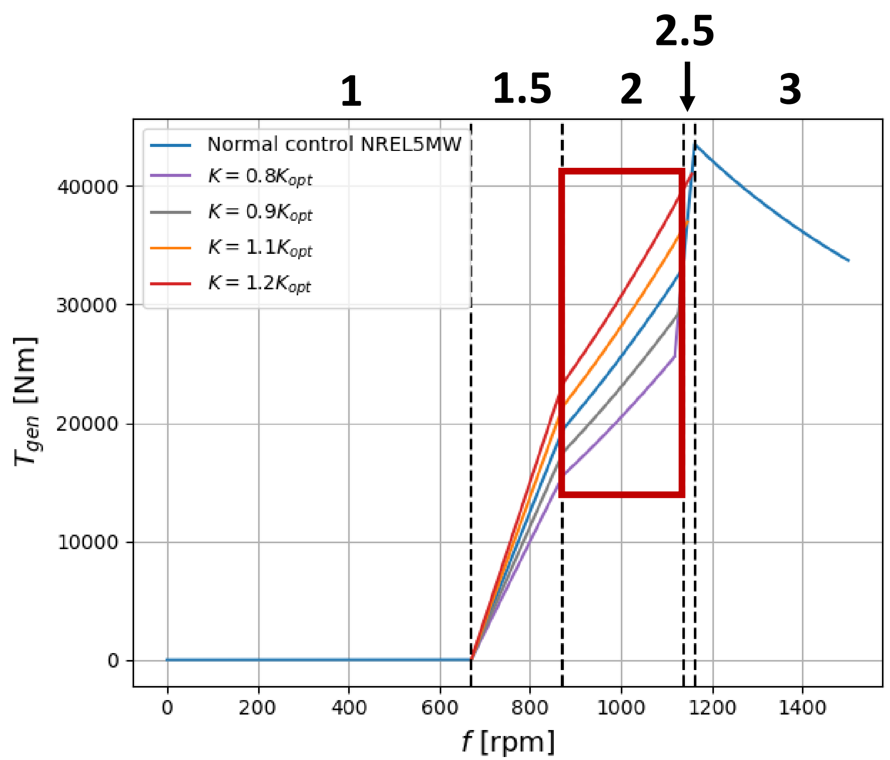
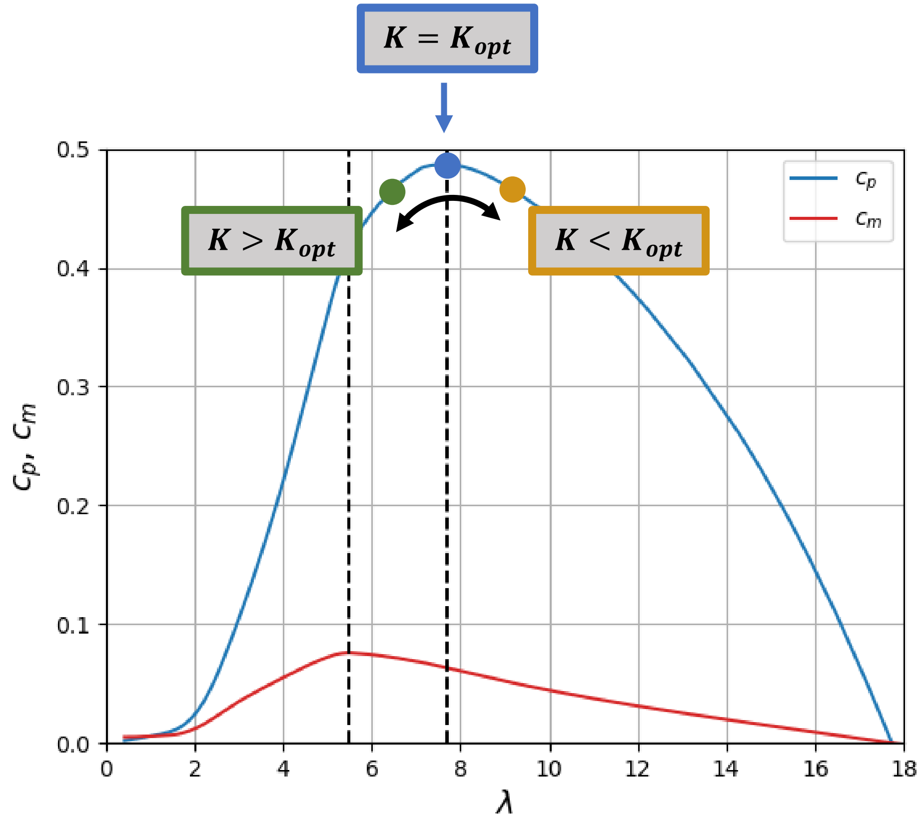




Focus on region 2, where: $T_{gen} = Kf^2 \rightarrow P = 2\pi K f^3$ → **vary K**

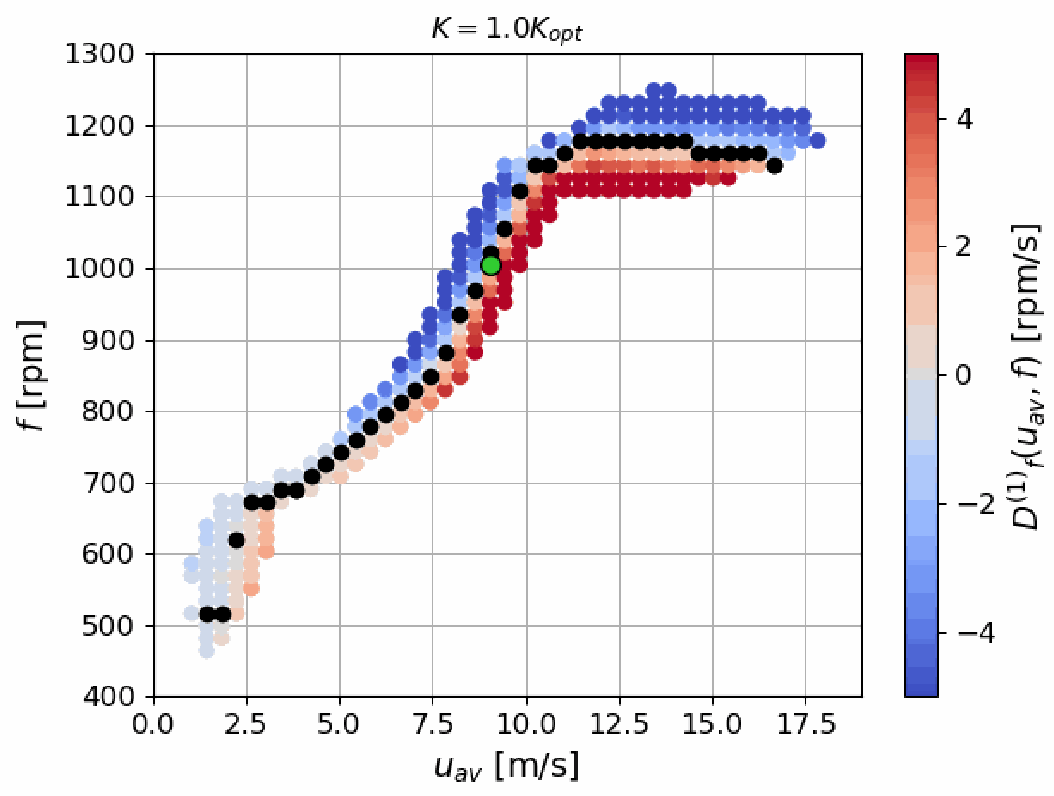
Torque control in stochastic Langevin model

How to introduce torque control to stochastic model?

Idea:

Train model (i.e. $D_f^{(1)}(f,u)$ and $D_f^{(2)}(f,u)$), for different $K \in (K_{opt}, 1.05K_{opt}, 1.1K_{opt}, 1.2K_{opt})$ in the training data

➢ dynamically switch between models for different K



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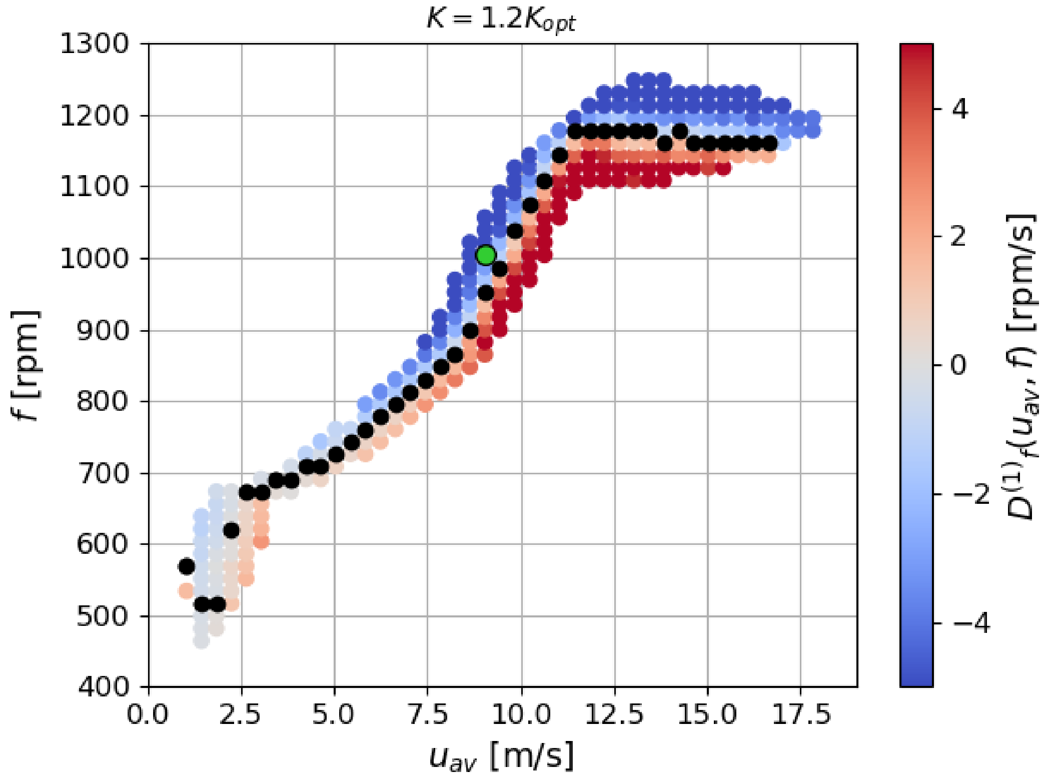


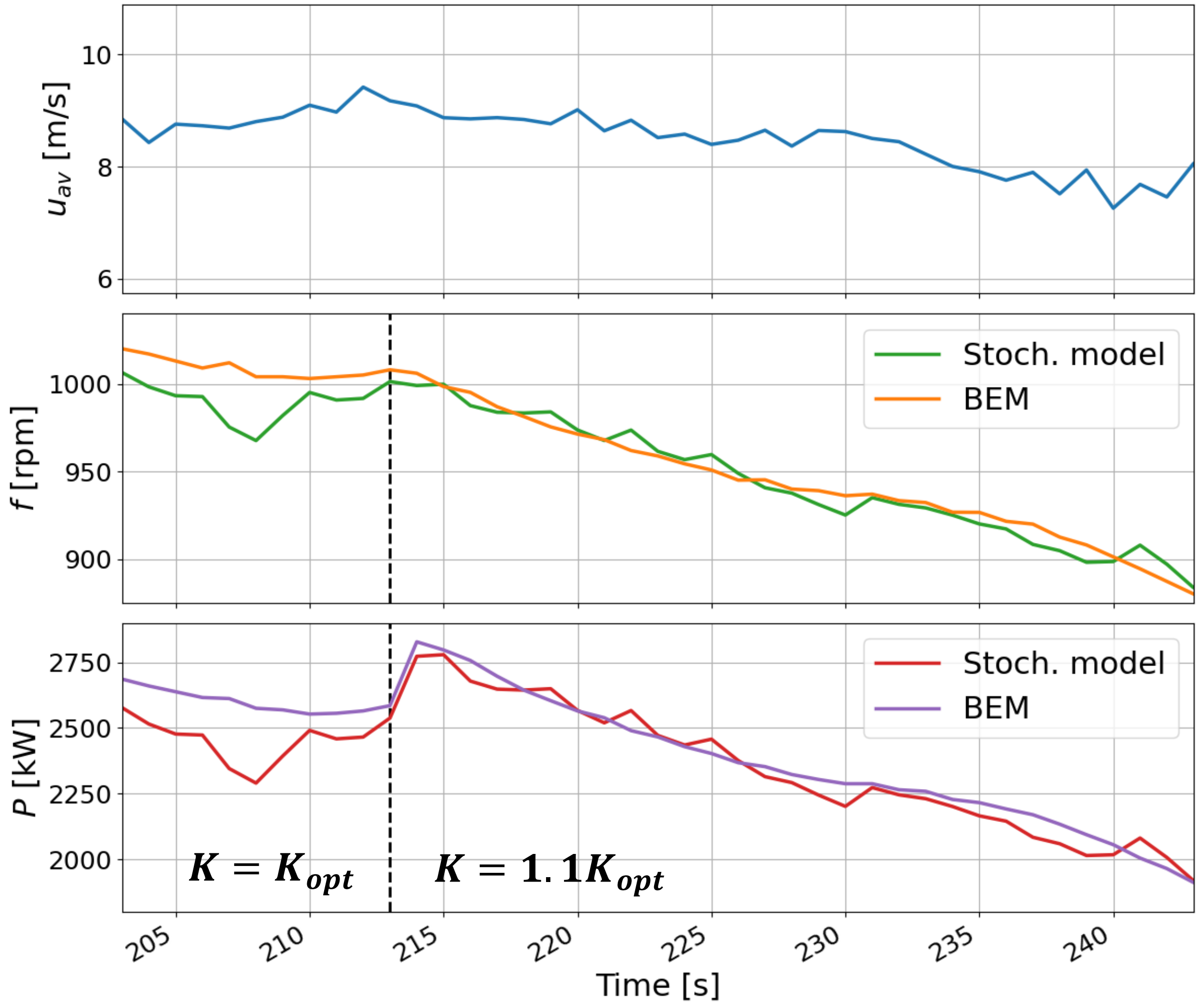
Torque control in stochastic Langevin model

Consider time series from before:

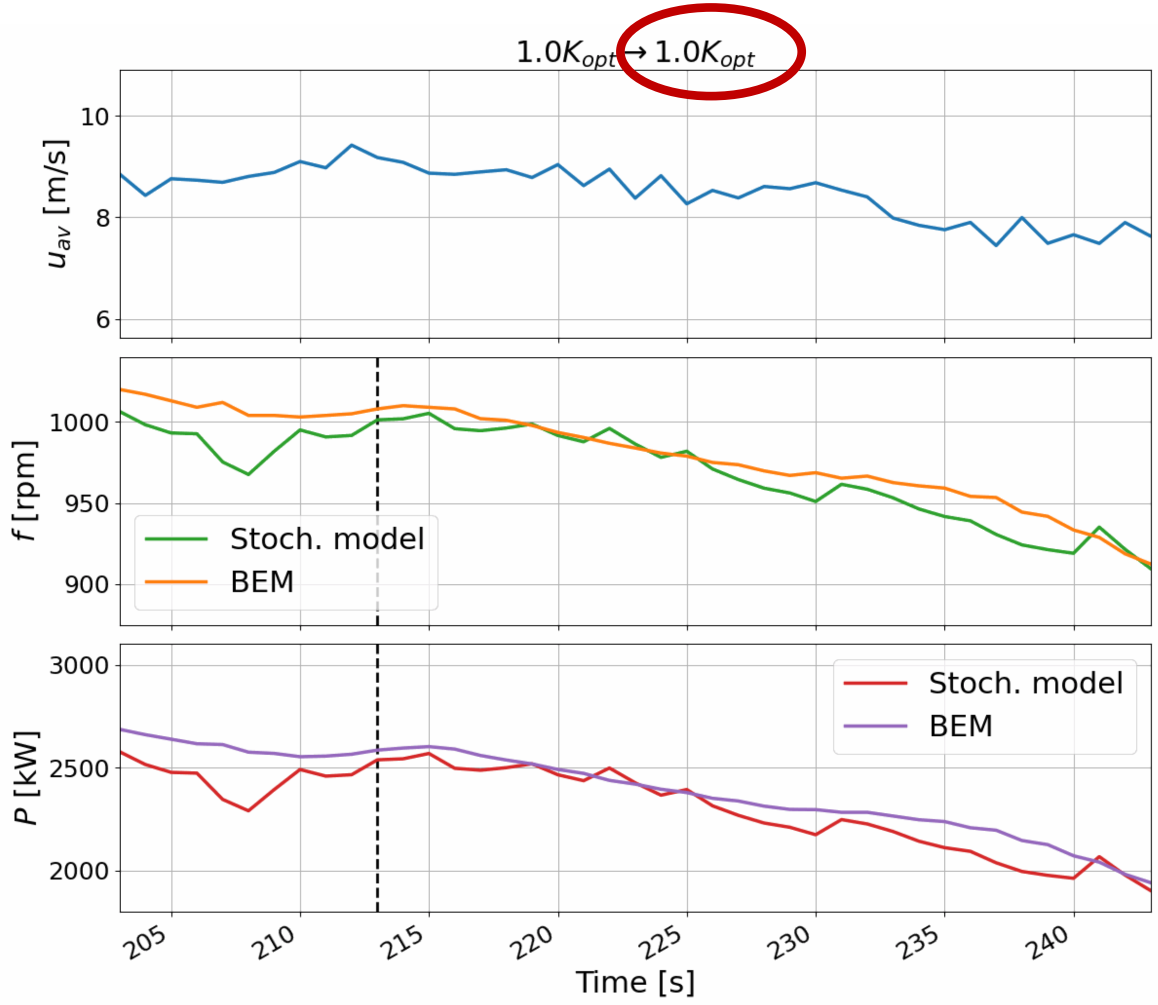
(mean wind speed 8.5 m/s, turbulence class B)

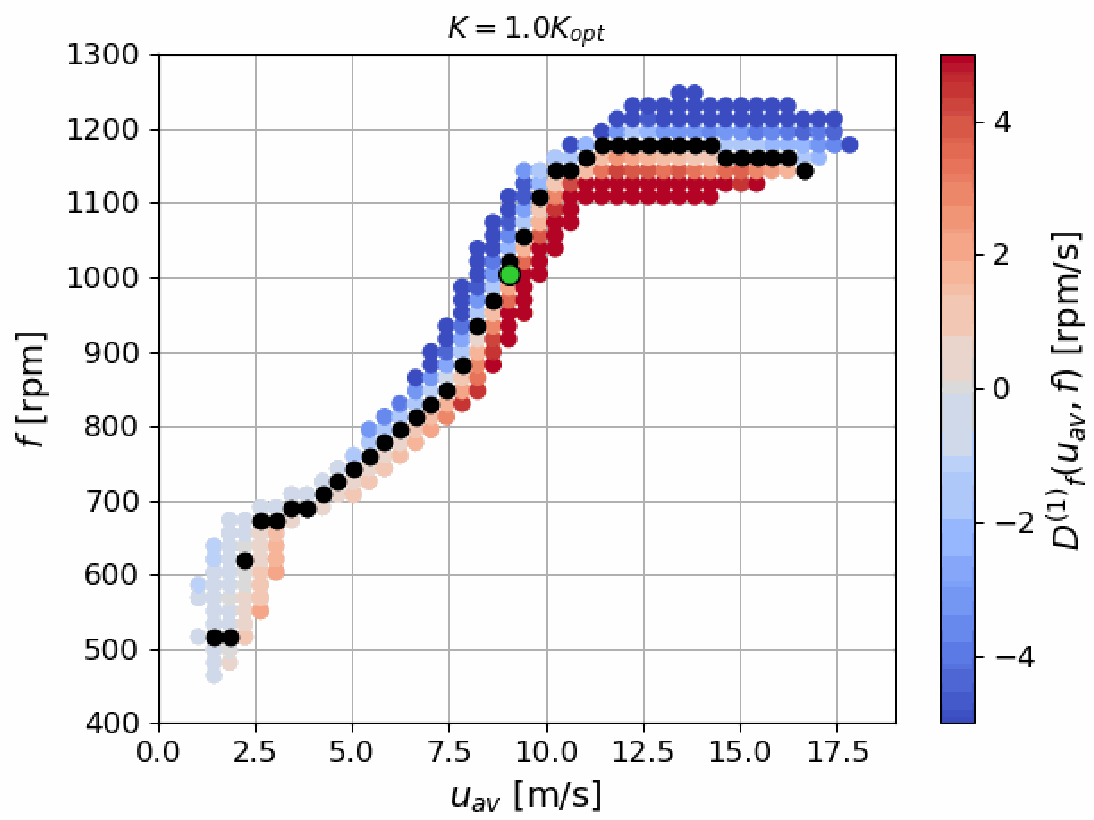
At certain time stamp, set $K = 1.1K_{opt}$:

- Generator torque and power are increased
- Turbine provides rotational energy



Torque control in stochastic Langevin model





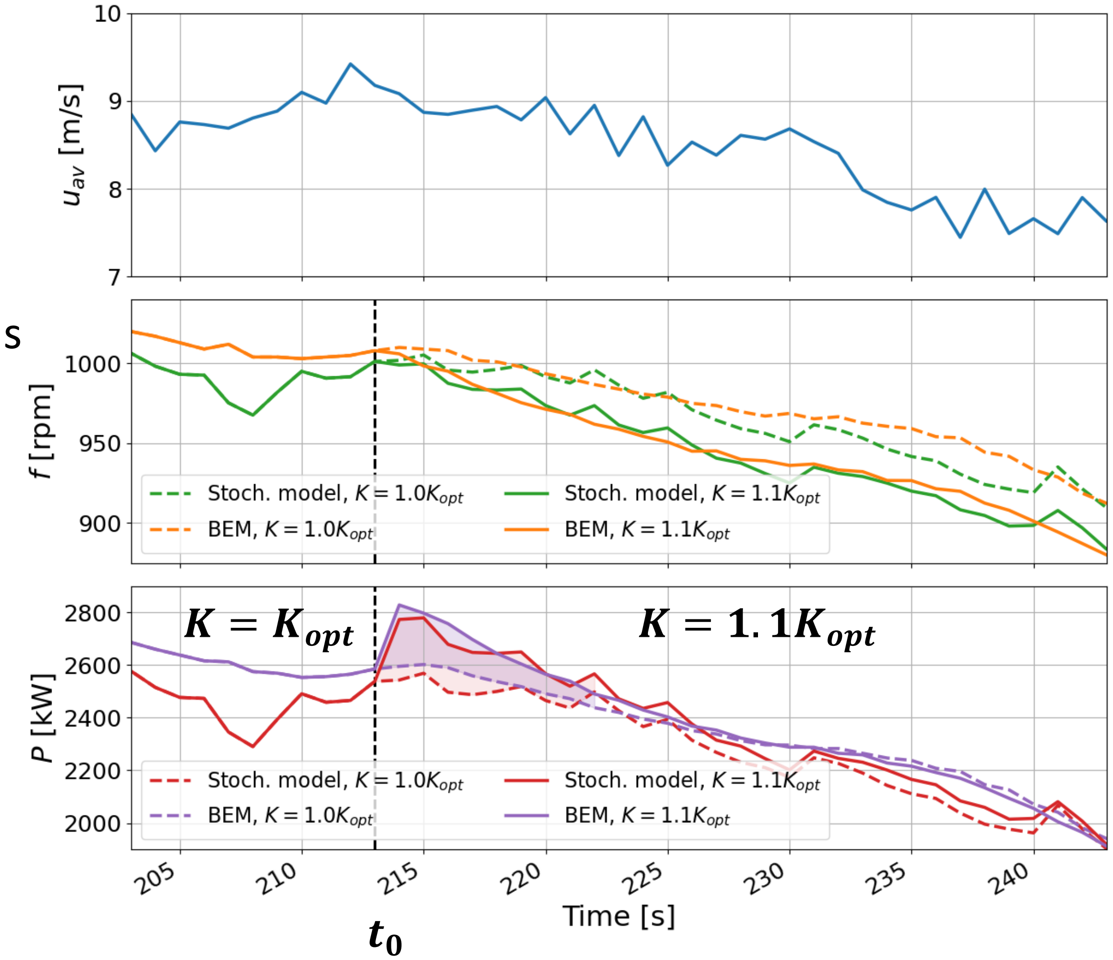
Quantification of rotational energy

Compute $E_{rot} \approx \int_{t_0}^{t_0+10s} P_{1.1K_{opt}}(t) \; - P_{1.0K_{opt}}(t)\, dt$:

➢ $E_{rot,\,BEM} = 1116\ \mathrm{kWs}$

Get uncertainty of stochastic model using $n = 20$ simulations with different noise from t_0:

➢ $E_{rot,\,Langevin} = (1404 \pm 108)\ \mathrm{kWs}$

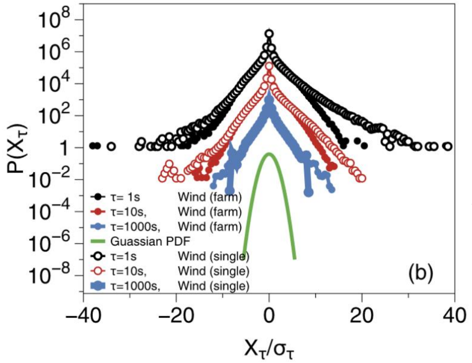


Quantification of rotational energy

Milan et al., PRL, 2013:

For one turbine, extreme 1s power increments of $\approx 25\ \%$ of the rated power occur

- ➢ In 10 seconds: $\approx 2500\ \frac{\text{kWs}}{\text{MW Nennleistung}}$



Anvari, *New J. Phys.*, 2016

Ullah et al., IEEE Trans. Power Syst., 2008:

At wind speeds $\geq 6.5\ \text{m/s}$, a wind turbine can access a rotational energy of $\approx 10\ \%$ of their rated power for $\approx 10\ \text{s}$.

- ➢ $\approx 1000\ \frac{\text{kWs}}{\text{MW Nennleistung}}$

Quantification of rotational energy

Milan et al., PRL, 2013:

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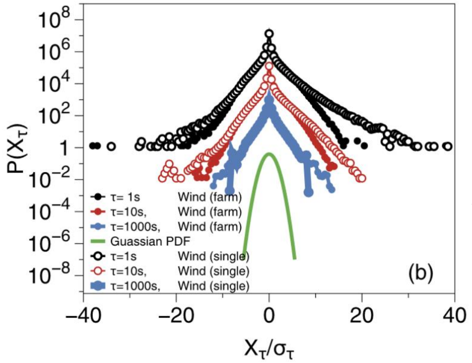


Anvari, *New J. Phys.*, 2016

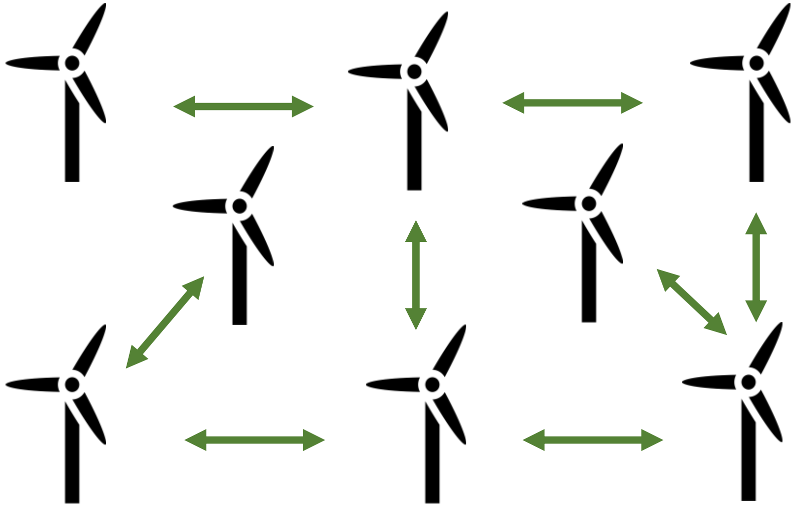
- ➢ need several turbines to compensate power increments of one turbine with rotational energy

Outlook

Examine synergy of multiple turbines to provide rotational energy

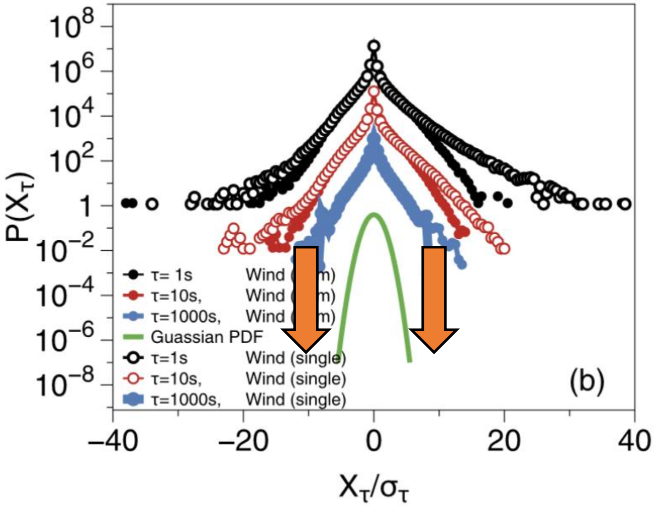
stochastic models

$f_1(t, f_2, \ldots, f_n, \ldots)$ $f_2(t, f_1, \ldots, f_n, \ldots)$ ...



Wind

Interaction?



Outlook

Picture: Jannis Maus

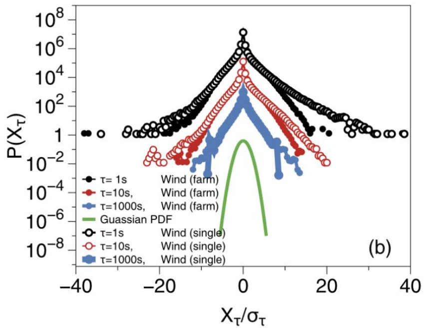
Verify model with experimental data (model turbines, $D = 0.6$ m)

Verify model with field data from WiVaIdi Research Wind Farm

Summary

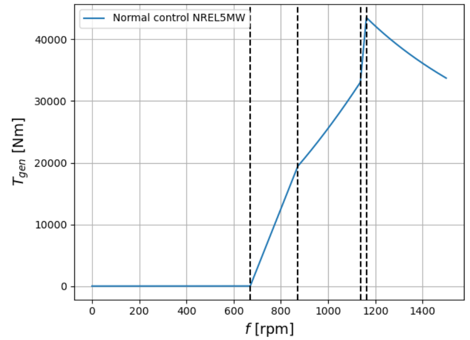
1. Motivation

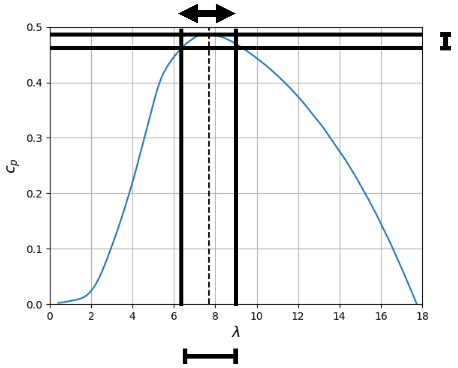
   - Intermittency exists on all scales and is relevant for power grid



2. Power Conversion of Wind Turbines

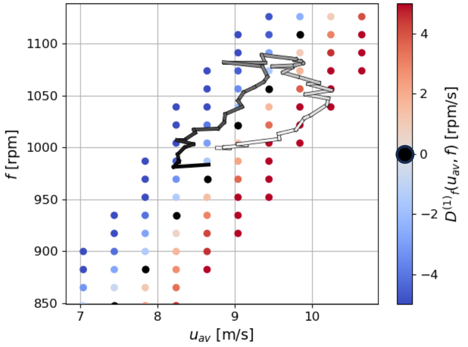
   - A torque balance between rotor and generator dominates the drive train dynamics
   - Variable speed wind turbines are state of the art
     - ➢ **Advantage:** Maximization of power production
     - ➢ **Disadvantage:** Removal of grid inertia
   - Using the generator torque, rotational energy can be accessed at minimal power loss





Summary

3. Stochastic Langevin Model
   - dynamical description of the wind turbine power conversion using stochastic approach
   - extraction of the deterministic dynamics from a noisy system is successful
   - gives a recursive model that agrees well with engineering model data



4. Accessing Rotational Energy in Langevin Model
   - train Langevin models for different torque controls
   - dynamic „torque control“ by switching between these models
   - after a switch: convergence back to fixed point gives transient of rotational energy provision