## Turbulence characterization from a forward-looking nacelle lidar

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#### M1: Lidar radial velocity spectra, filtered $\sigma_{v_e}^2$

• From Mann et al. (2009):

$$F_{\nu}(k_1) = n_i n_j \iint \left| \hat{\phi}(\boldsymbol{k} \cdot \boldsymbol{n}) \right|^2 \Phi_{ij}(\boldsymbol{k}) dk_2 dk_3, \qquad (1)$$

where  $\boldsymbol{n} = (-\cos\varphi, \sin\varphi\cos\theta, \sin\varphi\sin\theta)$ 

• Weighting function of CW lidar:

$$\phi(s) = \frac{1}{\pi} \frac{z_R}{z_R^2 + s^2} \Leftrightarrow \hat{\phi}(k_1) = \exp(-|k_1|z_R)$$
(2)

• Weigthing function of a pulsed lidar:

$$\phi(s) = \frac{z_R - |s|}{z_R^2} \Leftrightarrow \hat{\phi}(k_1) = \operatorname{sinc}^2(k_1 z_R/2)$$
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## M1: CW lidar, $\Gamma = 3$ , $\alpha \varepsilon^{2/3} = 0.1$ , $\varphi = 15^{\circ}$



## **M1:** pulsed lidar, $\Gamma = 3$ , $\alpha \varepsilon^{2/3} = 0.1$ , $\varphi = 15^{\circ}$



#### **M1:** For $\Gamma = 3$ , $\varphi = 15^{\circ}$

pulsed lidar in solid lines and CW lidar in dashed lines



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# M2: Doppler spectra info, $z_R/L = 0$ (no filtering), no turbulence model, unfiltered $\sigma_{v_r}^2$

Assuming homogeneous turbulence within the rotor area:  $\sigma_{v_r}^2(\theta) = \\
\sigma_{u}^2 \cos^2 \varphi + \sigma_v^2 \sin^2 \varphi \cos^2 \theta + \sigma_w^2 \sin^2 \varphi \sin^2 \theta - 2\overline{u'w'} \cos \varphi \sin \varphi \sin \theta$ 





#### Nørrekær Enge wind farm



### **10-min time-series examples**



# Wind reconstruction (for spectra and 18-s filtered variance analysis)



#### raw vs. noise-filtered velocity spectra (for M2)



# M2: $\sigma^2_{v_{r,unf}}$ Doppler spectra: bin 0 (left) and bin 31 (right)



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#### M2: Unfiltered vs 18-s based filtered variances



## Stability and wind speed ranges

class	z/L <sub>0</sub>	no. of 10-min samples	$\langle z/L_O \rangle$	$\langle U \rangle  [m  s^{-1}]$	$\langle u_* \rangle  [\text{m s}^{-1}]$
stability 1	-0.1 - 0.1	225	0.0625	12.75	0.68
stability 2	0.1-0.2	629	0.1489	12.54	0.61
stability 3	0.2-0.3	350	0.2435	11.34	0.48
stability 4	0.3-0.4	225	0.3475	10.71	0.42
stability 5	0.4-0.5	153	0.4457	10.02	0.35
class	$U [{\rm m}~{\rm s}^{-1}]$	no. of 10-min samples	$\langle U \rangle  [{\rm m \ s}^{-1}]$	z/Lo	$\langle u_* \rangle  [{ m m \ s}^{-1}]$
class speed 1	U [m s <sup>-1</sup> ] 5-7	no. of 10-min samples 93	$\langle U \rangle \ [m \ s^{-1}] $ 6.65	z/L <sub>O</sub> 0.5084	$\langle u_* \rangle  [\text{m s}^{-1}]$ 0.21
class speed 1 speed 2	U [m s <sup>-1</sup> ] 5-7 7-9	no. of 10-min samples 93 516	⟨U⟩ [m s <sup>-1</sup> ] 6.65 7.98	z/L <sub>O</sub> 0.5084 0.7196	$\langle u_* \rangle  [m  s^{-1}]$ 0.21 0.23
class speed 1 speed 2 speed 3	U [m s <sup>-1</sup> ] 5-7 7-9 9-11	no. of 10-min samples 93 516 506	$\frac{\langle U \rangle \ [\text{m s}^{-1}]}{6.65}$ 7.98 10.07	z/L <sub>0</sub> 0.5084 0.7196 0.3684	$\langle u_* \rangle \ [m \ s^{-1}]$ 0.21 0.23 0.37
class speed 1 speed 2 speed 3 speed 4	U [m s <sup>-1</sup> ] 5-7 7-9 9-11 11-13	no. of 10-min samples 93 516 506 741	$\frac{\langle U \rangle \ [m \ s^{-1}]}{6.65} \\ 7.98 \\ 10.07 \\ 11.94$	z/L <sub>0</sub> 0.5084 0.7196 0.3684 0.2133	$\begin{array}{c} \langle u_* \rangle \ [m \ s^{-1}] \\ 0.21 \\ 0.23 \\ 0.37 \\ 0.52 \end{array}$

#### M1: Atmospheric stability and wind speed ranges









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#### M1: Mann parameters behaviour



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### Conclusions

- Using the 10-min Doppler LOS spectrum, we are able to derive unfiltered  $\sigma_{\rm vr}^2$
- Comparison with cup reveals 2% bias for  $\sigma_u^2$
- Variances from noise-filtered lidar LOS spectra are well predicted by the Mann and spatial averaging lidar models
- Mann parameters derived from lidar LOS spectra agree with those from a sonic under high wind and neutral conditions
- For other conditions, this could be better done by increasing cone angle



## Thank you for the attention!

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More details in: Peña A., Mann J. and Dimitrov N. (2017): Turbulence characterization from a forward-looking nacelle lidar. Wind Energ. Sci. 2:133–152

