



#### Tuhfe Göçmen

# IEA Task 51 Minute-scale forecasting

### EA Task 51 Workstreams

#### **Minute Scale Forecasting**

WS:	WP1 Weather	WP2 Power	WP3 Applications	Deliverable	#, Due	Collaboration
Minute scale forecasting (WP2)				Workshop / Paper	D2.5 / M31, M36	Wind Tasks 32 Lidar, 44 Farm Flow Control and 50 Hybrids, PVPS T16

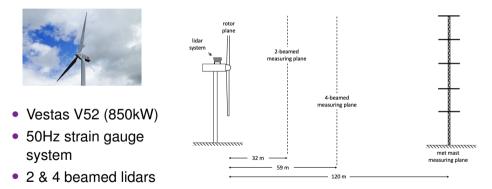
- **Objectives:** Assessment of state-of-the-art methods and performance levels for minutes ahead forecasting
- **Deliverable:** (D2.5) Workshop and paper on minute-scale forecasting for hybrid power plants or wind farm control, in conjunction with Task 32 on Lidars, Task 44 on Farm Flow Control and Task 50 on Hybrid Power Plants (M31, M36)



Cross-disciplinary examples: LiDAR based forecasting

### **Experimental Setup**

#### Test Turbine & nacelle mounted continuous wave lidar



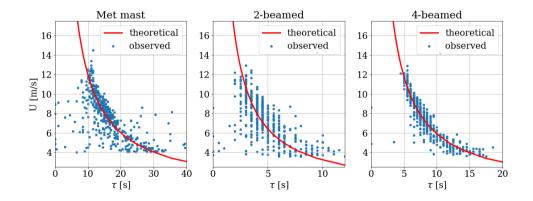
Met-mast

4



Cross-disciplinary examples: LiDAR based forecasting

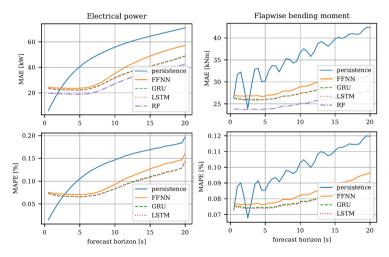
#### Met-mast vs. LiDAR - Time delay analysis





Cross-disciplinary examples: LiDAR based forecasting

#### Power & Load Forecast Performance: MAE & MAPE



- Benchmark is currently being extended
- Stay tuned for the upcoming article

Cross-disciplinary examples: DMD forecasts for WF(F)C at Lillgrund

## Streaming dynamic mode decomposition for short-term forecasting

sDMD is ...

- able to identify low-rank behaviour in a high-dimensional system  $\rightarrow$  Reduced computational costs
- compatible with classical control theory as it is able to estimate the system behaviour as a linear dynamic system
- able to update as new data become available  $\rightarrow$  Adapts to changing system conditions
- relatively simple in math  $\rightarrow$  Increased interpretability and explainability compared to the intelligent forecasting approaches

$$\mathbf{\mu}_{\mathbf{k}}^{\mathsf{AUG}} = \begin{bmatrix} \boldsymbol{\Omega}_{k-\mathsf{w}+1} & \dots & \boldsymbol{\Omega}_{k-1} & \boldsymbol{\Omega}_{k} \\ \boldsymbol{\Omega}_{k-\mathsf{w}} & \dots & \boldsymbol{\Omega}_{k-2} & \boldsymbol{\Omega}_{k-1} \\ \vdots & \vdots & \vdots & \vdots \\ \boldsymbol{\Omega}_{k-\mathsf{s}-\mathsf{w}+1} & \dots & \boldsymbol{\Omega}_{k-\mathsf{s}-1} & \boldsymbol{\Omega}_{k-\mathsf{s}} \end{bmatrix}$$

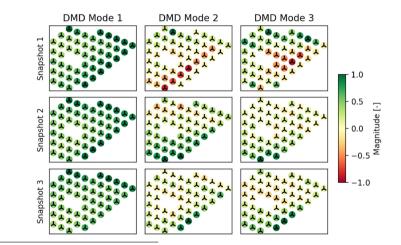
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Liew, J, Göçmen, T, Lio, WH, Larsen, GC. Streaming dynamic mode decomposition for short-term forecasting in wind farms. *Wind Energy*, 2021: 1-16



cross-disciplinary examples: DMD forecasts for WF(F)C at Lillgrund

### DMD 3-min ahead forecasts at Lillgrund : 24-h investigation

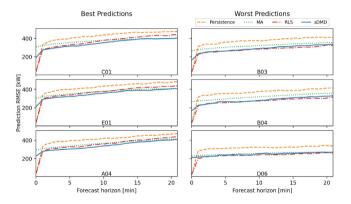


Snapshot  $1 - 3 \rightarrow \text{East} - \text{North}$ 



#### Cross-disciplinary examples: DMD forecasts for WF(F)C at Lillgrund

### DMD forecasts 3-min ahead at Lillgrund : 24-h investigation



- sDMD beats RLS & others after 30-sec forecasts (most of the time)
- More robust as it is based on low order
- Currently being implemented as the state observer/agent in reinforcement learning WFC



# **Outlook: Challenges & Prospects**

- Many inter-sections with other disciplines  $\rightarrow$  cross-collaboration is key!
- · Certainly a growing field collection of most recent works?
- Potential elicitation surveys to assess the challenges & research gaps
  → could build into road-maps / recommendations / best practices

