Zentrum für Sonnenenergie- und Wasserstoff-
Forschung Baden-Württemberg

Projekt ParkCast: Optimization of Power-Nowcasting for Offshore-Windfarms using long-range Lidar and Data Assimilation

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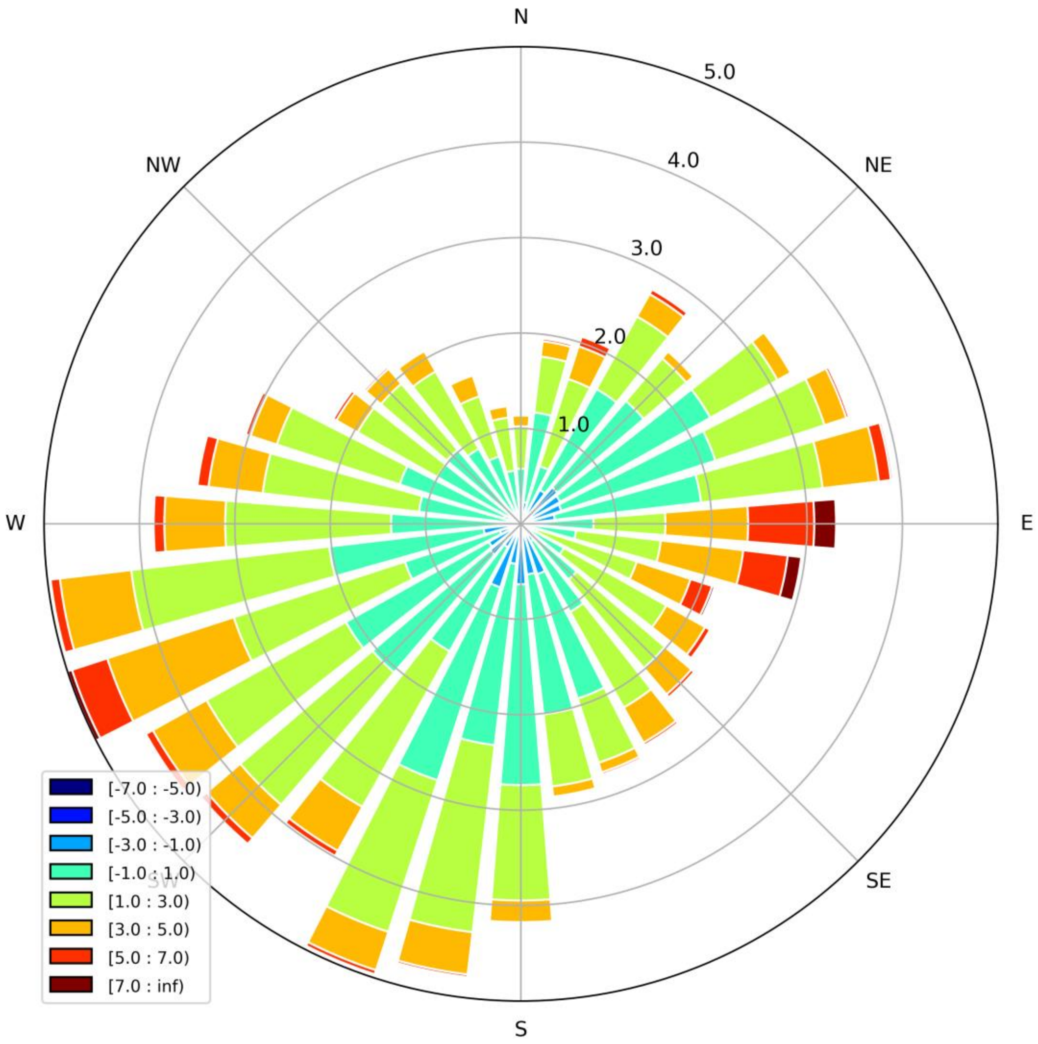
Motivation

On a time scale of minutes to hours…

- **Power generation** of wind turbines can be **highly variable**.
- Causes:
  - Ramp Events
  - Wake Effects due to nearby turbines
- These events are notoriously difficult to predict accurately using numerical models.

Observations from upstream is required → remote sensing.



- Model Errors of wind speed (WRF – FINO1, 1 Year of Simulation)

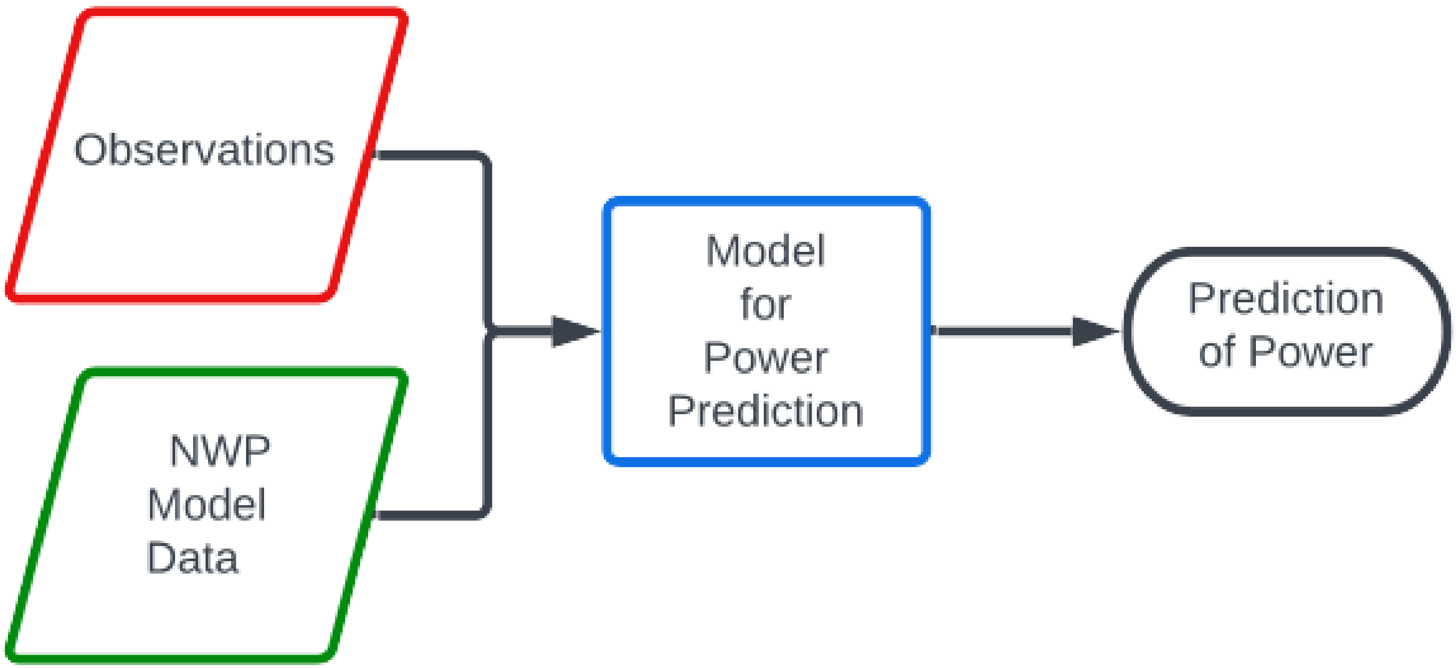
What is needed?

Observations: Long Ranged LIDAR

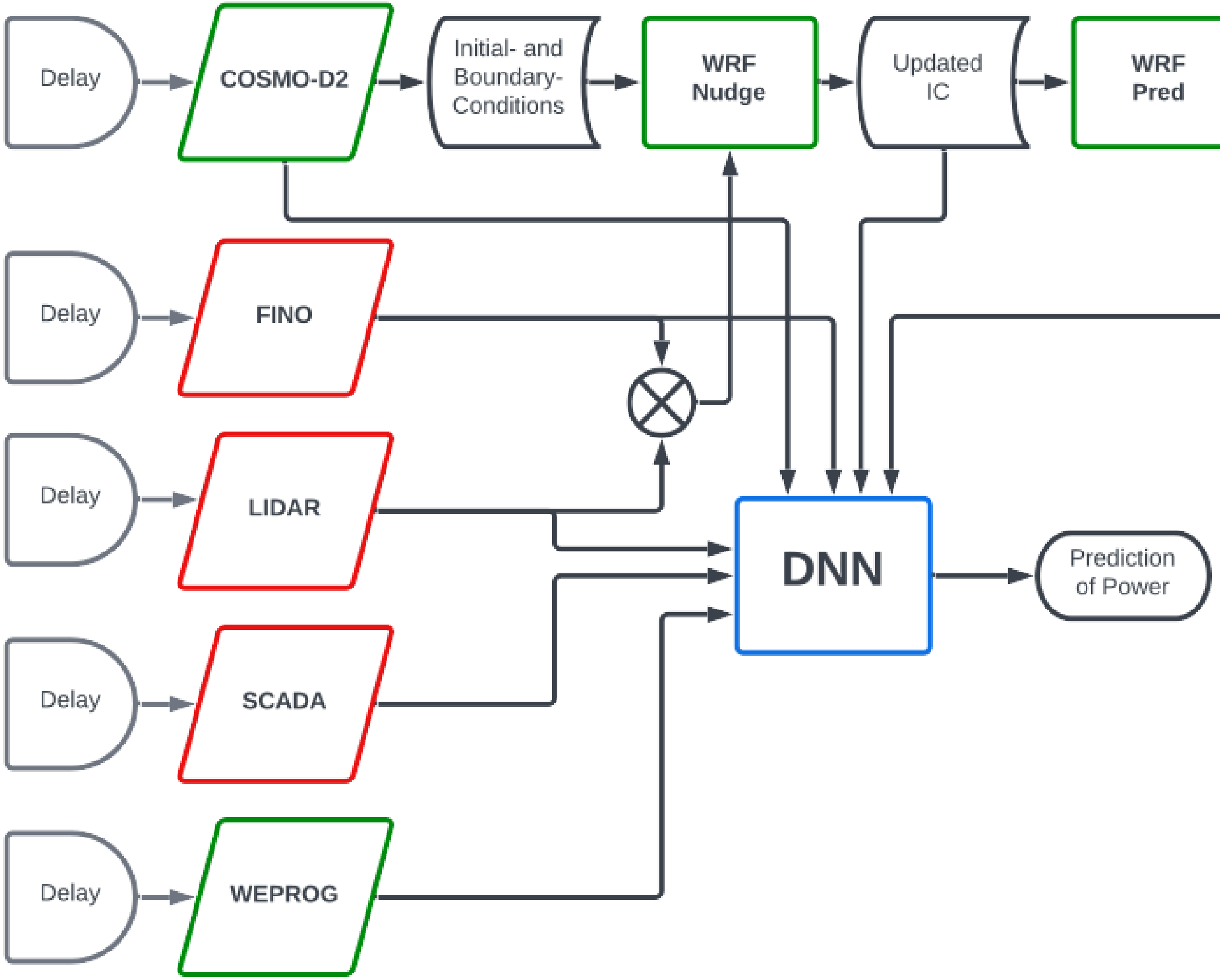
- Long Ranged (>= 10 km)
- Observe at least wind speed at hub height.
- Reliable and fast data transmission.

- **NWP Model Data**
  - Used to complement incomplete or missing Obs.
  - Used as a fallback

- **Model**
- Accurate & Sharp
- **Fast**
- Reliable



Nowcasting Process Chain



- **Fail-Save Design**
- Multiple DNN have been trained
- Each DNN is missing one or more Data sources. → A power prediction is always possible
- The best prediction can be done if all data sources are available.

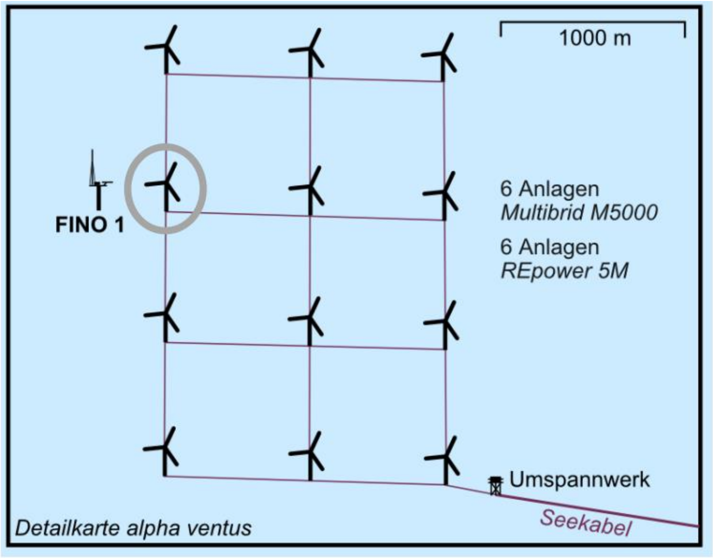
Observations and Model Data

Observations

- Lidar Observations: SWE (Univ. Stuttgart)
- FINO1 – Data: BSH
- SCADA – Data: RAVE Consortium

Model Data

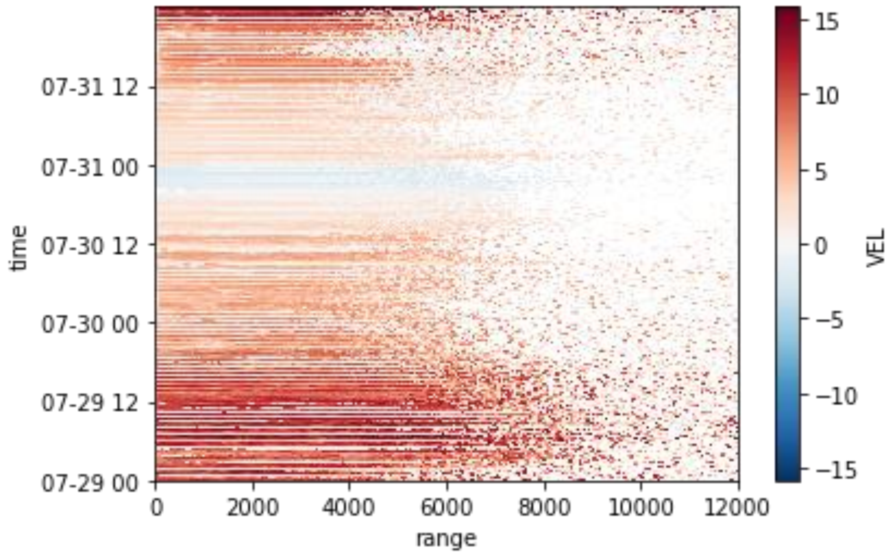
- COSMO-2 (DWD) (Δx = 2.2 km)
- WRF-Simulation (Δx = 733.33 m)
- WEPROG Ensemble Data

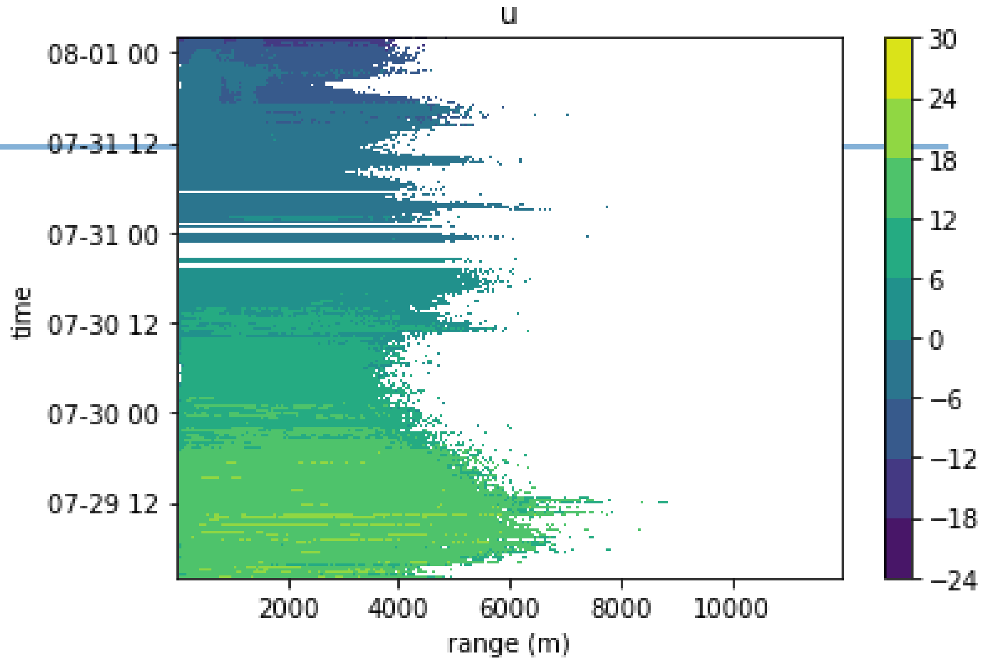


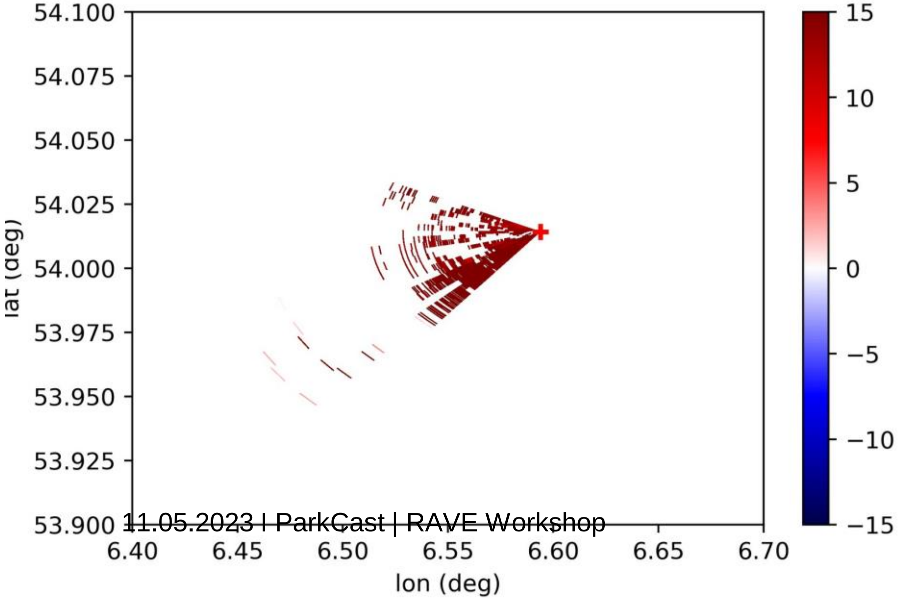
Weather & Energy Prognoses
WEPROG
inclusive physic. Uncertainty from Ensembles

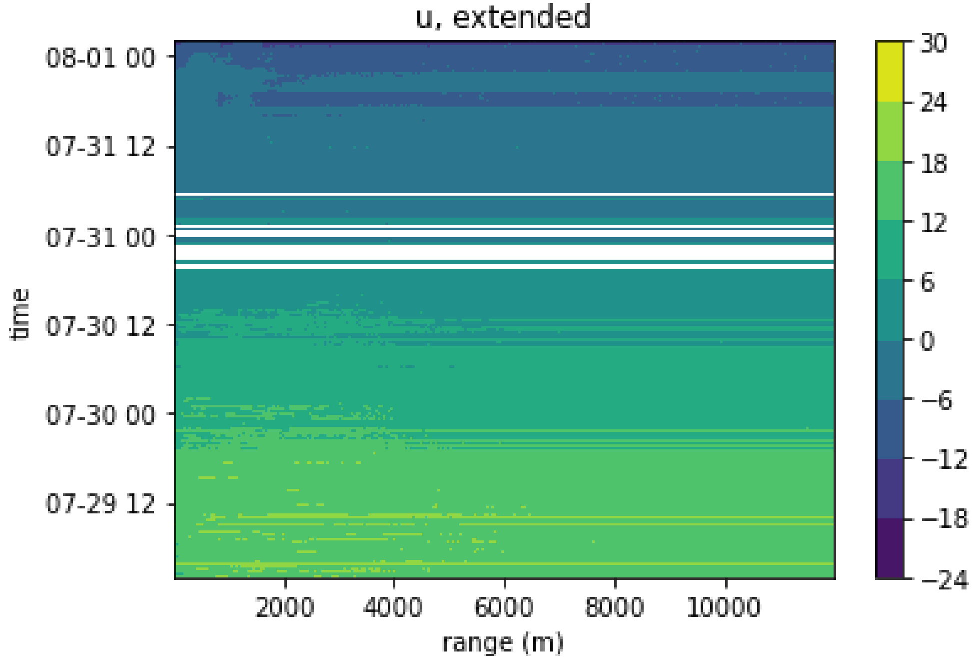
Multiple data sources as a **safeguard against failure**

Challenge 1: Processing of Lidar Data

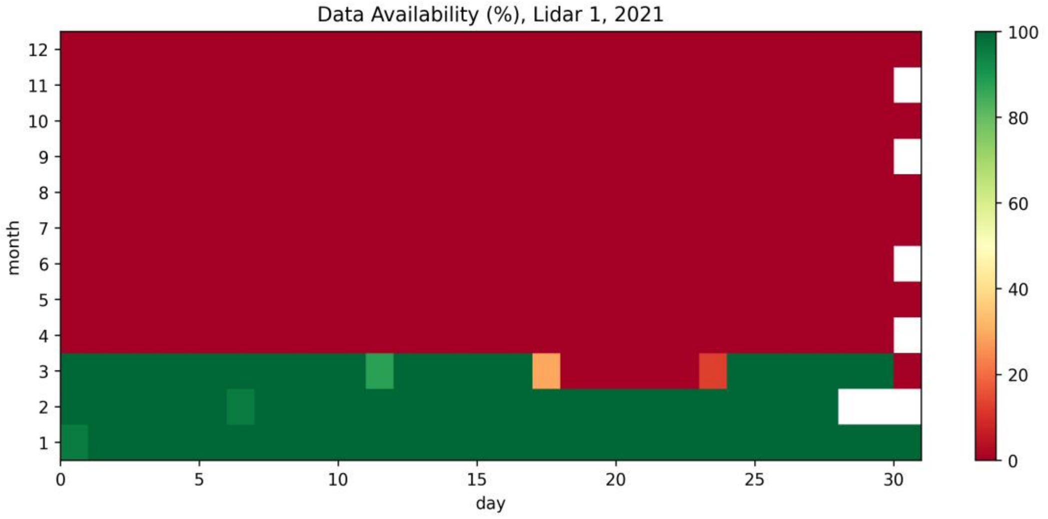


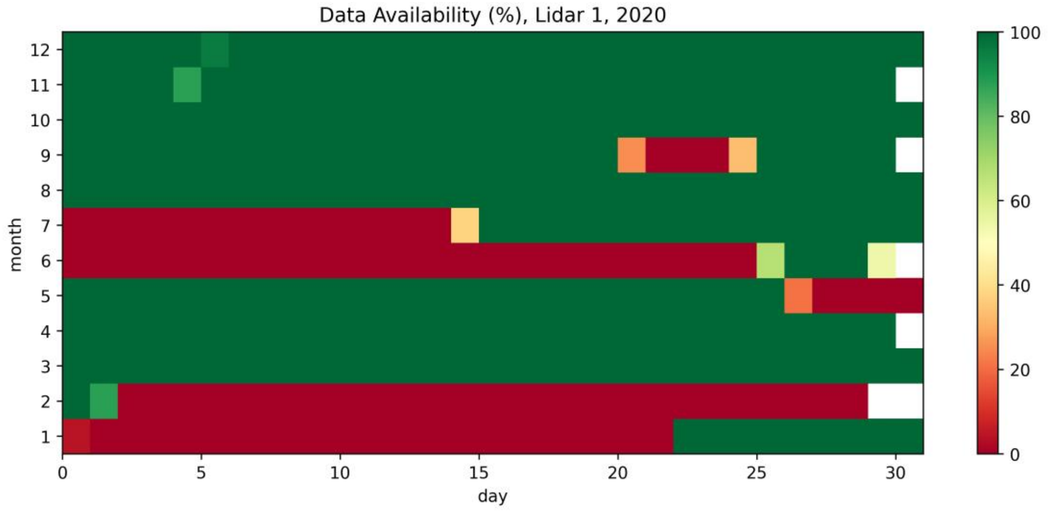


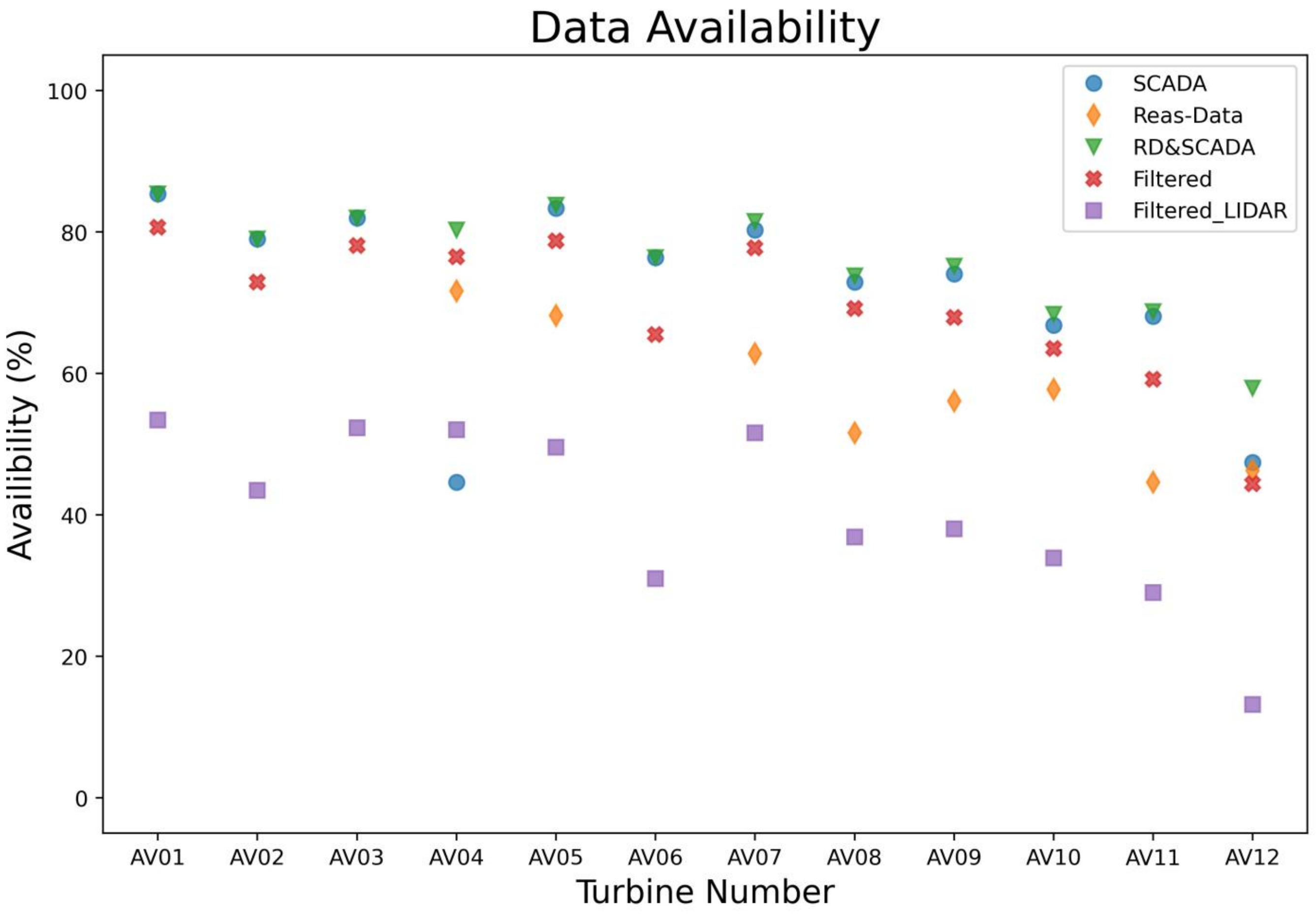




Challenge 2: Data Availability

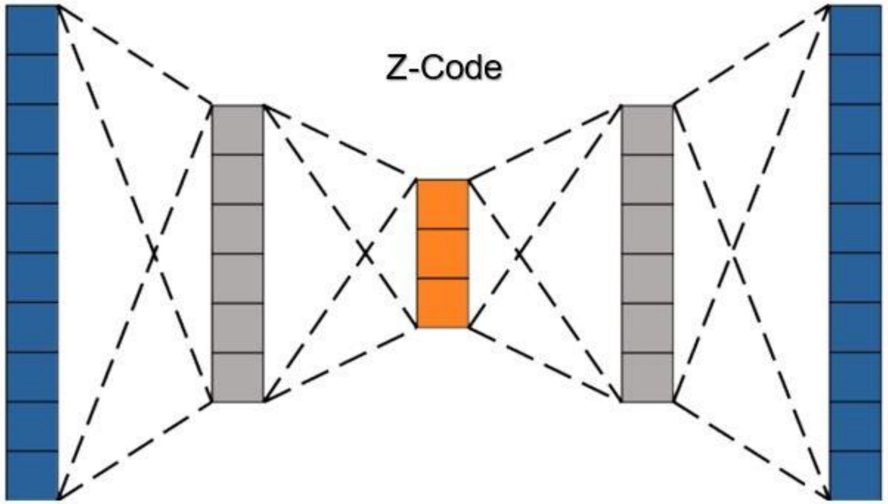


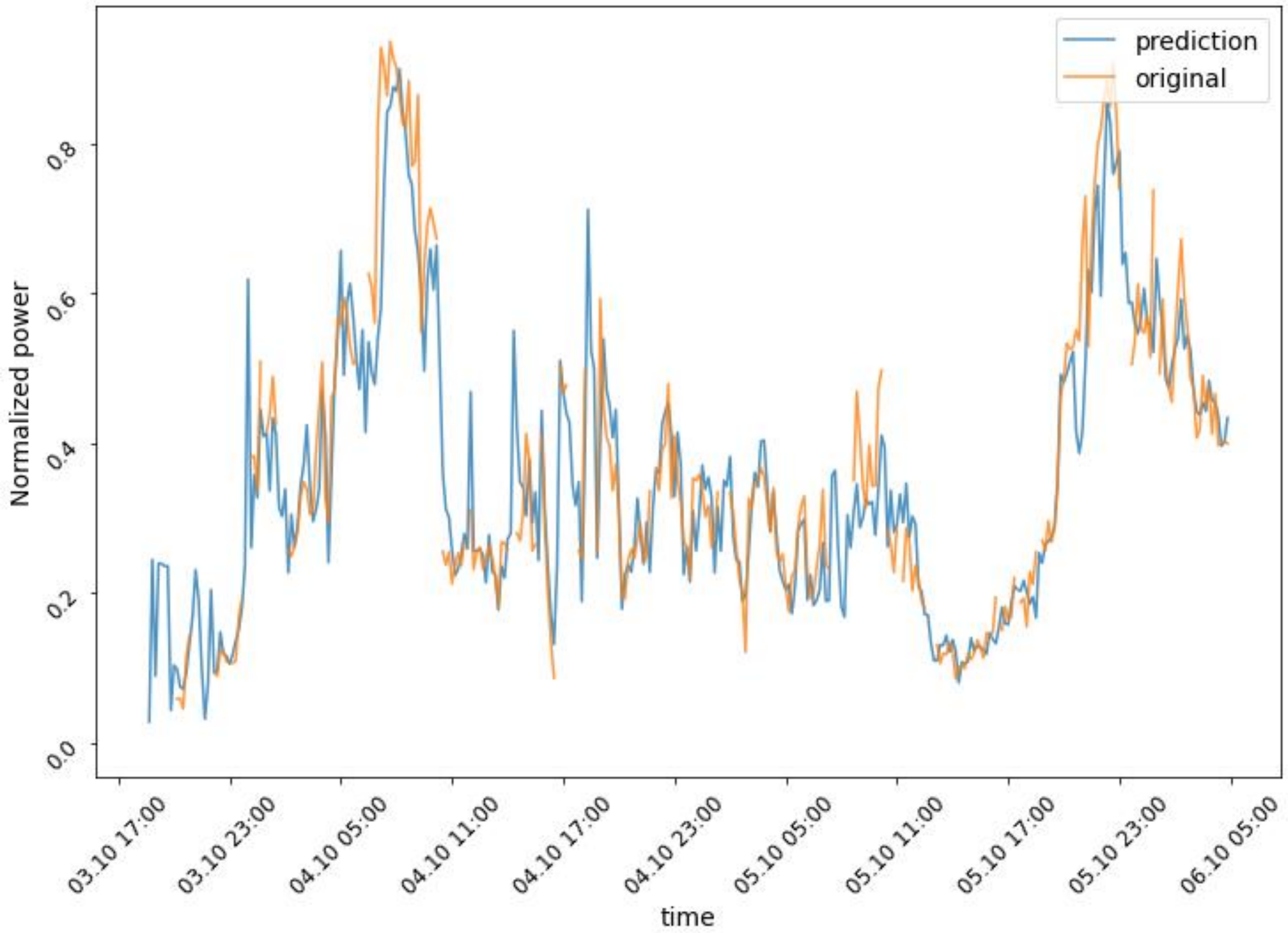




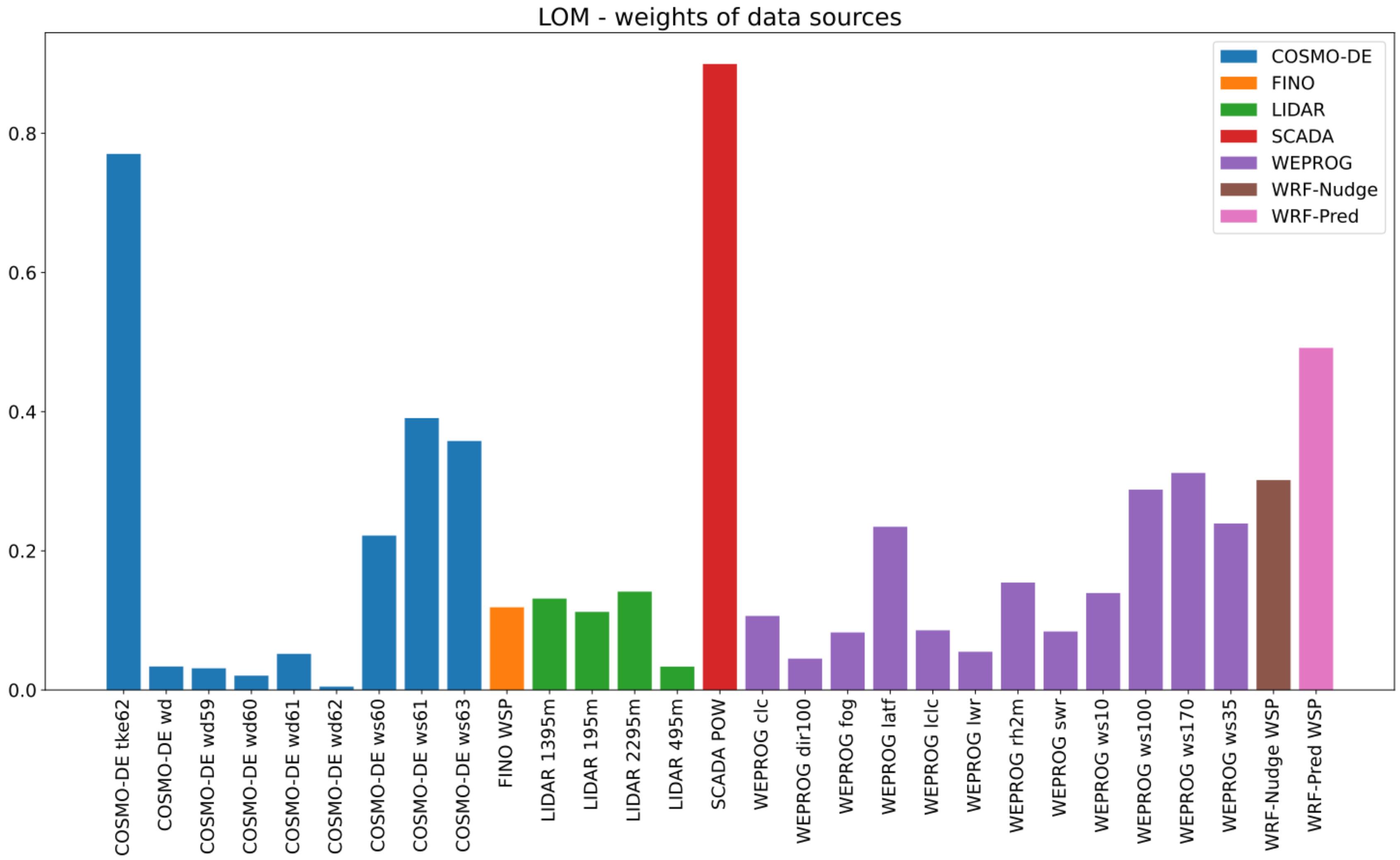
Challenge 2: Data Availability

- Autoencoder approach to fill gaps in available SCADA Data.
- Trained with “good” data only.
- Artificial gaps are put into these time series
- Machine Learning Model trained to fill the gaps with the most likely values based on observed patterns.
- Work only for relatively small gaps.





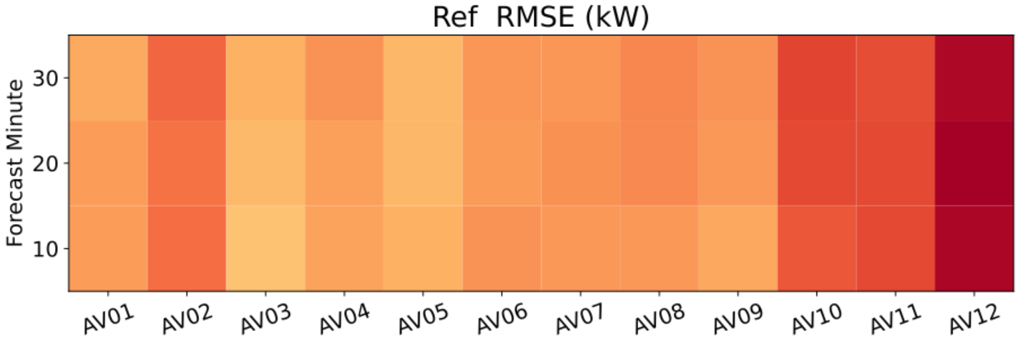
Training of the DNN: Which data sources are important?

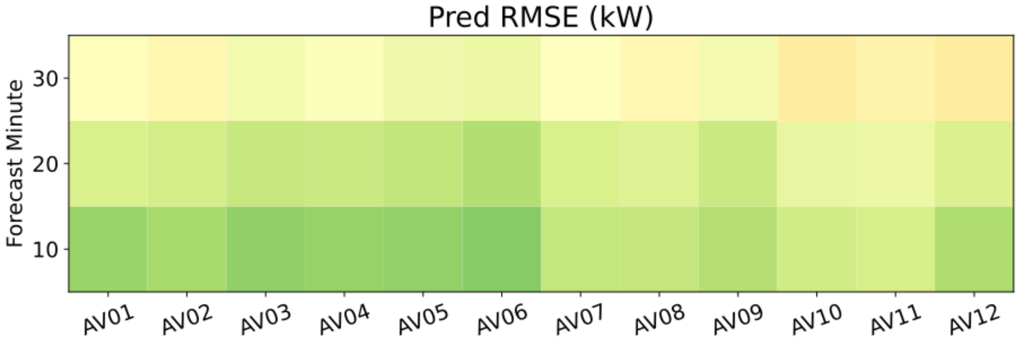


- **Feature Selection**
- Most important features:
  - SCADA POW,
  - COSMO-D2 TKE & WSP,
  - WRF Model Wind Speed.
- FINO and LIDAR Data are selected as well, but with smaller weights (limited range)
- WEPROG Data contributes considerably

Results

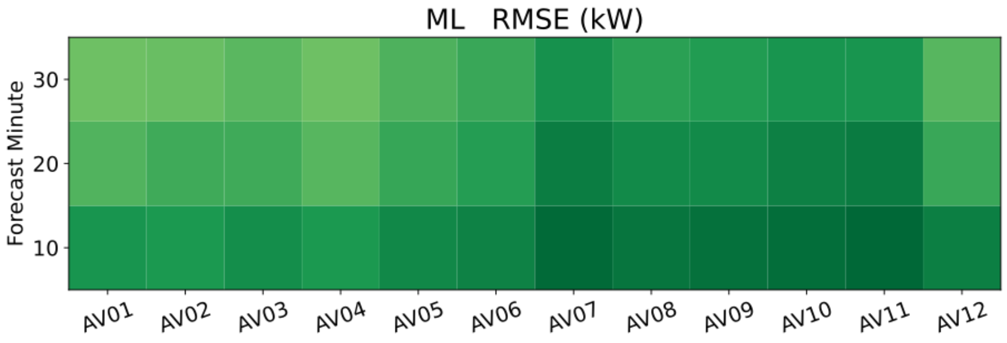
Reference: unmodified WRF

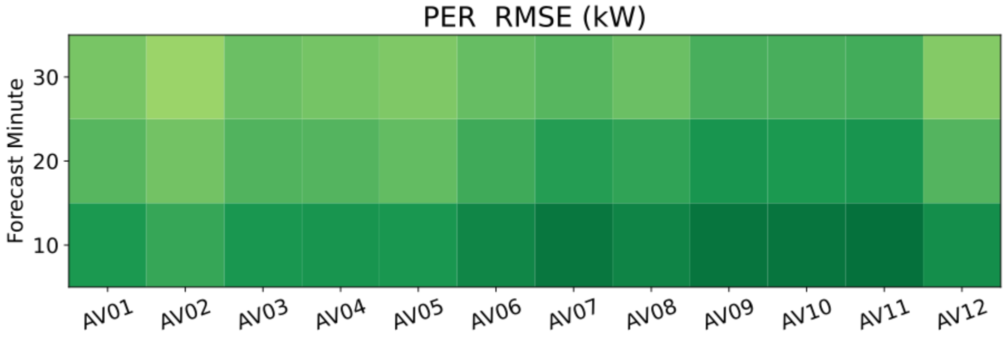


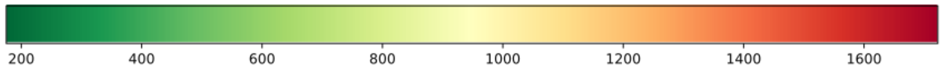


Reference: lidar-nudged WRF

Machine Learning (ML)



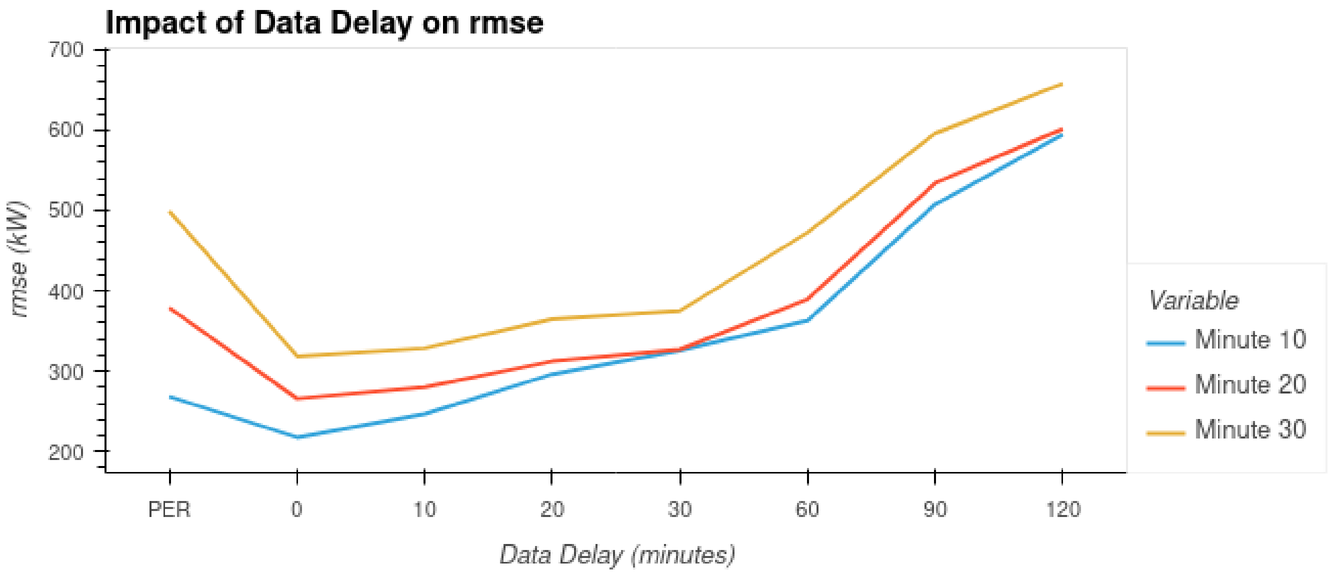


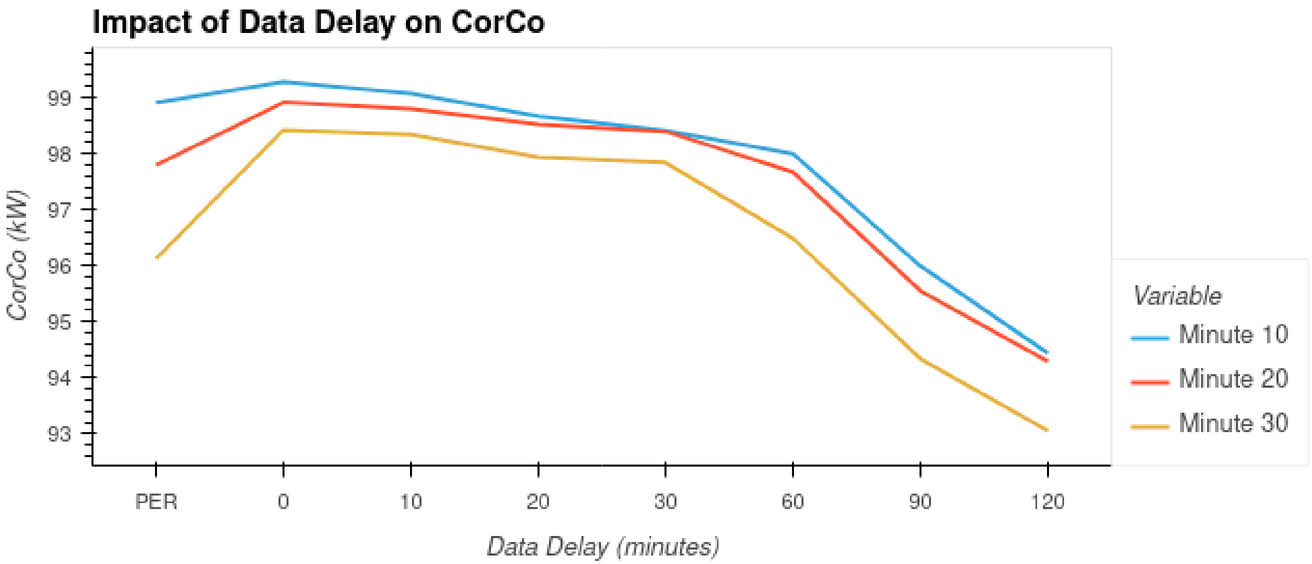


Persistence

Challenge 3: Data Delay

- Prediction of Power is better than Persistence for 10 Minute prediction.
- Using old data reduces the quality of the prediction drastically.
- Prediction for t+10 min:
  Data should be available as fast as possible.
- Prediction for t+20 min:
  Data with 30 Minute delay is still useful
- 10 Minute SCADA data was used as ground truth.





Conclusion

Using Machine Learning and Lidar Observations,

- it is possible to forecast the power production on time-scales < 1h
- with a skill (slightly) better than 10 minute Persistence
- provided the required data is available

Suggestions for future research and development

- Improvements in data availability and training with more data
- Using a lidar with a longer range or a network of lidars.
  - Floating Lidar
  - Lidar on other Turbines
- Cooperation between wind farm operators for data exchange would **enable systems that benefit all.**

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- WEPROG

RAVE
RESEARCH AT ALPHA VENTUS

Data Providers: RAVE, BSH

Universität Stuttgart