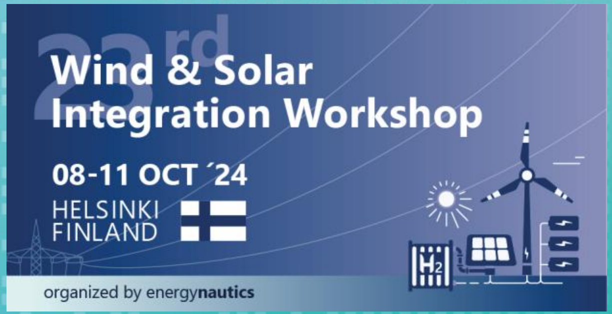
Fraunhofer IEE



Fraunhofer IEE – Dominik Beinert, Johannes Schütz, Dr. Axel Braun

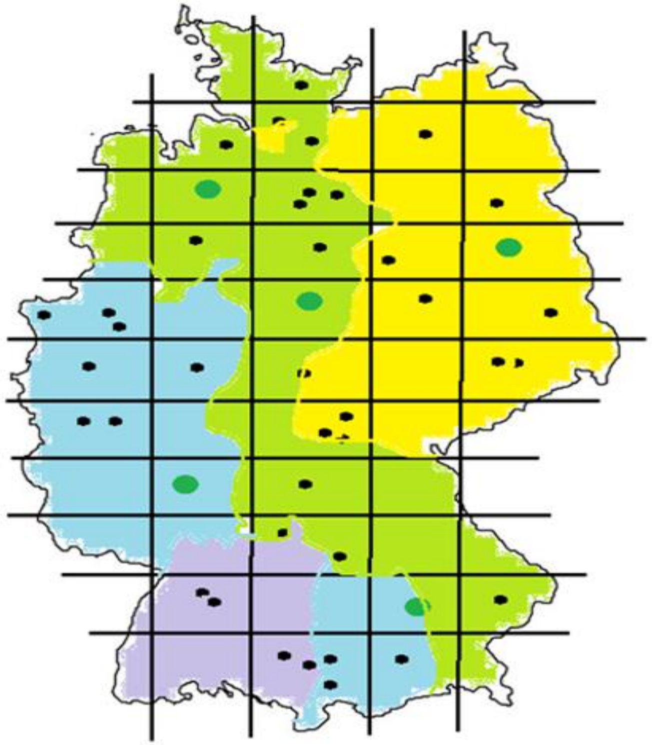
Wind & Solar Integration Workshop 2024, Helsinki

Estimation and aggregation of wind power forecasts utilizing master data and zero-shot learning

Motivation

Wind power forecasts for TSO control zones

Forecasts essential for transmission system operators



TSO control zones

Siefert, M., Hagedorn, R., Fundel, V., et al.: ‘Gridcast - Erhöhung der Netzsicherheit durch flexibilisierte Wetter und Leistungsprognosemodelle auf Basis stochastischer und physikalischer Hybridmethoden’, (Fraunhofer IEE,2022), pp. 65

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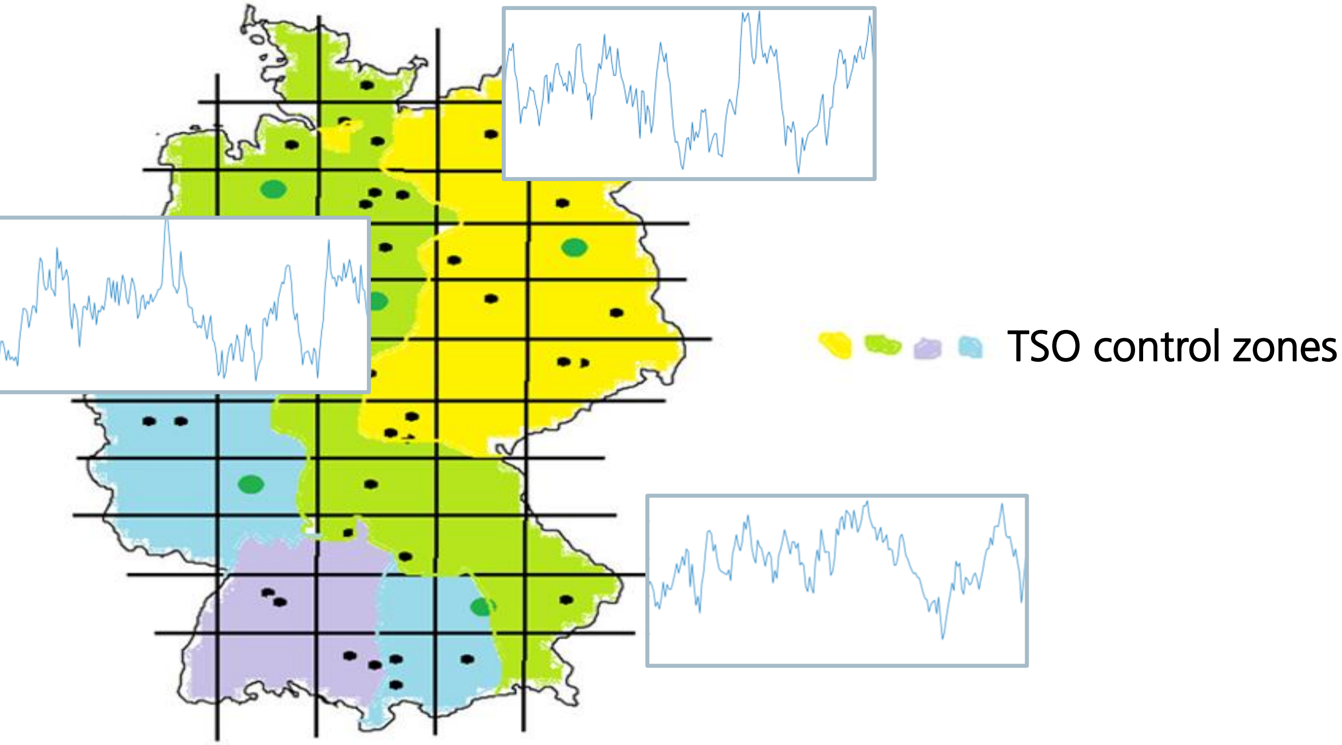

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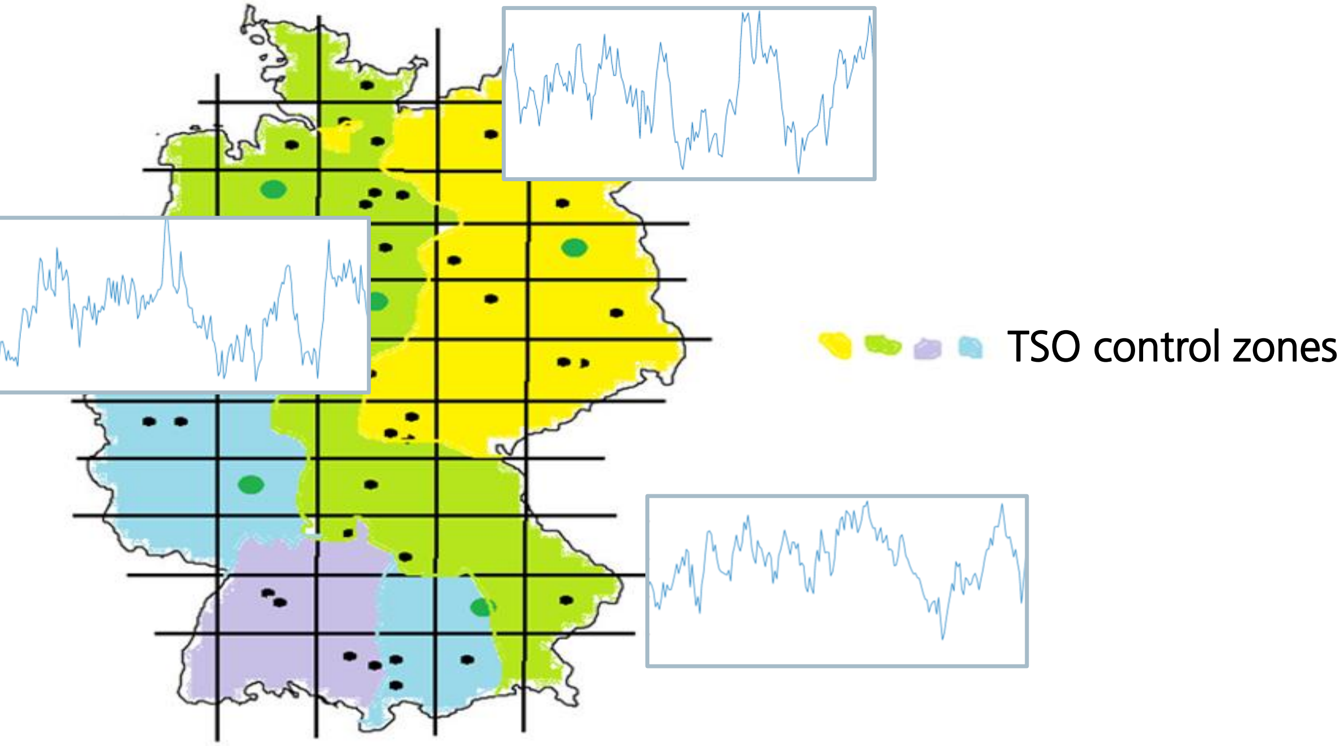

Typical approach

- Make local wind park forecasts
- Aggregate to control zones

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Fraunhofer IEE

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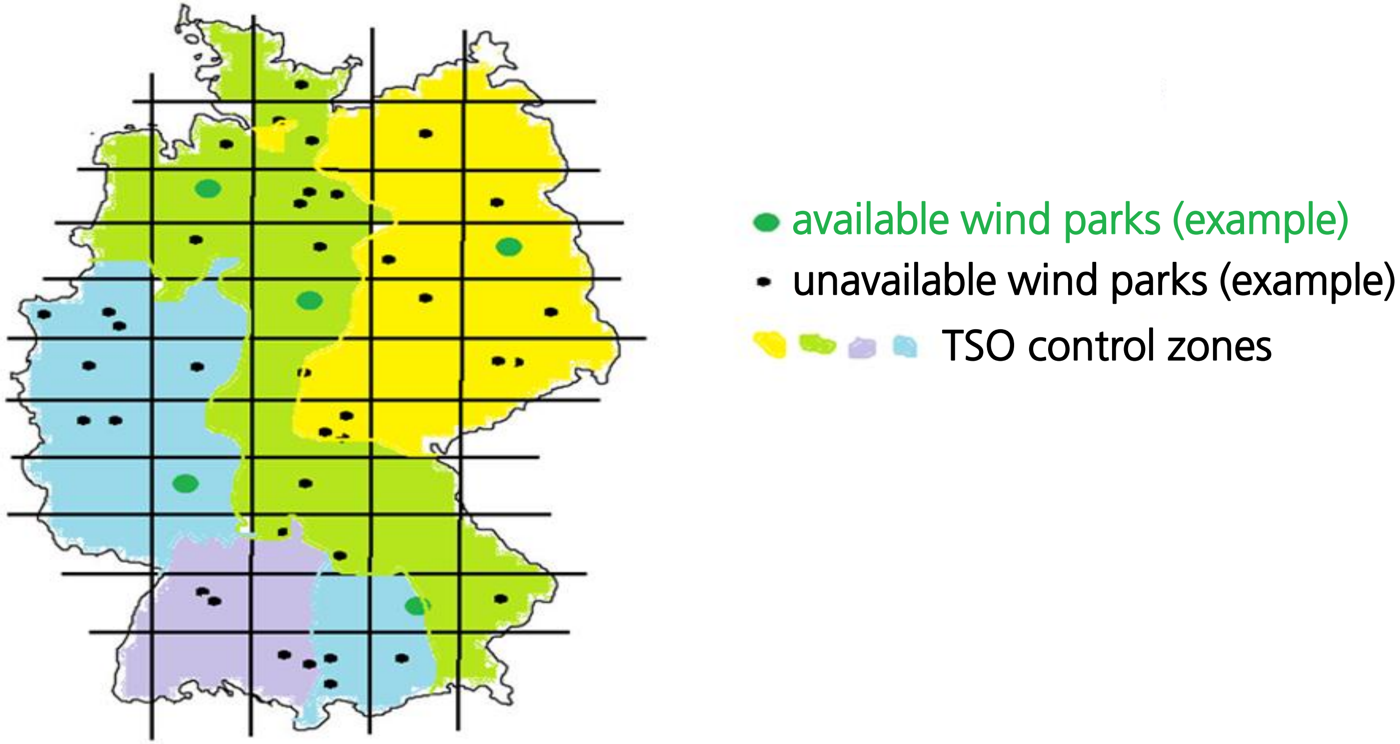

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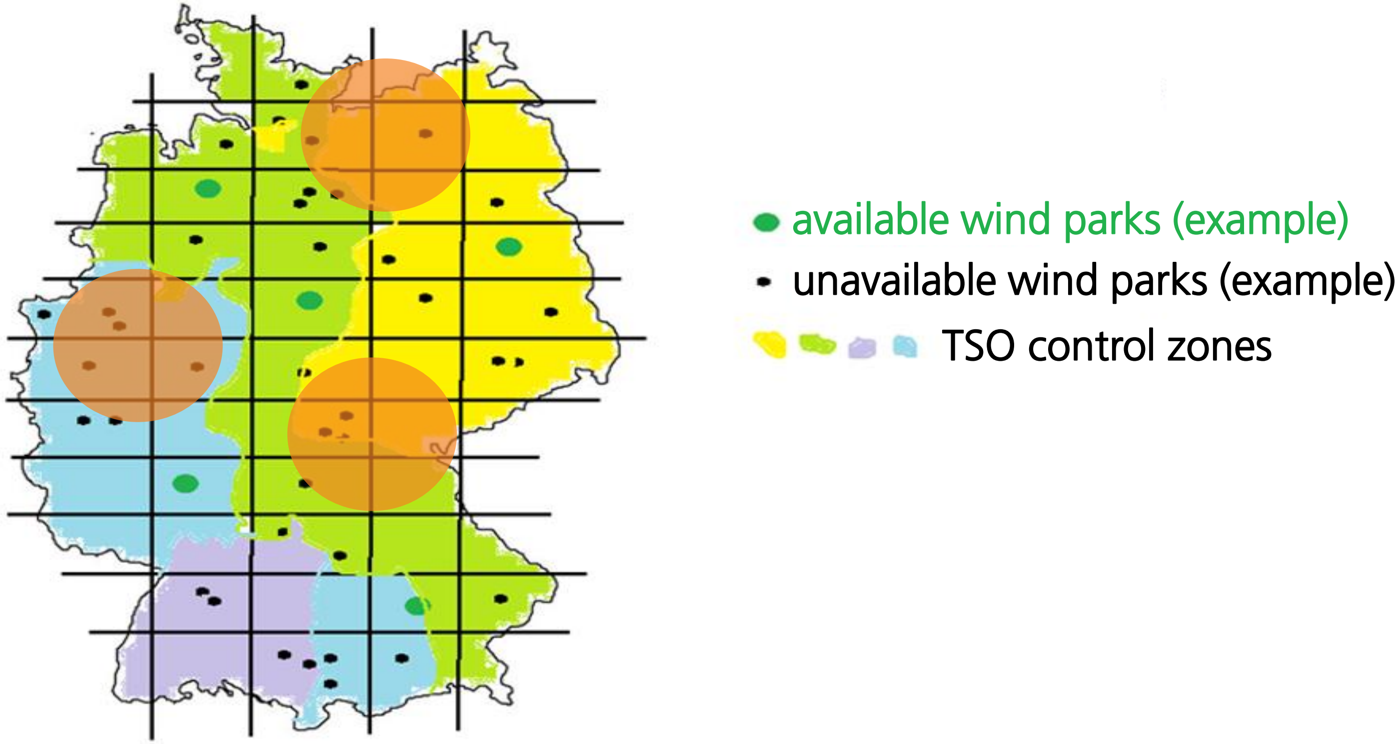

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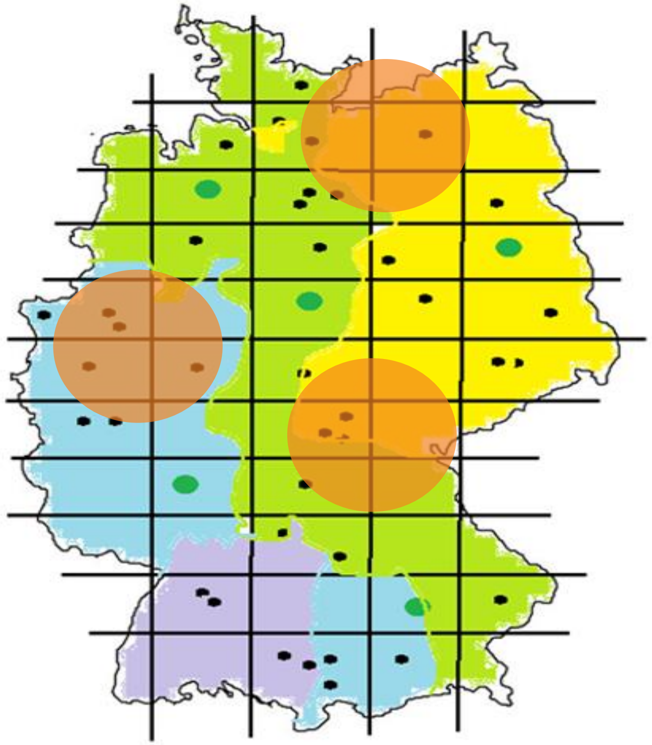


available wind parks (example)

unavailable wind parks (example)

TSO control zones

Siefert, M., Hagedorn, R., Fundel, V., et al.: 'Gridcast - Erhöhung der Netzsicherheit durch flexibilisierte Wetter und Leistungsprognosemodelle auf Basis stochastischer und physikalischer Hybridmethoden', (Fraunhofer IEE,2022), pp. 65

Typical approach

- Make local wind park forecasts
- Aggregate to control zones

Goal:
Publicly available master data
+
zero-shot learning model
=
forecasts at unavailable parks for aggregation

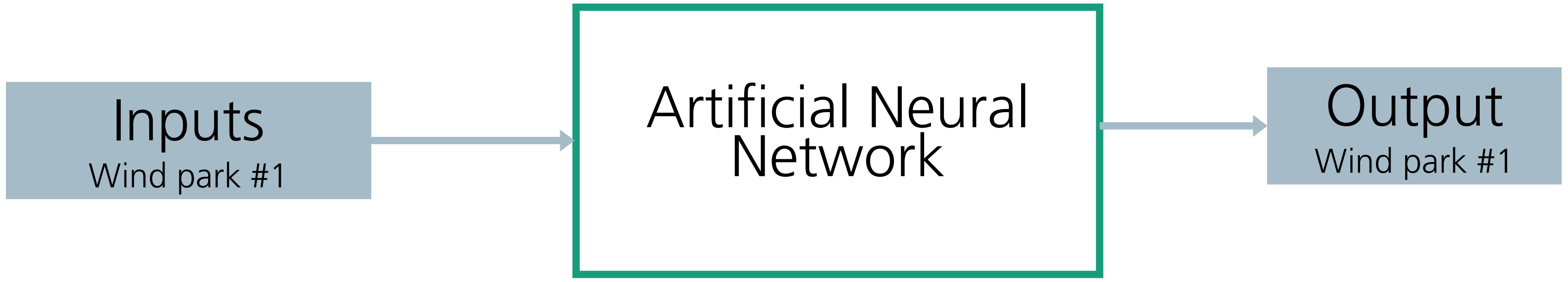
Question:

Do zero-shot forecasts at unavailable parks improve forecast accuracy at TSO control zones?

Zero-shot learning

Base model architecture

Bayesian Embedding Multi-Task Learning Multi Layer Perceptron (BE-MTL-MLP)*



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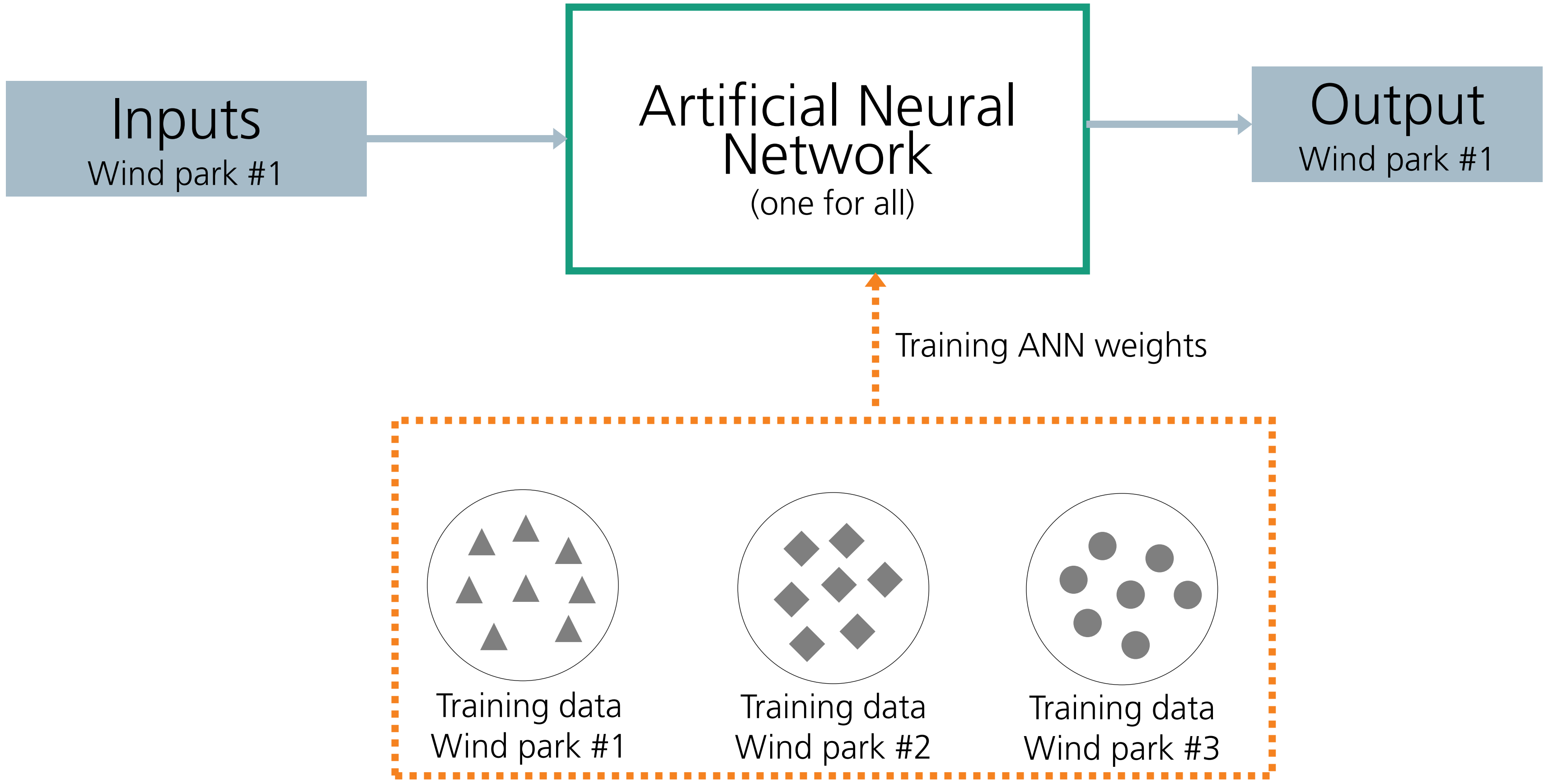

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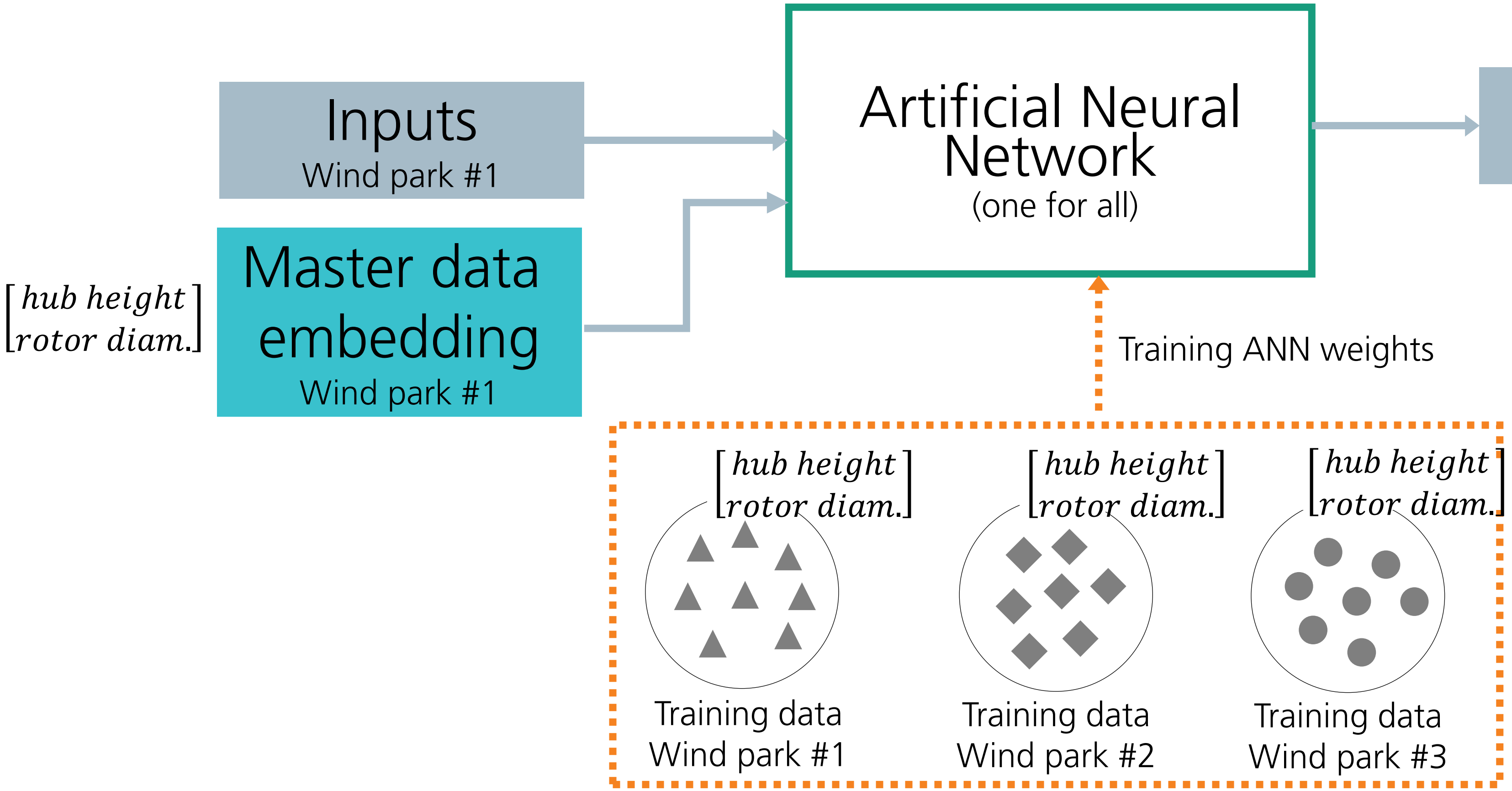

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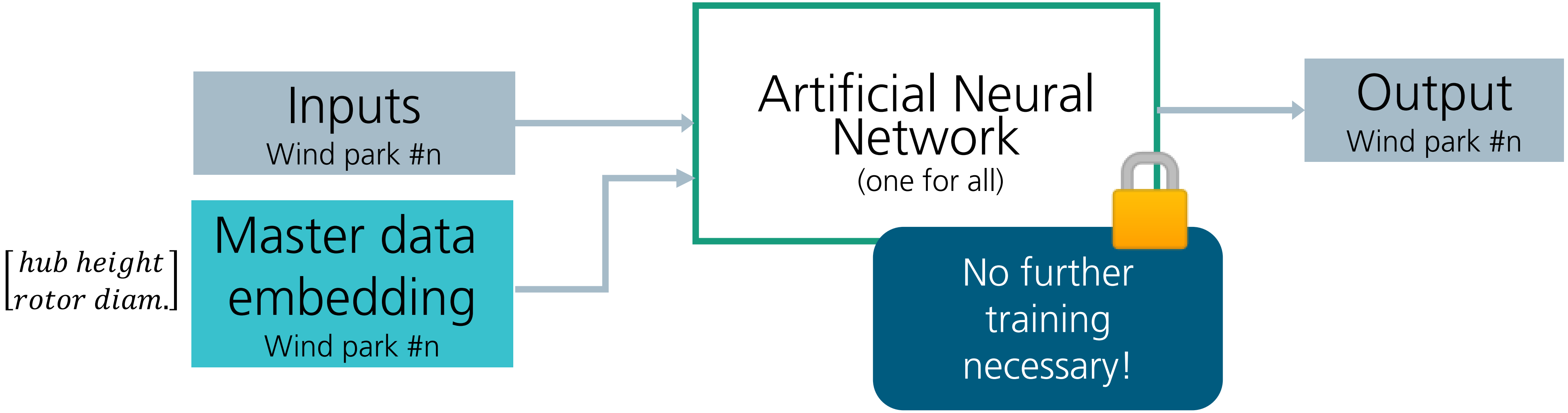
Zero-shot forecasts

Forecasts at new parks without further training



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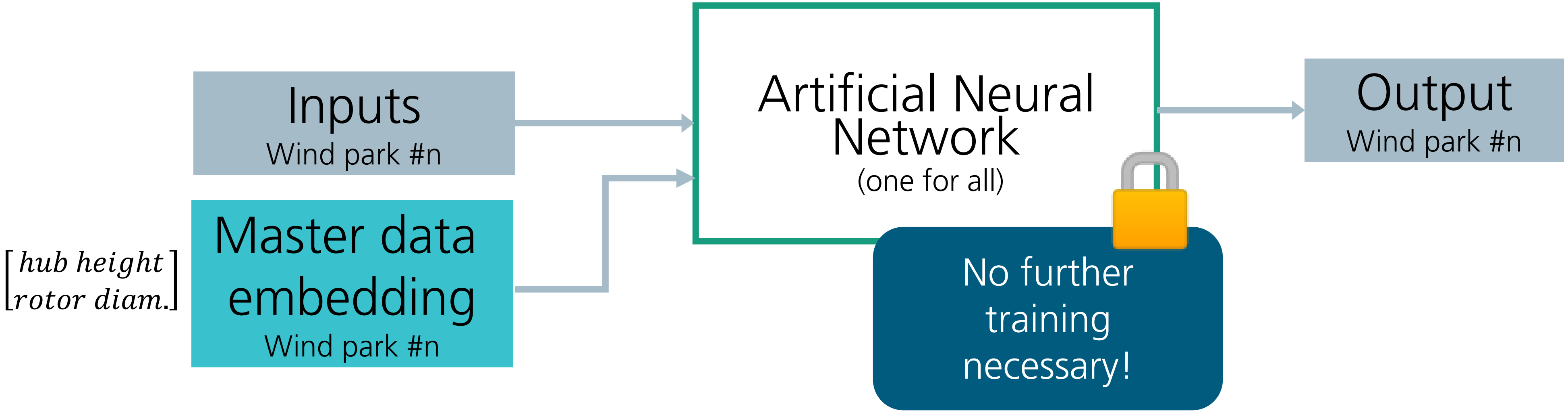

Zero-shot:

- Generate forecasts for parks without any measurements
- Only master data needs to be provided

→ **Zero-shot approach *v1***

Base model architecture – revisited

Little park-specific information

Base model architecture – revisited

Little park-specific information

More park-specific information

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Base model architecture – revisited

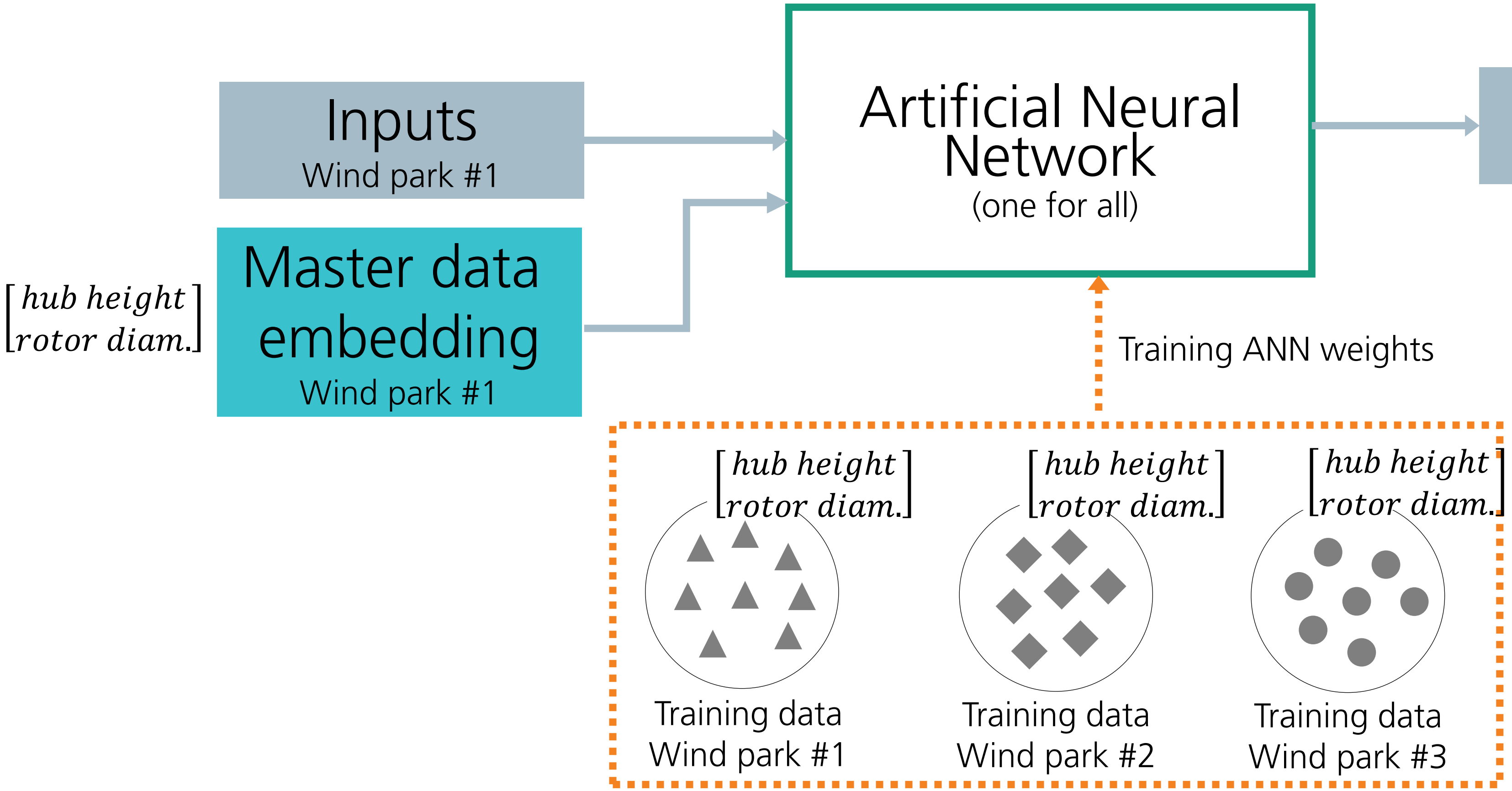
Little park-specific information

More park-specific information

Problem: Master data quality is not good enough to include more information

Base model architecture – *v2*

Bayesian Embedding Multi-Task Learning Multi Layer Perceptron (BE-MTL-MLP)*



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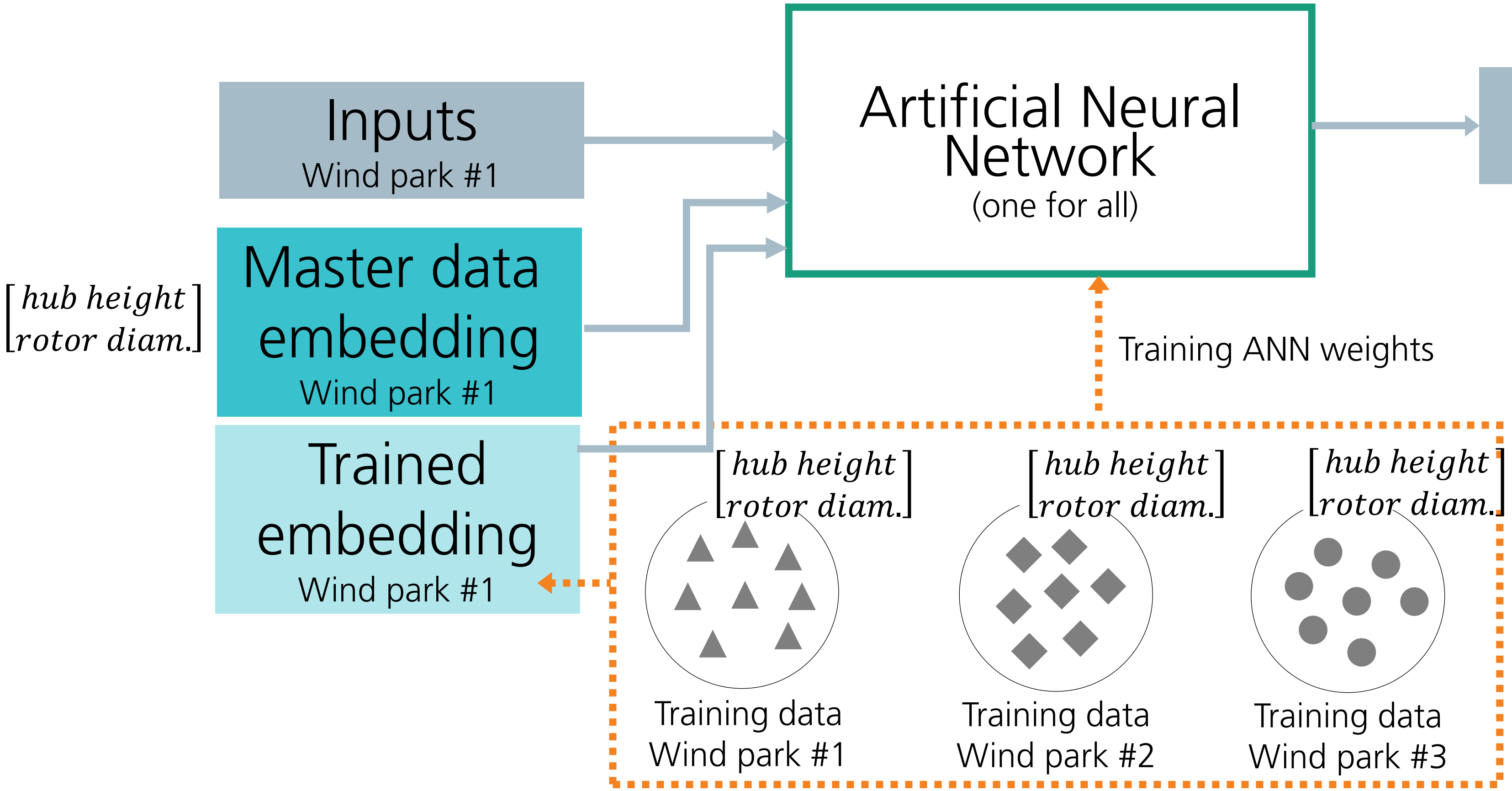

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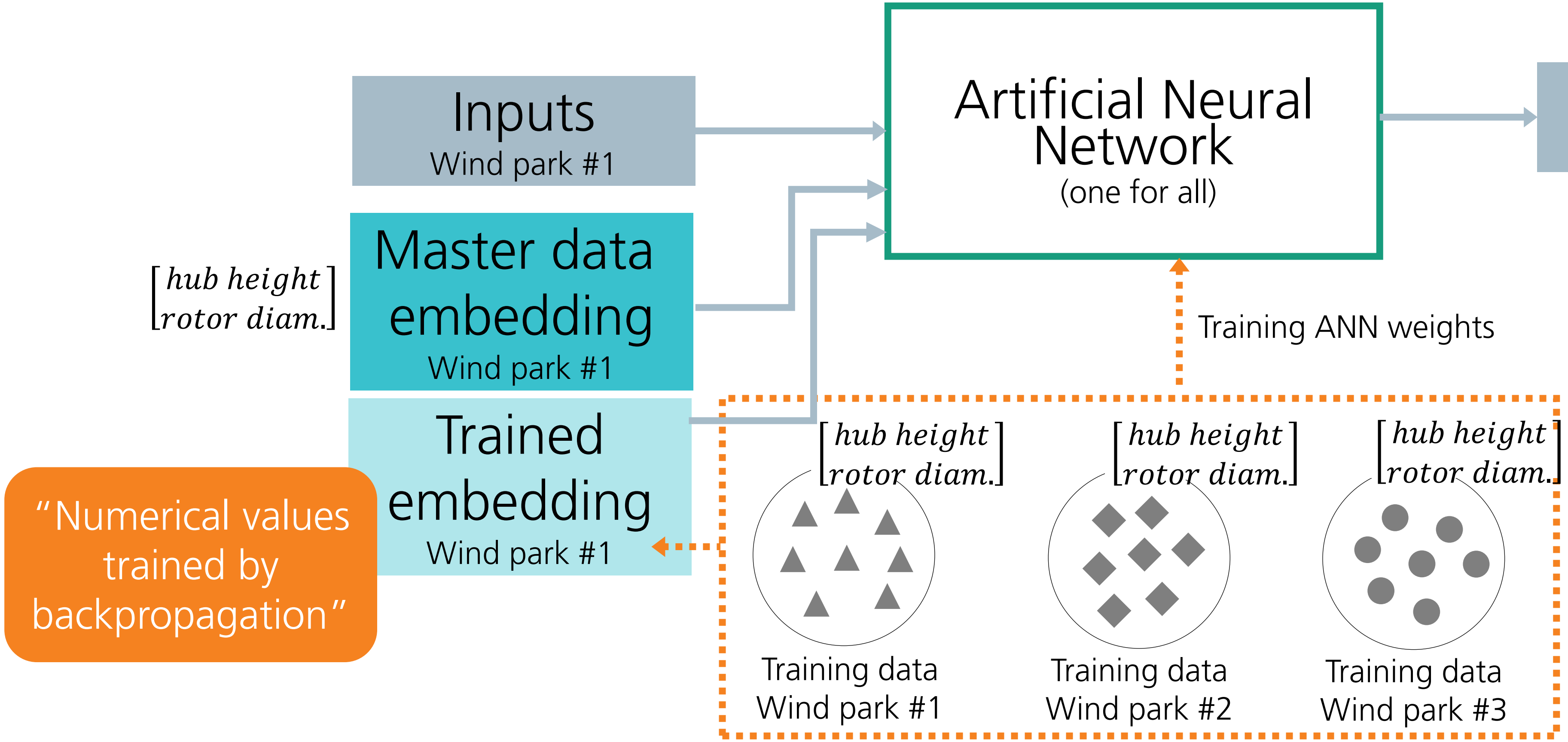

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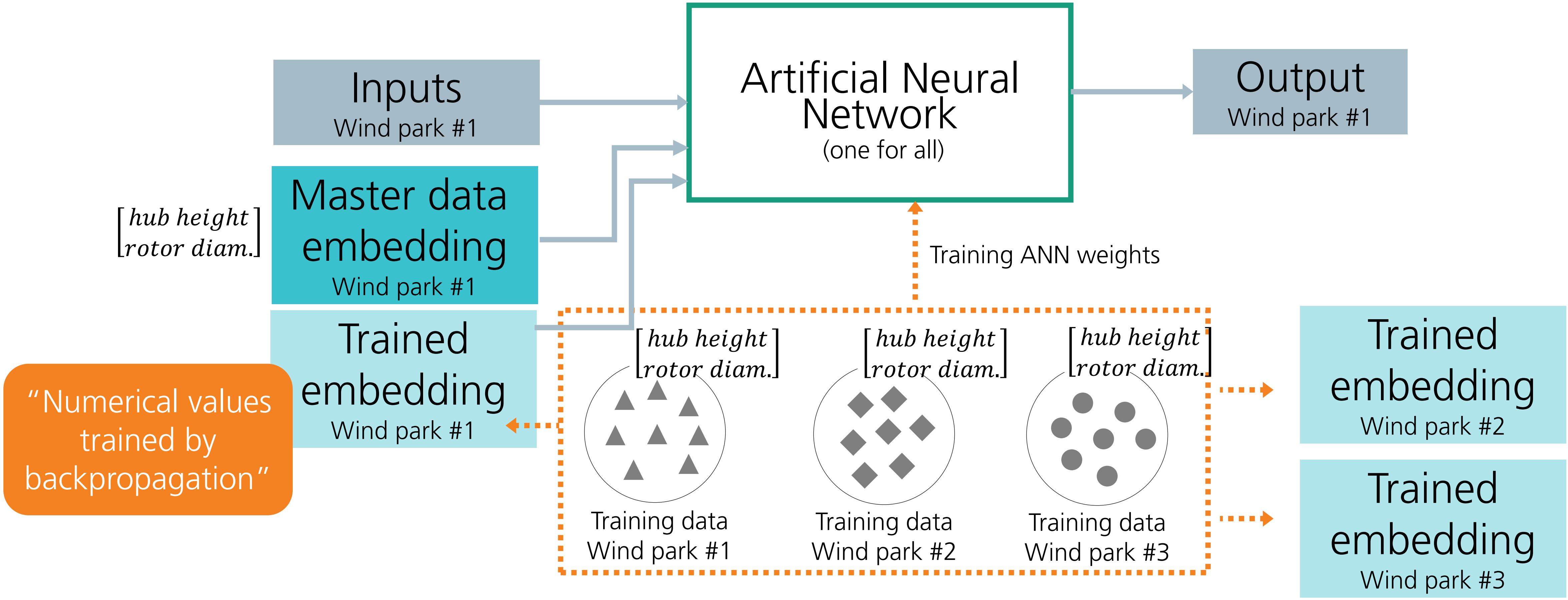

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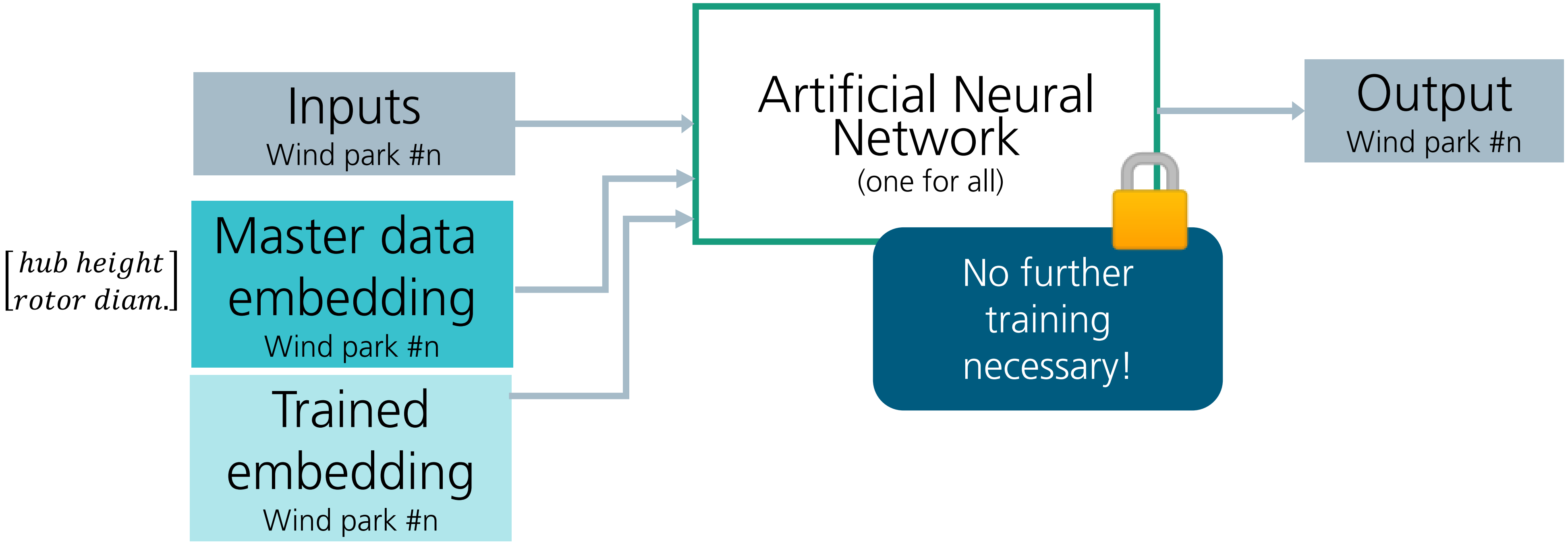
Zero-shot forecasts – *v2*

Forecasts at new parks without further training



Zero-shot forecasts – *v2*

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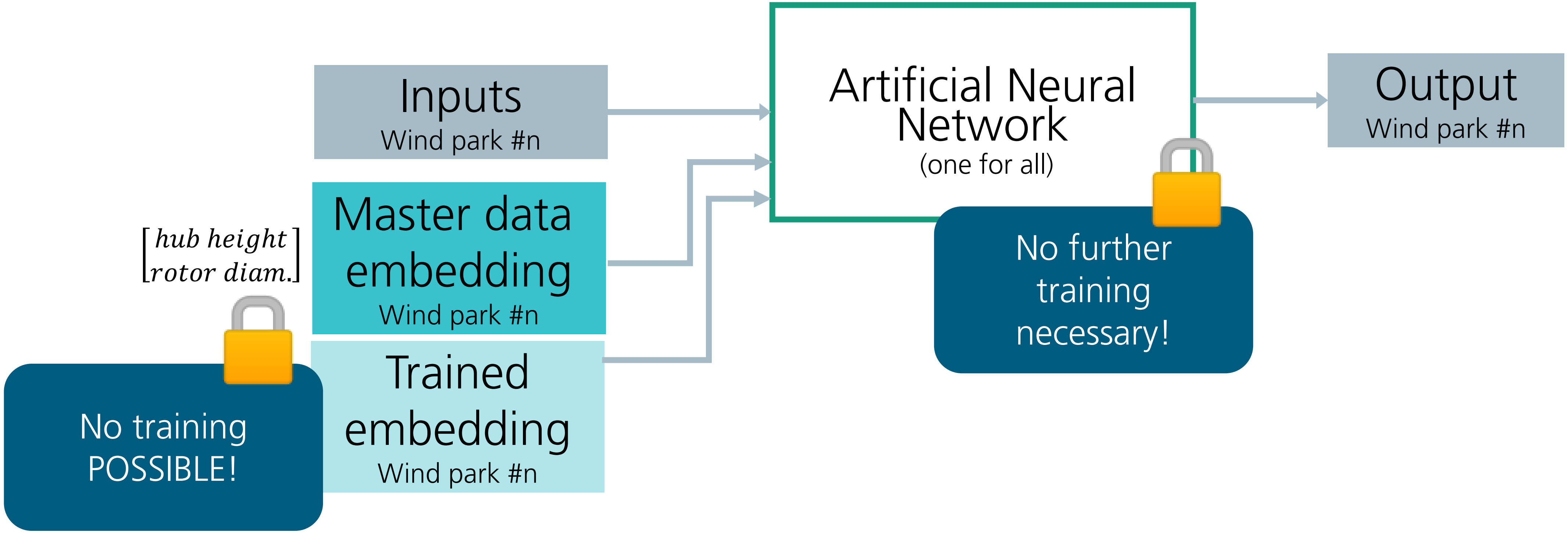

 15.10.2024

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Zero-shot forecasts – *v2*

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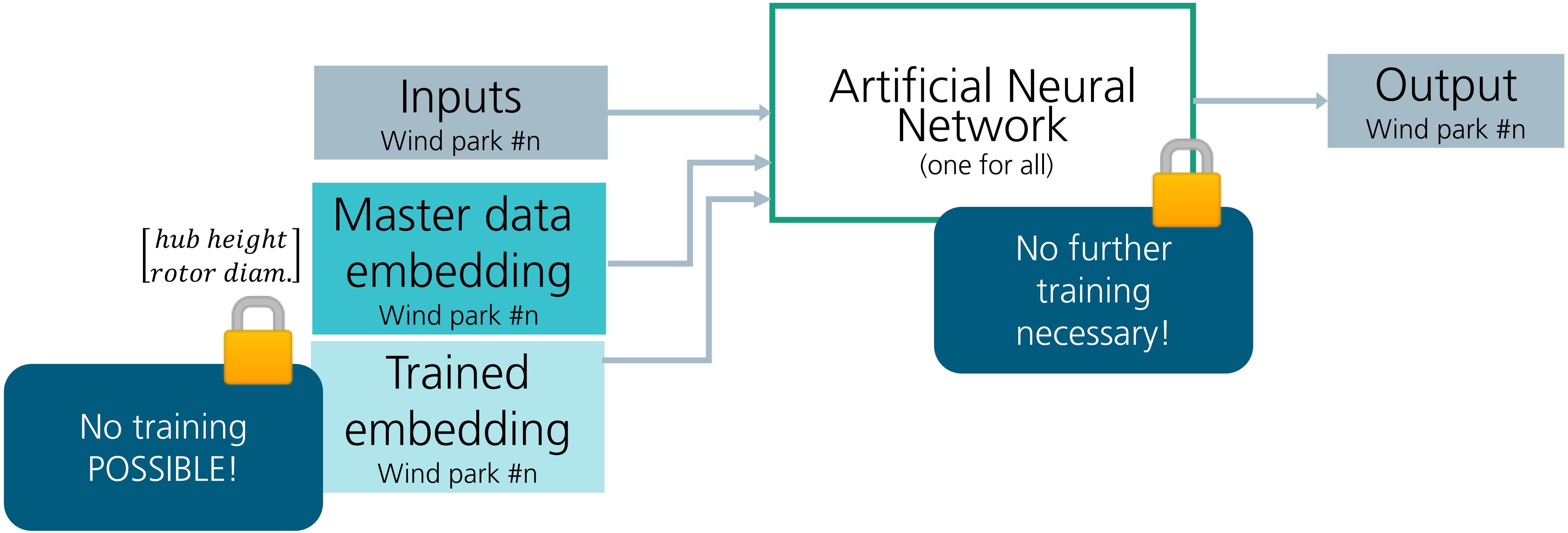

„Trick“: set all „trained“ embedding values to zero (= a priori assumption in our training setup)

→ Zero-shot approach *v2*

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From park forecasts to control zone forecasts

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From park forecasts to control zone forecasts

Auxiliary step – grid area forecasts

available wind parks
unavailable wind parks

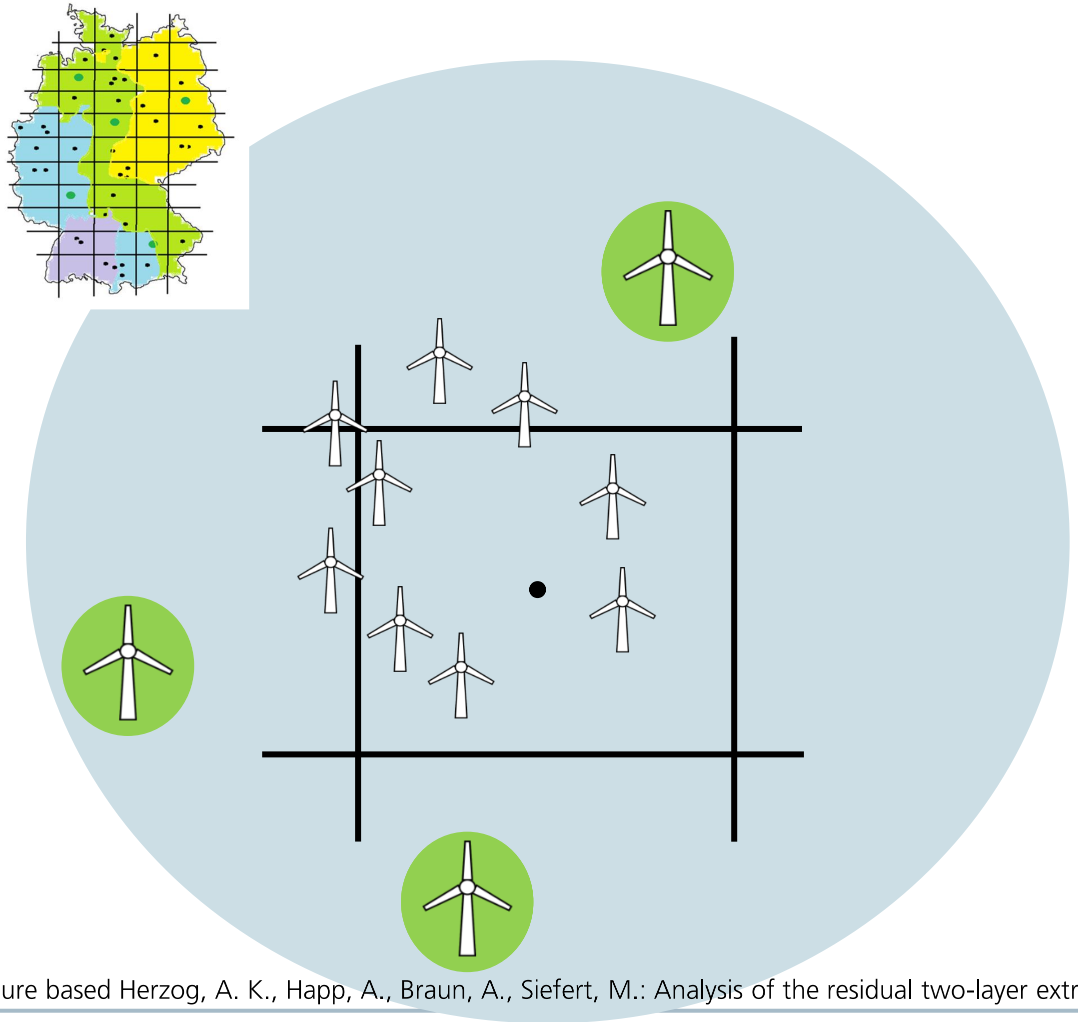
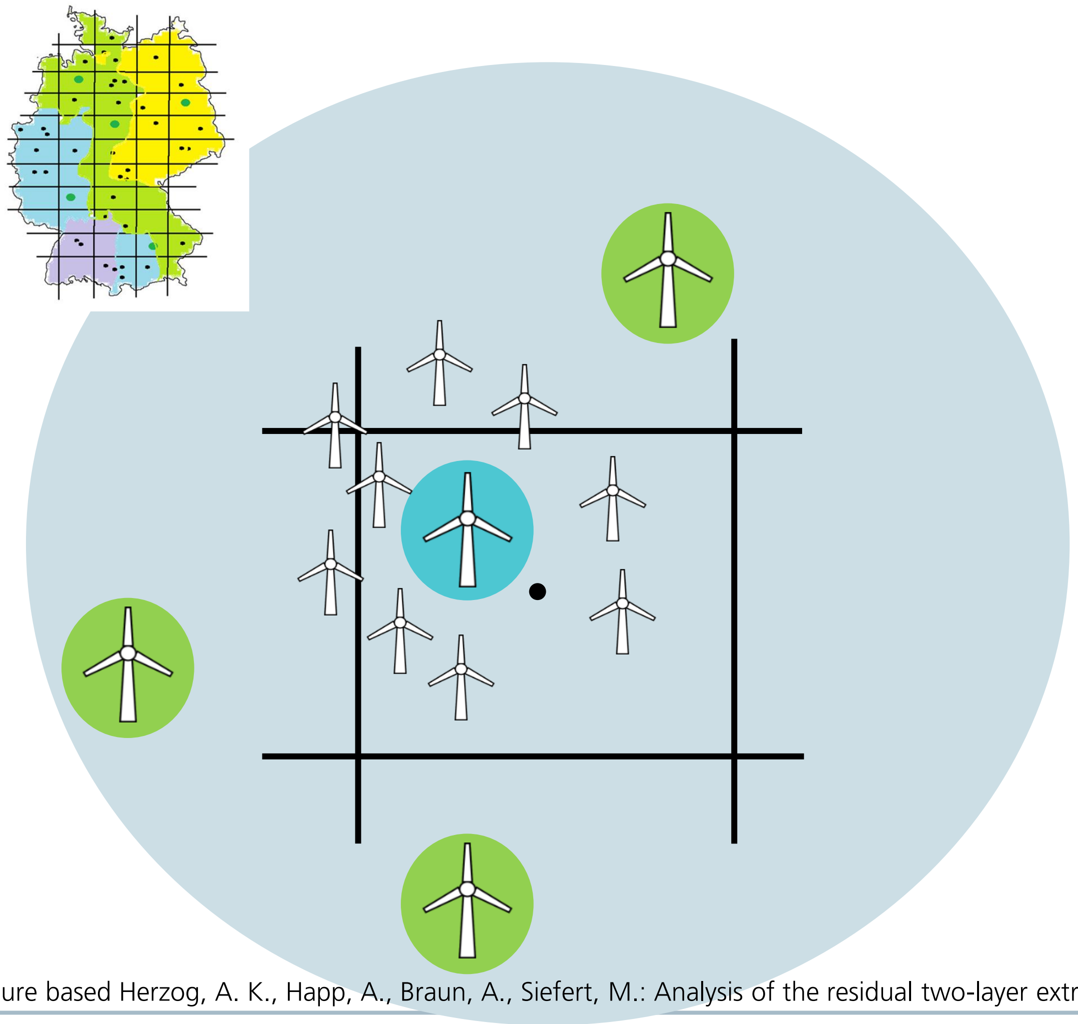


Figure based Herzog, A. K., Happ, A., Braun, A., Siefert, M.: Analysis of the residual two-layer extrapolation method for aggregated wind power estimation. In Proceedings 22nd Wind Integration Workshop, 2023

From park forecasts to control zone forecasts

Auxiliary step – grid area forecasts

available wind parks
unavailable wind parks
virtual wind parks



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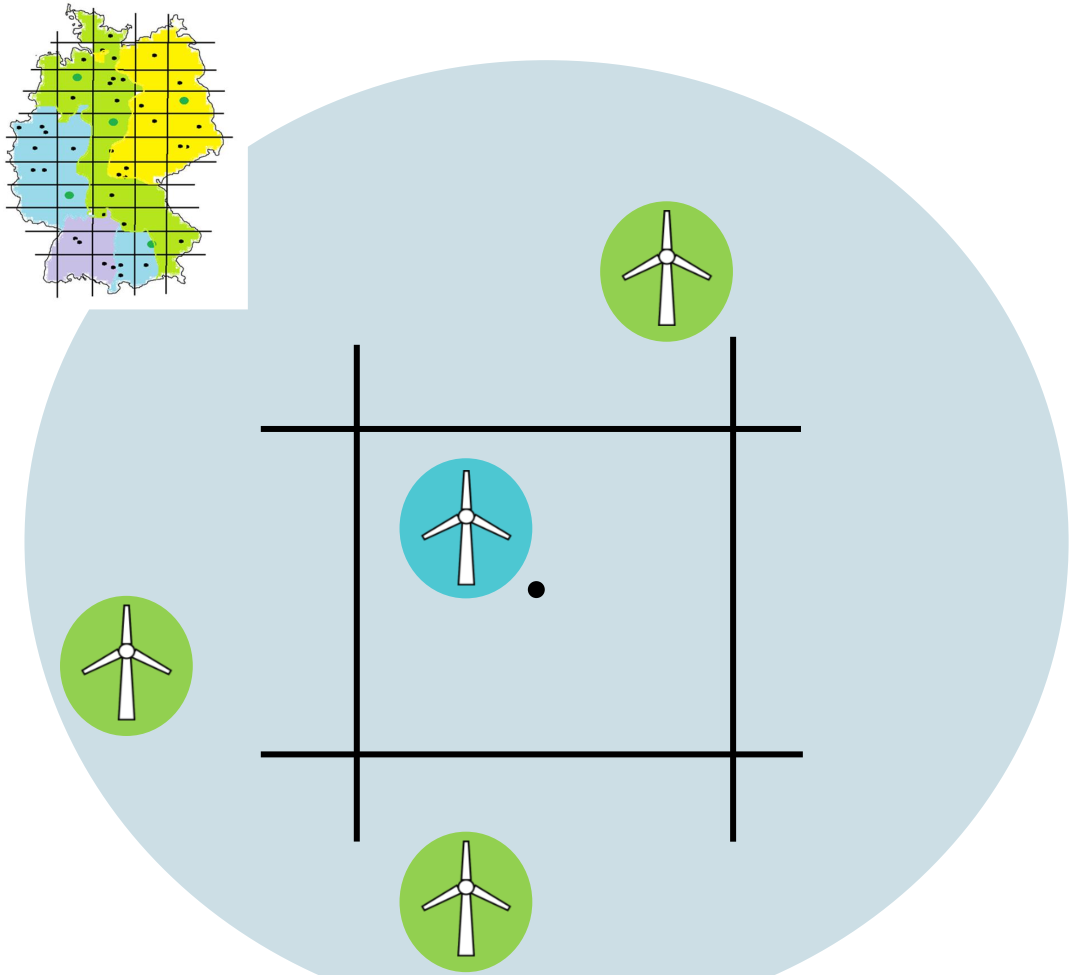

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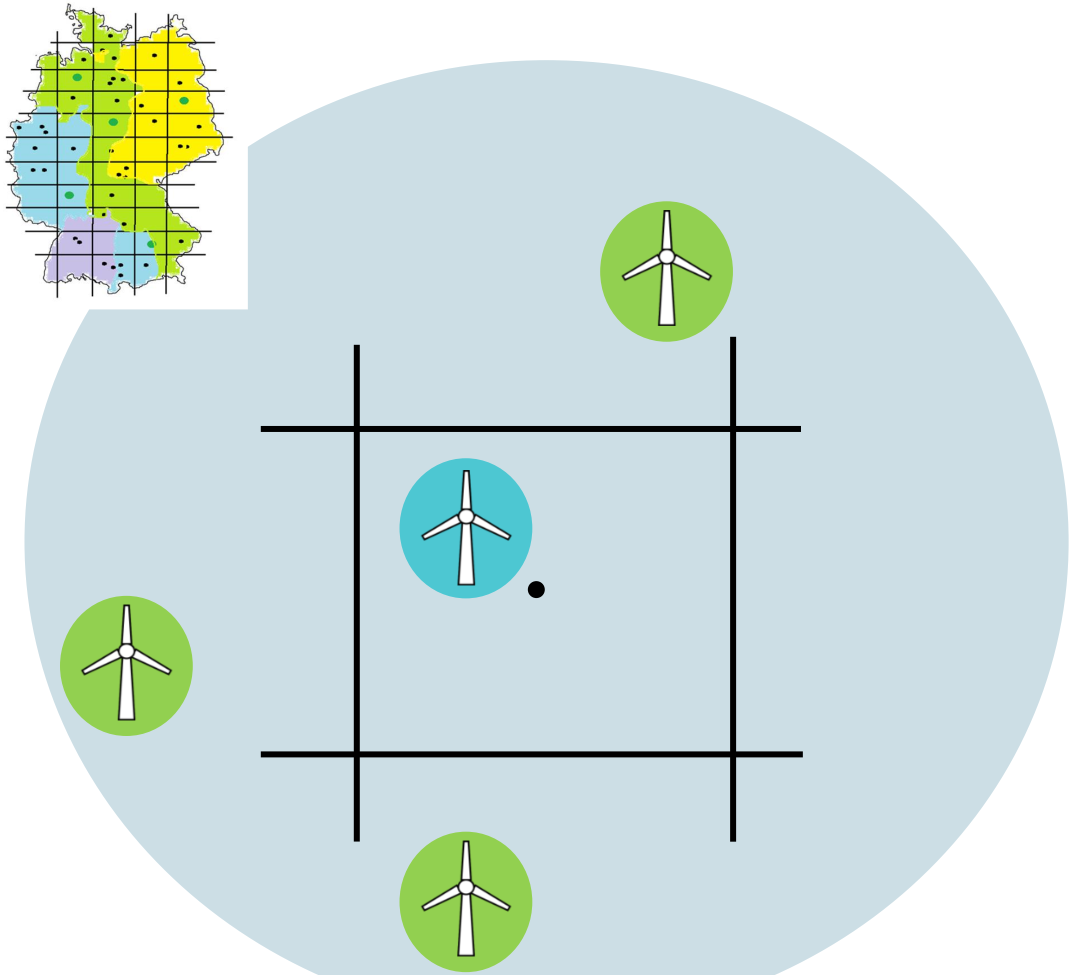

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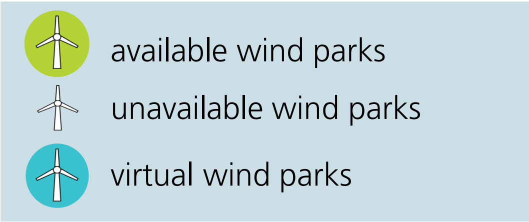

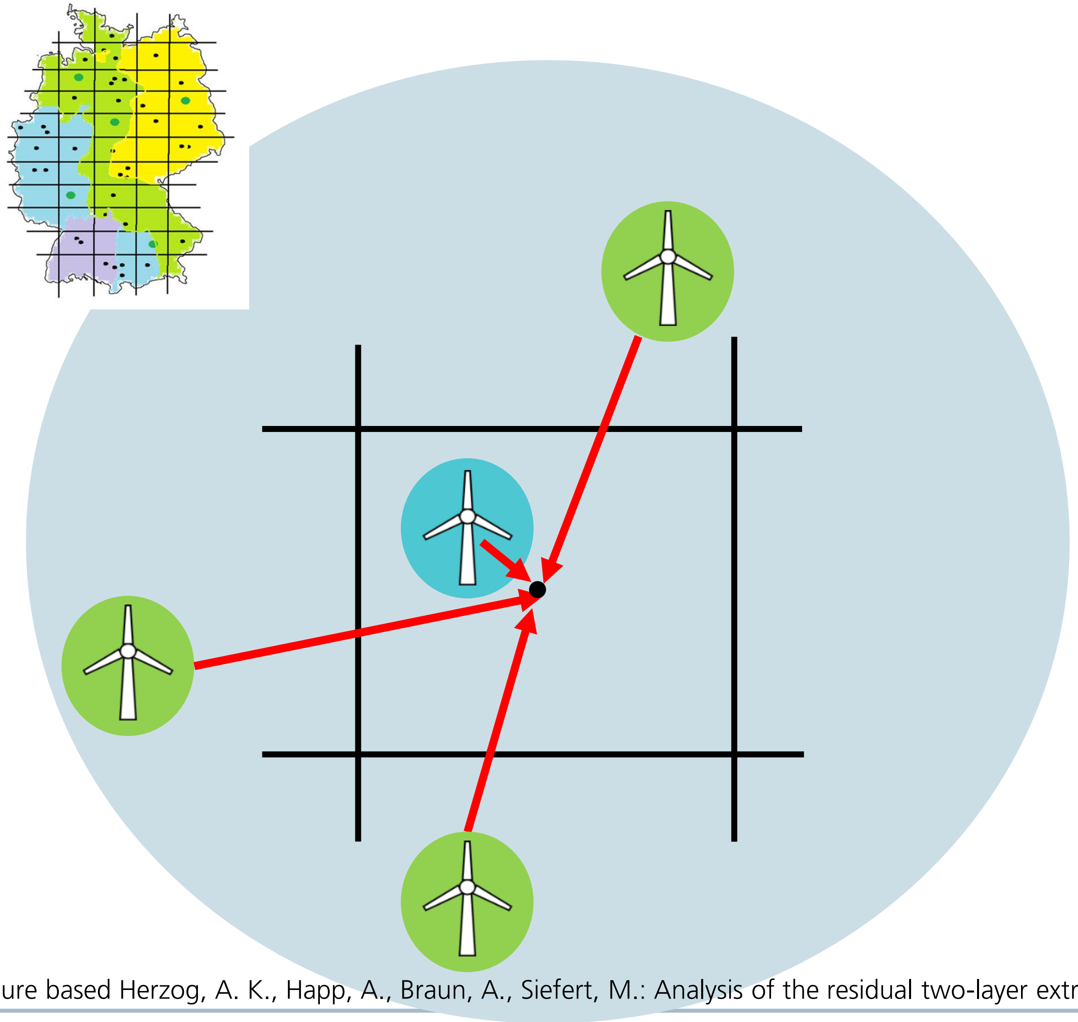

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2. **Project normalized park forecasts to grid areas (inverse-distance-weighting):**
   → normalized wind timeseries representing local power production.

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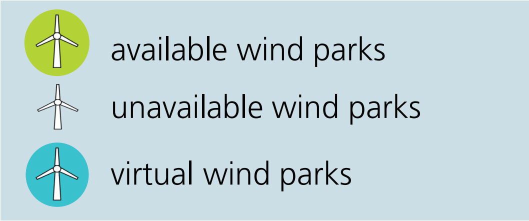
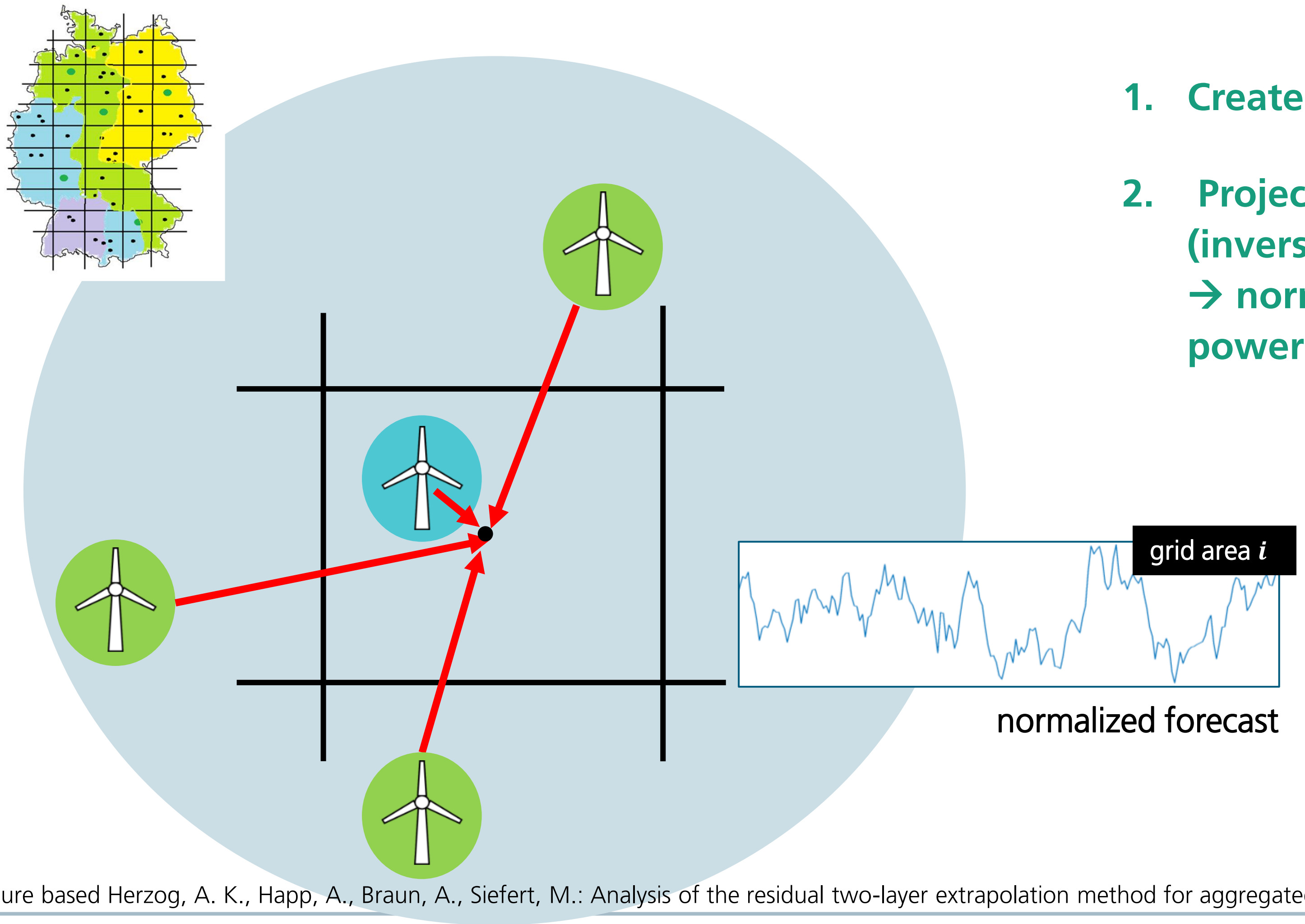
From park forecasts to control zone forecasts

Auxiliary step – grid area forecasts





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From park forecasts to control zone forecasts

Auxiliary step – grid area forecasts

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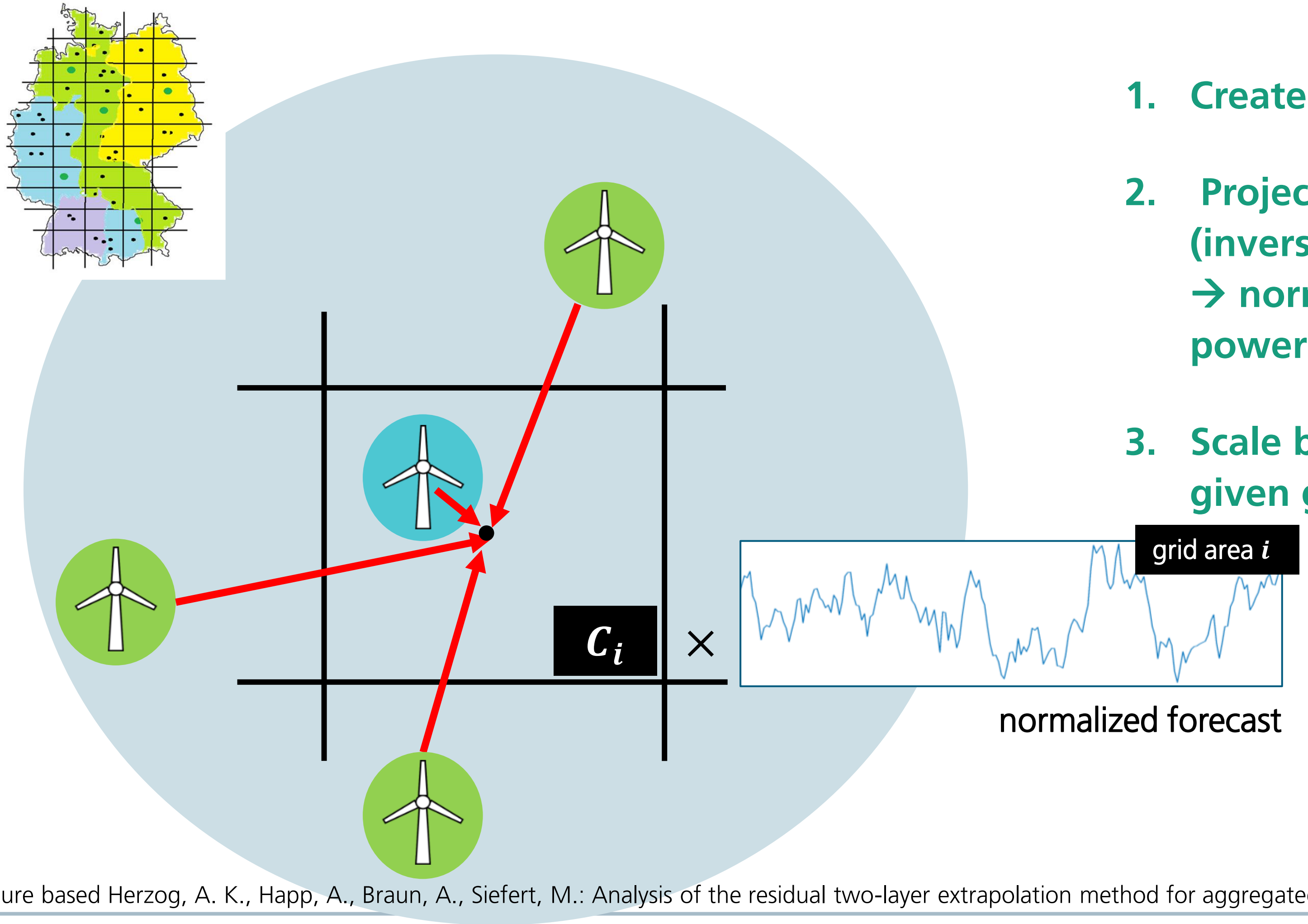

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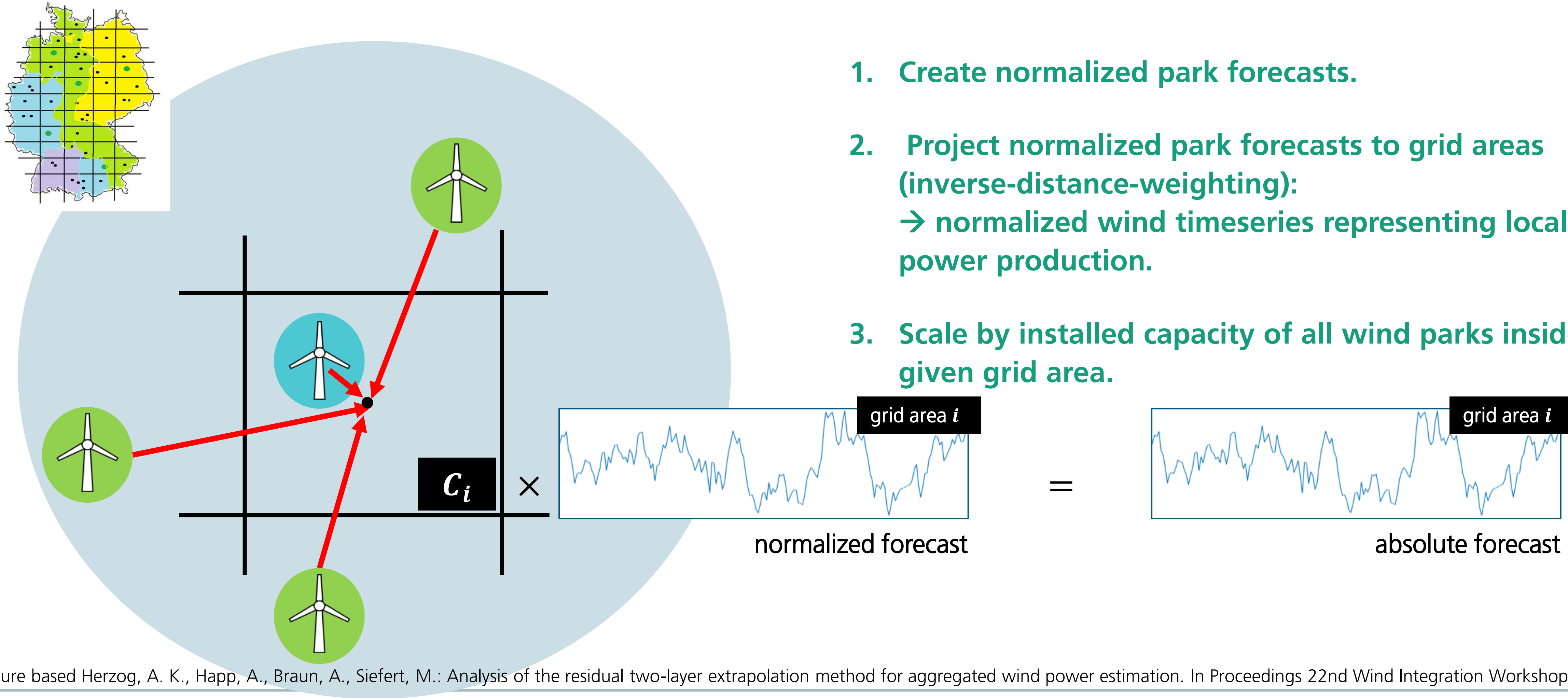

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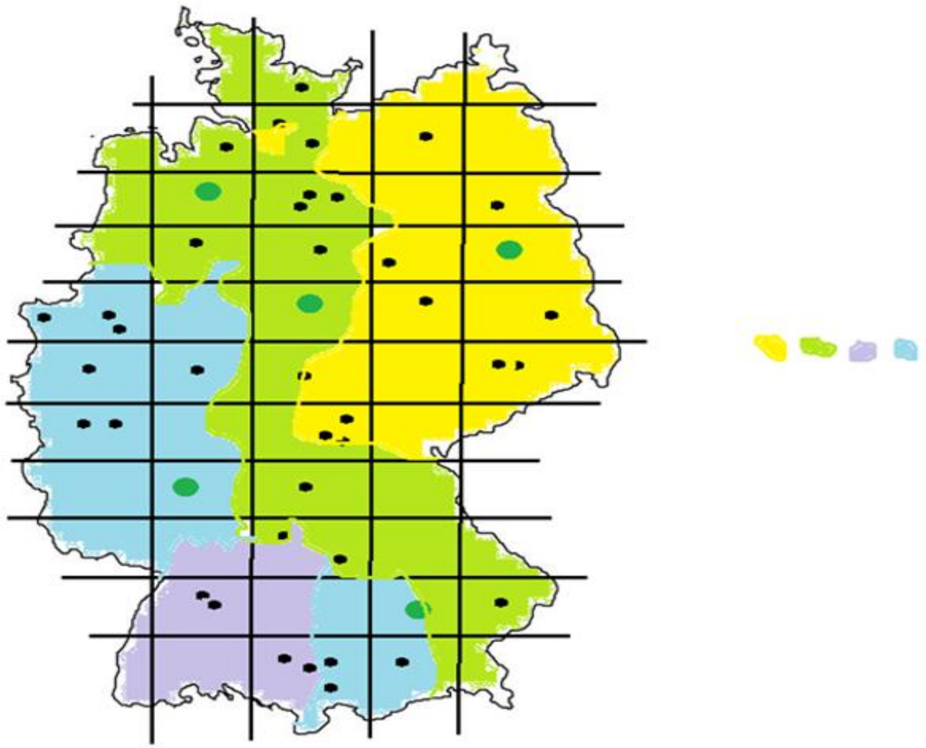
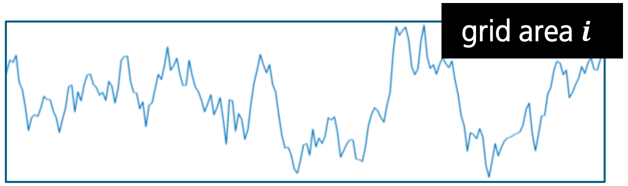
From park forecasts to control zone forecasts
Aggregation to TSO control zones



TSO control zones

$$\sum_{i \in I_{TSO}}$$



absolute forecast

Case study

Case Study
Experimental Design

- ~ 2 years of training data for Machine Learning model
- Day-ahead forecasts
- 1 year data for evaluation of aggregated forecasts
- Evaluation: three of the four German TSO control zones
- 907 available parks, 869 virtual parks
- For all 907 available parks, forecasts were created and used for aggregation (Machine Learning forecasts)

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- Benchmarks:
  - Approach without any virtual parks
  - Approach using a physical model for virtual park forecasts

Results

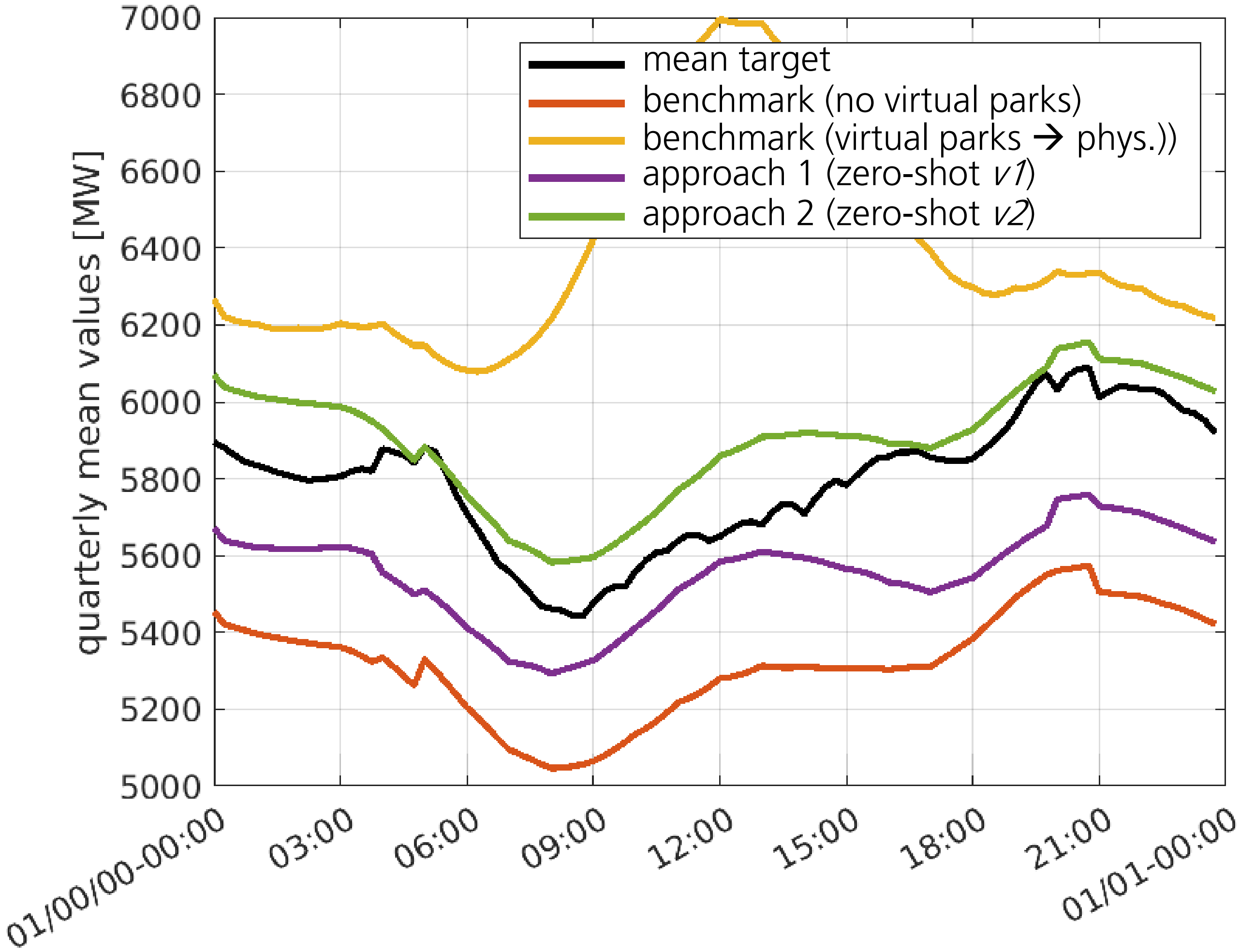
Results

RMSE values of TSO control zone forecasts as a percentage of installed capacity

Approach	TSO 1	TSO 2	TSO 3
Benchmark without vitual parks	8.05%	5.48%	5.46%
Benchmark virtual parks phys. model	7.89%	6.80%	6.80%
Approach 1 virtual parks with zero-shot *v1*	7.24%	4.98%	5.05%
Approach 2 virtual parks with zero-shot *v2*	6.82%	4.81%	4.97%

Results

Mean diurnal cycle of forecasts and target time series, example: TSO 2



Conclusion

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Summary

- **Zero-shot** forecasts at additional virtual power plants **improve aggregated forecasts**
- **More park-specific information** (approach *v2*) delivers **better results** than only hub height + rotor diameter (approach *v1*)
- Unlike physical models, Machine Learning models are able to **correct systematic errors / patterns**

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Additional paper content

- Comparison of zero-shot forecasts to physical model forecasts on park level → no improvements using zero-shot

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Outlook

- Include optimization techniques for aggregation
- Test approach for solar forecasts

Contact

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