ESTIMATION AND AGGREGATION OF WIND POWER FORECASTS UTILIZING MASTER DATA AND ZERO-SHOT LEARNING

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Abstract

The increasing integration of renewable energy, particularly wind power, necessitates enhanced forecast accuracy for effective grid management. Traditional methods that project wind power forecasts from a limited number of reference wind parks to larger grid areas often struggle with insufficient measurement data. We propose a zero-shot learning model utilizing publicly available wind park master data and local weather forecasts to generate locally distributed forecasts at new locations without prior training. This approach employs multi-task learning to embed parks based on master data, enabling comprehensive coverage when projecting forecasts across all wind parks. Our method, validated with field data, significantly improves forecast accuracy at the transmission system operator (TSO) control zone level compared to traditional methods and physical models, offering a robust solution for the growing demands of renewable energy forecasting.

1 Introduction

The shift towards renewable energy sources is a critical component of modern energy strategies, with wind power playing a significant role. Grid operators depend on accurate wind power forecasts to manage and plan grid operations effectively. As renewable energy contributions increase, so does the importance of refining forecast accuracy to ensure grid stability and efficiency.

In Germany, the unavailability of real-time and even historical data availability for many wind parks represents a significant challenge when calculating forecasts at TSO control zone level (or forecasts for other portfolios of wind power parks). Consequently, a typical approach relies on data from a limited number of reference wind parks and comprises two stages [1, 2].

First, missing information at individual wind parks is estimated by projecting forecasts from wind parks with available data (“reference wind parks”) to wind parks without data. This stage is in the following referred to as "projection". In a second stage, all park forecasts are aggregated to the target region or portfolio, in the following called "aggregation".

The projection process benefits from a wide spatial distribution of reference wind parks to capture local weather variations accurately. If only few reference park forecasts are available, the projection can fail to account for local weather conditions adequately, leading to less reliable forecasts. For parks without available measurements, usually only physical forecasting models can be applied, as measurement data is needed for training accurate machine-learning (ML) models. However, physical models generally achieve lower forecast accuracy than machine-learning methods [3]. The central challenge lies in enhancing the quality of wind power forecasts in areas where measurement data is limited. Therefore, there is a need for an innovative approach that can produce accurate forecasts across diverse locations without extensive training datasets.

To address these challenges, we introduce a zero-shot learning model that leverages publicly available wind park master data and local weather forecasts. This model generates forecasts without prior training at new sites with no available measurements, using a multi-task learning artificial neural network architecture trained on a portfolio of reference parks. As described in [4], the model is a hard-parameter sharing model, where only some embedding weights distinguish tasks from each other. Instead of relying on a trained embedding derived from measurement data, our zero-shot learning model uses master data such as hub height and rotor diameter to create characterizing embeddings for each park. This enables the model to produce accurate forecasts at new locations, offering a more comprehensive coverage for the projection process. The forecasts are projected using inverse-distance-weighting of wind parks to grid areas with known installed capacity and then aggregated to TSO control zones.

With our paper, we address two questions:

- Can the forecast quality of aggregated forecasts be improved by using parks without measurement data as additional reference wind parks?
- Can the forecast quality of aggregated forecasts be improved by using a zero-shot learning model instead of a physical model for reference wind parks without measurements?

To compute forecasts at TSO control zone level, different approaches can be found in the literature. In [5] the authors train an Artificial Neural Network (ANN) to directly predict the target power values at the TSO level. As input they utilize forecasts at spatially distributed wind parks, thereby accounting for local weather conditions. However, with the increasing number of wind parks, the question arises as to which park forecasts should be used as input into a direct forecasting model. A high number of inputs complicates the training of a robust model, while at the same time the model is required to continue producing forecasts even in the event of local data at a specific park being unavailable due to temporary data gaps. The authors in [1] and [2] propose a projection and aggregation process that is also used in this paper. The authors in [6] extend the approach by introducing the concept of virtual parks. In order to achieve a more comprehensive regional coverage of park forecasts, forecasts at the aforementioned virtual parks are created with the aid of a physical model. The authors concentrate on the aggregation stage and propose a residual two-layer extrapolation methodology. In this paper we adopt their approach of leveraging virtual parks, but we develop it further by adding master data information and zero-shot learning.

Zero-shot learning was introduced based on two perspectives [7]. There, the Input Space View describes the concatenation of input x and task descriptor $d(z)$, where z represents the task identity. Contrarily, the more general Model Space View assumes that the model $f_z(x)$ is a function of its descriptor $d(z)$, thus $g_{d(z)}(x)$. Furthermore zero-shot learning shows promising concepts in the domain of computer vision. Lampert et al. [8] proposed the object detection utilizing identification based on semantic attributes. Oreshkin et al. [9] investigate the interface of zero-shot learning and meta-learning for time series forecasting of various domains as tourism and traffic.

2 Methodology

This section presents an overview of the methodologies employed in the generation of forecasts at wind parks. It additionally describes the projection and aggregation process for the production of TSO control zone forecasts in greater detail.

2.1 Power forecasts for wind parks

Two different approaches can be employed for creating wind power forecasts. Physical models are typically used when no measurement data is available for training an ML model. If measurements are available, ML approaches generally provide better forecasting results. For reference park forecasts we use a multi-task learning model with an ANN architecture. A trained multi-task model can also be used for zero-shot learning without any measurements, offering an alternative to a physical model.

2.1.1 Physical model: For physical model forecasts we first interpolate wind speed from two height levels given by a numerical weather prediction to the power plants' hub heights. The wind speed then gets translated to power output using wind power curves developed by the TradeWind project [10].

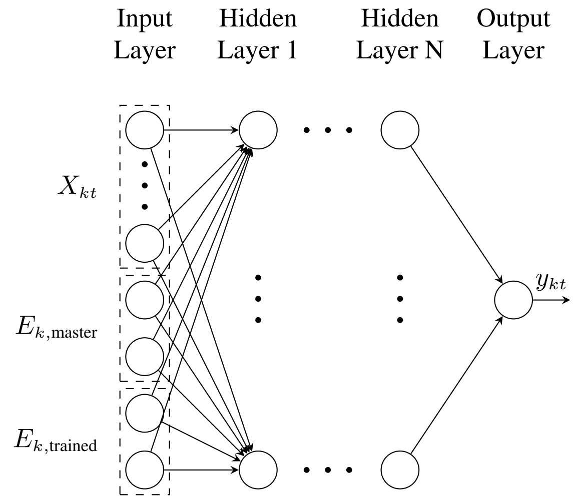

Fig. 1: ANN architecture of an MTL model with master data embedding and trained embedding

2.1.2 Multi-task learning model: Multi-Task Learning (MTL) refers to a ML setting where one model is trained and used to predict multiple tasks. In our case, one task corresponds to one wind park. We use a hard-parameter sharing ANN with a park-specific bayesian embedding as proposed in [4]. The model architecture is illustrated in Fig. 1. Given a model trained on a portfolio of K wind parks, a prediction for a specific park $k \in \{1, \dots, K\}$ at time t must be provided with local inputs X_{kt} as well as the park specific embedding E_k. The embedding can be interpreted as a static input to the neural network providing information about park-specific behavior.

The embedding can be trained by backpropagation during the normal ANN training process. All parks' data is used for training the shared ANN weights, while only each park's own training samples are considered when training its embedding. The embedding is regularized by assuming the standard normal distribution as a prior probability distribution, which is further described in [4].

Alternatively, the embedding can be set to fixed values and not trained at all. During the ANN training, the model then learns to use the given embedding to create park-specific predictions. Thus, it makes sense to define an embedding using master data like hub height or rotor diameter, which have a direct effect on how a wind park translates weather inputs to power output. The standardization of master data values ensures that discrepancies in magnitude between different input dimensions do not impede the model's capacity to accurately identify the relative importance of input parameters.

The model depicted in Fig. 1 employs a mixed embedding, comprising both master data $E_{k,\text{master}}$ and a trained embedding $E_{k,\text{trained}}$. It is, however, also possible to utilize only one or the other.

2.1.3 Zero-shot learning model: Given a trained hard-parameter sharing MTL model with embedding as described in the previous subsection, a zero-shot learning approach can be employed for any new wind park, where new corresponding

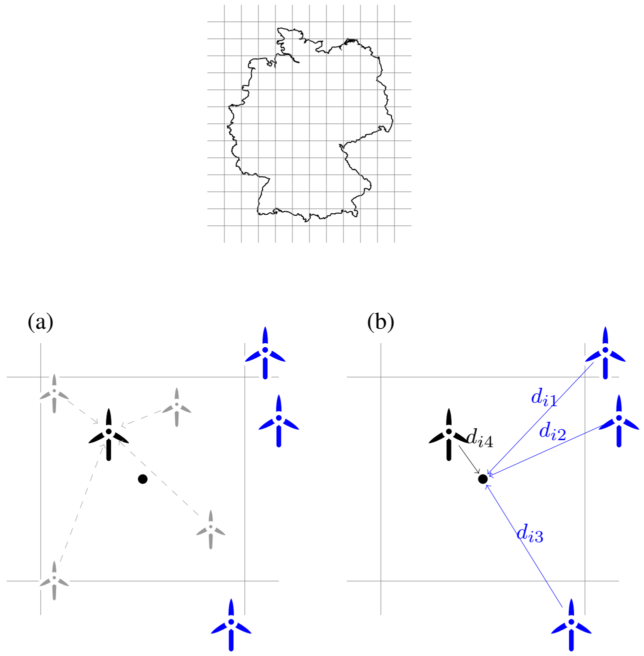

Fig. 2: Schematic illustration of the projection process to grid areas in Germany. In (a) master data of wind parks [grey] is averaged at one virtual park [black]. Forecasts at virtual parks as well as reference wind parks [blue] are projected to grid areas by an inverse distance-based weighting (b). The black dot marks the center of the grid area.

master data are available. An embedding based on master data information can be set to the new park's corresponding master data values. Subsequently, the model can be employed to generate forecasts for the park's location without the necessity for additional training.

In case of available measurements it is possible to optimize the appropriate location within the embedding space in addition to the model's standard training process. In the absence of measurement data in a zero-shot learning setup, the embedding value is set to zero, which corresponds to the expectation value of the prior probability distribution.

2.2 *Projection and aggregation process*

The objective of the projection and aggregation process is to accurately estimate wind power forecasts in any given region or control zone. The general idea is to first project forecasts at reference wind parks to all wind parks and then aggregate the projected forecasts to any target region. Due to the large number of wind parks in Germany, we choose a slightly modified approach [6]. First, normalized reference park forecasts are projected to small grid areas (approximately 10 km x 10 km), which are then multiplied by the installed wind capacity within each grid area. This way, the number of projected power forecasts is fixed to the number of grid areas. The projected power forecasts of the grid areas are then aggregated to the required target region.

The whole projection process is depicted in Fig. 2. As seen in the schematic example, the spatial distribution of reference parks is not always balanced. Therefore, we introduce new, virtual reference wind parks in under-represented areas as shown in Fig. 2 (a). For these virtual parks (black), master data of surrounding wind parks (grey) in a 10 km radius are averaged and used for creating a forecast with the zero-shot learning model described in 2.1.3. The projection process itself is shown in (b): An inverse distance-based weighting scheme is applied to the normalized forecast values of reference parks to determine a representative normalized power forecast for each grid area. For the projection, both real reference parks (blue) and virtual reference parks (black) are used. The weights

$$w_{ij} = \exp\left(-\frac{d_{ij}}{r_0}\right) \tag{1}$$

depend on the distance d_{ij} between the park j and grid area i as well as a parameter r_0. A smaller r_0 increases the impact of nearby parks. In the context of this paper, a fixed value of $r_0 = 40\ km$ was selected. Nevertheless, an optimization of r_0 is likely to yield further improvements in results.

The power forecasts P_i for grid areas i are then calculated by

$$P_i = C_i \sum_{j=1}^{n} \frac{w_{ij}}{\sum_{k=1}^{n} w_{ik}} p_j, \tag{2}$$

where

P_i :	power forecast for grid area $i, i = 1, \ldots, m$
C_i :	installed wind capacity in grid area i
p_j:	normalized forecast of reference park j
w_{ij}	inverse distance-based weight for reference park j and grid area i
m :	number of grid areas
n :	number of reference wind parks

Finally, forecasts at TSO control zone level are given by aggregating

$$P = \sum_{i \in I_{TSO}} P_i, \tag{3}$$

where I_{TSO} contains all grid areas that are located inside the target TSO control zone.

3 Case Study

A case study was conducted to evaluate the proposed approach on three of the four German TSO control zones: Amprion GmbH, Tennet (only onshore) and 50Hertz.

To gain deeper insight into the zero-shot learning approach, another experiment was conducted to assess the accuracy of zero-shot forecasts for reference wind parks.

3.1 *Set-up*

In the following the two configurations of our case study are described. For purposes of clarity, we group wind parks into categories A, B and C for reference wind parks and category V for virtual parks as defined in Tab. 1.

Table 1 Categories of wind parks defined for this case study

Cat.	Measurement data available	Master data available	Used in training model m_1	# parks
A	✓	✓	✓	142
B	✓	✓	✗	118
C	✓	✗	✗	647
V	✗	✓	✗	869

3.1.1 TSO control zone forecasts: In the course of our experiments, we conduct day-ahead forecasts of wind power feed-in at the control zone level. The configuration is illustrated in Fig. 3. The basis in this set-up are forecasts at wind parks. It has been demonstrated that the use of measurements for the training of the embedding leads to a reduction in error compared to the use of master data embeddings for individual wind parks [11]. Accordingly, an MTL model with a trained embedding (for general model architecture, see Fig. 1), henceforth designated as m_0, is employed for reference wind parks.

Forecasts at virtual wind parks are computed using zero-shot learning based on a second model m_1. This model is an MTL model with master data integrated into the embedding space. Model m_1 was trained on a subset of representative reference parks. The master data utilized in the context of virtual parks is derived from that of actual wind parks, which is further explained in section 3.2. Two versions of model m_1 are trained and evaluated. One version $v1$ of the model utilizes a master data embedding space, comprising solely the $E_{k,\text{master}}$ data set. The alternative version $v2$ employs a mixed embedding comprising both $E_{k,\text{master}}$ and $E_{k,\text{trained}}$. The hyperparameters set for models m_0 and m_1 are listed in Tab. 2.

3.1.2 Zero-shot learning for reference wind parks: In a second set-up, we want to further analyse zero-shot forecasts on a wind park level. We perform zero-shot forecasts for individual reference wind parks and analyse parks of category B by comparing a basic physical model with the zero-shot approach. The experiment mirrors the domain, forecasting objects, and models introduced in subsection 3.1.1.

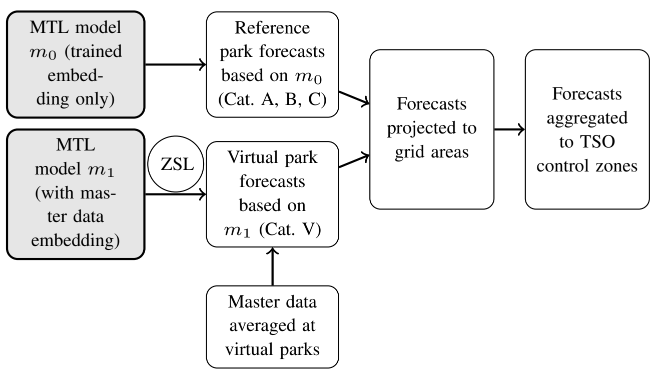

Fig. 3: Set-up for projection and aggregation experiments with virtual wind parks and zero-shot learning (ZSL).

Table 2 MTL ANN parameters

	m_0	m_1
# hidden layers	3	
# neurons per layer	50	
learning rate	0.001	
batch size	256	
activation function	leaky ReLu	
L2 regularization	1e-2	
dimension of $E_{k,\text{master}}$	0	2
dimension of $E_{k,\text{trained}}$	8	$\{0, 6\}$
regularization of $E_{k,\text{trained}}$	1e-8	{none, 1e-8}

3.2 Data

The data used in this case study consist of input and target data for training MTL models that produce power forecasts for wind parks, as well as park master data and target data on control zone level.

3.2.1 Data for ML training and evaluation: Power measurements of reference wind parks are used as target data to train forecast models m_0 and m_1. For this study, 142 parks (category A, Tab. 1) were used for training both MTL models, while more parks with measurements (categories B and C) were available and used in the evaluation of the zero-shot learning approach.

The measurements are given in a 15 minute resolution with available data from Feb 1, 2022 to Feb 1, 2024. October and November 2023 are excluded from the training set and designated as a test set for the MTL and zero-shot learning model at park level.

As inputs into the model, the following numerical weather predictions (NWP) with forecast horizons of +24 to +48 hours are used together with additional solar position features:

- Wind speed (at 42m, 96m and 167m, with time lags & leads)
- Wind direction (at 96m, with time lags & leads)
- Temperature
- Dew point temperature
- Air pressure
- Turbulent kinetic energy (at 96m, with time lags & leads)

We use the weather model ICON-EU provided by the *Deutscher Wetterdienst* [12]. All input features get standardized before training.

3.2.2 Master data: In this study, the hub height and rotor diameter information are employed as master data. In the case of reference parks, the available master data is used directly, while we average master data of power plants without measurements to locations of virtual parks. The source for the aforementioned master data is the *Marktstammdatenregister* [13], which registers all power plants in Germany. As we can define locations for virtual parks as needed, we introduce virtual parks according to the 10 km x 10 km grid utilized in the projection stage. A virtual park is created for each grid area in which there are wind power plants. In this manner, 869 virtual parks were defined for the experiment, with data from power plants situated within a 10 km radius aggregated.

3.2.3 TSO wind power time series: The evaluation of the aggregated forecasts is conducted over a one-year period, commencing on February 1st, 2023, and concluding on February 1st, 2024. We evaluate forecasts for three of the four German TSO control zones: Amprion, Tennet (only onshore) and 50Hertz.

3.3 Results

3.3.1 TSO control zone forecasts: The forecasts at the control zone level for TSOs Amprion, Tennet and 50Hertz are evaluated by comparing the root mean square error (RMSE) values with the results of benchmark approaches. The results are presented in Tab. 3. The projection and aggregation process is initially performed as a benchmark by using the portfolio of real wind parks with available measurements (categories A, B and C). A second benchmark is provided by including physical model forecasts for virtual parks. In the proposed approach that employs zero-shot learning for virtual park forecasts, the first experimental run (*v1*) utilizes a zero-shot model that is solely based on a master data embedding $E_{k,\text{master}}$. The second run (*v2*) is based on a model with a mixed embedding, combining the master data embedding $E_{k,\text{master}}$ with the trained data embedding $E_{k,\text{trained}}$. As already mentioned in section 2.1.3, all embedding values of $E_{k,\text{trained}}$ are set to zero for generating zero-shot forecasts.

Table 3 RMSE values of TSO control zone forecasts as a percentage of installed capacity

based on parks categories	Amprion	Tennet	50Hertz
A, B, C	8.05%	5.48%	5.46%
A, B, C & V (phys. model)	7.89%	6.80%	6.80%
A, B, C & V (zero-shot, *v1*)	7.24%	4.98%	5.05%
A, B, C & V (zero-shot, *v2*)	6.82%	4.81%	4.97%

The results demonstrate that the proposed approach reduces forecast errors for all three control zones. Run *v1* achieves lower errors than both benchmarks, while run *v2* further reduces errors compared to *v1*.

A comparison of the two benchmarks reveals that the incorporation of physical forecasts for virtual parks has a positive impact on the forecast for TSO Amprion, while simultaneously introducing an increase in errors for Tennet and 50Hertz. This may be attributed to the relatively limited coverage of Amprion's control zone with available reference wind parks. The virtual park forecasts may result in the incorporation of weather information from additional park locations, thereby counterbalancing the potential negative impact of unsuitable physical forecasts.

The reduced errors observed in the zero-shot approach suggest that across all control zones, additional weather and master data information is advantageous. Moreover, the findings indicate that the ML model is more effective than a physical model at representing generic park behavior when aggregated to a broader region. This discrepancy may be attributed to the absence of rotor diameter information in the physical model. An additional potential explanation is that ML models are capable of correcting systematic inaccuracies that may be present in the input features, such as biases inherent to the NWP.

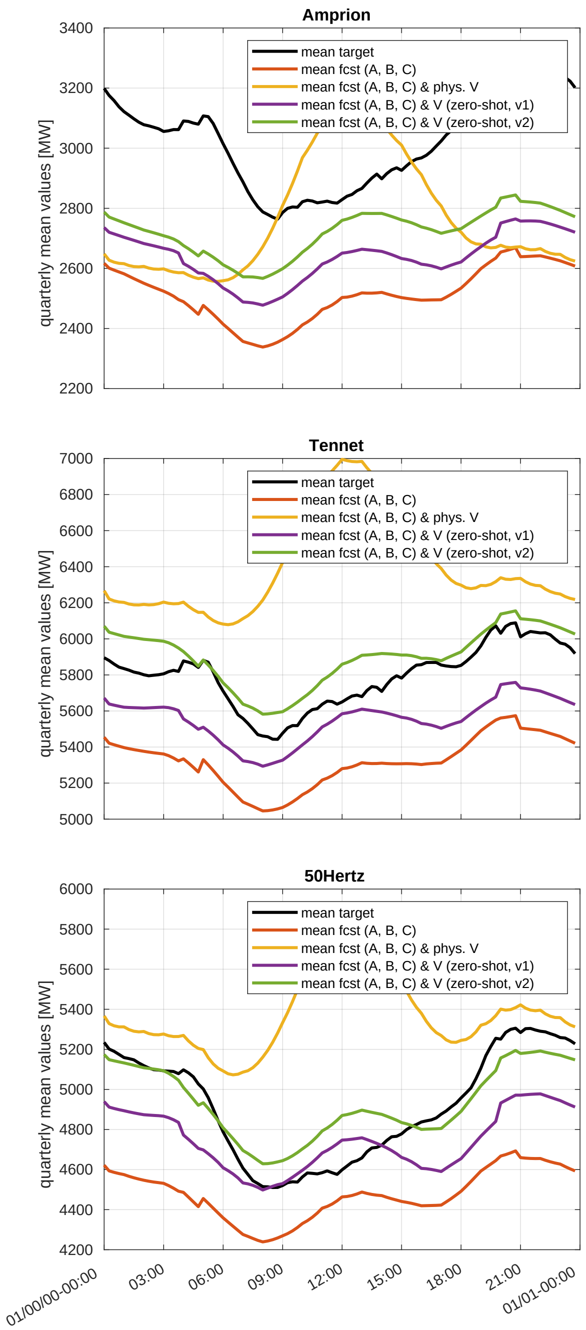

Fig. 4: Mean diurnal cycle of forecasts and target time series

This assumption is supported by Fig 4, which depicts the mean diurnal cycle of the forecasts and the target time series, i.e. all time series spanning one year are averaged to 96 mean values, one for each quarter-hour of the day. The benchmark

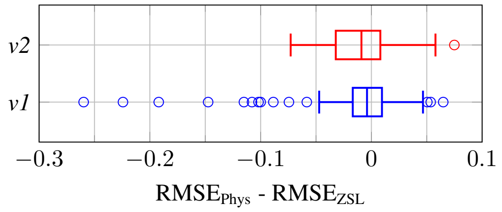

Fig. 5: Parkwise difference in RMSE for physical reference model and zero-shot learning approaches (blue: *v1*, red: *v2*).

forecast which does not take into account the use of virtual parks produces an underestimation of the target values for all three regions. In contrast, the second benchmark utilizing physical forecasts at virtual parks, tends to overestimate the target values. In particular, the physical model forecasts result in a distinct pattern when examining the course of the day, exhibiting a pronounced peak around noon that is not evident in the target values. This phenomenon may be caused by either systematic errors in the NWP's wind speed forecast or the physical model's inability to accurately depict park behavior during the day, which could be influenced by factors such as curtailments. Both approaches that employ zero-shot learning demonstrate superior alignment with the observed daily pattern, while simultaneously mitigating the bias observed in the benchmark results.

The superior performance of run *v2* in comparison to run *v1* may be explained by the ability of the mixed embedding to leverage a greater number of embedding dimensions. The master data utilized in the fixed embedding dimensions is restricted to hub height and rotor diameter as the most reliable available data points. The model used in *v1* is constrained to classify wind parks based on only these two values, which are insufficient for fully explaining all aspects of a wind park's behavior. Consequently, the model may potentially misinterpret the influence of master data on the target values. By incorporating additional trainable embedding dimensions in run *v2*, the model is better positioned to learn the actual connections between master data and park behavior. The role and interpretation of the model's embedding space is further discussed in section 3.3.2.

3.3.2 Zero-shot learning for reference wind parks: Evaluating zero-shot models on park level shows mixed results. Comparing both approaches *v1* and *v2* with the reference physical model, on average zero-shot parks perform worse. In general, *v1* yield more outlier parks and therefore seems to generate more sensitive results (Fig. 5).

This impression can further be validated by examining model results based on hypothetically varying master data. By modifying master data inputs per model, the park specific model sensitivity is visualized in Fig. 6-8. For comparison, two parks are picked regarding the results of respective models without trained embedding. While park 1 generates worse results (Fig. 6), park 2 significantly outperforms the physical reference model (Fig. 7). White markers indicate the park specific master data. Rotor diameter and hub height are standardized with regard to the data set.

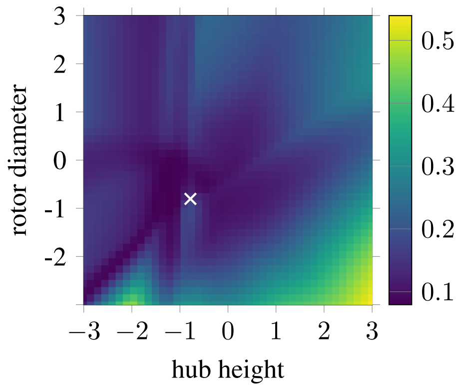

Fig. 6: Park 1 $\mathrm{RMSE}_{\mathrm{ZSL,v1}}$ without trained embedding dimensions.

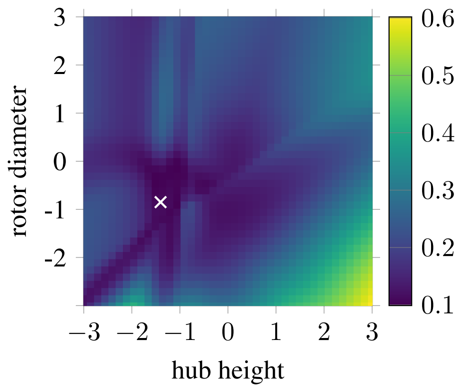

Fig. 7: Park 2 $\mathrm{RMSE}_{\mathrm{ZSL,v1}}$ without trained embedding dimensions.

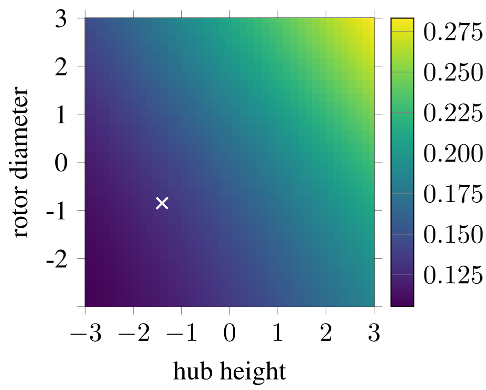

Fig. 8: Park 2 $\mathrm{RMSE}_{\mathrm{ZSL,v2}}$, with trained embedding dimensions set to zero values.

Both parks display a similar heat map pattern, while pointing out a minor but decisive difference in the marker position. For park 2 (Fig. 7), master data is located in the dark blue area, bringing optimal RMSE results for this trained model and related target data. Contrarily, park 1 (Fig. 6) misses the dark blue and therefore optimal master data region.

This observation corresponds to the more sensitive model behavior of approach *v1*. Minor deviations in master data result in significantly higher RMSE values. Adding trained embedding dimensions to the model, as in approach *v2*, heat maps for both parks become more uniform and less sensitive with regard to master data input (Fig. 8), which might cause previously observed improvements on the aggregation level.

4 Conclusion

In conclusion, our study demonstrates the efficacy of employing a zero-shot learning model that includes master data information for improving wind power forecast accuracy at TSO control zones in Germany, where limited measurement data poses a significant challenge. The results from our experiments indicate that both versions of the zero-shot model (*v1* and *v2*) outperform benchmarks that do not employ zero-shot learning, including those that utilize physical models. Specifically, *v2*, which incorporates a mixed embedding strategy, provides the most accurate forecasts by effectively utilizing additional trainable embedding dimensions that capture more nuanced aspects of wind park characteristics. When comparing forecasts on wind park level, the zero-shot learning approach does not outperform physical model forecasts.

Further research could investigate the potential for incorporating additional master data information. The promising results also justify the subsequent trial of a more computationally expensive approach, in which zero-shot learning could be employed to generate forecasts at all German power plants, as opposed to utilizing a reduced number of virtual parks. Moreover, the approach can be integrated with optimization techniques for the projection and aggregation stages, such as the residual two-layer extrapolation method proposed in [6]. Another approach for future investigation is the potential integration of TSO target data into the training process, with the objective of developing forecast models that are capable of making accurate power predictions at both the local and aggregated levels. Finally, we intend to extend the experiments to the use case of solar power predictions.

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