WindDragon: Enhancing Wind Power Forecasting with Automated Deep Learning

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Context and contributions

1. **Accurate forecasts of wind power generation is mandatory to meet the 2050 net zero scenario.** Remarkable progress has been made since 2010, when global electricity generation from wind power was 342 TWh, rising to 2,100 TWh in 2022. The IEA targets approximately 7,400 TWh of wind-generated electricity by 2030 to meet the zero-emissions scenario.

2. **How to efficiently combine Deep Learning (DL) methods and wind speed forecast maps from Numerical Weather Prediction (NWP) models?** In this work, we propose to leverage the spatial information in NWP wind speed maps for national wind power forecasting by exploiting the capabilities of DL models.

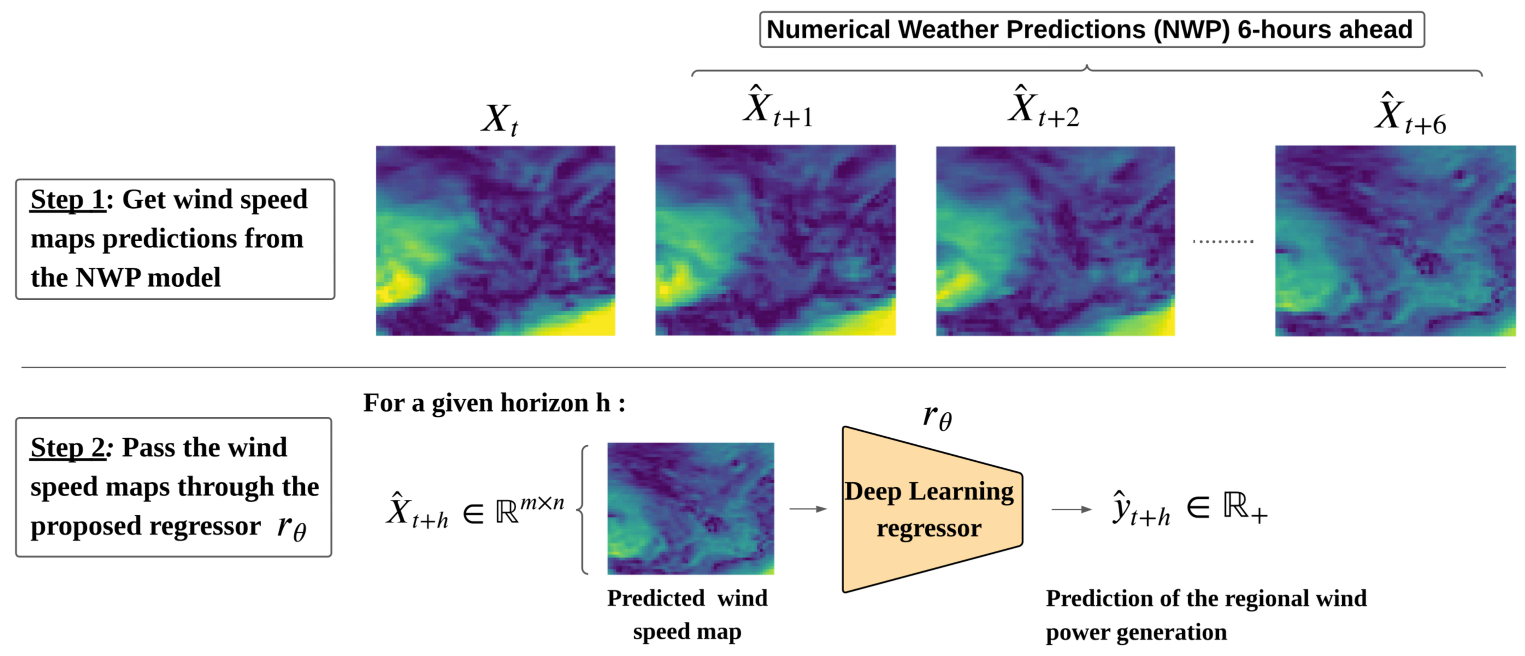

Figure 1: Global scheme for wind power forecasting. Every 6 hours, the NWP model produces hourly forecasts. Each map is processed independently by the regressor which maps the grid to the wind power corresponding to the same timestamp.

3. **How can a performing DL architecture be automatically found that leverages the spatial information in NWP wind speed maps for national wind power forecasting?** In this work, we present WindDragon, a DL optimization framework based on the package DRAGON which automatically finds a good DL architecture for short-term wind power forecasting using NWP wind speed maps and optimizes its hyperparameters.

WindDragon: a framework for regression on wind speed maps

1. **The DRAGON framework.** DRAGON is an AutoDL framework which generates well-performing DL models for a given task. Compare to other AutoDL frameworks, DRAGON provides a flexible search space adaptable to any task and is well-adapted when the type of architecture to use is unclear.

2. **WindDragon.** The DL models in DRAGON are represented as directed acyclic graphs, with nodes representing the layers and the edges the connections between them. In our case, the graphs are restrained to a meta model represented in Figure 2. A first graph processes 2D data (the wind speed maps), then a flatten layer and a second graph processing 1D data follow. A final MLP layer is added at the end of the model to convert the latent vector to the desired output format (the generation forecast). We optimized the solutions from our search space using an evolutionary algorithm.

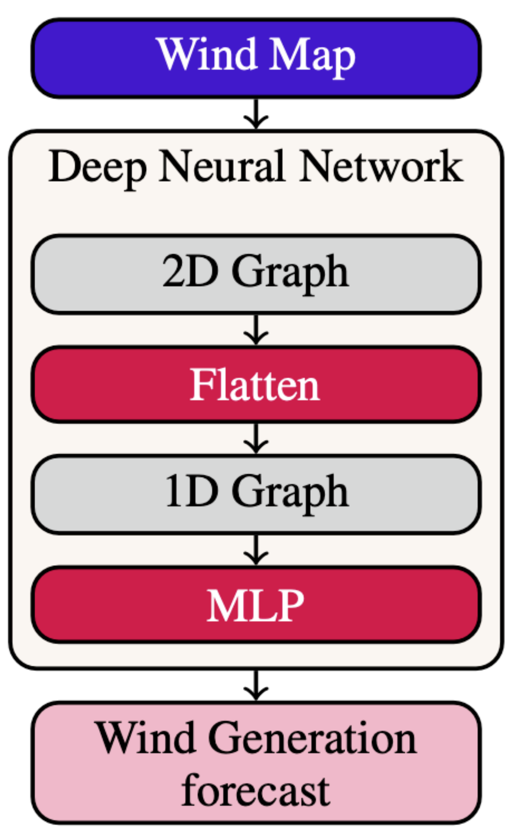

Figure 2: WindDragon's meta model for wind power forecasting

Datasets and data preparation

1. **NWP wind speed maps.** 100-meter high forecasts at a 9 km resolution provided by the HRES model from the European Centre for Medium-Range Weather Forecasts (ECMWF).

2. **Wind power generation record.** The hourly french regional and national wind power generation data came from the French TSO (open data). Years from 2018 to 2019 are used to train the models, and data from 2020 is used to evaluate how the models perform

3. **Data preparation.** The french national signal is obtained by summing the forecasts of the 12 administrative regions of France. As the wind turbines are not evenly distributed across the maps of the regions, we selected areas around each wind farm in the region and took the convex hull of all the considered points to get a seamless map with all the turbines. Installed capacity data for each region - the maximum wind power a region can produce - is used to scale the wind power target.

Experiments

1. **Baselines.** We produce hourly forecasts for an horizon h (h ∈ {1, ..., 6}) with 4 models: a persistence which predicts the future value at time t + h as equal to the observed value at time t, an XGB based on the mean wind speed for the considered region using NWP forecasts, a Convolutional Neural Networks (CNNs) and a Vision Transofmrer (ViT) based on the wind speed maps.

2. **Quantitative results.** First, the regression approach with the average predicted wind speed and the XGB regressor outperforms the naive persistence baseline. Then, DL regressors on NWP maps can capture more complex patterns which improves the forecast accuracy. Finally, WindDragon outperforms all baselines, showing an improvement of 22 MW (6%) over the CNN. It corresponds to the equivalent of the annual consumption of a French town of 32,000 inhabitants (~193 GWh).

Table 1: National results: sum of the regional forecasts for each models. The best results are highlighted in bold and the best second results are underlined.

	WindDragon		CNN		ViT		XGB on mean		Persistence	
	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE
France	**346.7**	**7.7 %**	369.0	8.1 %	385.7	8.5 %	416.7	9.2 %	779.7	17.3 %

Table 2: Regional results. The best results are highlighted in bold and the best second results are underlined.

	WindDragon		CNN		ViT		XGB on mean		Persistence	
Region	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE	MAE (MW)	NMAE
Auvergne-Rhône-Alpes	**19.5**	**14.9 %**	19.6	15.0 %	21.6	16.5 %	29.2	22.4 %	28.7	22.0 %
Bourgogne-Franche-Comté	**32.9**	**14.8 %**	34.1	15.4 %	37.2	16.8 %	42.3	19.1 %	58.7	26.6 %
Bretagne	**36.1**	**14.1** %	38.0	14.9 %	39.9	15.6 %	47.1	18.4 %	67.2	26.3 %
Centre-Val de Loire	**53.3**	**15.0 %**	57.3	16.1 %	59.0	16.6 %	61.9	17.5 %	96.7	27.3 %
Grand Est	**125.6**	**12.5 %**	130.5	13.1 %	161.0	16.1 %	148.8	14.9 %	251.2	25.1 %
Hauts-de-France	**159.7**	**12.1 %**	167.6	12.7 %	177.0	13.4 %	178.8	13.5 %	320.1	24.2 %
Île-de-France	**6.8**	**22.6 %**	7.17	23.7 %	7.4	24.3 %	7.5	24.9 %	9.5	31.5 %
Normandie	**29.6**	**12.7 %**	30.8	13.2 %	31.2	13.4 %	36.8	15.8 %	55.9	24.0 %
Nouvelle-Aquitaine	**43.1**	**15.7 %**	44.0	16.4 %	48.4	17.6 %	53.7	19.6 %	77.9	28.4 %
Occitanie	**51.2**	**12.3 %**	55.8	13.5 %	64.1	15.5 %	91.6	22.1 %	96.3	23.2 %
PACA	**3.5**	**32.4 %**	**3.5**	**32.4** %	4.0	37.2 %	4.5	41.4 %	4.3	39.5 %
Pays de la Loire	**37.1**	**13.6 %**	39.0	14.3 %	39.9	14.7 %	41.9	15.4 %	74.9	27.5 %

3. **Qualitative results:** Figure 4 shows that the CNN and the model found by WindDragon produce accurate forecasts, but DRAGON demonstrates superior accuracy, particularly in predicting high peak values.

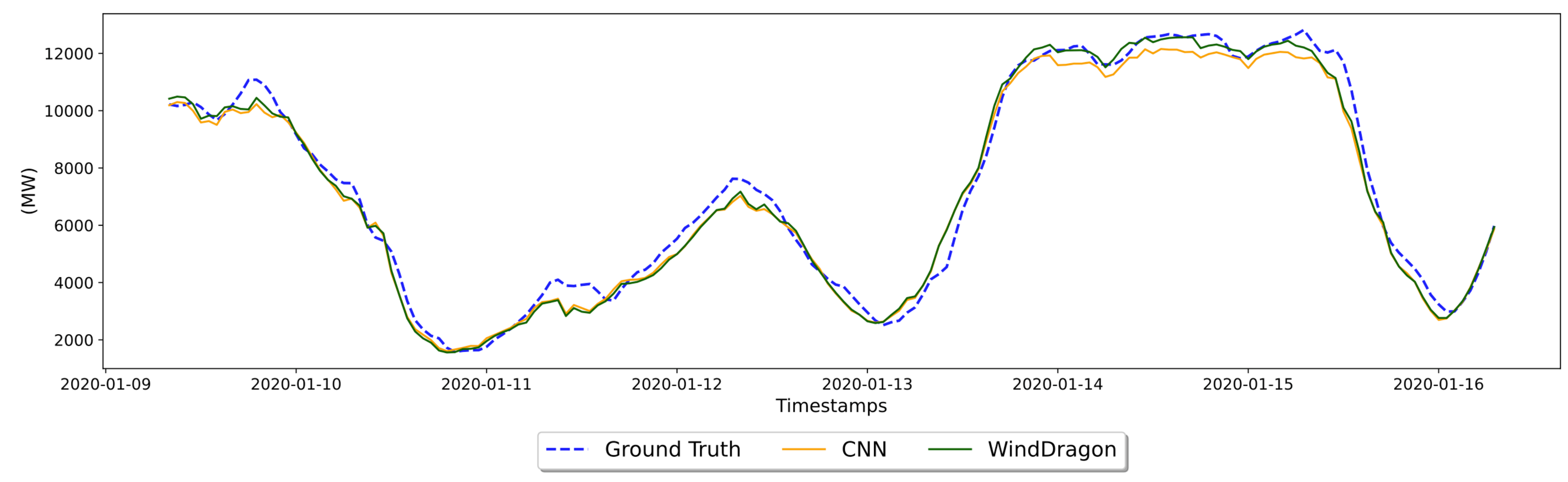

Figure 4: Wind power forecasts for a week in January 2020. The figure displays the ground truth as dotted lines, and the forecasts from the two top-performing models, WindDragon and the CNN.

4. **Example of an architecture found by WindDragon.**

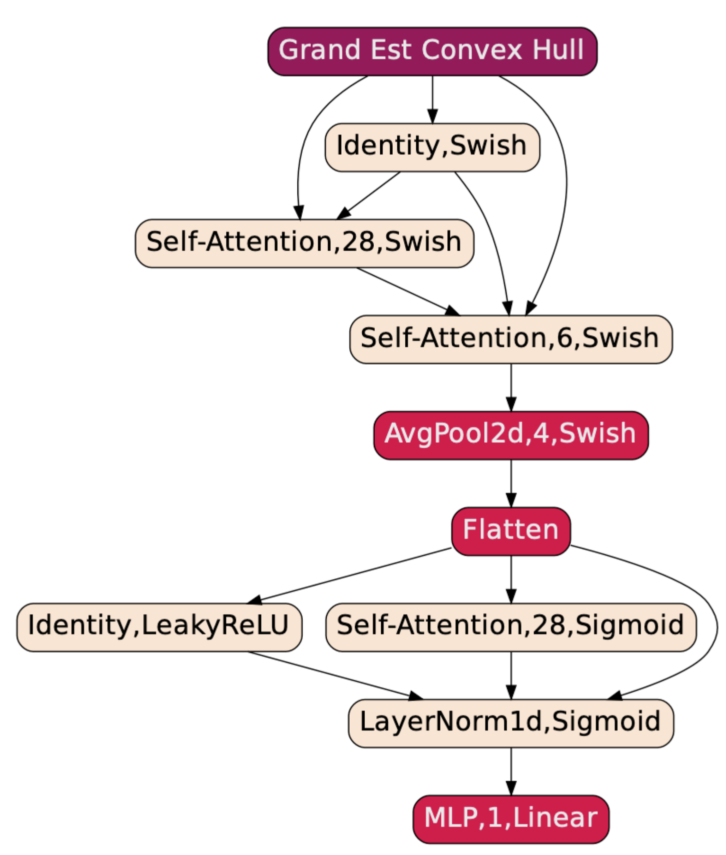

Figure 5: Dragon automatically found architecture applied on the Grand Est region.

* equal contribution

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