Enhanced Renewable Power Forecasting through NWP and Historical Power Data Integration

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ITISE 2024

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 864276

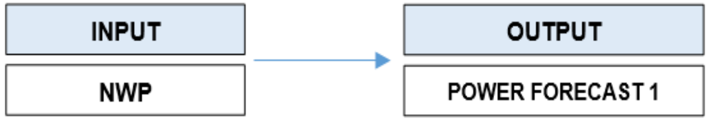
INTRODUCTION

- Recent efforts have focused on predicting power output from wind and solar power plants and electricity demand. A key challenge is integrating variable renewable energy sources (vRES) like wind and solar into power systems in a cost-effective and sustainable way.
- Transmission system operators (TSOs) must balance electricity generation and demand precisely, relying on accurate forecasts of vRES production and consumption to minimize costly energy balancing in reserve markets.
- **This study explores three forecasting approaches of vRES production:**
  - **NWP-based using meteorological data,**
  - **power-based using historical power data, and**
  - **hybrid model.**
- These methods are part of the EU-funded TradeRES project for a ~100% renewable European power system.

Power forecast approaches implemented in TradeRES to increase vRES market value

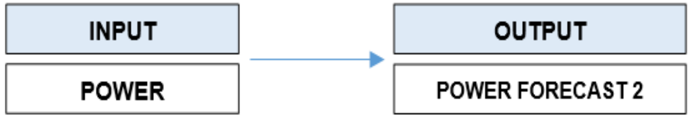
1 - NWP-based model

Employing NWP data and TradeRES methodology.



2 - Power–based model

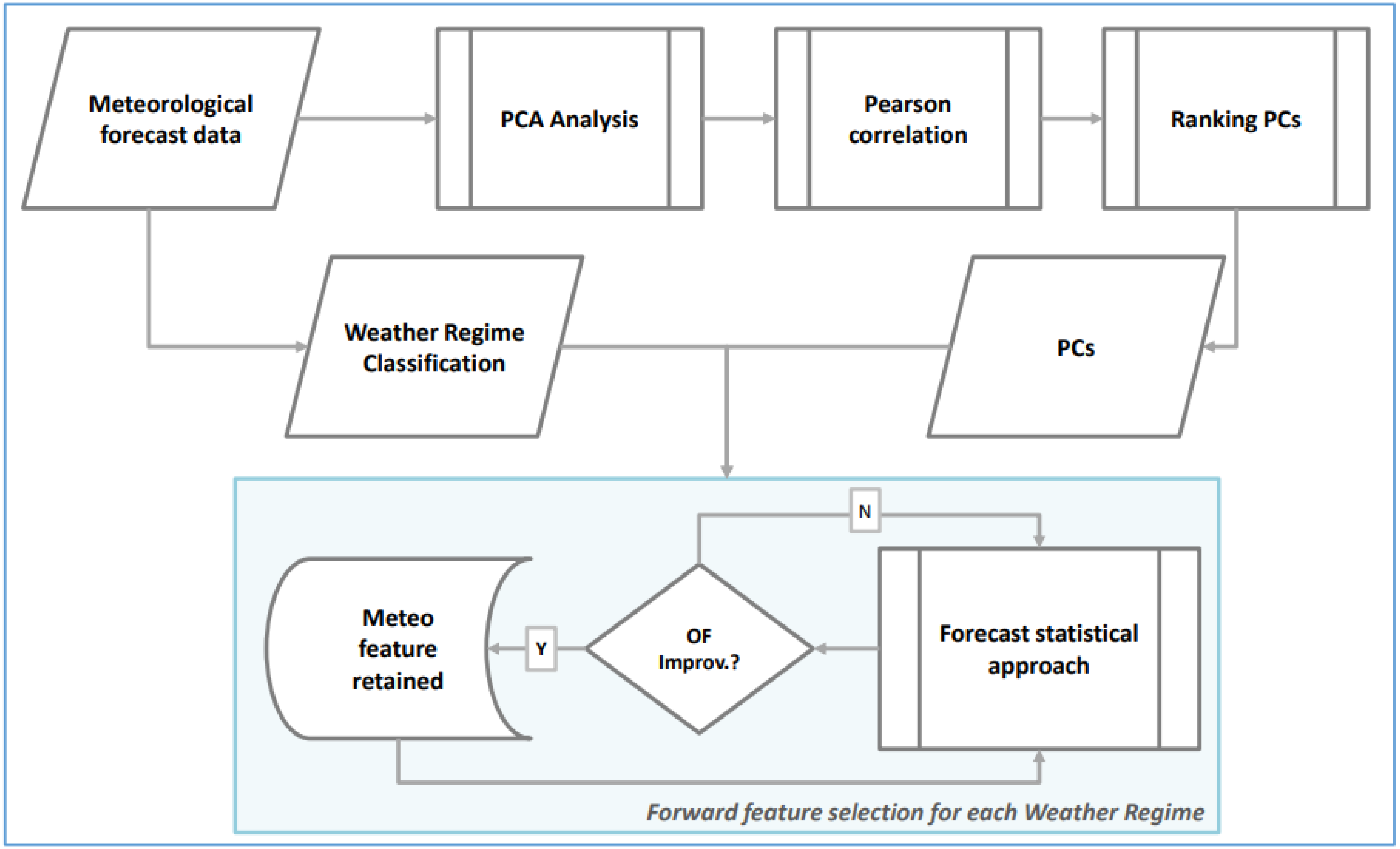
Black-box model using only power information from the historical power series (“autoregressive”) .



3 - Hybrid model

Combination of the previous two models – combining NWP and historical power series data.

NWP-based model (TradeRES)



NWP-based model

- Key points
    - Meteorological forecast data
    - Dimensionality reduction techniques
    - Weather regime classification
    - Forecast statistical approach
        - feature selection
        - different regression algorithms
        - power forecasts per weather regime

Power-based model

For the power-based model, the power timeseries were iteratively integrated, covering power from the last hour up to the previous 24 hours and, additionally, power from multiples of 24 hours up to a week was considered due to the high autocorrelation for these periods.

Hybrid approach

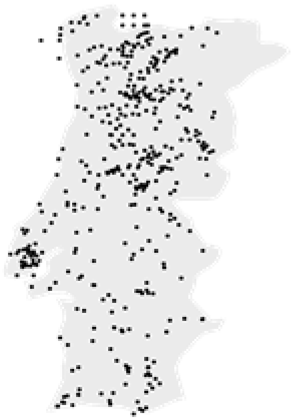
The hybrid approach combines NWP features, represented by principal components retained for weather indicators, with historical power series data, including various time lags from the prior hour to a week.

Persistence

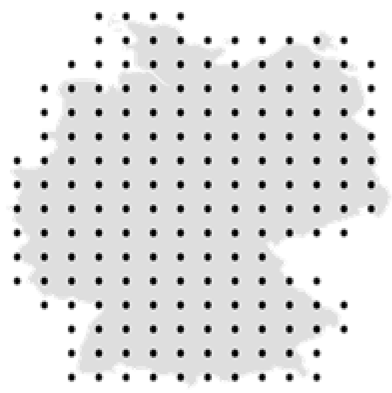
Model that maintains the power value for the initial forecast hour

SIMULATIONS

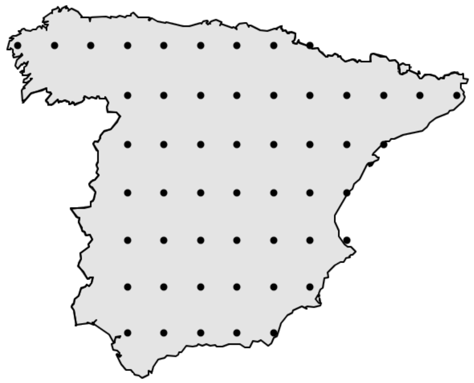
PORTUGAL



GERMANY



SPAIN



Wind and solar power generation for different spatial levels

- **National level**: Portugal, Spain, and Germany,
- **Park level:** 27 wind parks and 8 solar parks in Portugal.

SIMULATIONS

- **Forecasting horizon**
  - **Day-Ahead Market (DAM):** forecast for the 24 hours of the next day
  - **Period-Ahead Market (PAM) :** forecasts for 6 hours ahead with four updates during the day.

- The models were **trained on data from 2018** and then **evaluated on the complete dataset from 2019**.

DATA

- **Meteorological data** were derived from **Global Forecast System** (GFS)
  - Includes common variables like wind speed and direction, along with less common parameters such as the atmospheric boundary layer and geopotential height

- **Target variable**:
  - **National case studies:** Ninja.Renewables database
  - **Power plant case studies: hourly observed power production**

Variable (and heights, when applicable)
Wind speed (at 10m, 50m and 100m)
Wind gust (at 10m)
Wind direction (at 10m, 50 m and 100m)
Temperature (2m, 80 m)
Mean sea level pressure
Radiation
Relative Humidity (2m)
Geopotential height (at 500, 850 hPa)
Planetary boundary layer height

ERROR METRICS

The evaluation of the performance is based on the **RMSE** and normalized **RMSE:**

$$RMSE = \sqrt{\frac{\sum_{t=1}^{T}\left(Forcast\ \ (t) - Observed\ \ (t)\right)^2}{T}}$$

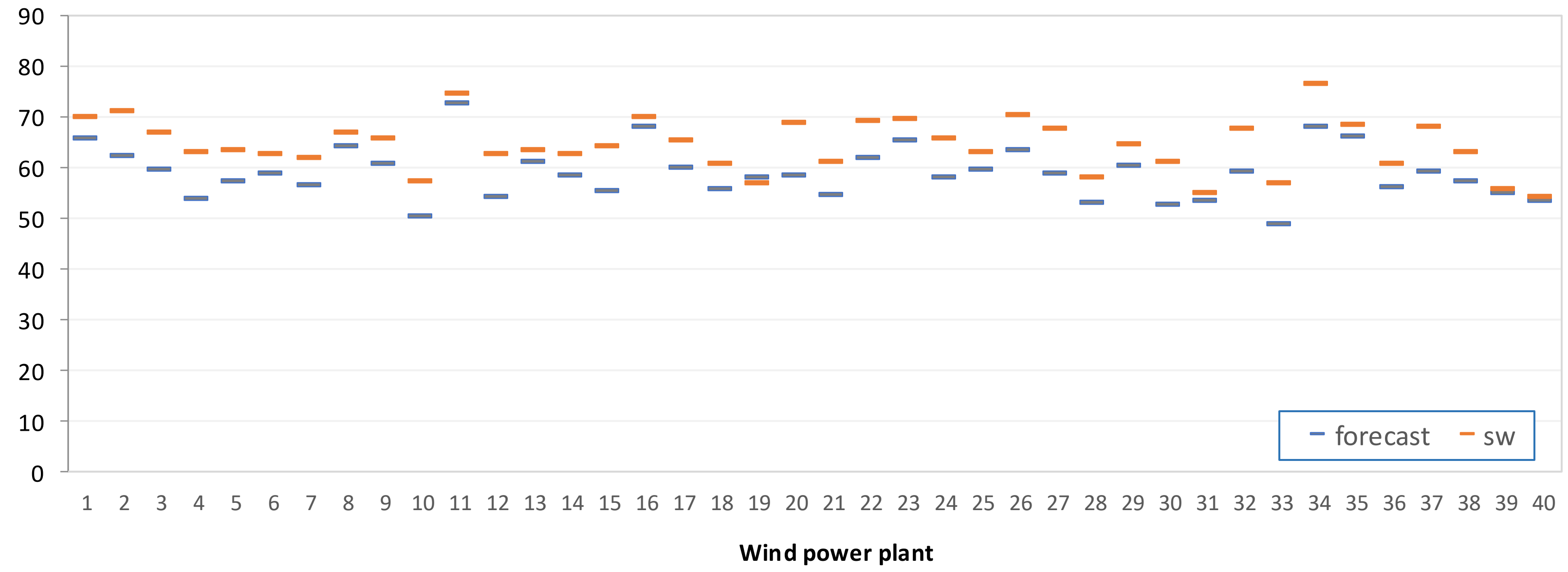
$$NRMSE = \frac{RMSE}{\frac{\sum_{t=1}^{T} Observed\ \ (t)}{T}}$$

To quantify the performance improvement:

$$\varepsilon(\%) = \left(1 - \frac{Forecast}{Forecast_{Benchmark}}\right) \times 100$$

RESULTS

$N_{AVG}RMSE$ (%)



TradeRES forecast approach enable to reduce NRMSE when compared to the Smartwatt approach:

- **Average decrease :** 5.47%
- **Max decrease:** 10.13%

Performance improvement:

$$\varepsilon = \mathbf{8.45}\%$$

RESULTS FOR SCENARIOS SIMULATIONS

Wind power: DAM *vs* PAM results (NRMSE)

Market design	Simulation	Portugal	Germany	Spain	27 Wind Parks Av.
DAM	Historical Power	70.50	73.19	51.78	98.50
	Historical Power + NWP	**31.16**	23.72	**21.29**	**66.52**
	NWP	31.86	**21.67**	21.79	71.78
PAM	Historical Power	24.70	28.75	20.37	57.59
	Historical Power + NWP	**21.99**	**18.04**	**13.39**	**51.64**
	NWP	24.02	20.10	18.15	60.92

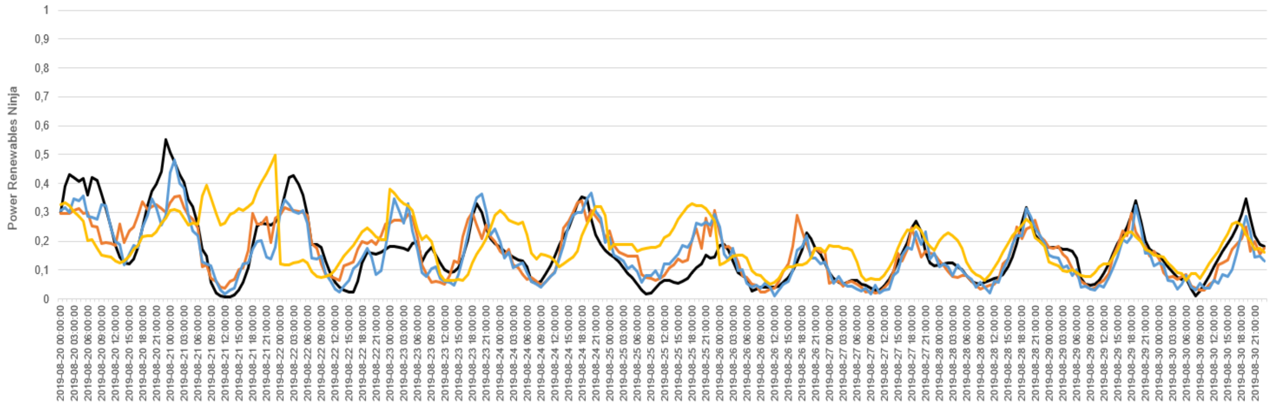
- **Hybrid model (Historical + NWP) presents** in almost all simulations and case studies **the best performance**.

- The historical-based model has a very poor performance for the DAM.

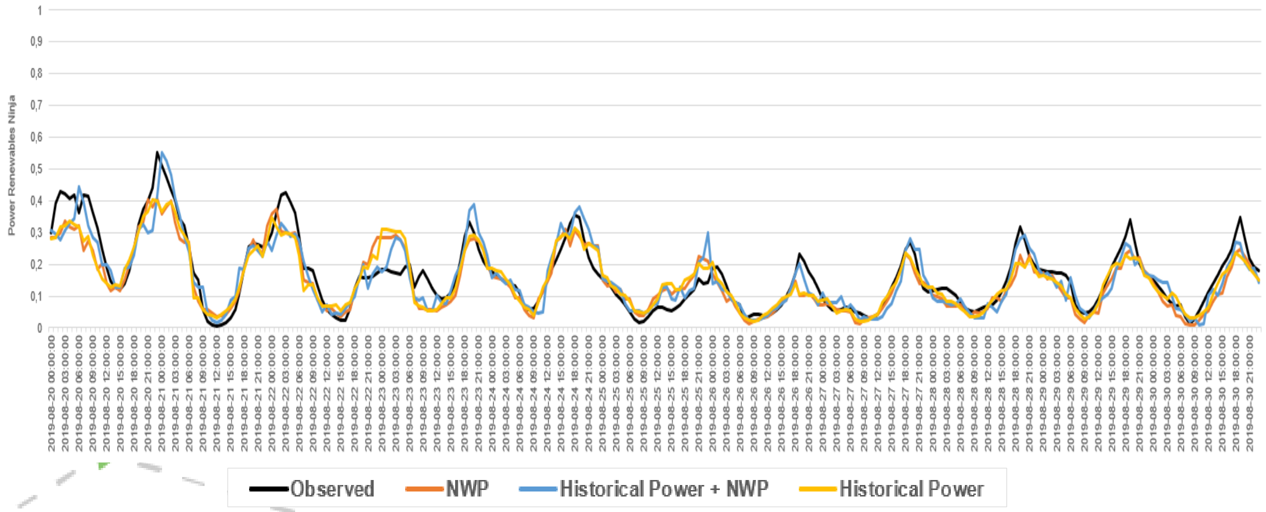
Wind power: DAM *vs* PAM results

- Example of wind power forecast for Portugal

DAM:



PAM:



- Significant errors are observed in the DAM forecast, especially for the "Historical Power".

Results for scenarios simulations

Solar power: DAM *vs* PAM results (NRMSE)

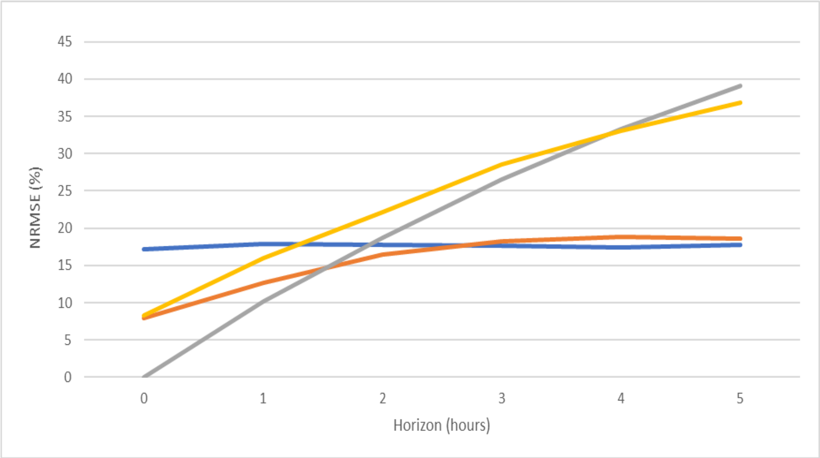
Market design	Simulation	Portugal	Germany	Spain	8 Solar Parks Av.
DAM	Historical Power	34.98	46.74	25.07	60.53
	Historical Power + NWP	**24.85**	**34.89**	**19.97**	**50.34**
	NWP	32.69	30.99	20.53	58.21
PAM	Historical Power	24.29	33.41	17.85	52.75
	Historical Power + NWP	**19.16**	**29.56**	**15.64**	**47.23**
	NWP	27.82	30.69	20.61	52.58

- The outcomes align with those obtained for the wind power case.
- **Hybrid model presents the best performance for DAM and PAM.**

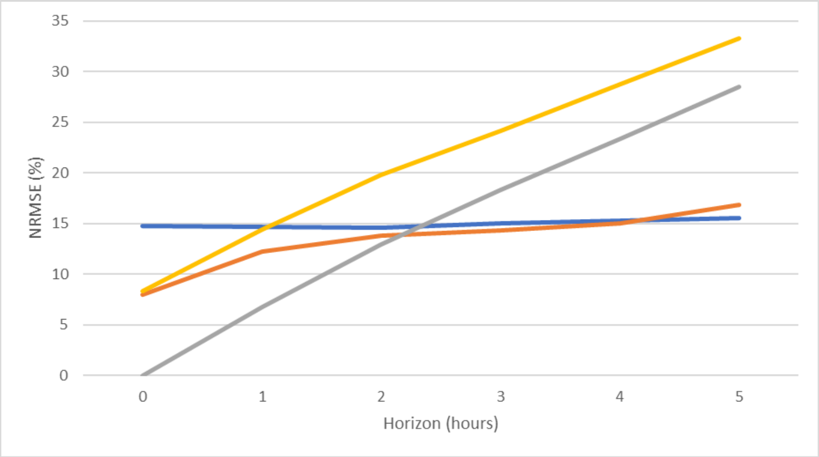
Persistence model

- Wind power NRMSE for different time horizons

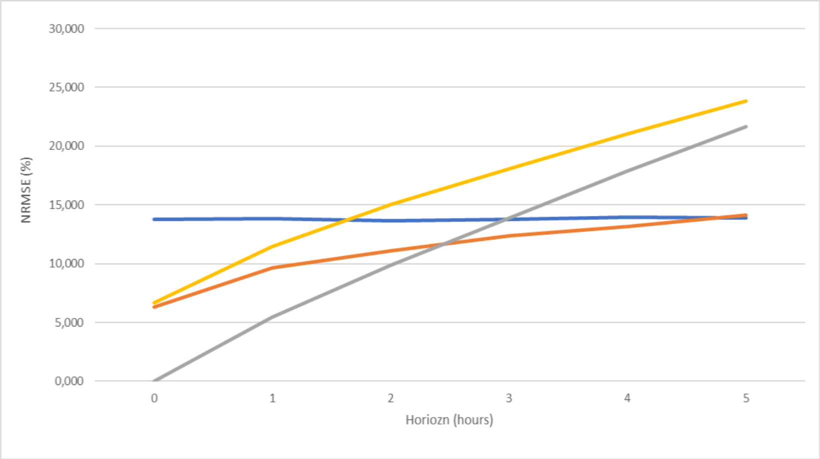
  - *Portugal*



  - *Germany*



  - *Spain*



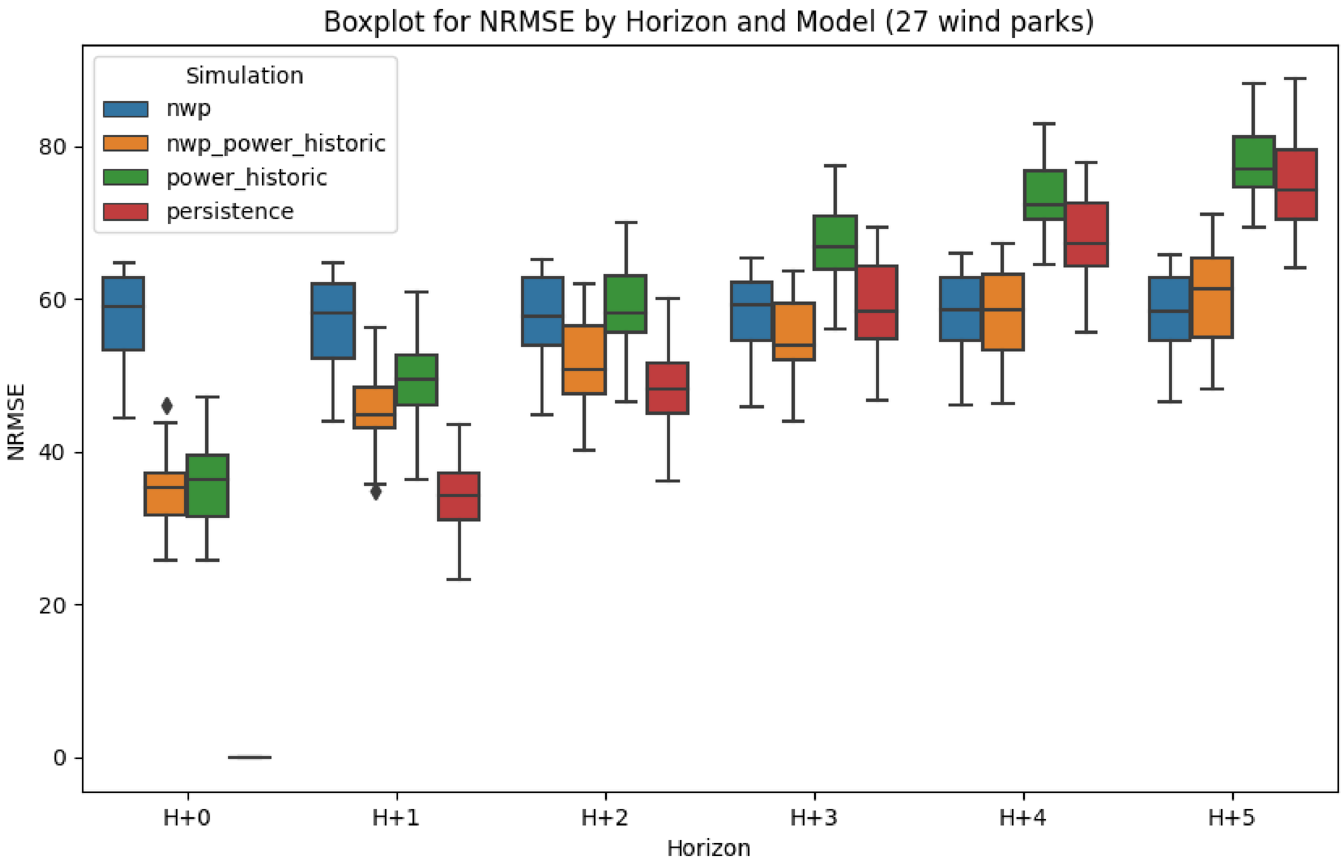
NWP NWP + Historical power series Persistence Historical power series

- The **persistence model** exhibits the **best performance up to the next two hours**.

- The **hybrid model (NWP + Historical power) outperforms the NWP in the first four hours**, after which they become very analogous in terms of error.

Wind power: results for PAM

- Wind power normalised root mean square error for different time horizons || Park level



Same behavior as observed in the national cases

- Over time, persistence error and historical model errors increase.
- Extending the horizon slightly degrades hybrid model performance.

FINAL REMARKS

- A **new numerical weather (NWP)-based approach was proposed in TradeRES**.
  - ✓ Incorporating grid data and non-conventional meteorological variables, such as the atmospheric boundary layer, are crucial for enhancing the accuracy of vRES power forecasts.
  - ✓ The use of a grid of meteorological points guarantees a better performance compared to a forecast based on a single meteorological point.
  - ✓ The clustering process, for identifying typical weather patterns, also plays an integral role in performance enhancement.

- For **the timeframe of the day-ahead market (DAM),** wind and solar PV technologies **continue to show significant errors**, **even assuming a postponement** of their bids **to an hour closer to real-time**.
  - ✓ A 6 hours **period-ahead market (PAM) enables to reduce significantly the power forecast errors**.

- **Combination of NWP and the historical production series proved to be advantageous**.
  - ✓ It is **recommended** for power producers **to create conditions for obtaining real-time data to increase the performance of the power forecasts**.

CONCLUSIONS

Even with the forecast improvements achieved with the proposed methodology **significant errors are expected for wind power producers in the day-ahead market.**

New market designs are needed to deal with the intrinsic characteristics of wind power production without jeopardizing the potential benefits of wind power producers in the electricity market environments.

Market designs with shorter forecast timeframes can significantly reduce power forecast errors. Power producers should prioritize real-time access to observed power data to improve forecast accuracy for providers