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Wind power forecasting based on bagging extreme learning machine ensemble model

PUCPR

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Background

- Renewable energies are featured as non-polluting and clean energy resources.
- Cities with wind and solar farms had a positive impact on their Human Development Index and Gross Domestic Product.
- Wind power generation is influenced by climatic and demographic changes, as well as by the wind farms layout, making forecasting wind power generation harder.
- To ensure reliable forecasting results, the combination of individual models provides improvements in forecasting performance by averaging model errors, thus reducing the uncertainty.

Data

- Wind power data from two wind farms in Bahia state, in the northeast of Brazil.
- The sampling rate of the data set was of 6 steps per hour, meaning each step advances 10 minutes in time.
- WDF1 is located in São Sebastião do Alto and has an installed capacity of 19.20 megawatt (MW). In turn, the WDF2 is located in Rio Verde and has an installed capacity power of 31.92 MW.

Proposed Model

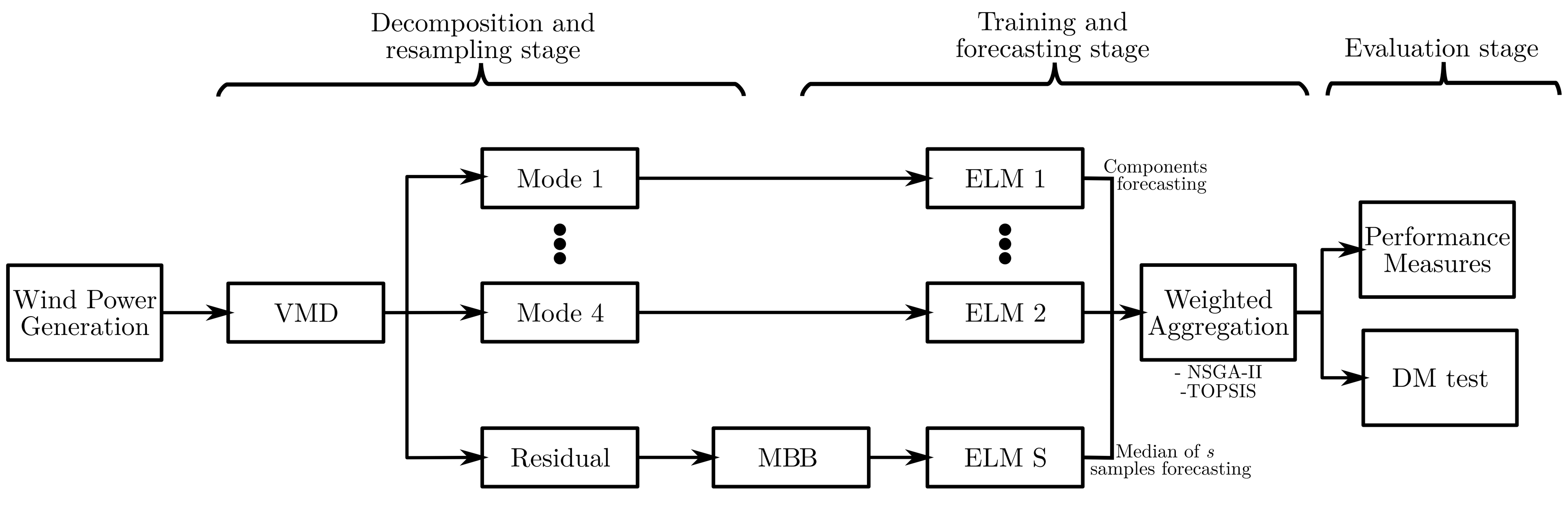
- **The proposed model comprises:**
  - Variational Mode Decomposition (VMD).
  - Moving Block Bootstrapping (MBB).
  - Extreme Learning Machine.
  - Multi-objective optimization.

- **The Horizons are:**
  - 10, 30, 60 and 120 minutes.

- **The model was compared with**
  - ANFIS, ELM, CNNs, RNN, LSTM, GRU, NAIVE, THETA, TBATS, ARIMA, XGBoost, RF, KNN, SVR, Stacking.

- **The used evaluation metrics were**
  - RMSE, MAE, MAPE.

- The training step used only the training data.
- A recursive strategy is employed for the multi-step-ahead forecasts.
- The ELMs are tuned using grid search.
- The residuals are resampled using MBB.
- The weights of the aggregation of the ELMs modes and the residual are obtained using a Nondominated Sorting Genetic Algorithm – version II (NSGA-II), minimizing MAE and variance of error signals.



- The statistical significance of the difference in the errors of the proposed model and the compared models was tested using a Diebold-Mariano (DM) test.

Results

- Using DM test, the proposed model had a difference in the error signal to a significance of 1% with all other tested models.
- The proposed model achieved better results in comparison with the other tested models in all forecasting horizons.
- Results suggest that the proposed ensemble achieved better forecasting performance than bootstrap stacking, machine learning, artificial neural networks, and statistical models, with values of approximately 12.76%, 25.25%, 31.91%, and 34.76%, respectively, in terms of root mean squared errors reduction for out-of-sample forecasting.

WDF	Horizon (min)	Criteria	Proposed model	Best of Other models
1	10	RMSE (kWh)	**912.02**	1098.04
		MAE (kWh)	**663.08**	826.52
		MAPE	**13.22%**	13.89%
	30	RMSE (kWh)	**1205.31**	1254.00
		MAE (kWh)	**816.97**	938.33
		MAPE	**13.99%**	15.10%
	60	RMSE (kWh)	**1373.39**	1559.15
		MAE (kWh)	**950.88**	1156.46
		MAPE	**14.99%**	17.13%
	120	RMSE (kWh)	**1756.43**	2154.69
		MAE (kWh)	**1143.90**	1554.80
		MAPE	**16.29%**	21.00%
2	10	RMSE (kWh)	**1763.24**	2122.72
		MAE (kWh)	**1281.95**	1596.52
		MAPE	**13.32%**	13.87%
	30	RMSE (kWh)	**2330.27**	2422.31
		MAE (kWh)	**1579.47**	1812.34
		MAPE	**14.05%**	15.09%
	60	RMSE (kWh)	**2655.23**	3013.41
		MAE (kWh)	**1838.36**	2228.96
		MAPE	**15.09%**	17.09%
	120	RMSE (kWh)	**3395.76**	4152.88
		MAE (kWh)	**2211.54**	3005.33
		MAPE	**16.59%**	20.84%