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Wind energy multi-step ahead forecasting based on variational mode decomposition

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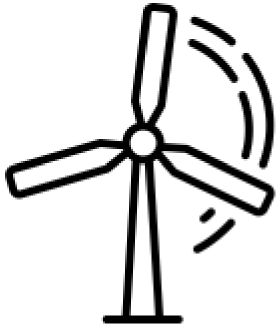


Agenda

- Introduction
- Dataset
- Methodology
- Results
- Conclusion
- Acknowledgments

Introduction

Wind energy has been increasing its operation in the energy matrix in the last decades in many countries around the world.

Even in Brazil, whose electrical power system is majority composed by hydroelectric systems, the wind energy already has a great parcel of the national energy matrix.

The wind energy generation supplies 88.5 million people and represents 17% of the energy consumed in National Interconnected System.

Introduction

Wind energy is classified as an intermittent source, due to nonlinear behavior and fluctuations

Forecasting wind energy as accurate as possible is a challenge

Variational mode decomposition (VMD) can handle the time series

Diverse artificial intelligence (AI) models for multi-step ahead forecasting

Introduction

Objective

- To develop a decomposition framework for wind energy forecasting multi-step ahead (30 minutes, 1 and 2 hours ahead).
- The proposed model is composed by VMD and heterogeneous AI approaches.

Dataset

- Datasets comprises the days **23rd, 24th, and 26th August 2017**, respectively.
- There are **144 samples** for each dataset.

Table 1. Output and inputs of the system

Type	Description	Unit Measure
Output	Power	kW
Input	Generator Bearing Temperature	Celsius
Input	Generator Bearing 2 Temperature	Celsius
Input	Generator Speed	RPM
Input	Wind Speed	m/s
Input	Absolute Wind Direction	Degrees
Input	Nacelle Direction	Degrees
Input	Ambient Temperature	Celsius

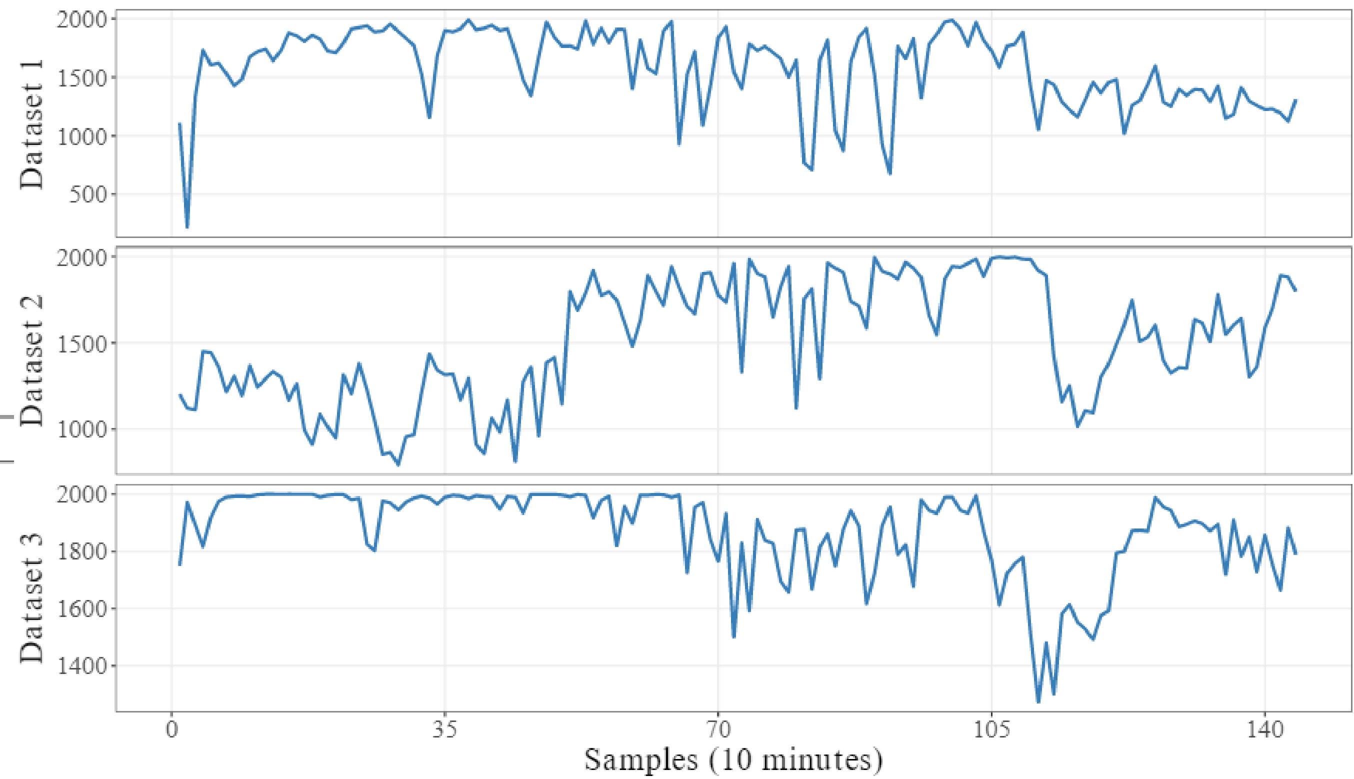
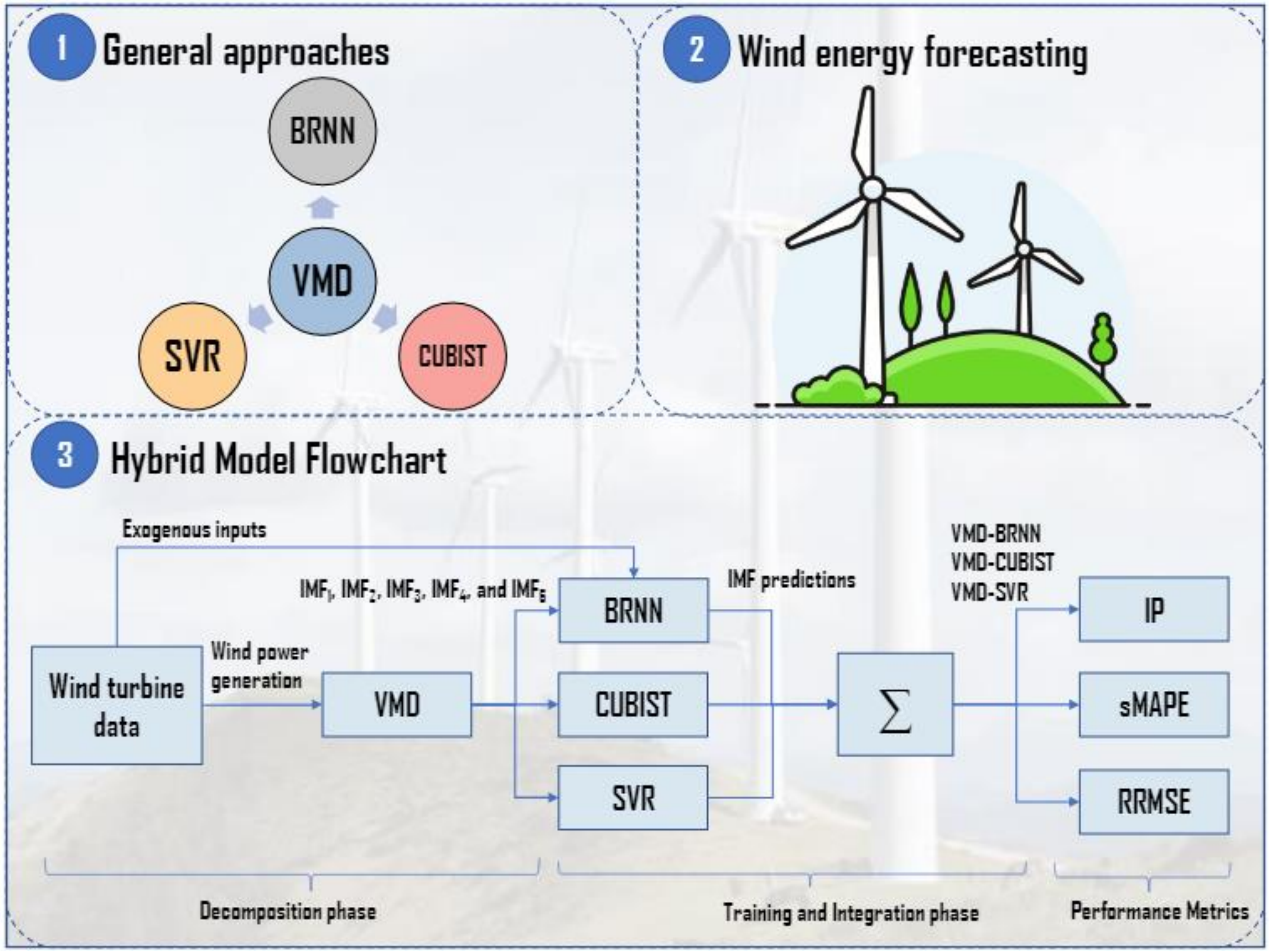


Figure 2. Datasets for August 23rd, 24th, and 26th, 2017

Methodology

- **VMD** decomposed the data into 5 components
- Three different algorithms:
  - **BRNN** (Bayesian Recurrent Neural Network)
  - **CUBIST** Regression.
  - **SVR** (Support Vector Regression with Linear kernel)
- Performance measures:
  - **RRMSE** (Relative root mean square error)
  - **sMAPE** (Symmetric mean absolute percentage error)



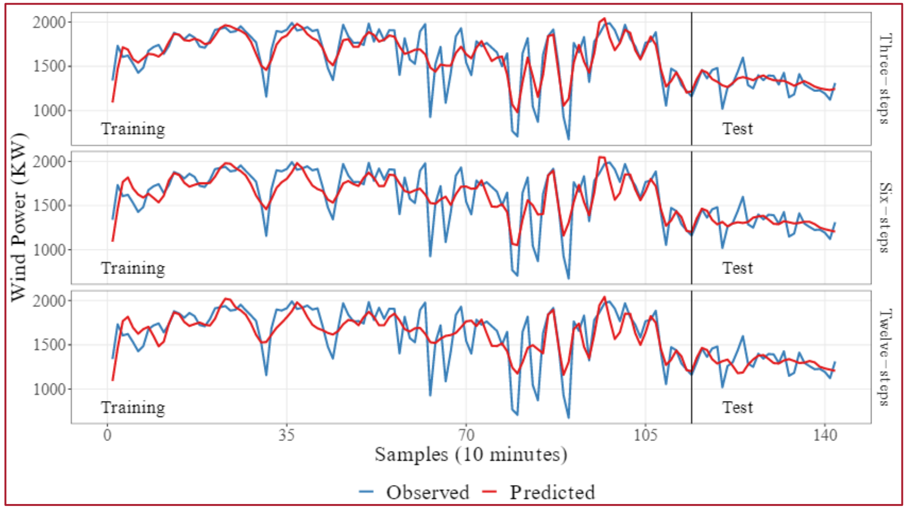
Results

Table 2. Performance measures of the single and decomposed models

Dataset	Forecasting Horizon	Criteria	Model					
			BRNN	CUBIST	SVR	VMD–BRNN	VMD–CUBIST	VMD–SVR
1	Three-steps	RRMSE	21.96%	17.60%	22.01%	8.63%	**7.35%**	18.08%
		sMAPE	22.03%	16.70%	23.22%	7.39%	**5.86%**	18.13%
	Six-steps	RRMSE	20.94%	17.60%	22.25%	13.07%	**8.70%**	18.44%
		sMAPE	20.47%	16.70%	23.61%	11.51%	**6.57%**	18.46%
	Twelve-steps	RRMSE	20.56%	17.60%	22.28%	17.65%	**10.53%**	18.72%
		sMAPE	19.94%	16.70%	23.63%	15.35%	**7.79%**	18.76%
2	Three-steps	RRMSE	17.17%	14.38%	10.84%	5.51%	**5.34%**	8.78%
		sMAPE	12.89%	11.08%	9.18%	4.81%	**4.51%**	6.59%
	Six-steps	RRMSE	17.55%	14.38%	11.00%	8.07%	**7.51%**	12.72%
		sMAPE	13.22%	11.08%	9.21%	6.89%	**6.39%**	10.21%
	Twelve-steps	RRMSE	17.85%	14.38%	11.02%	12.60%	**9.20%**	13.19%
		sMAPE	13.34%	11.08%	9.25%	10.32%	**7.59%**	10.79%
3	Three-steps	RRMSE	17.71%	4.56%	7.11%	3.09%	**2.96%**	5.35%
		sMAPE	14.01%	3.59%	5.20%	2.48%	**2.34%**	4.84%
	Six-steps	RRMSE	15.57%	8.73%	7.40%	5.55%	**3.16%**	5.18%
		sMAPE	12.20%	7.87%	5.43%	4.48%	**2.45%**	4.70%
	Twelve-steps	RRMSE	14.84%	10.15%	7.39%	7.79%	**4.04%**	5.13%
		sMAPE	11.79%	8.22%	5.43%	6.13%	**3.16%**	4.67%

Results

1



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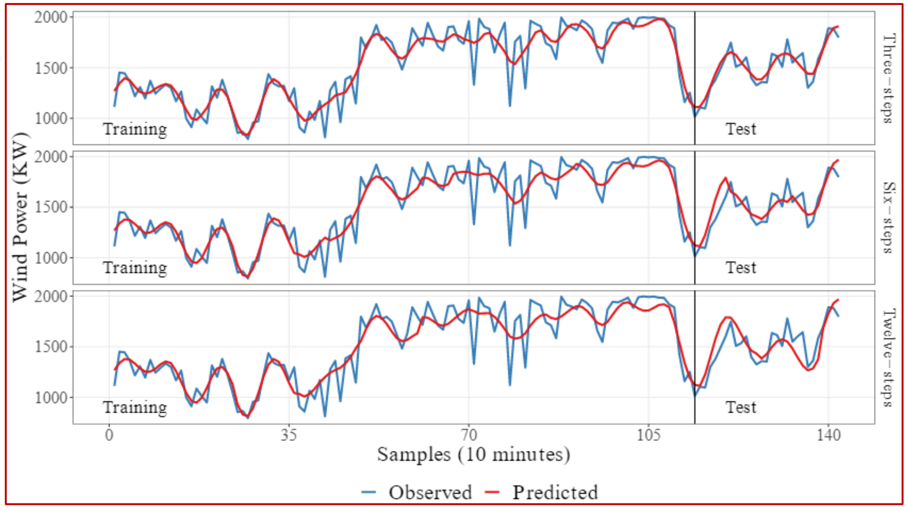

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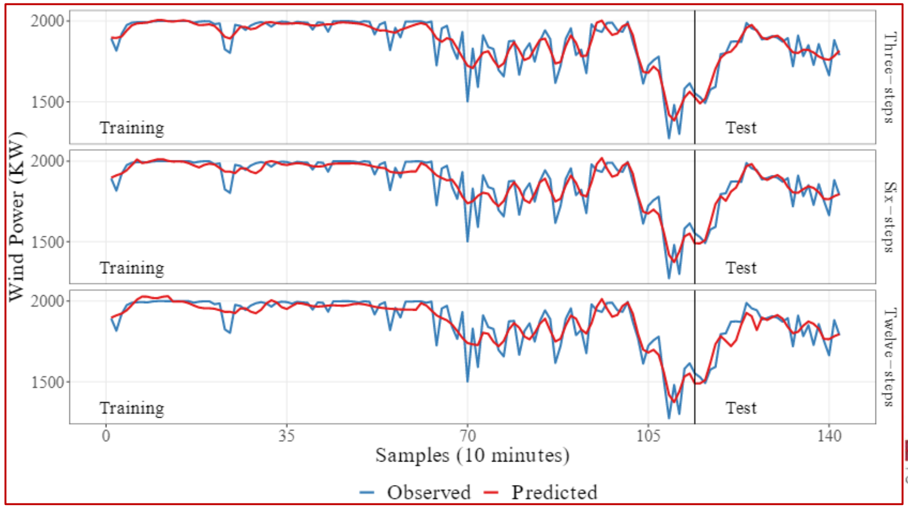

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Conclusion

- This study proposed a decomposition model by using **VMD** and **AI models** to forecast Wind Energy multi-step ahead.
- The **VMD** was coupled with **BRNN**, **CUBIST**, and **SVR** as forecasting models.
- Indeed, the **VMD-CUBIST** approach had a **better** performance than compared models in all forecasting horizons.
- **For future works**
  - Coupling stacking ensemble learning approach.
  - Adopting different signal decomposition approaches.
  - Optimizing the hyperparameters of the forecasting models by using multi-objective optimization.

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Thank you!

Any questions?