I WORKSHOP BRASILEIRO SOBRE MODELAGEM DA ATMOSFERA
APLICAÇÕES NA ÁREA DE ENERGIA EÓLICA
CTGAS-ER | NATAL-RN
14 e 15 junho de 2018

Previsão a curto prazo da potência de saída de centrais eólicas

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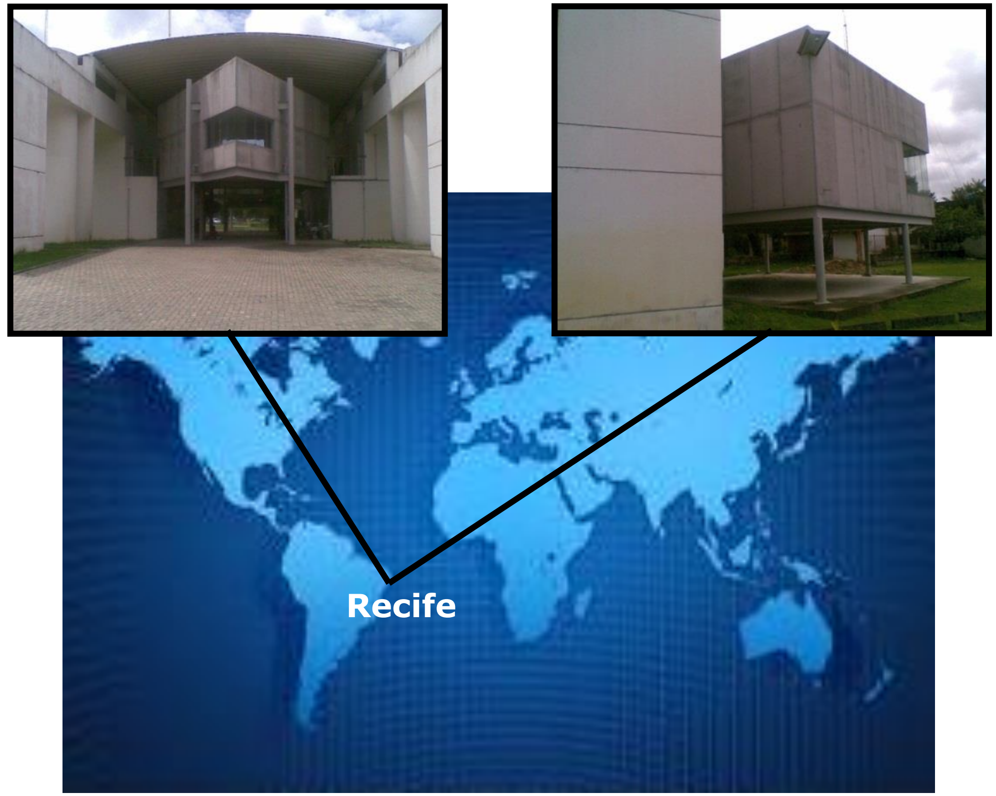
CER-UFPE
CENTTRO DE ENERGIAS RENOVÁVEIS
DA UNIVERSIDADE FEDERAL DE PERNAMBUCO

Centro de Energias Renováveis da UFPE



O CER-UFPE nasceu em 2013 integrando o conhecimento do Grupo FAE (criado no início dos anos 70) e antigo CBEE (criado no início dos anos 90)

Equipes do CER-UFPE

Solar

Permanente:
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Profa. Dra. Elielza Moura
Prof. Dr. André Cunha

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todos em projetos de P&D

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Prof. Dr. Pedro Rosas

Colaboradores:
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Prof. Dr. Gustavo Medeiros
Prof. Dr. Paulo Régis

25 Estudantes
(PhD, MSc e graduandos)
todos em projetos de P&D

Apoio técnico-administrativo: 12 pessoas

Projeto EOLIPREV

Projeto EOLIPREV

Financiado pelo CNPq ao amparo da Chamada MCTI-CNPq 74/2013 sobre Capacitação Laboratorial e Formação de Recursos Humanos em Energia Eólica e Energia Heliotérmica

Bolsas para postdoc, mestrado e iniciação
Aquisição do cluster Papaléguas
Upgrade do Papaléguas pelo projeto HPC4E

HPC4E Consortia

Projeto HPC4E https://hpc4e.eu
Financiado pela RNP-MCTIC
e EU Programa H2020

European Consortium:

Barcelona Supercomputing Center – Centro Nacional de Supercomputación
Gobierno de España – Ministerio de Economía y Competitividad – Ciemat – Centro de Investigaciones Energéticas, Medioambientales y Tecnológicas
Lancaster University
Inria – Inventeurs du monde numérique
Iberdrola
Total – Committed to better energy
Repsol

3ª Chamada BR-EU em TIC

Brazilian Consortium:

COPPE UFRJ – Instituto Alberto Luiz Coimbra de Pós-Graduação e Pesquisa de Engenharia
Laboratório Nacional de Computação Científica
CER
Universidade Federal de Pernambuco
.inf Instituto de Informática UFRGS
ITA
BR Petrobras
ONS

HPC4E Workpackages

WP leaders

WPX: BR leader; EU leader

WP1: COPPE-UFRJ; BSC

WP2: INF-UFRGS; BSC

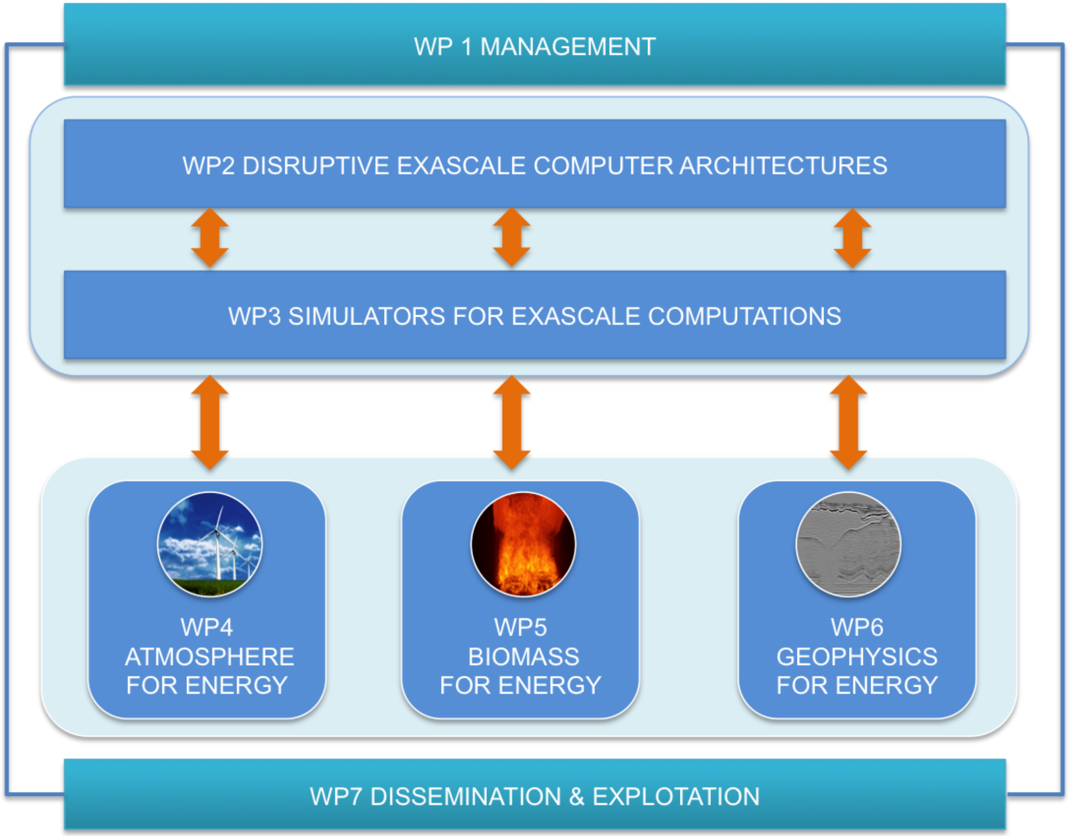
WP3: LNCC; INRIA

WP4: **CER-UFPE**; IBERBROLA

WP5: COPPE-UFRJ; ULANC

WP6: ITA; REPSOL

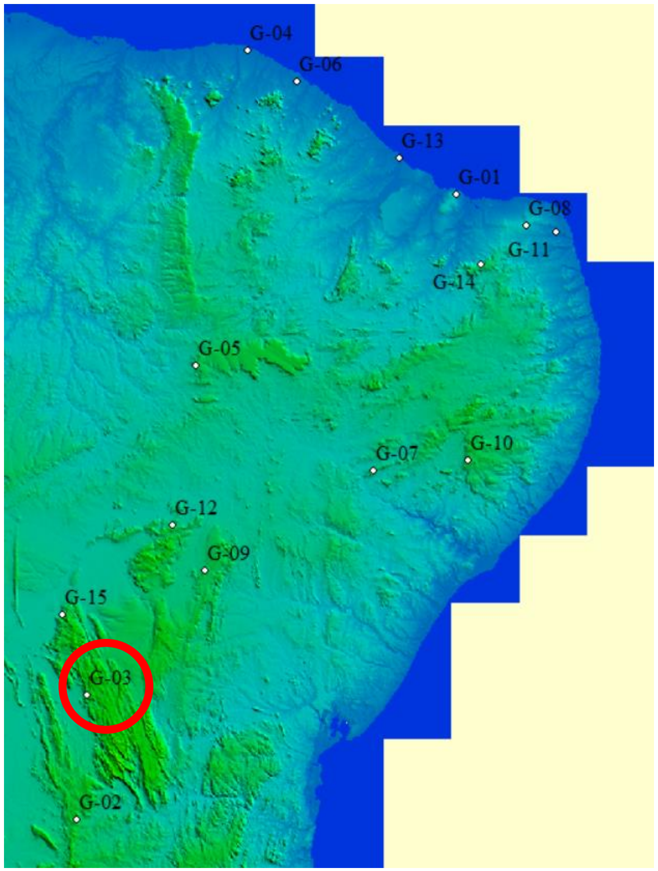
WP7: COPPE-UFRJ; BSC



https://hpc4e.eu/the-project/work-plan/wp4

HPC4E WP4 Forecasting Strategies

Northeast Region of Brazil



15 centrais eólicas selecionadas pelo ONS e CER-UFPE

HPC4E
High Performance Computing for Energy

D4.6 Forecasting Strategies
Version 2.0

Document Information

Contract Number	689772
Project Website	https://hpc4e.eu/the-project/work-plan/wp4

HPC4E
High Performance Computing for Energy

Technical Note on
D4.8 Deployment of the wind farm production forecast
Version 1.0

Document Information

Contract Number	689772
Project Website	https://hpc4e.eu/the-project/work-plan/wp4

CER-UFPE Forecasting Tool (CFT)

current version of the tool is oriented to short-term wind power prediction

horizon: 24 hours

time-step: 30 minutes

https://cer.ufpe.br/forecast/

(Password protected. Please, request user and password sending an email to forecast.cer.ufpe@gmail.com)

Center for Renewable Energy
Federal University of Pernambuco

CER UFPE Forecasting Tool

HOME ABOUT DOCUMENTATION CONTACT

Welcome

This is the CER-UFPE Forecasting Tool. It uses a variety of techniques to provide short term forecasts of the power produced at a selected wind farm oriented to the dispatch of renewable energy plants into the grid.

The CER-UFPE forecasting tool is being funded by two main R&D projects: the EOLIPREV project, funded by CNPq and the HPC4E project, funded by RNP.

Please see the documentation for more details.

Please select a wind farm below

G03

Wind Turbine in Germany by Molgreen is licensed under CC BY 2.0

CER-UFPE Forecasting Tool Team

1. General Coordination
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Prof. Olga Vilela
Prof. Ramiro Willmersdorf
Prof. Dóris Veleda
MSc Pablo Sousa
Gabriel Dantas (M)

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3. HPC Implementation
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Renan Soares (U)
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Othon Souza (U)
Danilo Lima (U)
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6. Statistical Downscaling
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7. CFD Modelling
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8. Power Curve Modelling
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Valentin Perruci (D)
Macela Zovka (U)

9. Forecast Combination
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Valentin Perruci (D)
Pedro Alves (M)

10. Quality Assurance/Control
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Prof. Alexandre Costa
Gabriel Dantas (M)
José Guilherme Souza (U)

11. Solar PV Plants
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Prof. André Cunha
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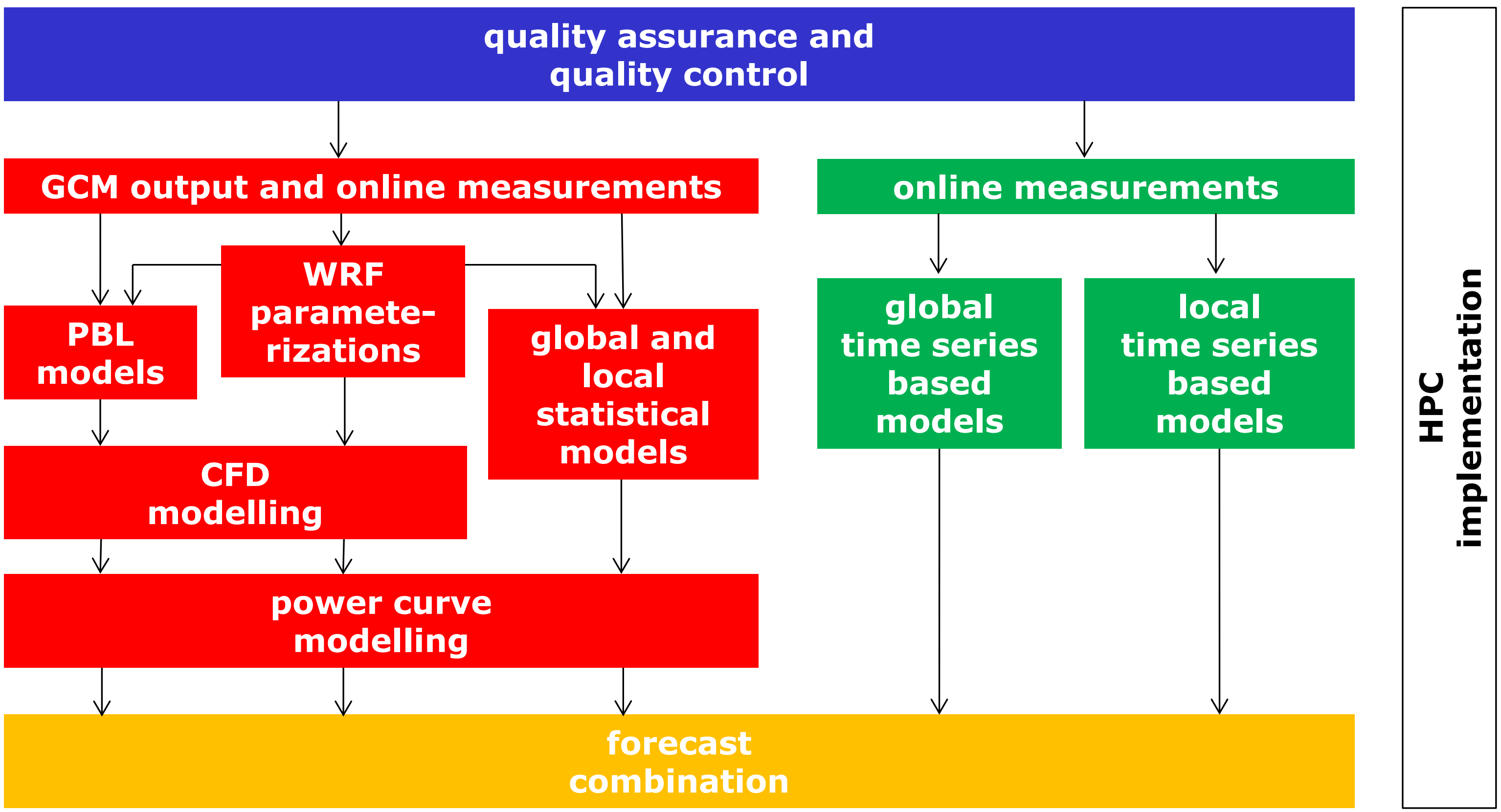
Urbano Secundes (D)
Janis Galdino (M)
Leonardo Petribu (U)
Heitor Barros (U)

07 Professors
02 Postdoc (PD)
03 PhD students (D)
05 MSc students (M)
11 Undergraduate (U)

28 Total

External Collaborations...

CER-UFPE Forecasting Tool Methodology



Quality | Time series | HPC | Downscaling | Combination

Statistical Downscaling

Models

Adopted domain setup for each individual model
(note that IBL stands for Bilinear Interpolation; MLR, Multilinear Regression;
AN, Analog Based Model; NN, Neural Network; DS, Domain Selection Based Model).

Domain					
4 grid points[1]	**16 grid points[1]**	**36 grid points[1]**	**360 grid points[2]**	**900 grid points[1]**	**9000 grid points[2]**
IBL, MLR1, AN1	NN	MLR2, AN2	MLR3, AN3	DS1, DS3	DS2, DS4

[1]at a given model level; [2]embracing the 10 model levels closest to surface.

Bilinear interpolation

Downscaling Combination

Analogs

MLR

Neural Network

Domain Selection

(Perruci, 2017; Dantas, 2017; Perruci et al., 2018; Dantas et al., 2018)

Statistical Downscaling

GCM

Adopted domain setup for each individual model
(note that IBL stands for Bilinear Interpolation; MLR, Multilinear Regression;
AN, Analog Based Model; NN, Neural Network; DS, Domain Selection Based Model).

Domain					
4 grid points[1]	**16 grid points[1]**	**36 grid points[1]**	**360 grid points[2]**	**900 grid points[1]**	**9000 grid points[2]**
IBL, MLR1, AN1	NN	MLR2, AN2	MLR3, AN3	DS1, DS3	DS2, DS4

[1]at a given model level; [2]embracing the 10 model levels closest to surface.

GFS-4

Spatial resolution: 0.5 degree

Cycle: 4 releases per day (00 06 12 18 UTC)

Forecast Horizons: 03 06 09 12 15 18 21 24 hours ahead

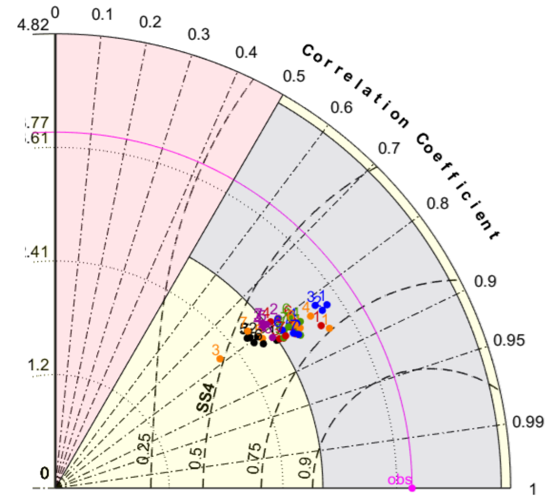
Statistical Downscaling

Results for Wind Farm G3

Adopted domain setup for each individual model
(note that IBL stands for Bilinear Interpolation; MLR, Multilinear Regression; AN, Analog Based Model; NN, Neural Network; DS, Domain Selection Based Model).

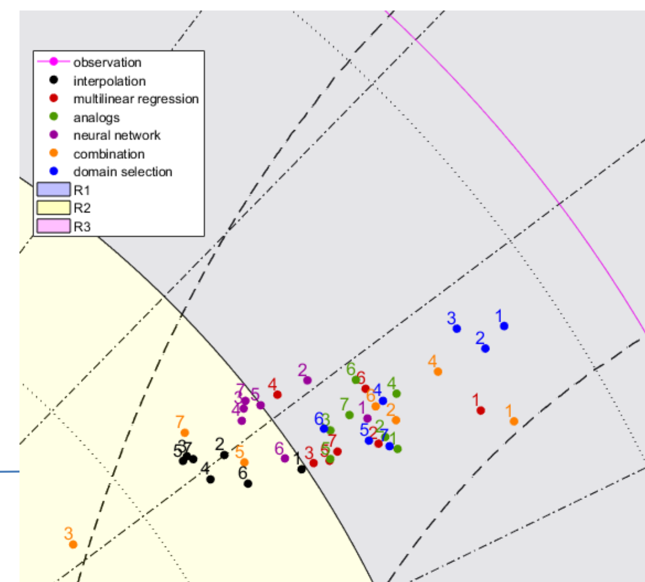
Domain					
4 grid points[1]	16 grid points[1]	36 grid points[1]	360 grid points[2]	900 grid points[1]	9000 grid points[2]
IBL, MLR1, AN1	NN	MLR2, AN2	MLR3, AN3	DS1, DS3	DS2, DS4

[1]at a given model level; [2]embracing the 10 model levels closest to surface.



$$SS4 = \frac{(1+R)^4}{4(\hat{\sigma} + 1/\hat{\sigma})^2}$$

(Taylor, 2001)



HPC4E WP4 D4.6
Report on Forecasting Strategies

WRF

Parameterizations for mesoregions in the Northeast Region of Brazil which concentrates around 80% of the national wind power installed capacity

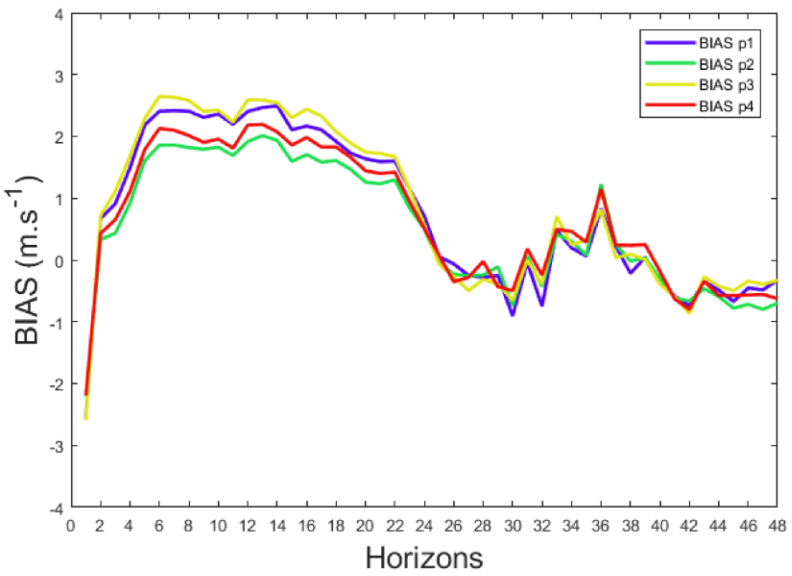
Horizontal resolution: 5 km

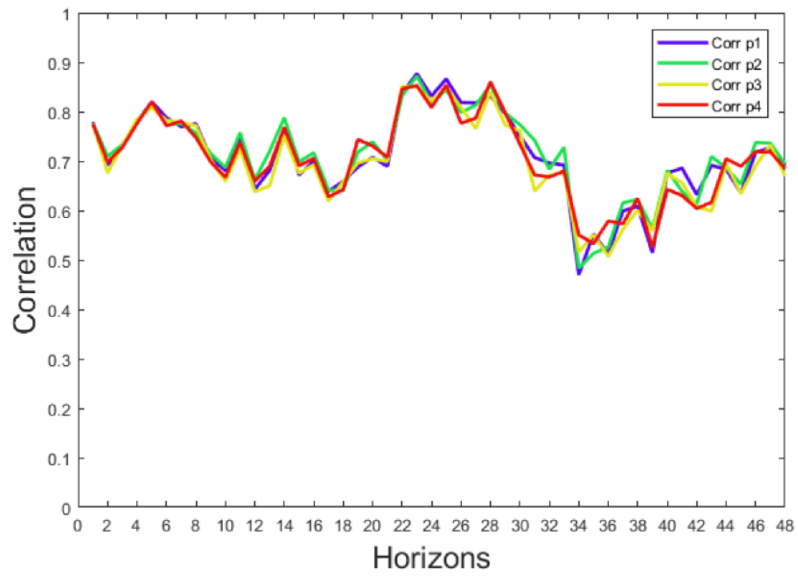
Vertical level with refinement in the Boundary Layer

2-way nested approach

- Large Domain: 10 km resolution
- Smaller Domains: 5 km resolution

WRF





HPC4E WP4 D4.6
Report on Forecasting Strategies

p1 to p4: WRF grid points closest to the met mast

wind farm G3: complex orography area

PBL Models

Direct coupling between large and local scale

Group 1: Neutral atmospheric condition

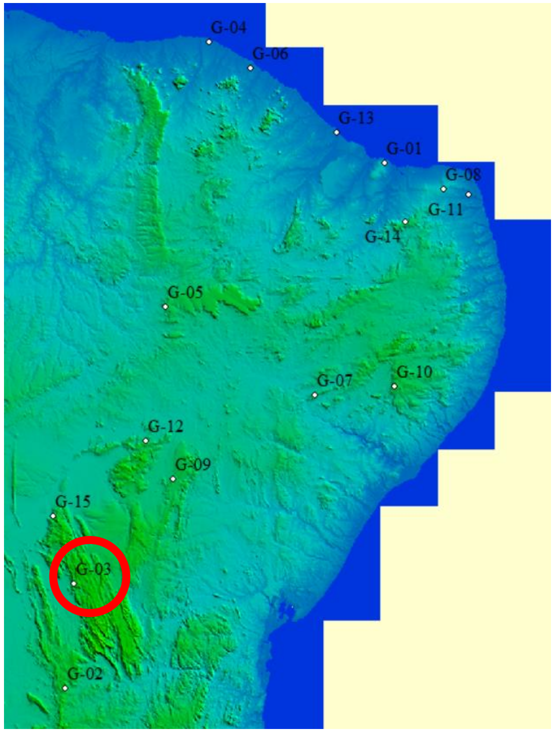
Group 2: Based on vertical temperature gradient

Group 3: Based on horizontal temperature gradient

Group 4: Based on vertical and horizontal temperature gradients

Group 5: A statistical approach is used to get the best parameterization

Northeast Region of Brazil



(Aquino, 2017; Aquino et al., 2018)

PBL Models

Direct coupling between the large and local scale for wind farm G3

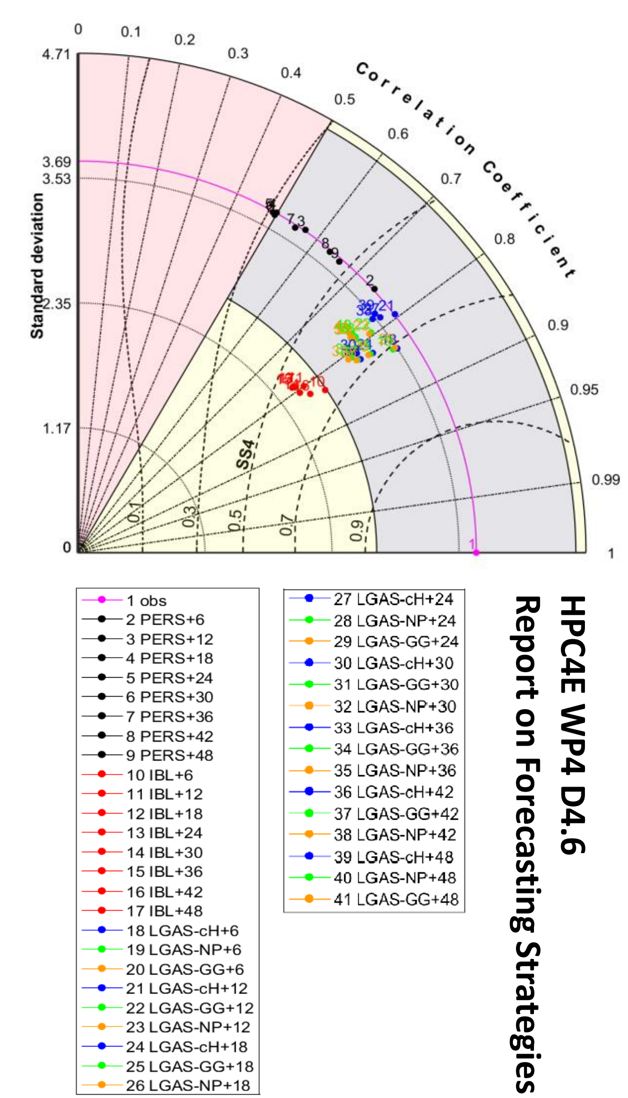
Group 5: A statistical approach is used to get the best parameterization

LGAS-NP estimates constants A and B for each GCM model level for the whole time series adopting GCM output as an estimate of the geostrophic wind.

LGAS-GG model adopts GCM output as an estimate of the gradient wind.

LGAS-cH takes a different GCM model level for each time-step ahead, i.e., for a given forecast horizon it takes the GCM model level which maximizes SS4 skill score.

LGAS-cH reference height is not the PBL height itself. It is a height equivalent to a fraction of the PBL height.



HPC4E WP4 D4.6 Report on Forecasting Strategies

Time Series Based Models: Global Approach

two steps multiscale prediction model

It discriminates the frequencies with largest contribution to power spectral density.

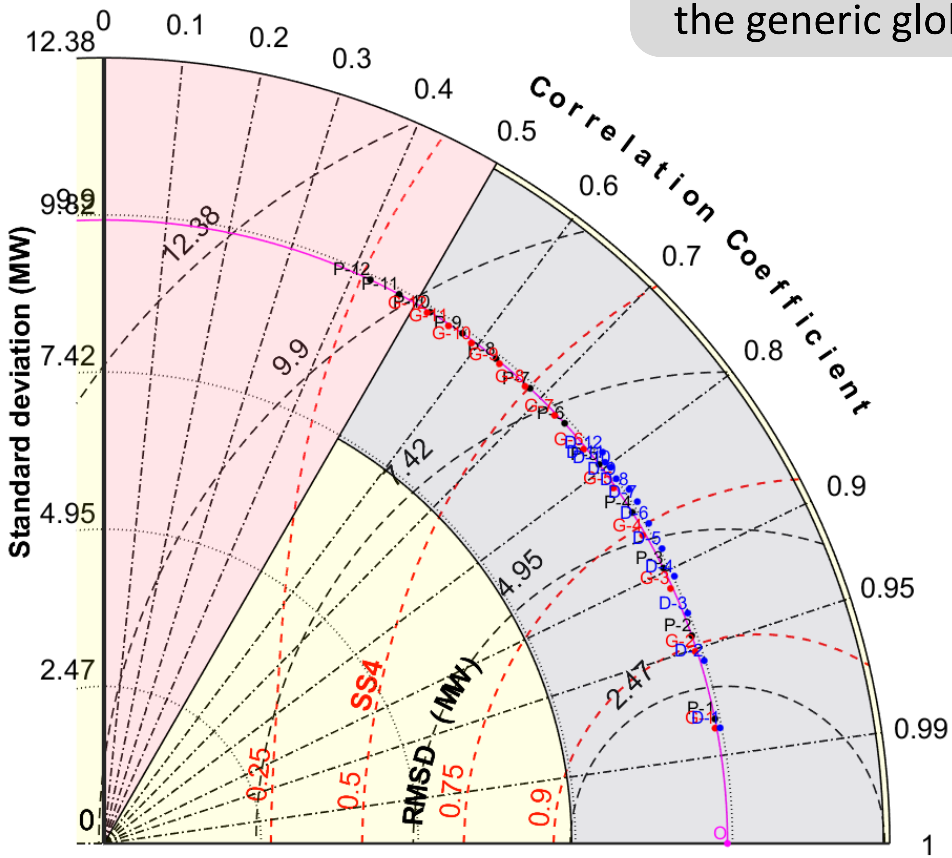
For each of those spectral components, a first neural net is trained for each horizon.

A second set of neural nets (calibrated for the whole time-series) aggregates the separeted components into a single final forecast.

(Cabral, 2018; Cabral et al., 2018)

Time Series Based Models: Global Approach

Results for wind farm G3 show a significant improvement of the double decomposition model over the generic global neural net.



HPC4E WP4 D4.6
Report on Forecasting Strategies

Forecast Combination

Preliminary approach

Multilinear Regression

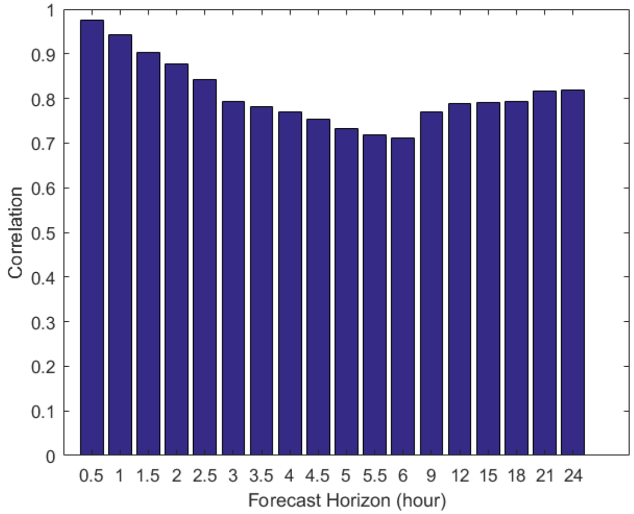
Predictors: Best outputs from each branch (downscaling and time series based models)

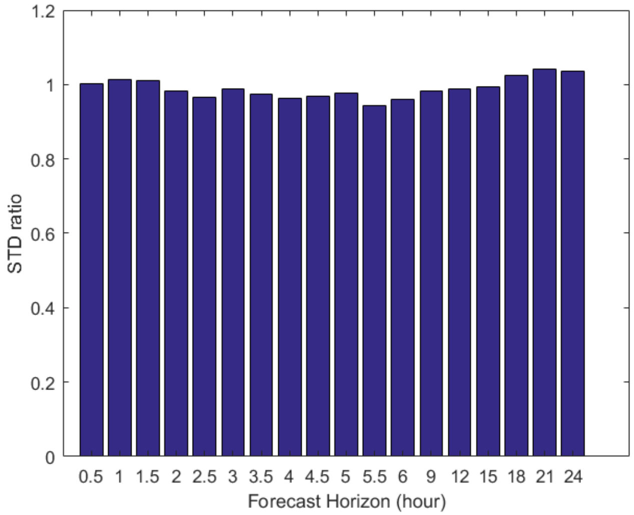
TSBMs covering up to 6 hours ahead (with steps of 30 minutes)

Downscaling models covering 1 day ahead (with steps of 3 hours)

(Perruci et al., 2018)

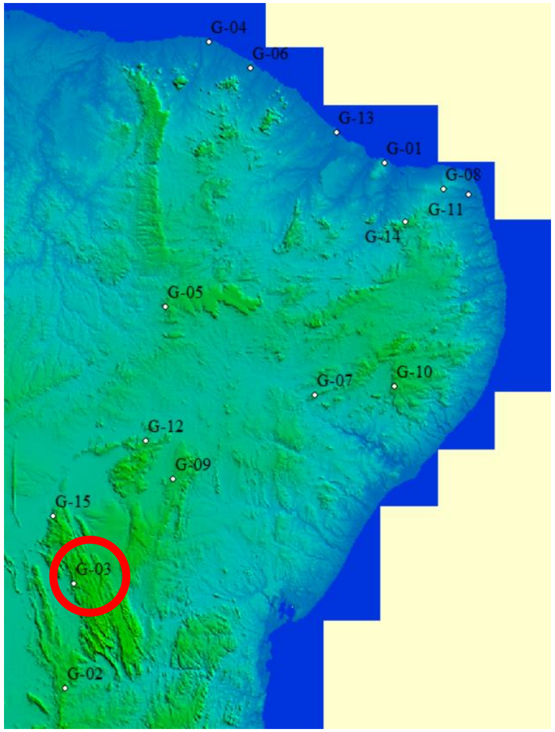
Forecast Combination





HPC4E WP4 D4.6
Report on Forecasting Strategies

Combination is able to reproduce observational data aspects with a good performance over all horizons in a complex orography area.



Northeast Region of Brazil

Very short-term

8 time series based models variants

Some of them taking into account only data from the wind farm of interest.

The rest taking into account also data from an upwind farm.

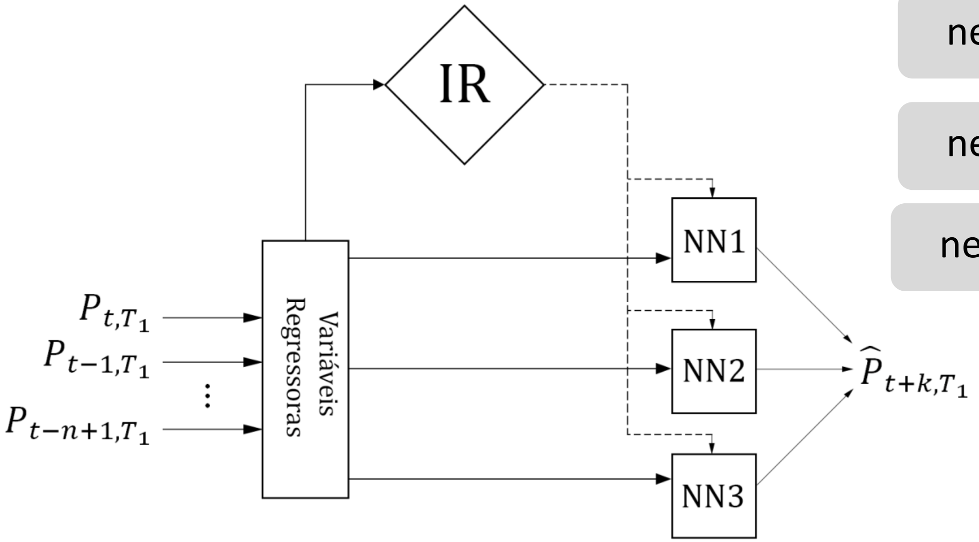
(Clemente et al., 2018)

Very short-term

Variant 1

It's based on a non-parametric approach to establish the ramp identifier, which is a percentage of the rated power for a single time-step.

In order to predict for the *k*-horizon, 3 neural nets are trained for different regimes in a regime switching approach.



network 1: trained for ramp up

network 2: trained for ramp down

network 3: trained for no ramp

(Clemente et al., 2018)

Very short-term

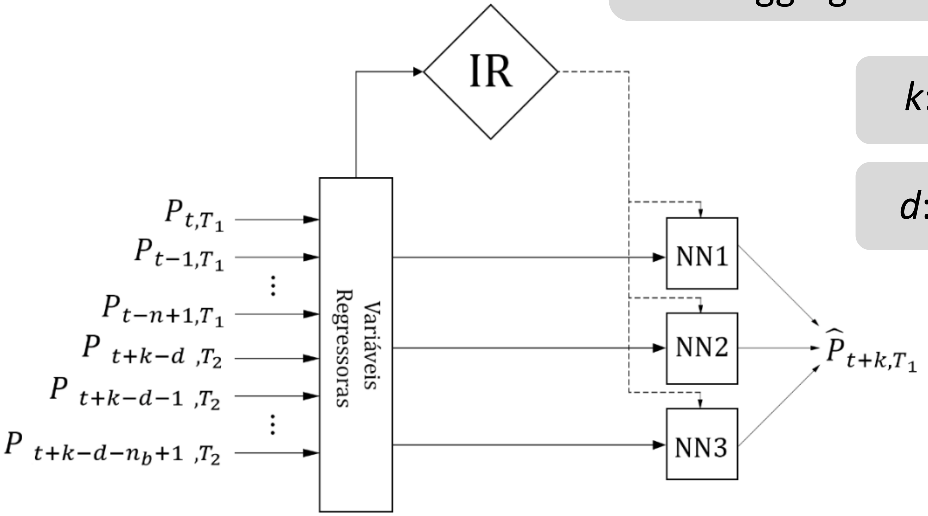
Variants 2, 3 and 4

Main difference between these approaches and the previous one is that: these approaches make also use of data from an upwind wind farm, which is called T2.

On the other hand, main differences between L2, L3 and L4 are the lagging between the time series as a function of:

k: the forecast horizon

d: the time-lag between wind farms

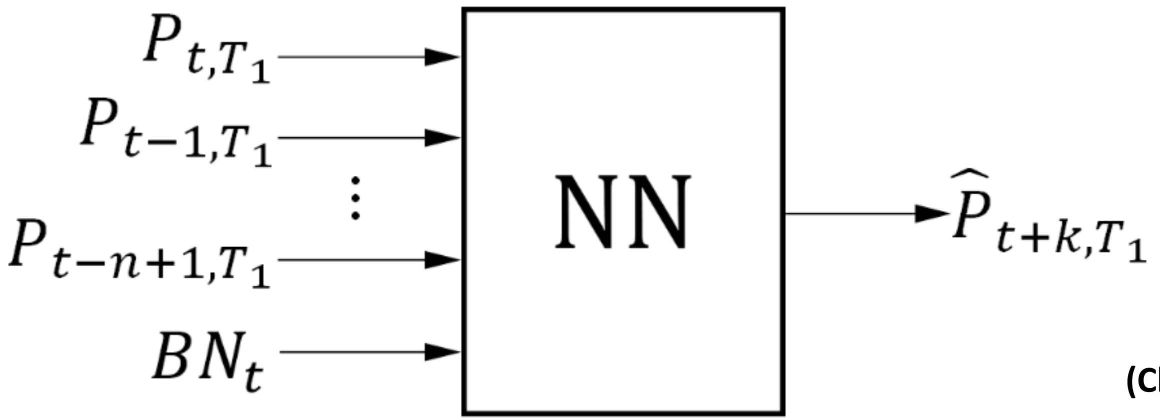


(Clemente et al., 2018)

Very short-term

Variant 5

In this case, a single neural net is used to forecast for all regimes, being one of the regressor variables the output from a Bayesian network which takes data from an upwind farm in order to make inference about the regime at the wind farm of interest.

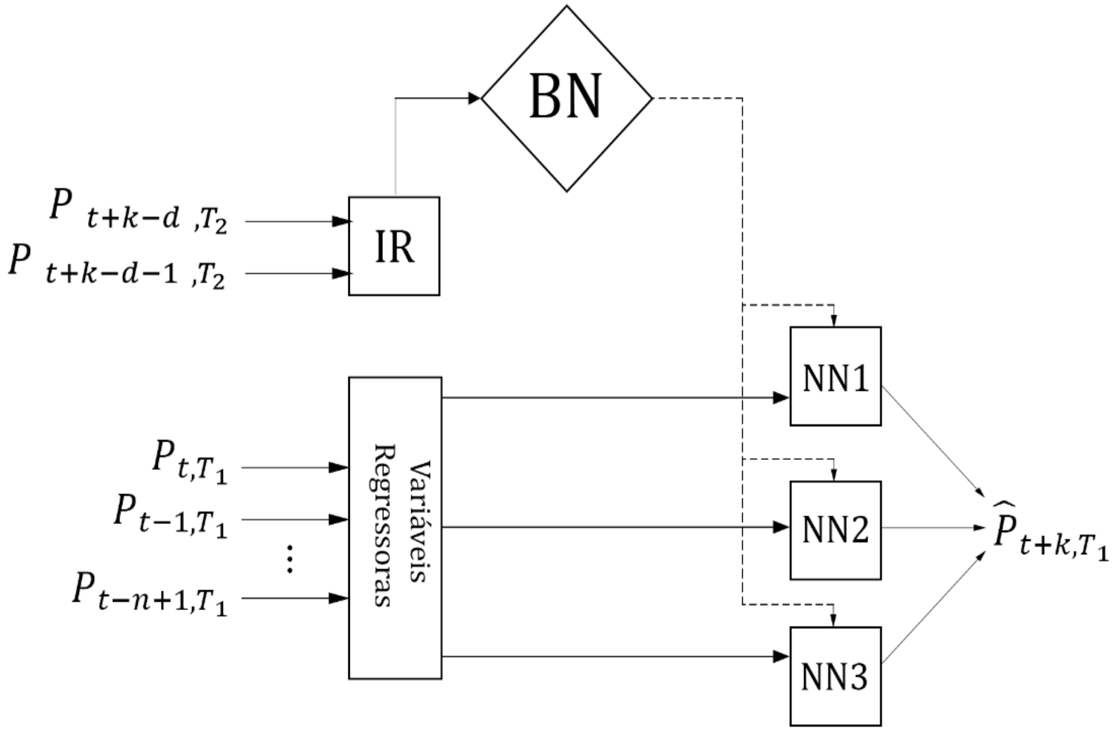


(Clemente et al., 2018)

Very short-term

Variant 6

In this case, Bayesian network is used to select the appropriate neural network as a function of the ramp regime.



(Clemente et al., 2018)

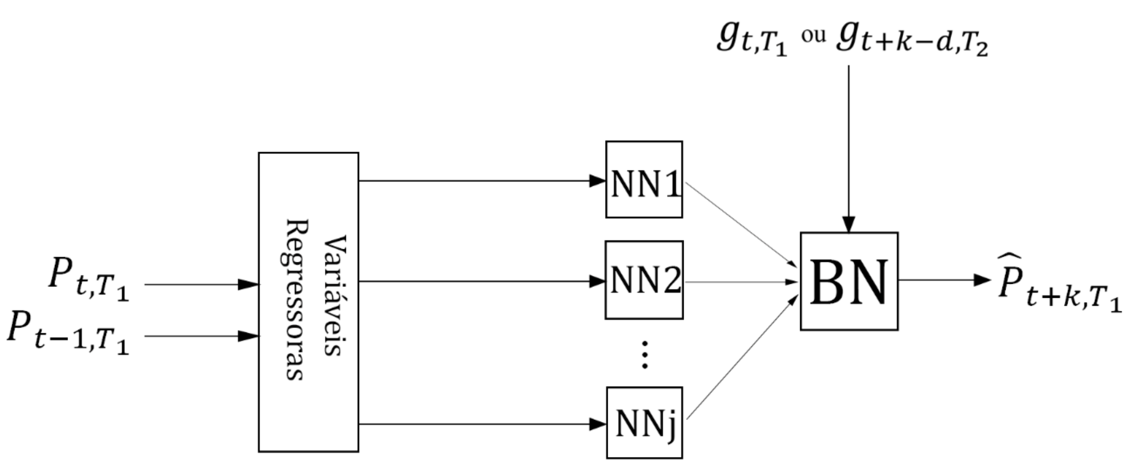
Very short-term

Variants 7 and 8

Each neural network is trained for a different gradient range, being the outputs weighted by a Bayesian network.

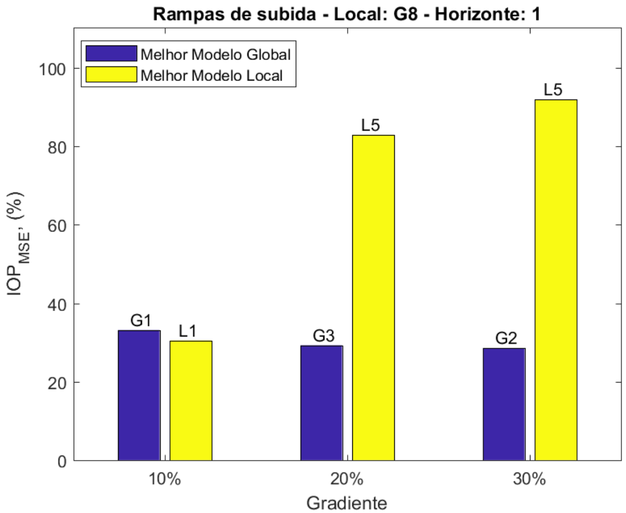
Variant 7: data from an upwind farm is being considered.

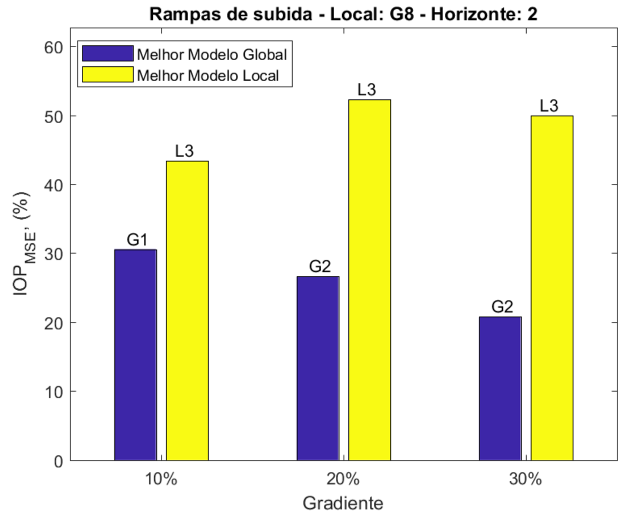
Variant 8: only data from the wind farm of interest is being considered.



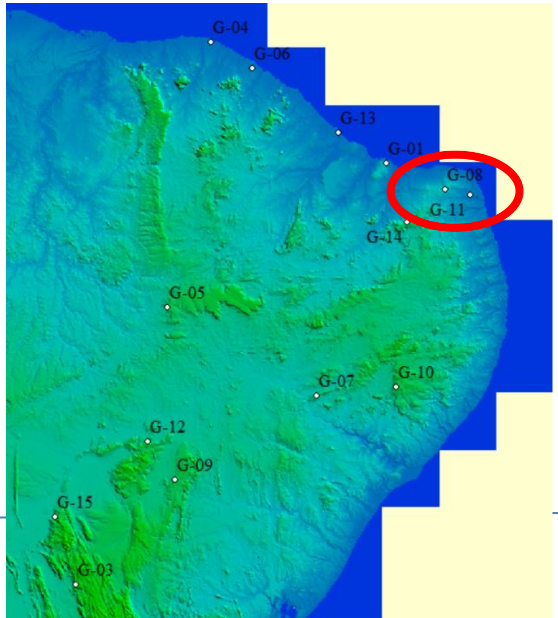
(Clemente et al., 2018)

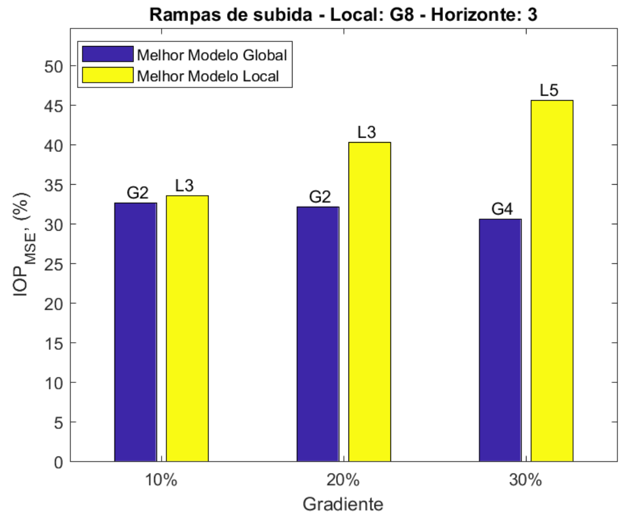
Resultados Preliminares





Nordeste do Brasil





Melhor desempenho para rampas de subida

central de interesse: G8

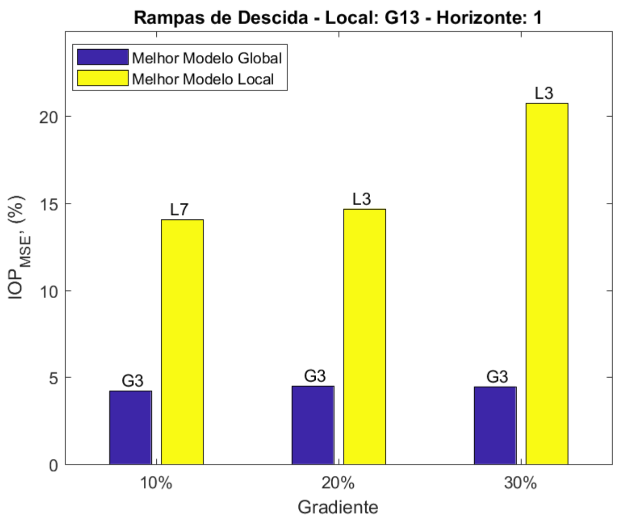
central a barlavento: G11

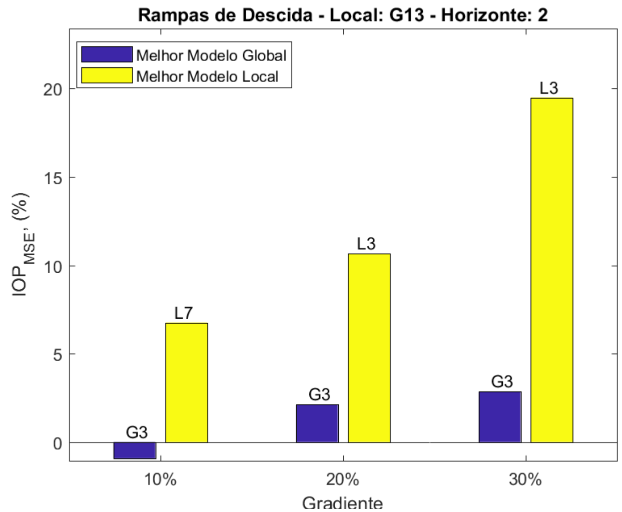
time-step: 10 min

$IOP_{MSE}=100x(MSE_P-MSE_M)/MSE_P$

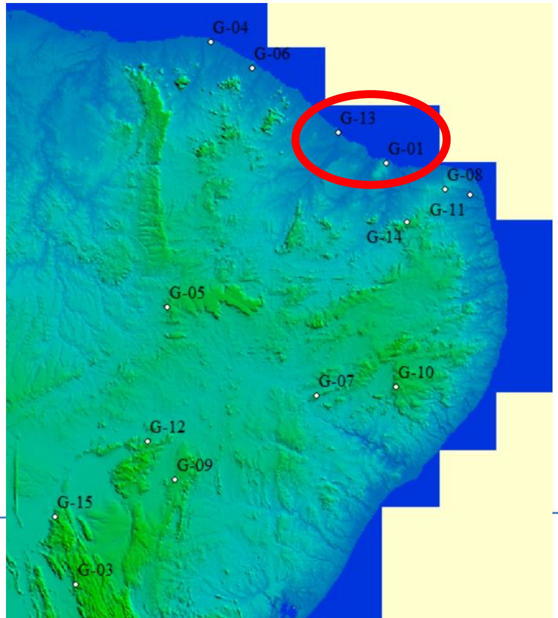
(Clemente et al., 2018)

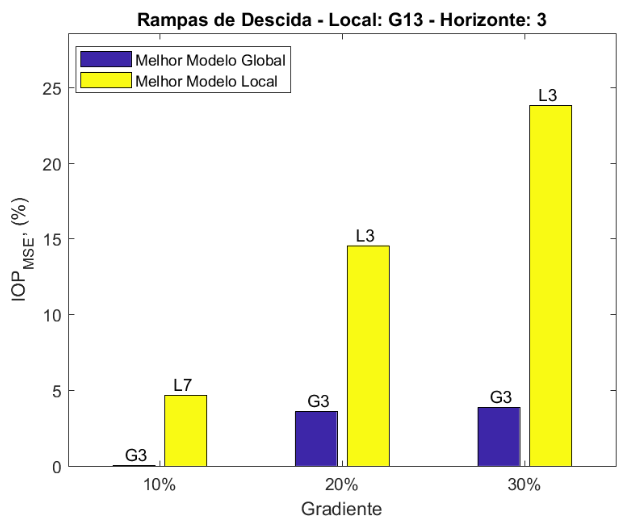
Resultados Preliminares





Nordeste do Brasil





Melhor desempenho para rampas de descida

central de interesse: G13

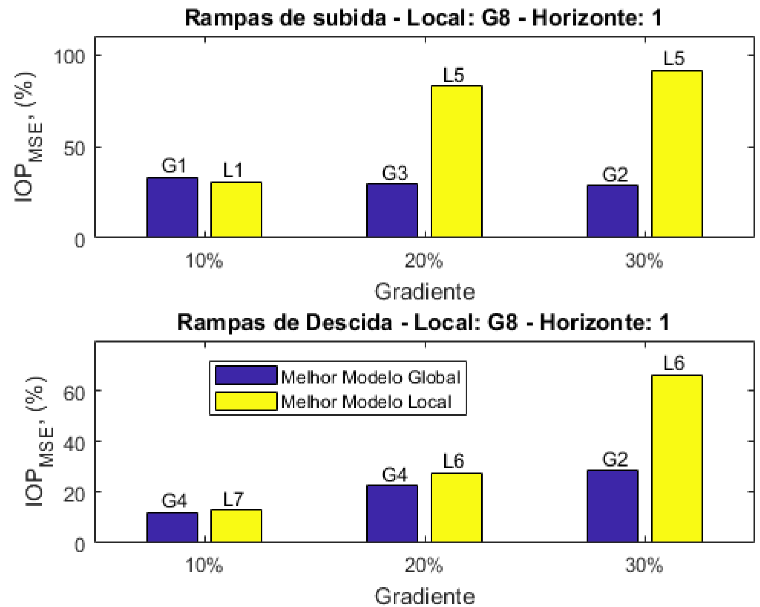
central a barlavento: G1

time-step: 10 min

$IOP_{MSE}=100x(MSE_P-MSE_M)/MSE_P$

(Clemente et al., 2018)

Resultados Preliminares



Melhor desempenho para 1 time-step à frente

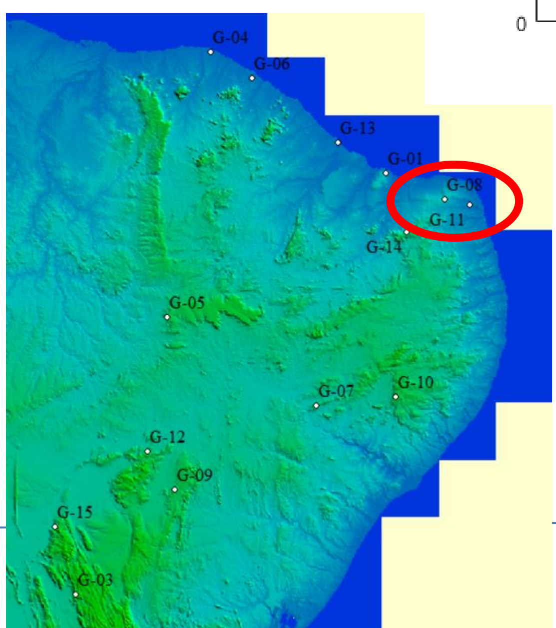
central de interesse: G8

central a barlavento: G11

time-step: 10 min

$IOP_{MSE}=100x(MSE_P-MSE_M)/MSE_P$

Nordeste do Brasil

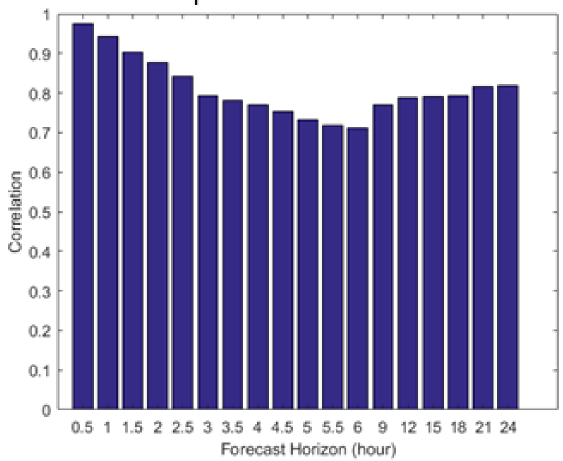


(Clemente et al., 2018)

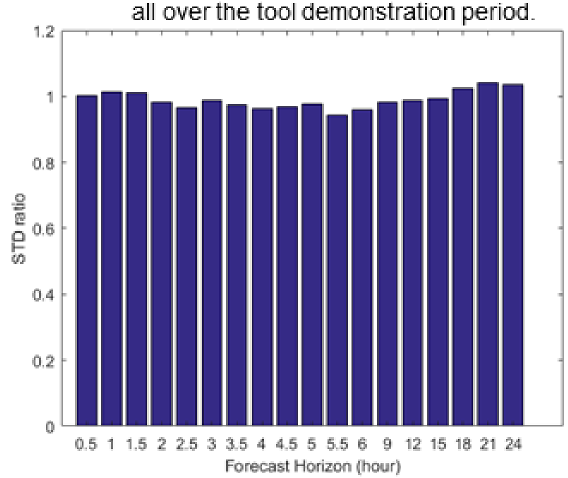
WP4 Main Results

Task 4.3. Forecasting strategies (M13-M24): DEPLOYMENT D4.8 AND REPORT D4.6

Correlation between the forecasting tool output and observed wind farm output all over the tool demonstration period.



STD ratio (which is the ratio between predicted standard deviation and observed wind farm output standard deviation) all over the tool demonstration period.



- 3 different clusters were used to develop the forecasting tool: Santos Dumont (LNCC), Lobo Carneiro (COPPE) and Papaleguas (CER-UFPE);
- The use of such machines was essential to guarantee that many forecasting strategies were studied, compared and the best ones were selected and combined providing a robust forecasting tool;
- Different parallelization solutions were requested by many different forecasting strategies;
- The operational forecasting procedure itself is much less demanding of computing resources than the calibration procedure. Except for WRF operation, each forecast can be done on a single core in a few minutes. However, for instance the inclusion of any new wind farm will impose the full calibration procedure to be performed again;
- The necessary operations to generate real time forecasts are being executed in Papaleguas (CER-UFPE), but the addition of new wind farms will require the use of external resources. As this very high computational demand is not constant, this would be a prime candidate to be implemented in a cloud computing environment.

Next Steps

In general:

- CFD modeling will be implemented in order to try to increase forecast accuracy mainly in zones with complex orography;
- By now, PBL models and statistical downscaling models have a time-step (3 hours) different than that for TSBMs (30 minutes). This limits the forecast combination. To try to overcome this, time resolution for the former models will be increased by using WRF outputs;
- By now, power curve models are purely based on wind speed and wind farm power data. In order to take into account wake effects, also the wind direction will be considered, as an exogenous variable;
- Probabilistic forecasts should be considered to give more complete information to the user (e.g., expected value as well as confidence bands);
- Some solar PV forecasting approaches are being investigated in order to expand CER-UFPE Forecasting Tool capabilities;
- Cloud computing environment should be considered in order to take into account the non-constant very high computational demand related to the addition of new wind farms.

Next Steps

Very short-term:

• Preliminary results are interesting. However, ramp down forecasts need to be better addressed. It's more difficult to overcome persistence during ramp down events. Also, ramp down is more relevant for the system operator because the required time to start hydro power units (say 500 MW) is order of 10 minutes;

• Specific quality checks will be developed to assess observational data which are used to train ramp forecasting models. Conventional quality checks tend to filter out extreme events within the time series, significantly decreasing the number of ramp events;

• Exogenous variables will be adopted to try to get better explanation on the ramp behavior. In this sense, synoptic scale motion as well as meso and microscale phenomena will be addressed. Numerical weather predictions will be combined with purely statistical (time series based) forecasts;

• Short- and medium-term bias corrections will be implemented.

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