COMBINING MONTHLY INFLOW AND WIND UNCERTAINTIES IN THE OPERATION PLANNING OF HYDRO-DOMINATED SYSTEMS

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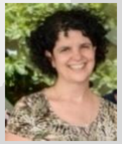

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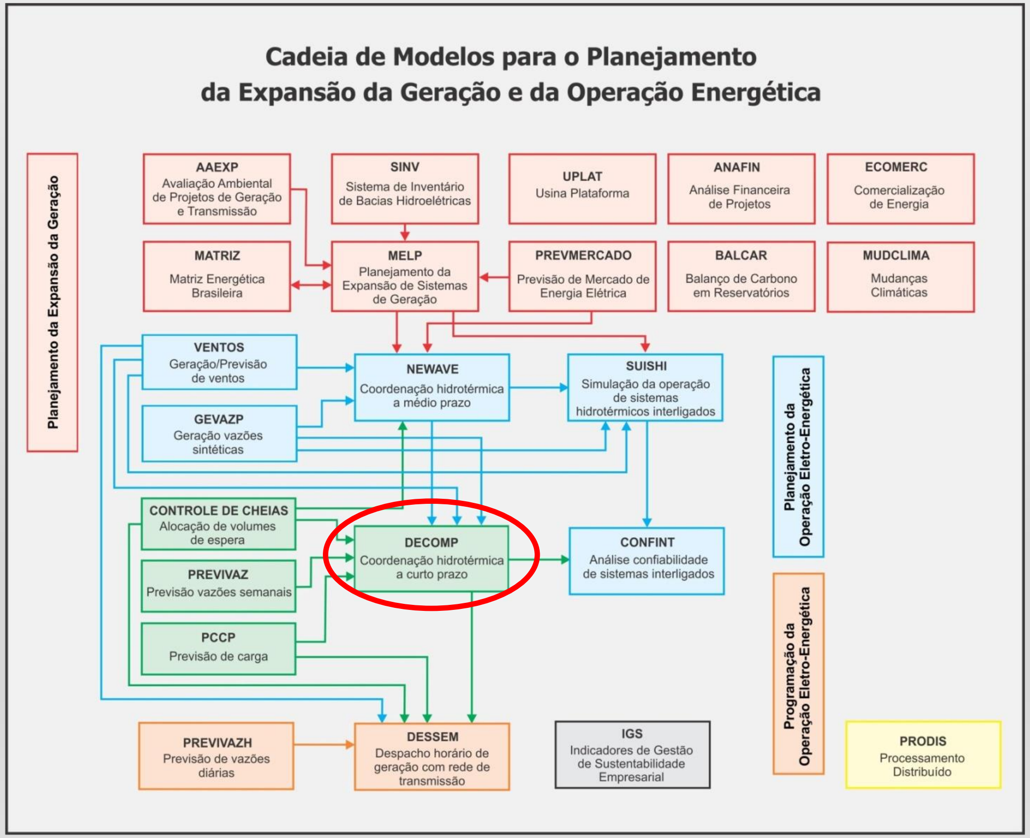
INTRODUCTION

RENEWABLES IN BRAZIL

The Brazilian electricity matrix has a high share of renewable sources, mainly with a preponderance of hydroelectric technology



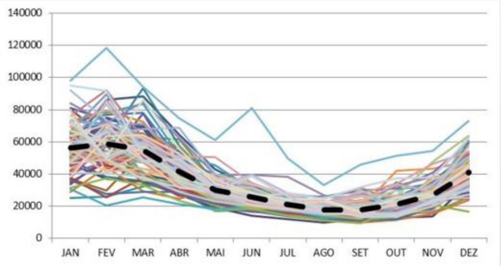
In last decade wind power grew 13 times, reaching 19 GW of installed capacity (10% share); it is also estimated that in the period 2020-2029 its share will increase 2.5 times and reach 40 GW (17.3%)

Electrical system expansion and operation planning requires even more sophisticated models and tools to deal with the intermittent behavior and uncertainties associated with renewable technologies

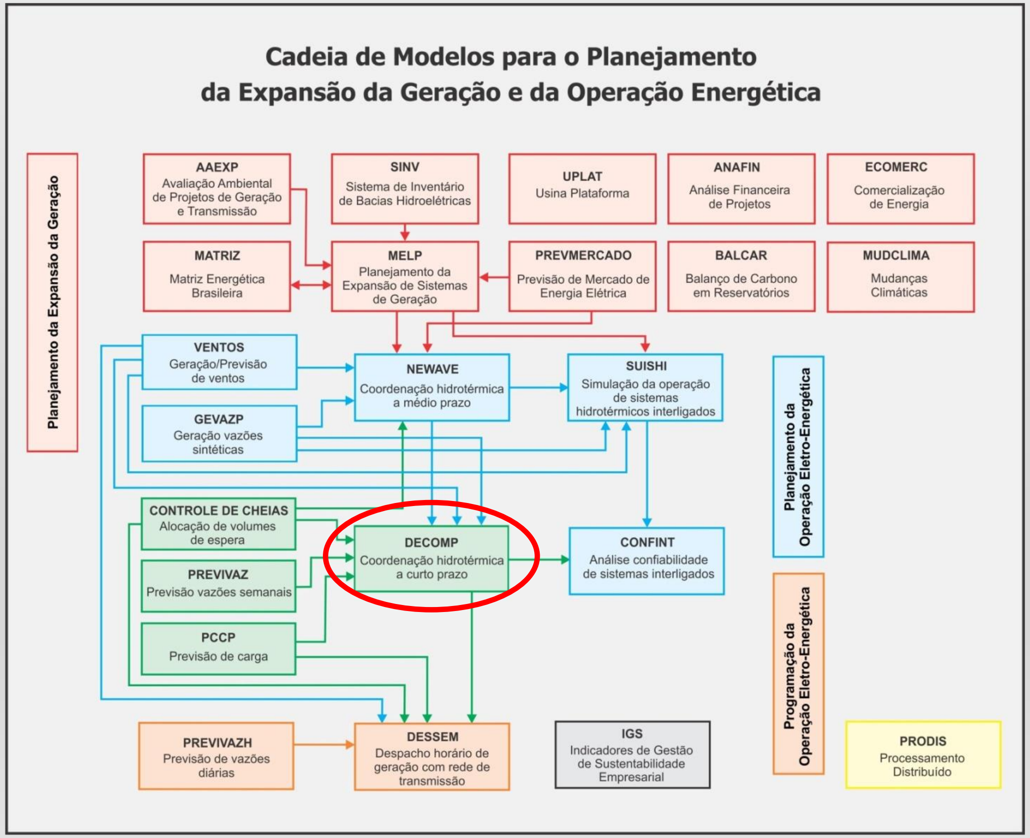
In the case of Brazil, this problem is divided into expansion planning (long term), operation planning (medium and short term), and operation programming, being solved through a chain of computational models

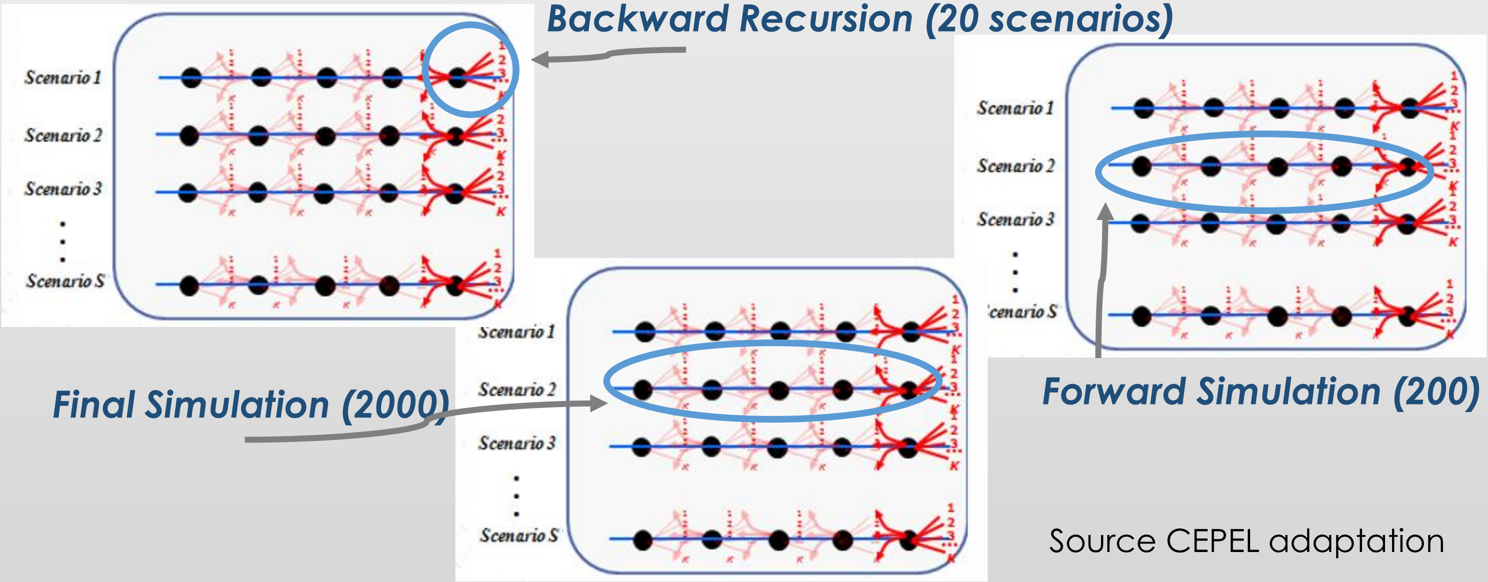
INTRODUCTION

RENEWABLES IN BRAZIL



One of the key models is *NEWAVE*, based on the Stochastic Dual Dynamic Programming – SDDP, which since 1998 has been used in official studies and real decision making regarding the Brazilian Interconnected Power System





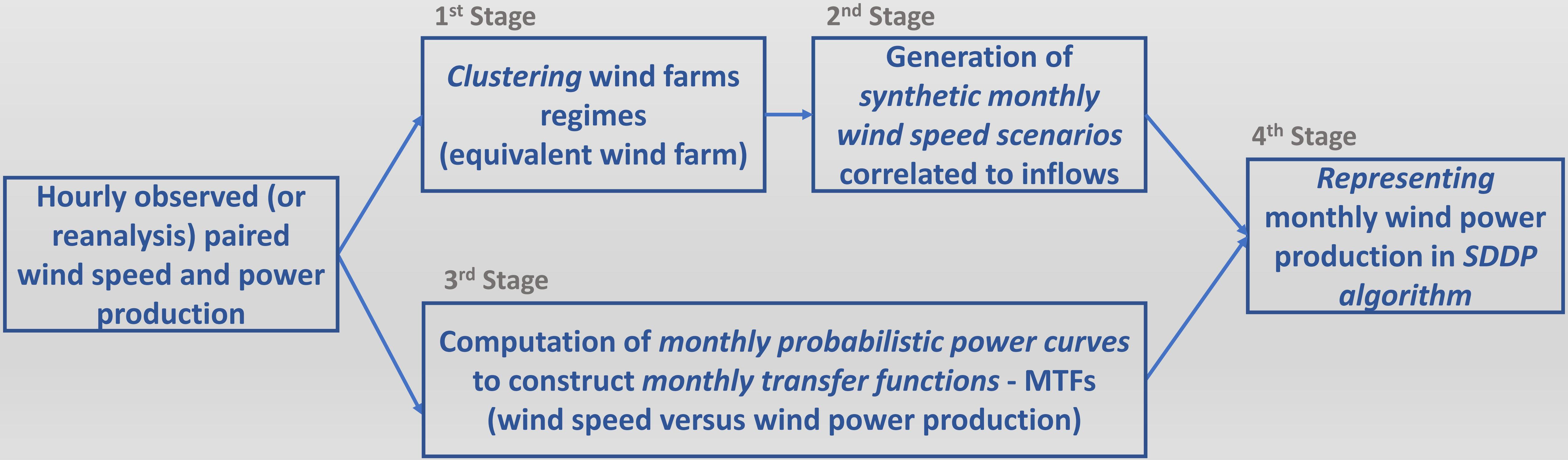
Source CEPEL adaptation

Currently, in accordance with the *guidelines of the Electricity Regulatory Agency, the representation of wind power in the NEWAVE model is carried out in a simplified manner*, based on the *monthly average of the last five years of net generation of each wind farm* (WF)

COMBINING MONTHLY INFLOW AND WIND UNCERTAINTIES IN THE OPERATION PLANNING OF HYDRO-DOMINATED SYSTEMS

OBJECTIVE

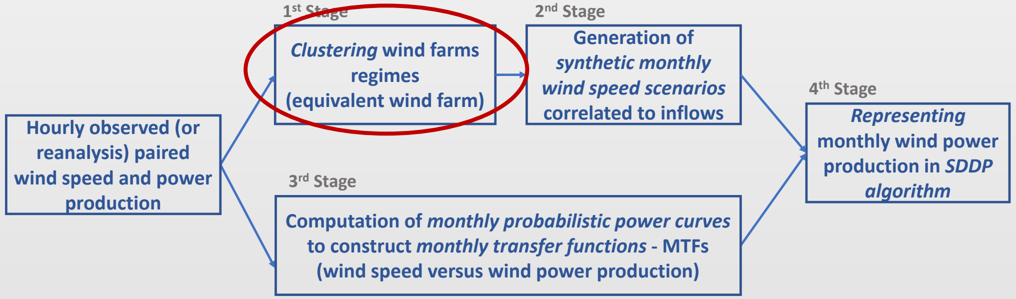
To describe an approach to be used by the Brazilian power industry to represent the uncertainties of monthly wind power in the SDDP algorithm applied in the long-term operation planning model, keeping the large-scale stochastic problem still computationally viable



Schematic diagram of the proposed approach

PROPOSED METHODOLOGY

1st STAGE - Statistical clustering of wind regimes based on multivariate statistical methods



WIND SPEED

↓

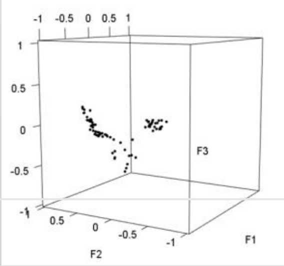
Exploratory Factor Analysis

↓

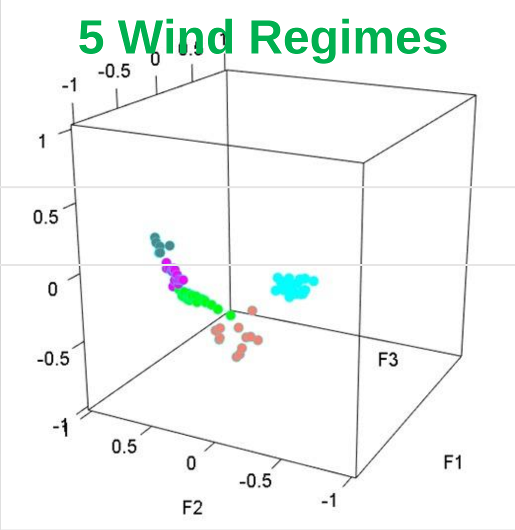
Clustering Analysis K-Means

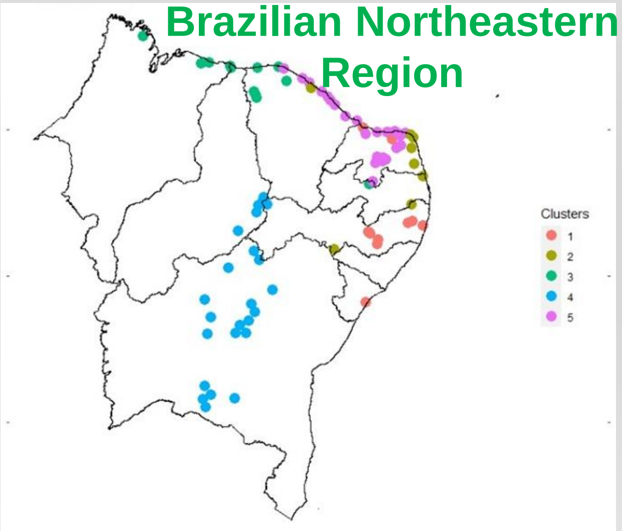
- The ***Exploratory Factor Analysis* technique** is applied to the data matrix in which each column holds the time series wind speeds **(hourly or monthly)** in a wind farm.

Thus, the wind speed in each wind farm is expressed by the weighted sum of latent F-factors (representing wind regimes) plus a residual term ε, *reducing the dimensionality of the data*



3 Latent F-factors

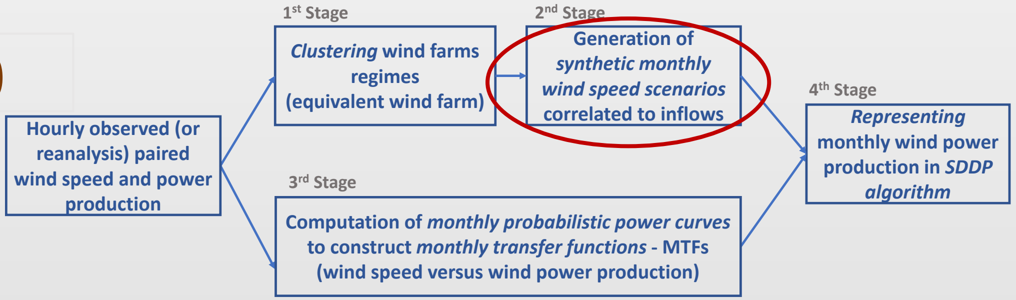




- the ***identification of groups of wind farms with correlated wind regimes*** can be performed **by means of statistical clustering analysis of, e.g.,** the K-Means or Ward algorithm

PROPOSED METHODOLOGY

2nd STAGE - Integrated model for generating synthetic wind speed and inflow scenarios



Inflows

Periodic autoregressive model of order p - PAR(p)

$$\left(\frac{ENA_{t,i} - \mu_{m,i}}{\sigma_{m,i}}\right) = \sum_{j=1}^{p_{m,i}} \phi_{t,j,i} \left(\frac{ENA_{t-j,i} - \mu_{m-j,i}}{\sigma_{m-j,i}}\right) + a_{t,i}$$

Positive skewed random noises (0, σ_a^2(m))

Wind Speeds

$$\left(\frac{W_{t,j} - \mu_{m,j}^{v}}{\sigma_{m,j}^{v}}\right) = regression\ component + a_{t,j}$$

Positive and negative skewed random noises (0, σ_a^2(m))

- μ_m^w → ***Monthly* wind records in several WFs of Brazil don´t present *monthly* serial correlation**

Correlation between W_t and W_{t-1}

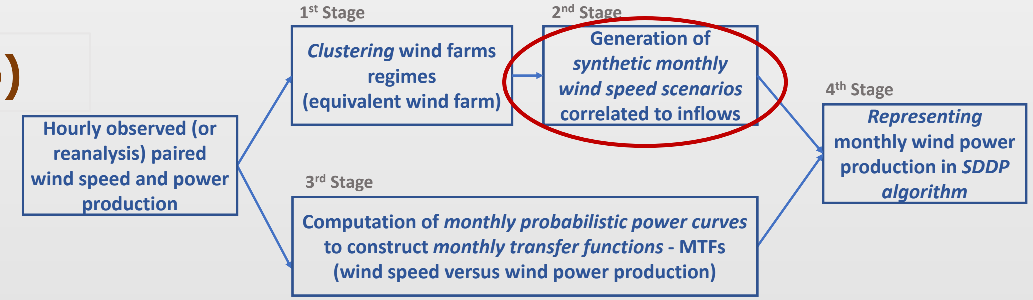
- $\vartheta^m \left(\frac{W_{t-1} - \mu_{m-1}^{w}}{\sigma_{m-1}^{w}}\right)$ → **For ones that present monthly serial correlation**

Correlation between W_t and Z_t

- $\varphi^m \left(\frac{ENA_t - \mu_m}{\sigma_m}\right)$ → **Monthly wind records in several WFs of Brazil present monthly dependence with inflows to HPPs**

PROPOSED METHODOLOGY

2nd STAGE - Integrated model for generating synthetic wind speed and inflow scenarios



Inflows

Periodic autoregressive model of order p - PAR(p)

$$\left(\frac{ENA_{t,i}-\mu_{m,i}}{\sigma_{m,i}}\right) = \sum_{j=1}^{p_{m,i}} \phi_{t,j,i}\left(\frac{ENA_{t-j,i}-\mu_{m-j,i}}{\sigma_{m-j,i}}\right) + a_{t,i}$$

Positive skewed random noises (0, σ_a^2(m))

Wind Speeds

$$\left(\frac{W_{t,j}-\mu^{v}_{m,j}}{\sigma^{v}_{m,j}}\right) = regression\ component + a_{t,j}$$

Positive and negative skewed random noises (0, σ_a^2(m))

- 100 thousand of uncorrelated **N(0,1)** random noises **a_t are generated for the HPPs and EWFs**
- K-Means method is applied to reduce the cardinality of the original sample

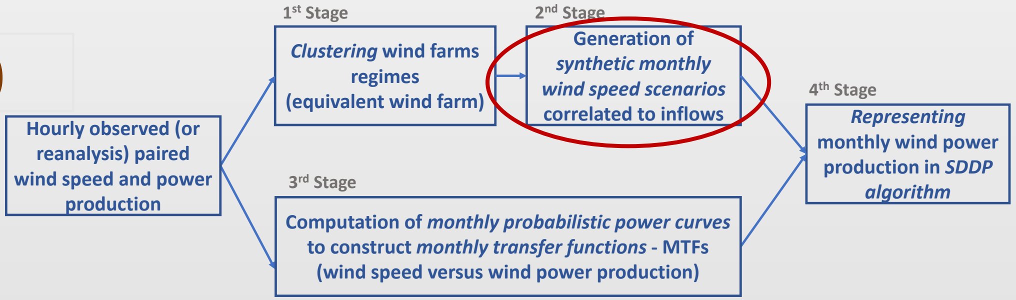
To generate correlated monthly inflows and wind speeds

- **The random noises (HPP and WF) are transformed in spatially correlated noises by applying the correlation matrix**

  Inflows x inflows; wind speeds x wind speeds; *inflows x wind speeds*

PROPOSED METHODOLOGY

2nd STAGE - Integrated model for generating synthetic wind speed and inflow scenarios



Inflows

Periodic autoregressive model of order p - PAR(p)

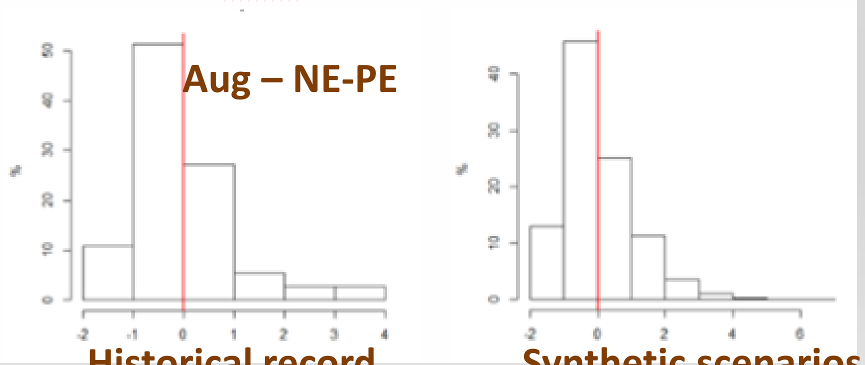
$$\left(\frac{ENA_{t,i}-\mu_{m,i}}{\sigma_{m,i}}\right)=\sum_{j=1}^{p_{m,i}}\phi_{t,j,i}\left(\frac{ENA_{t-j,i}-\mu_{m-j,i}}{\sigma_{m-j,i}}\right)+a_{t,i}$$

A 3-parameter Lognormal distribution is fitted to the spatially correlated residuals to better reproduce the observed positive skewness

Wind Speeds

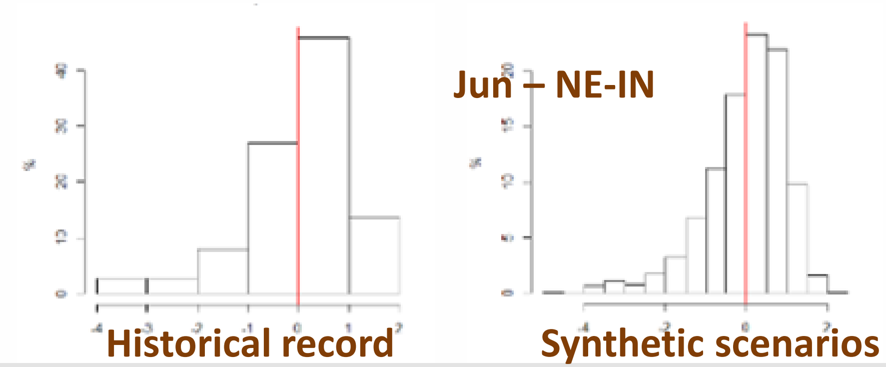
$$\left(\frac{W_{t,j}-\mu^{v}_{m,j}}{\sigma^{v}_{m,j}}\right)=regression\ component+a_{t,j}$$

The **monthly wind speed** residuals can present positive as well as negative skewness



a 3-parameter Weibull distribution is then used

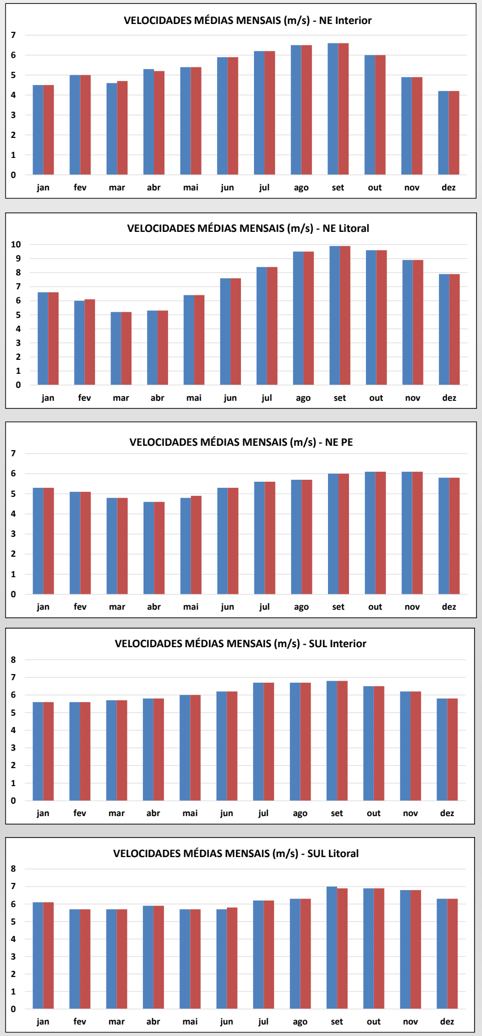
a special purpose algorithm was developed



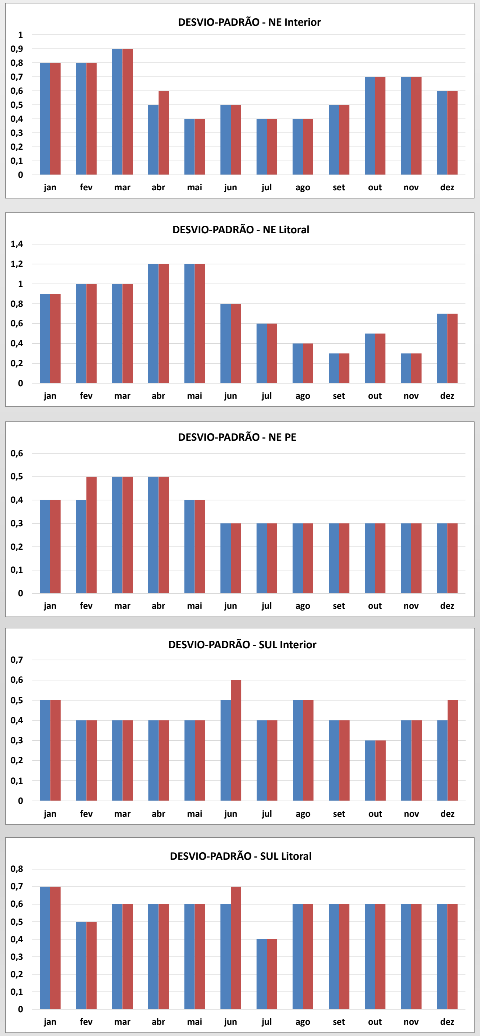
PROPOSED METHODOLOGY

2nd STAGE - Integrated model for generating synthetic wind speed and inflow scenarios

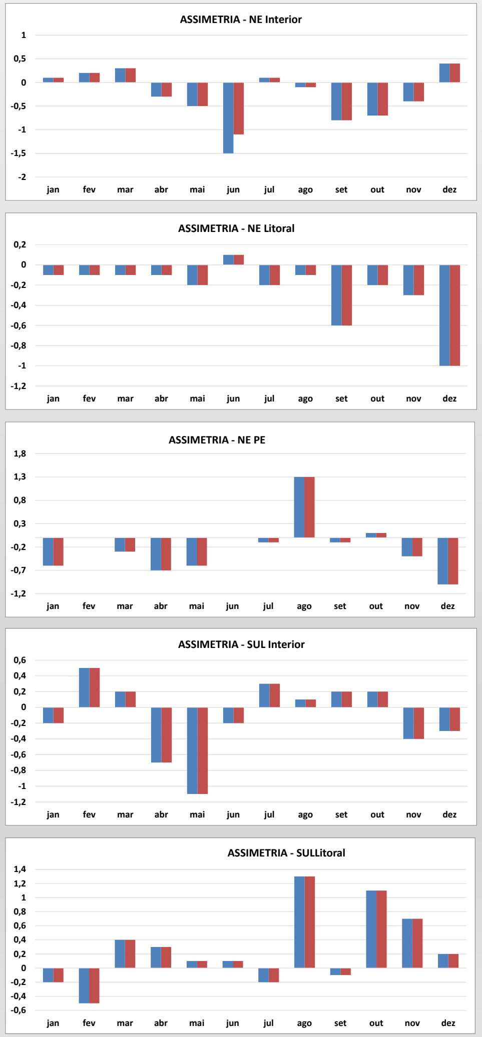
Monthly Average

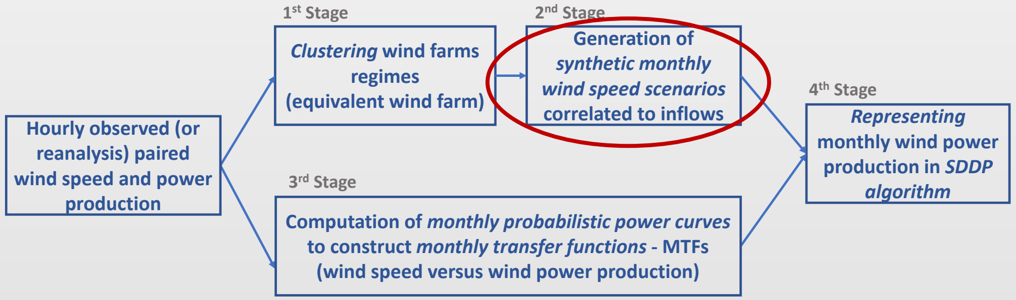


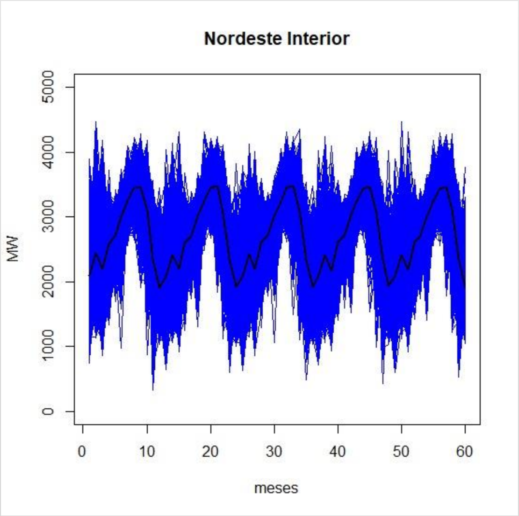
Monthly Standard Deviation

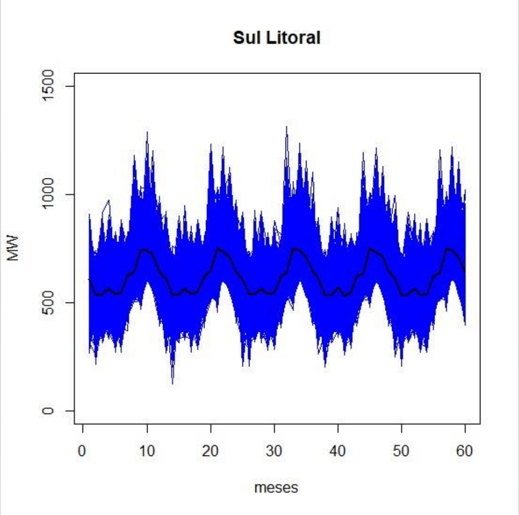


Monthly Skewness



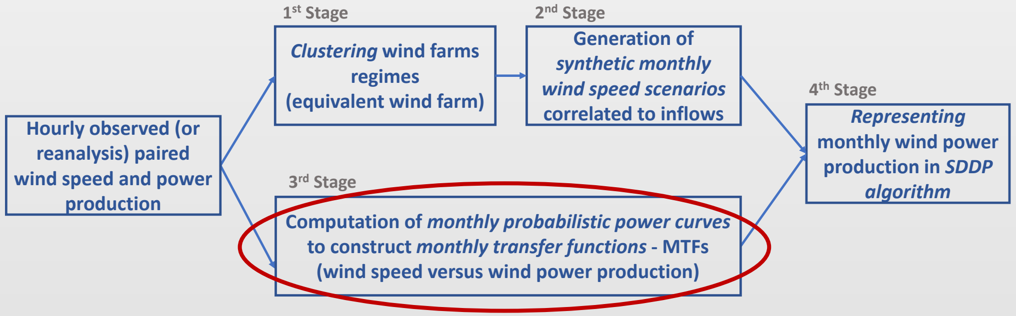






PROPOSED METHODOLOGY

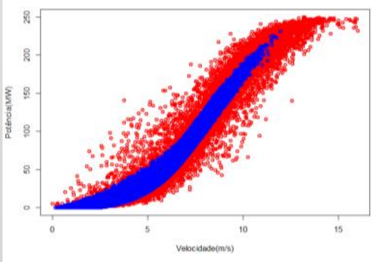
3rd STAGE - Construction of Monthly Transfer Functions (MTFs) between wind speed and wind power production



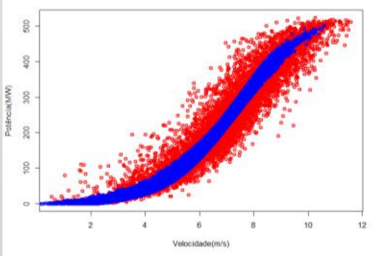
MTFs - mathematical functions, that relate the monthly averages of wind speed with the monthly averages of energy production in each equivalent wind farm

From paired data of wind speed and wind power:

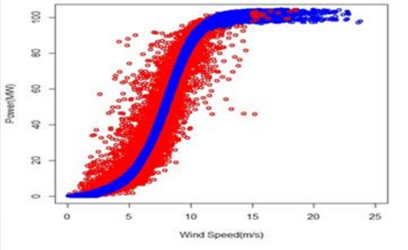
Probabilistic Power Curves – Hourly



PEE NE-I



PEE NE-PE

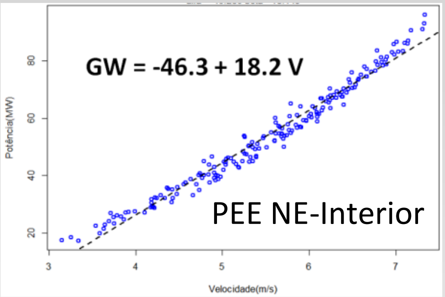


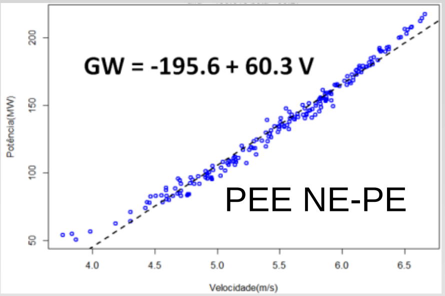
PEE Sul-L

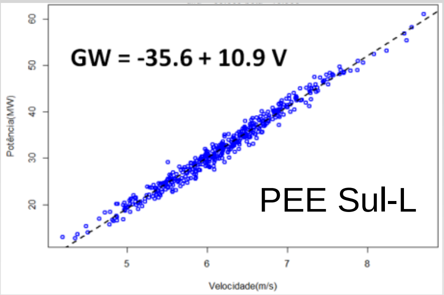
MTFs are obtained through *linear regression models* - simple or piecewise - adjusted to the monthly probabilistic power curves of each (equivalent) wind farm

Probabilistic Power Curves – Monthly

High correlations (above 98,5%)







PROPOSED METHODOLOGY

4th STAGE - Representing monthly wind production in the SDDP algorithm

Objective Function

$$z_t = \min \sum_{m=1}^{NSBM}\left(\sum_{c=1}^{NPMC}\left(\sum_{j=1}^{NUT_m} cterm_{t,m,j}\cdot GT_{t,m,j,c}\right)+\sum_{idef=1}^{NPDF} CDEF_{t,idef}\cdot DEF_{t,m,idef,c}\right)+\sum_{v=1}^{\substack{nviol\in NSBM,\\ NREE}} c_{t,v}\,.\,viol_{t,m,k,c} + \frac{1}{1+\beta}\cdot\alpha_{t+1}$$

Load supply equation in subsystem m in the load level c and period t

$$\sum_{k\in NREE_m}(GH_{t,c,k}+fpeng_{t,c}\,GFIOL_{t,c,k}) + \sum_{j\in NUT_m} GT_{t,c,j} + \sum_{j=1,j\neq m}^{NSBM}\left(INT_{t,c}(i,k) - INT_{t,c}(k,i)\right) + DEF_{t,c,m} - EXC_{t,c,m} +$$

$$\sum_{u=1}^{NPEE_m} GW_{t,u,c} = merc_{t,m,c} - \left(submot_{t,m}+pqusi_{t,m}+\sum_{j\in NUT_m} gtmin_{t,m,j}\right).fpeng_{t,c}$$

Controllable energy balance equation in REE k and period t

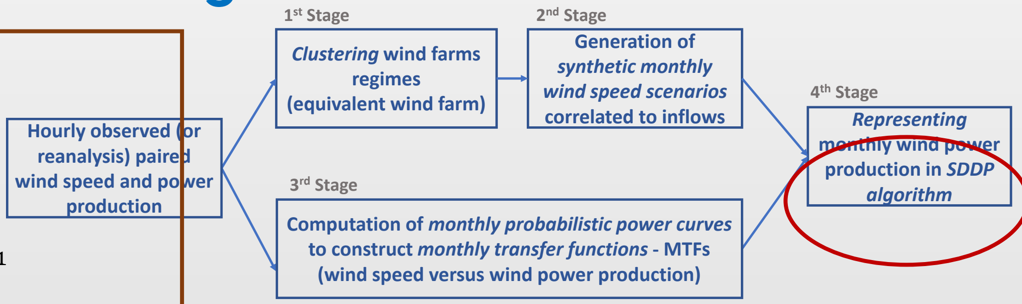
$$EA_{t+1,k} = FDIN_{t.k}\,EA_{t,k} + FC_{t,k}\,EC_{t,k} - GH_{t,c,k} - EVT_{t,k} - EVP_{t,k} - EDVC_{t,k}$$

Wind power production through the MTFs in WF/EWF u (simple linear regression) in WF/EWF u and period t

$$\sum_{c=1}^{NPMC} GW_{t,u,c} \le b^{W}_{t,u} + a^{W}_{t,u}\,V_{t,u}$$

Set of multivariate linear constraints (Benders cut) representing the cost-to-go function

$$\alpha_{t+1} - \sum_{k\in NREE} \bar{\pi}_{EA_{1,t+1,k}}\,EA_{t+1,k} + \sum_{j=1}^{p} \bar{\pi}_{EAF_{1,j,t+1,k}}\,EAF_{t-j+1,k} \ge \bar{\delta}_{1,t+1}$$

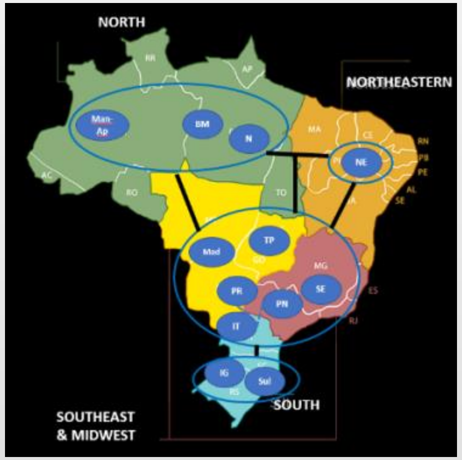


The wind production is represented in the SDDP dispatch problem as an available generation source with null operating cost

The MTFs are used with the synthetic monthly wind speed scenarios to obtain the wind power production

The *Benders cuts* of SDDP algorithm must incorporate a new term related to the dependence of the wind speed with the inflows, depending on the adopted *regression component*

COMPARING THE OPERATION POLICIES



1st Case - Without uncertainty

Average monthly wind power of the Northeast and South subsystems were determined by applying the MTFs of the 5 EWFs to their respective historical monthly wind speeds and then obtaining the monthly averages of the resulting values

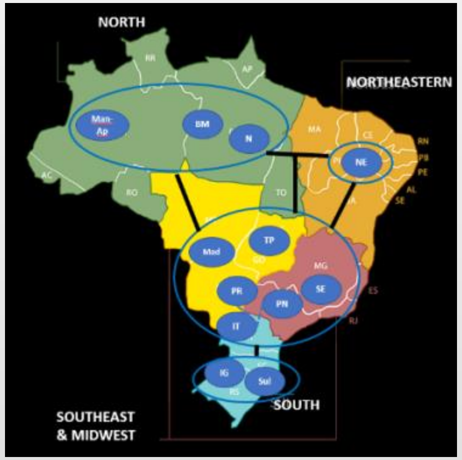
Generation of non-dispatched plants in NEWAVE to emulate the approved current procedures

2nd Case - With uncertainty

Wind power uncertainty was modeled through the generation of synthetic sequences of monthly average wind speeds in the EWFs for the *backward* and *forward* passes of the SDDP algorithm and also for the final simulation

Then they are transformed into synthetic sequences of wind power through the MTFs, which are also explicitly used in each operation dispatch problems

COMPARING THE OPERATION POLICIES



System performance indices are obtained with a simulation of the system operation with 2,000 synthetic wind and inflow scenarios

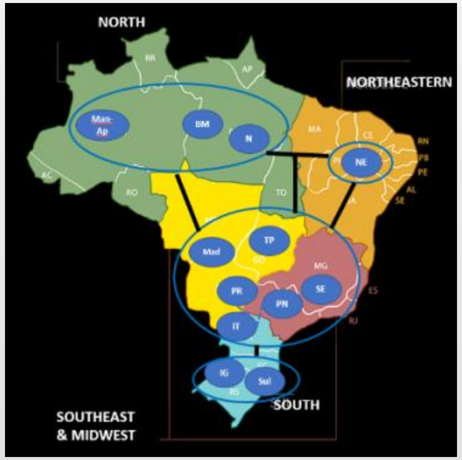
Expected Total Operation Cost, Annual Deficit Risk, Annual EENS

YEAR	SOUTHEAST RISK %	SOUTHEAST EENS MWMONTH	SOUTH RISK %	SOUTH EENS MWMONTH	NORTHEAST RISK %	NORTHEAST EENS MWMONTH	NORTH RISK %	NORTH EENS MWMONTH
Without_Uncertainty Case								
Expected Total Operation Cost = 25,790.54								
2021	0,2	1,4	0,1	0,2	0,0	0,0	0,0	0,0
2022	0,1	0,4	0,1	0,3	0,0	0,0	0,0	0,0

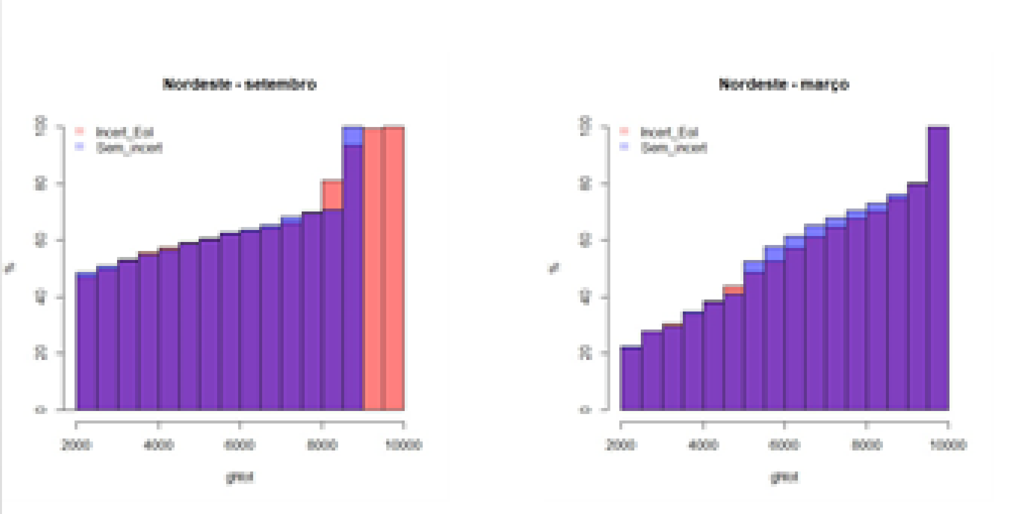
Reduction in the expected total operation cost of 2.16% (560 M R$)

YEAR	SOUTHEAST RISK %	SOUTHEAST EENS MWMONTH	SOUTH RISK %	SOUTH EENS MWMONTH	NORTHEAST RISK %	NORTHEAST EENS MWMONTH	NORTH RISK %	NORTH EENS MWMONTH
Uncertainty_Wind Case								
Expected Total Operation Cost = 25,234.37								
2021	0,3	0,5	0,1	0,2	0,0	0,0	0,0	0,0
2022	0,0	0,0	0,1	0,1	0,0	0,0	0,0	0,0

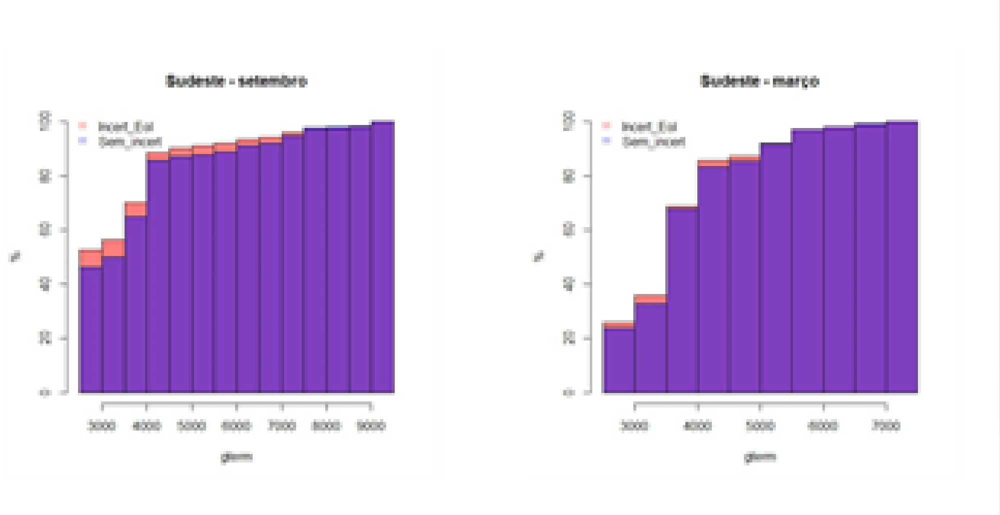
COMPARING THE OPERATION POLICIES



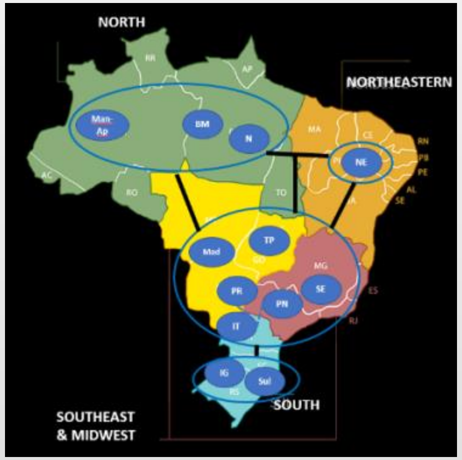
Monthly Hydro Generation



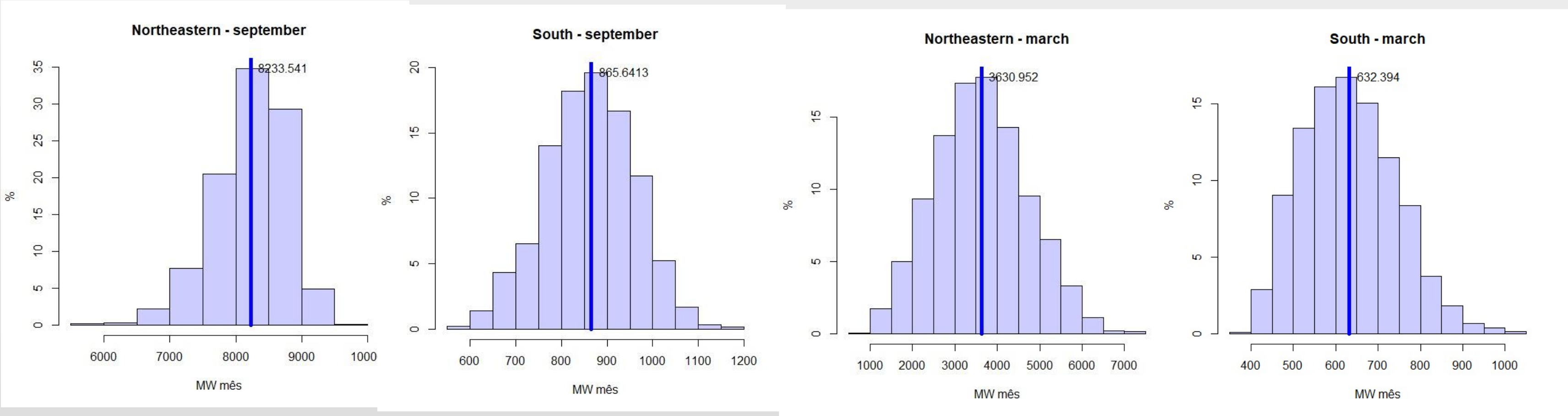
Monthly Thermal Generation



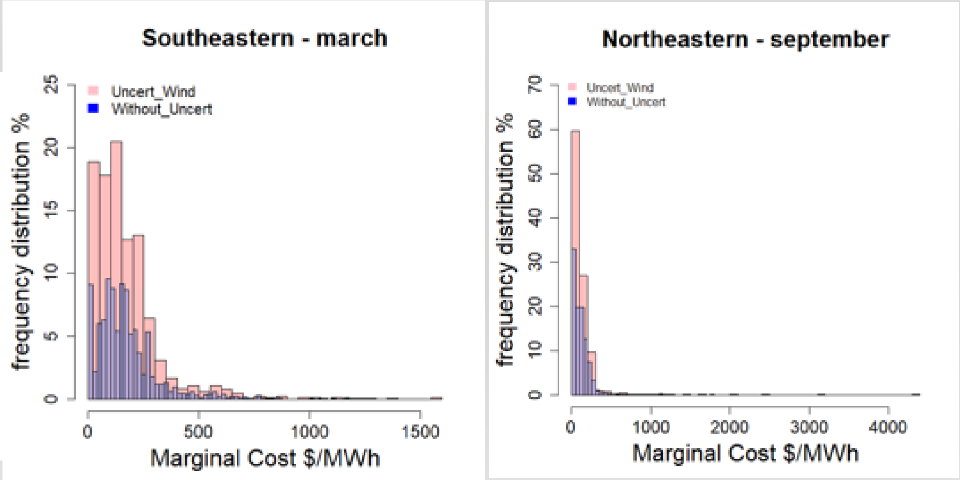
COMPARING THE OPERATION POLICIES



Frequency distribution of the synthetic wind power production



Operation Marginal Cost - March



CONCLUSIONS

Currently, in accordance with the guidelines of the Electricity Regulatory Agency, **the representation of wind power in the NEWAVE** model **is carried out in a simplified manner**

The objective of this work **was to** describe an approach **to be used by the Brazilian power industry** to represent the uncertainties of monthly wind power in the **operation dispatch problem, solved by** SDDP algorithm

(i) statistical **clustering of wind regimes** and definition of EWFs;

(ii) an **integrated model** for the **generation of monthly multivariate synthetic sequences of inflows** and **winds**, considering the correlations between wind speeds, between inflows and between wind speeds and inflows;

(iii) evaluation of **monthly transfer functions** (MTFs) between wind speed and power production

(iv) representing monthly wind power through MTFs, **to be used in the SDDP algorithm.**

The effectiveness of the proposed approach was illustrated with a real configuration of the Brazilian interconnected system

Thank you!