

***Session HS5.2/ERE2.7 – Innovation in Hydropower Operations and Planning
to integrate renewable energy sources and optimize the Water-Energy Nexus***

***An Approach to Representing Wind Uncertainties
in the Long-Term Operation Planning
of Systems with Hydropower Predominance***

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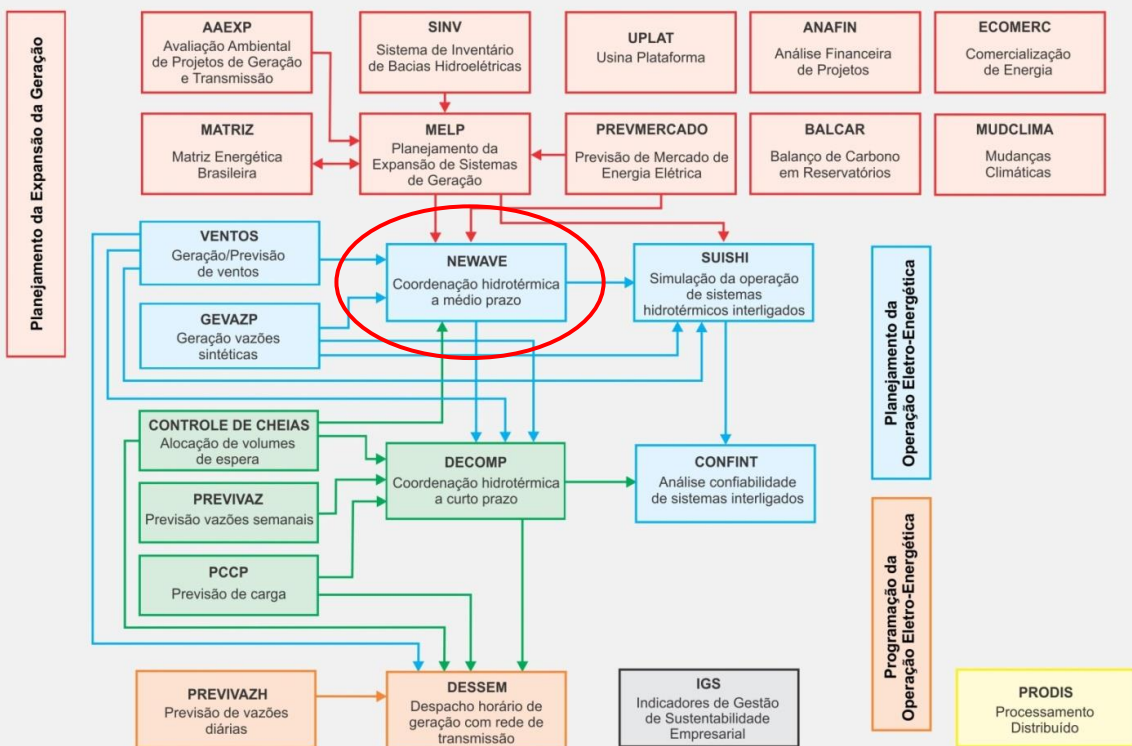
Introduction

Energy Optimization and Centralized Dispatch of the Whole Interconnected System

A Key model is the **NEWAVE** model

- has been used in the routine and official activities of sector entities
 - generation dispatch by the National System Operator
 - calculation of the spot prices by the Whole Sale Energy Market Entity
 - expansion planning by the Ministry of Mines and Energy and the Energy Research Company
 - parameters of public auctions for the purchase of electricity by the Electricity Regulatory Agency
 - by utilities of the power industry to develop corporate strategies
- The long/medium-term operation planning problem is represented as a multistage stochastic linear programming problem, with monthly steps
- It is solved by using a stochastic dual dynamic programming (SDDP) algorithm.
- In the current SDDP implementation, a periodic auto-regressive model - PAR(p) - is used
 - to generate the energy/water monthly inflows scenarios in the forward and backward passes of SDDP
 - and in simulating the system operation with the calculated operation policy

Cadeia de Modelos para o Planejamento da Expansão da Geração e da Operação Energética

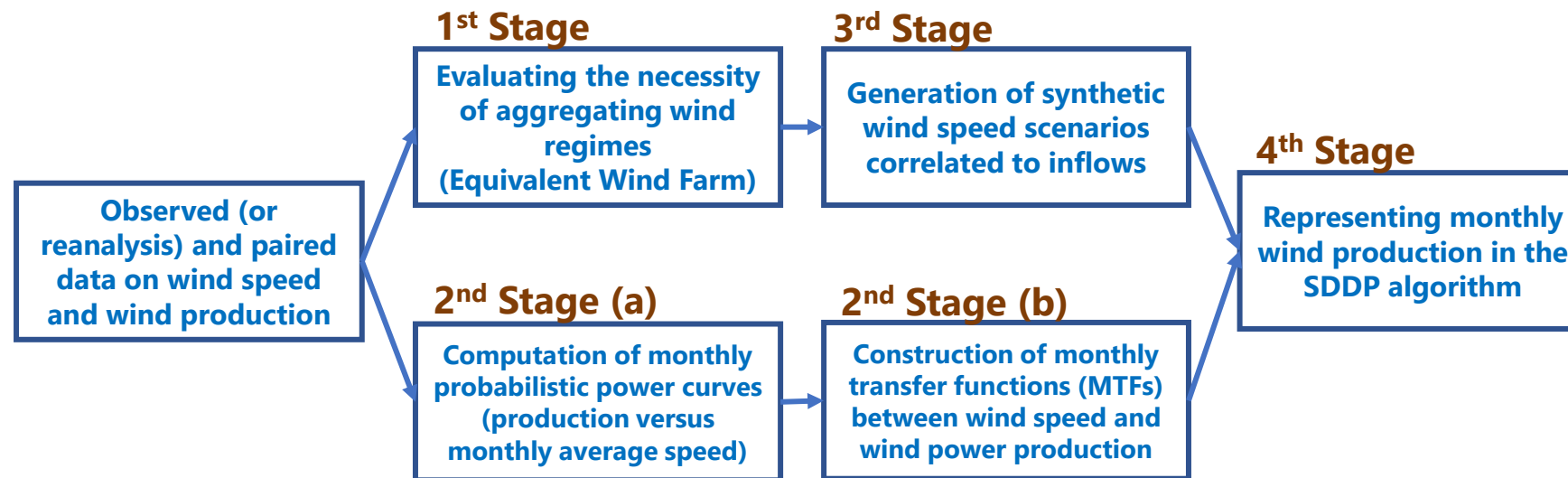


Proposed methodology - Objective

Brazil: 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 39,500 MW (17.3%)

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) or aggregated wind farms (EWF).*

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

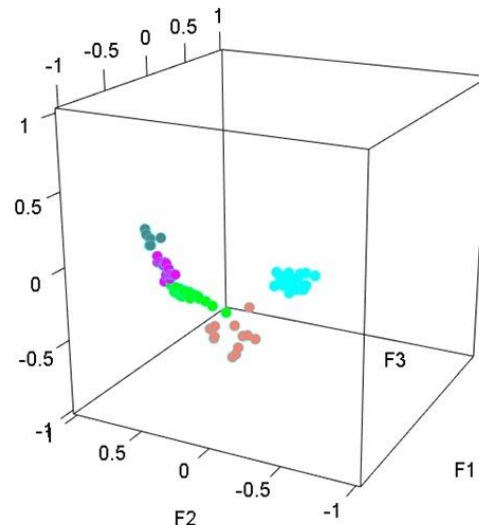
1st Stage - statistical clustering of wind regimes based on multivariate statistical methods

wind speed

Exploratory
Factor Analysis

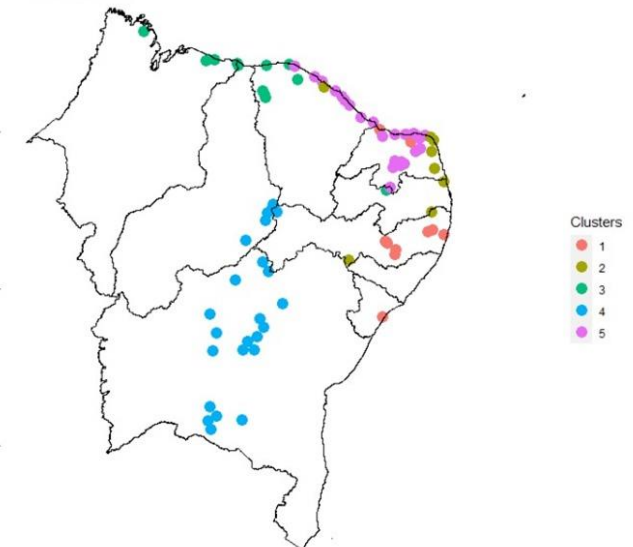
Clustering
Analysis K-Means

- the Exploratory Factor Analysis technique is applied to the data matrix in which each column holds the time series wind speed (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
- 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



Brazilian
Northeastern Region

5 Wind Regimes



Proposed methodology

2nd Stage – Integrated model for generating synthetic wind speed and inflow scenarios

Inflows

Positive skewed random noises

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

Wind Speeds

Positive/Negative skewed random noises

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

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

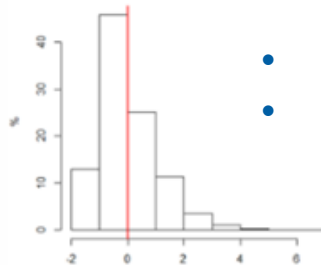
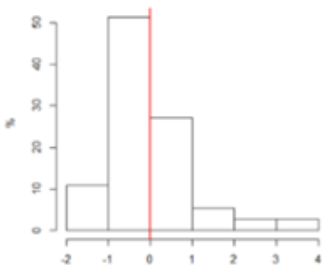
To generate correlated monthly inflows and wind speeds

- 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

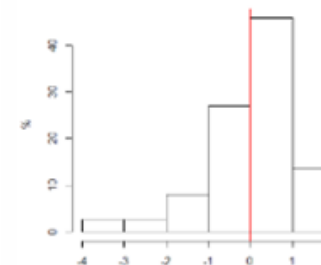
Inflows: A 3-parameter Lognormal distribution is fitted to the spatially correlated residuals in order to better reproduce the observed skewness

Wind Speeds: the monthly wind speed residuals can present positive as well as negative skewness

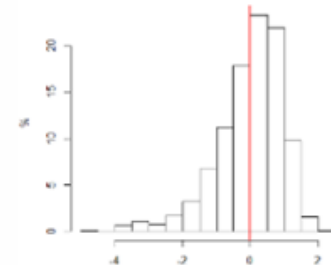
- a 3-parameter Weibull distribution is then used
- a special purpose algorithm was developed



Ago – NE-PE



Jun – NE-IN



Proposed methodology

2nd Stage – Integrated Model for Generation of synthetic wind speed and inflow scenarios

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

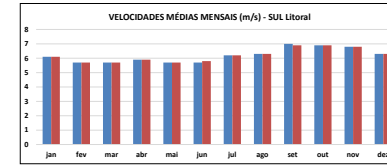
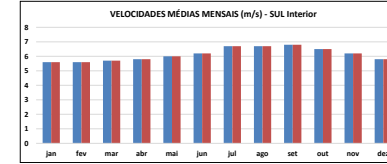
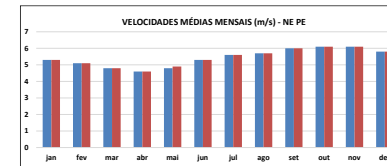
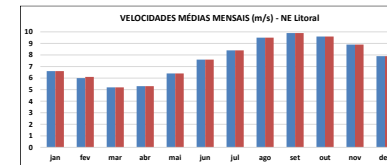
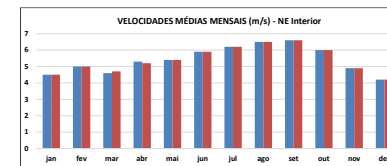
$$V_{t,j} = \mu_{m,j}^v + \sigma_{m,j}^v a_{t,j}$$

$$V_{t,j} = \mu_{m,j}^v + \theta_{t,j,i} \sigma_m^v \left(\frac{ENA_{t,i} - \mu_{m,i}}{\sigma_{m,i}} \right) + \sigma_m^v a_{t,j}$$

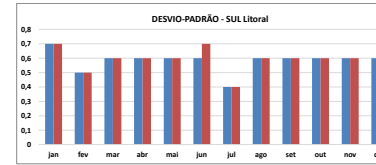
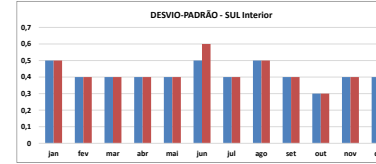
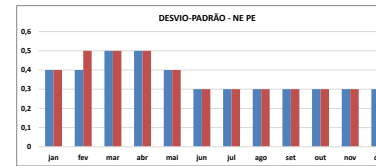
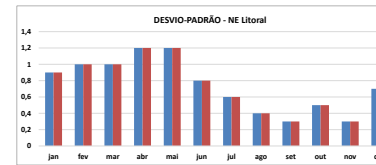
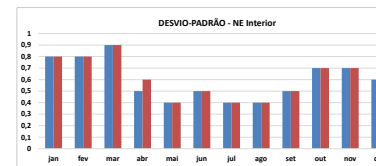
$$V_{t,j} = \mu_{m,j}^v + \delta_{t,j} \sigma_m^v \left(\frac{V_{t-1,j} - \mu_{m-1,j}^v}{\sigma_{m-1,j}^v} \right) + \sigma_m^v a_{t,j}$$

Monthly wind speeds

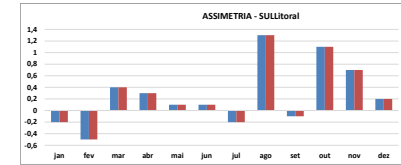
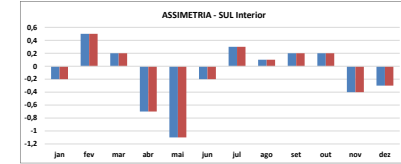
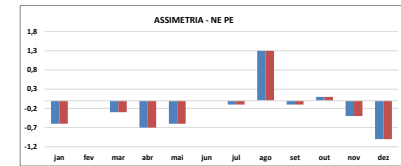
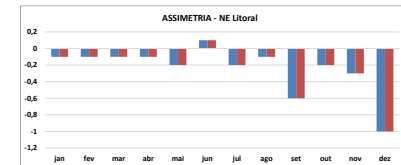
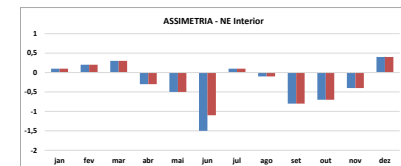
Mean



Standard-Deviation



Skewness coefficient

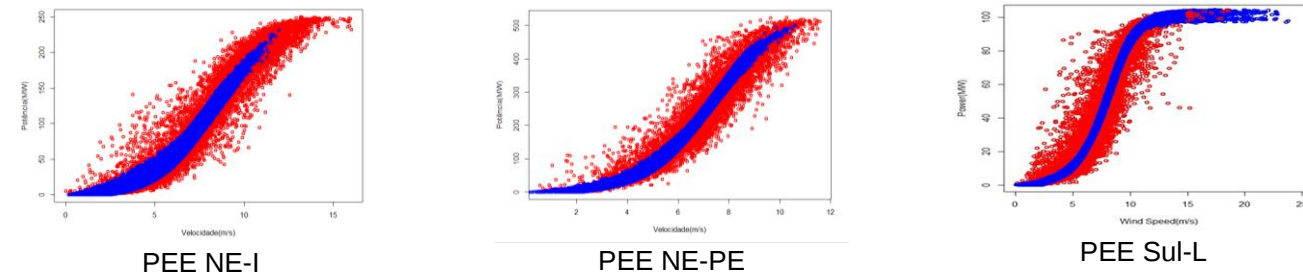


Proposed methodology

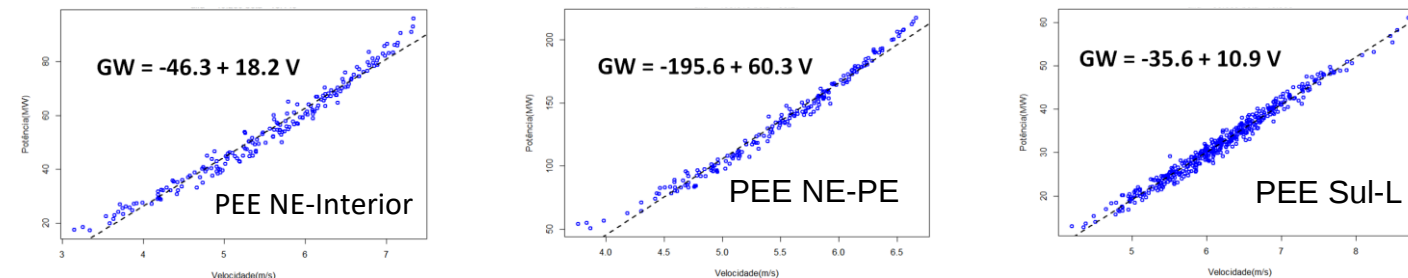
3rd Stage – Construction Monthly Transfer Functions (MTFs) between wind speed and wind power production

From paired data of wind speed and wind power

Probabilistic Power Curves – Hourly

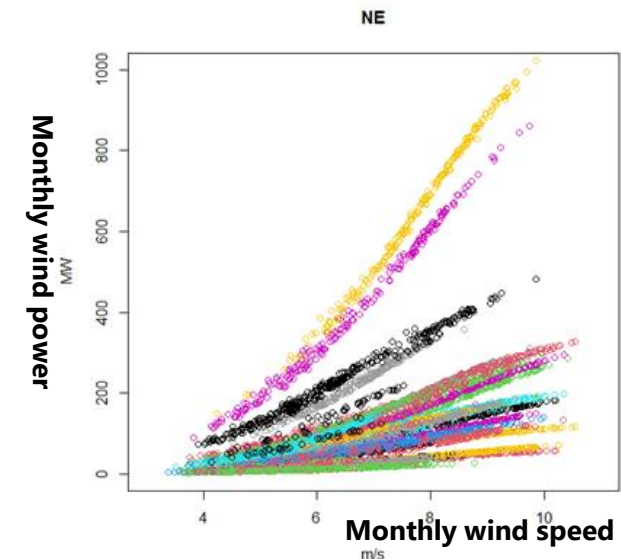


Probabilistic Power Curves - Monthly



High correlations (above 98,5%)

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



For 35 hub substations – Northeastern system

Proposed methodology

4rd Stage – Representing monthly wind production in the SDDP algorithm

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

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

Objective Function

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

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

$$\sum_{k \in NREE_m} (GH_{t,c,k} + fpeng_{t,c} GFIO_{t,c,k}) + \sum_{j \in NUT_m} GT_{t,c,j} + \sum_{j=1, j \neq m}^{NSBM} (INT_{t,c}(i, k) - INT_{t,c}(k, i)) + DEF_{t,c,m} - EXC_{t,c,m} + \sum_{u=1}^{NPEE_m} GW_{t,u,c} = merc_{t,m,c} - \left(submot_{t,m} + pquasi_{t,m} + \sum_{j \in NUT_m} gtmin_{t,m,j} \right) \cdot fpeng_{t,c}$$

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

$$\sum_{c=1}^{NPMC} GW_{t,u,c} \leq b_{t,u}^W + a_{t,u}^W V_{t,u}$$

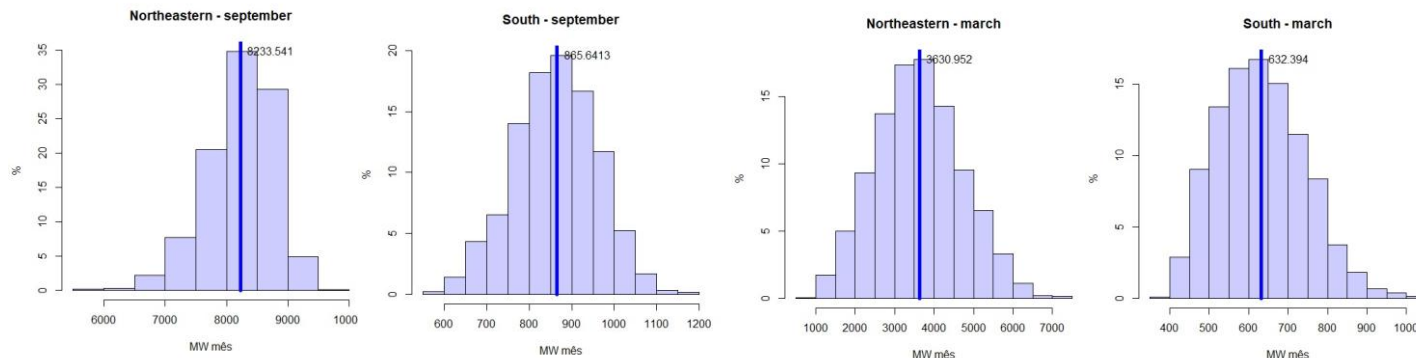
Set of multivariate linear constraints (Benders cut) representing the cost-to-go function

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

Comparing the Operation Policies

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

Frequency distribution of the synthetic wind power production

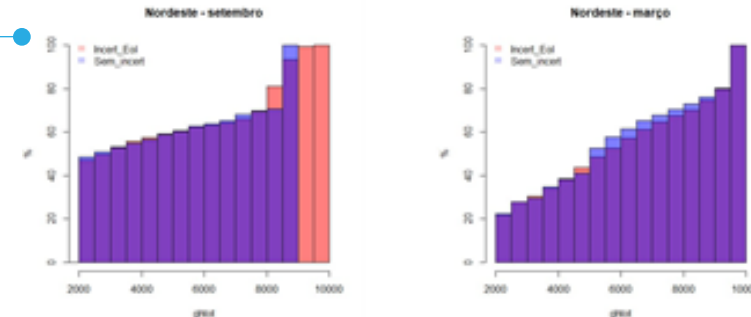


Expected Total Operation Cost, Annual Deficit Risk, Annual EENS

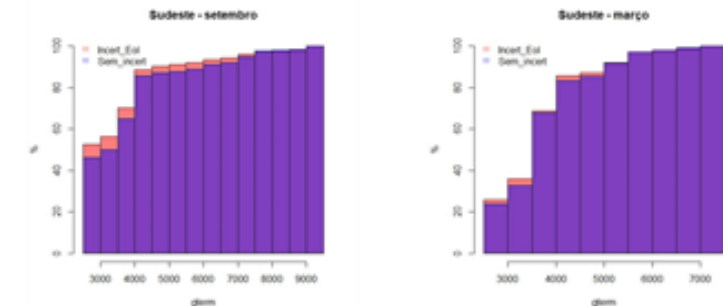
YEAR	SOUTHEAST		SOUTH		NORTHEAST		NORTH	
	RISK	EENS	RISK	EENS	RISK	EENS	RISK	EENS
	%	MWMONTH	%	MWMONTH	%	MWMONTH	%	MWMONTH
Without_Uncertainty Case								
Expected Total Operation Cost = 25,790.54 10 ⁶								
2021	0,2	1,4	0,1	0,2	0,0	0,0	0,0	0,0
2022	0,1	0,4	0,1	0,3	0,0	0,0	0,0	0,0
Uncertainty_Wind Case								
Expected Total Operation Cost = 25,234.37 10 ⁶								
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

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

Monthly Hydro Generation



Monthly Thermal Generation



Operation Marginal Cost

