Improvements in the Current Brazil's Energy Dispatch Optimization: Load Forecast and Wind Power

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Abstract: In the last years, Brazil has been passing through some significant changes into its electricity matrix, where natural gas, wind power and other renewables sources are increasing its share on power generation. Those on going changes represent a challenge to power generation dispatch, demanding improvements and major changes on its management and optimization, especially due to growing levels of wind power generation. From the power demand perspective, the use of too optimist power demand forecasts for energy planning and dispatch optimization purposes affects it directly. This article intends to address those two issues, as it proposes an alternative model to forecast electricity demand and conceives a procedure to integrate wind power generation on the power dispatch model currently used in Brazil. The article study the Brazilian Northeast region as it is where most of the wind power farms are located. Power demand forecasts are obtained via electricity consumption forecasts made using Autoregressive Distributed Lag – ADL models, considering macroeconomics perspectives to estimate it. To integrate wind power integration on the actual dispatch model, the Markov Chain Monte Carlo method – MCMC was used to simulate wind power generation and calculate the net power demand, which was considered in the dispatch model.

1 INTRODUCTION

In the last years, Brazil has been passing through some significant changes into its electricity matrix which itself represents a challenge to the dispatch management and optimization. Renewables like wind and solar generation are gaining space and improvements into the actual dispatch model are necessary to produce results that are more reliable. Challenges also exists from the power demand point of view to better represent the future perspective of this variable, which also, indirectly, affects the dispatch optimization and management. Those are the two main issues considered in this article: provide an alternative to the actual electricity demand forecasts applied into the dispatch model and conceive a procedure to introduce wind power generation into the dispatch model.

1.1 Dispatch Optimization

Brazil has one of the cleanest electricity matrix in the world, but aiming to better diversify it and due to other environmental issues, other renewables (besides from the hydropower generation) are gaining space and thermal generation is migrating to natural gas. Figure 1 presents power generation matrix in 2017, where around 42,3 thousand gigawatts are generated through wind, being responsible for 7.39% of the electricity generation (ONS, 2018). In 2015, wind power had a share of just 3.90% of the electricity generation. Observing the wind power generation and its installed capacity numbers, for the last 10 years, it possible to notice its constant growth, where in January 2018, reached a total installed capacity of 12 GW (Figure 2).

Moreover, in the newer future, wind power tends to keep increasing both its share in the Brazilian electricity matrix (installed capacity) and its generation share. Therefore, the actual power

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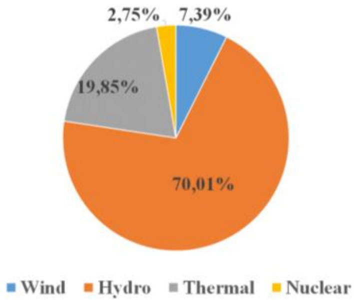
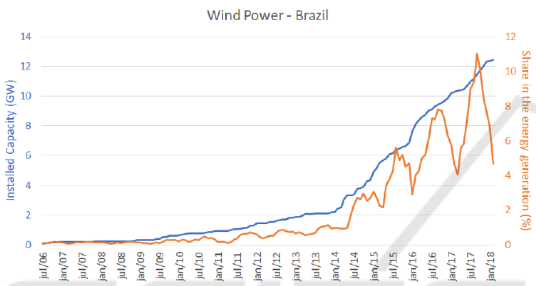
dispatch model used in Brazil must be adapted to be able to better represent this new configuration and to produce more reliable results.



Source: Brazilian Power System Operator (ONS)

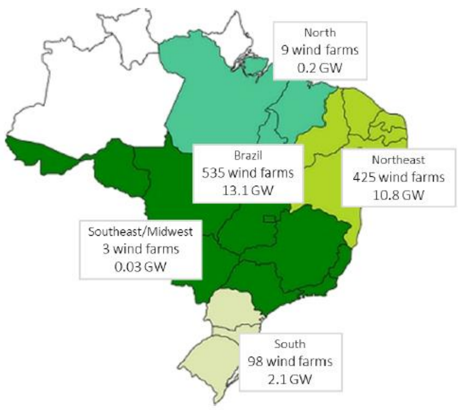
Figure 1: Brazilian Power Generation Matrix – 2017.



Source: Brazilian Power System Operator (ONS)

Figure 2: Wind Power Installed Capacity and Generation.

When it comes to wind power plants localization, most of them are located on Brazilian northeast region, where the environmental conditions are most suitable (ANEEL). Figure 3 presents the installed capacity per region and it is possible to notice that almost 82.44% is located on the northeast and that´s the main reason why our study focus the analysis in this region.



Source: Brazilian Regulatory Authority (ANEEL)

Figure 3: Wind Power Farms Sites.

It is also important to mention that in Brazil, wind power generation has a regime that is complementary with hydroelectric generation. Therefore, in the dry season wind power generation is able to fulfill the gap left by hydropower generation decrease. This benefits countries like Brazil that have most of its power provided by hydropower. It also helps the country to fulfill its greenhouse gas emissions targets.

As one of the article main purposes is to provide a procedure to introduce wind power generation on the Brazilian dispatch model, might be important to give a brief overview of the power dispatch optimization decision-making occurs. To manage the Brazilian power sector, the system operator have to decide whether to use all the water available in the present moment or to save it for the future (Oliveira, 2015). In other words, it is mainly a decision between dispatching hydroelectric or thermal plants.

As can be seen in Figure 4, wind power generation is not considered in the decision-making process. Actually, to consider wind power generation in some way, the system operator discounts the amount of wind power generation forecasted deterministically from the power demand considered in the decision-making process. Therefore, the dispatch model uses a net demand (power demand discounted the amount of wind power generation forecasted), estimated deterministically. In the article, we propose the use of stochastic wind power simulations, calculated via Markov Chain Monte Carlo (MCMC), as an alternative method to estimate the net demand. This represents the first step towards the conception of a hydrothermal-wind dispatch model.

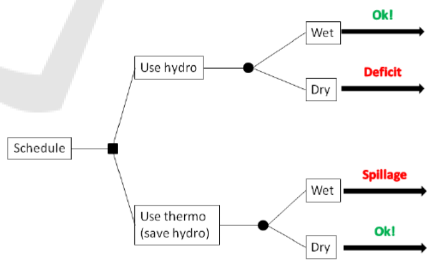


Figure 4: Power Dispatch Optimization.

1.2 Power Demand Modelling

As mentioned in Subsection 1.1, the net demand is obtained taking from the power demand forecasted the amount of wind power generated. Therefore, power demand forecasts also have considerable impacts on the results obtained during the decision-making and the dispatch optimization process. Thus, the more accurate the forecasts considered the better. Inaccurate forecasts might give wrong price signals or power dispatch signalizations to stakeholders (Oliveira, 2015).

Nowadays, the Brazilian dispatch model consider deterministic power demand forecasts instead of probabilistic forecasts or even scenarios forecasts.

This article provides power demand scenarios using electricity consumption forecasts conceived using Additive Distributed Lags – ADL models. The use of ADL models enables the use of explanatory variables into the model. Three alternative scenarios (baseline, optimist and pessimist) are elaborated.

1.3 Article Structure

The article has four sections including the introduction. The second section contains the methodology used both to the power dispatch modelling and to the power demand forecasting. Section 3 presents the results derived from the power demand forecasting, wind power simulation and net demand forecasts. It also contains the dispatch optimization results considering both the actual model used by the system operator and four alternative scenarios. Section 4 contains the major conclusions derived from both analyses.

2 METHODOLOGY

2.1 Load Forecasting

Monthly power demand scenarios were conceived using monthly electricity consumption forecasts, which were elaborated using Autoregressive Distributed Lag - ADL modelling. The forecasts were made by subsystem, on a monthly basis, for four years ahead. The following mathematical equation represents the ADL model:

$$Y_{t=}\sum_{i=1}^{k}\beta_i(L)X_{i,t}+\frac{1}{a(L)}\varepsilon_t \tag{1}$$

Where:
Y_t: Dependent variable;
$X_{i,t}$: Explanatory variables;
$\beta_i(L)=\frac{b_i(L)}{a(L)}$ and $a(L),b_1(L),\dots,b_k(L)$ are finite order lag polynomials with degree $r,s_1,\dots,s_k$;
ε_t: White noise.

ADL enables to model relationship between independent and dependent variables and, in this article, variables like income, gross domestic product - GDP, retail sales, tariffs, temperature and rainfall were used as explanatory variables. The electricity consumption forecasts were made for each consumer class; thus, a procedure was used to obtain power demand forecasts scenarios from the electricity consumption forecasts scenarios.

Figure 5 contains a flowchart of the procedure. Initially, network losses are added on the monthly consumption forecasts, generating monthly electricity load forecasts. Then the monthly electricity load forecasts are transformed into monthly power demand forecasts.

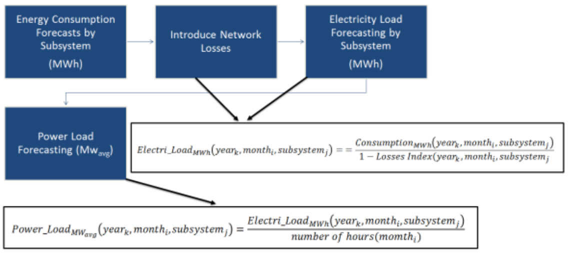


Figure 5: Power Demand Scenarios Calculation.

The power demand forecasts and the official forecasts (named NEWAVE) are evaluated via Mean Absolute Percentage Error – MAPE to verify if the scenarios conceive provides more accurate forecasts than the ones considered by the system operator.

2.2 Wind Power Generation and Net Demand

Before presenting the wind power generation forecasts method and net demand estimation, a brief overview is given of how wind power generation is considered nowadays on the dispatch model.

The dispatch model considers wind power generation together with, the so-called, non-simulated plants, which are power plants that power generation are added into the dispatch model deterministically. All of them are taken into account on the dispatch model through the net demand. The net demand is the demand to be fulfilled in the dispatch optimization and corresponds to the difference between the total demand to be attended and the non-simulated plants generation.

$$Net\ Demand = Demand - (non\ simulated\ plants) \tag{2}$$

To estimate the wind power generation, stochastic simulation is used and then these results are used to calculated the net demand. This represents a different where the net demand is calculated using historic wind power generation data.

In our study, an analytical method of frequency and duration is applied to combine wind power generation and power demand to estimate the net demand. The analytical method uses Markov chain and discrete convolution techniques. This procedure was conceived based on Almutairi et al (2016) study.

Figure 6 presents a procedure based on three steps (historical data, MCMC model and Net Demand Model) elaborated to treat wind power generation on a stochastic manner.

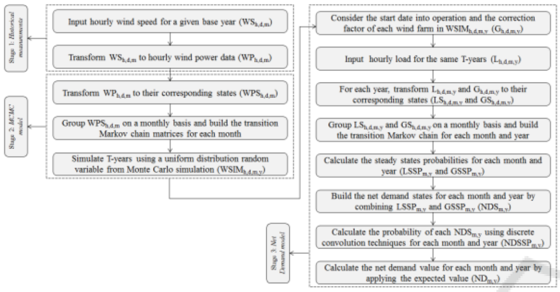


Figure 6: Procedure Step by Step.

2.2.1 Historical Data

Papaefthymiou and Klöckl (2008) understand that a stochastic model based on wind power generation is more reliable and have more advantages than models based on wind speed data. Therefore, in this study, historical data of wind power generation is used. Historical data for wind speed was obtained through the Climate Forecast System Reanalysis - CFSR (Saha et al., 2011) and as it enables the data gathering by geographic coordinates (using a spatial resolution between 0.25º to 0.25º), it was possible to associate a wind speed data to each wind farm located on the northeast region.

The wind speed data gathered was transformed into wind power generation using turbine parameters from each wind farm. The following parameters were considered: turbine model, number of turbines, average height and wind power load curve. More information about this data is available at the Regulatory Authority - ANEEL, the System Operator - ONS and manufactures website.

Height correction errors were considered to relate the wind speed gathered with each wind farm. The correction is made using the following equation.

$$HF_i = \frac{\log(HT_i)}{\log(HM_i)} \tag{3}$$

Where:

HF_i: Height correction factor;

HT_i: Turbine height;

HM_i: Measurement height associated with the wind farm i.

Wind power load curve associates a wind power to a certain wind speed, therefore using the height correction factor is possible to transform the wind speed data ($WS_{h,d,m}$) on wind power using the wind power load curves.

2.2.2 Markov Chain Monte Carlo Model

The Markov Chain Monte Carlo - MCMC modelling is divided into seven steps, explained below.

1. Aplication of k-means clustering techniques (MacQueen, 1967) to transform the wind power data ($WP_{h,d,m}$) into a finite number of states ($WPS_{h,d,m}$): it is important to emphasize the in the end of the k-means clustering the wind power calculated is replaced by the centroids from the clusters where they belong;
2. Calculates Markov Chain transition matrices (P_{ind}) where each row ends with 1: the transition matrices are calculated for each month and have $k \times k$ dimension;
3. Calculate the cumulative probability transition matrices where each row ends with 1: calculate the transition probability ($p_{(i,j)}$) from the state i to the state j, for all the matrix elements;
4. Select the initial state *i* randomly;
5. Produce a random value between 0 and 1 by uniform random number generator;
6. Select the next state by comparing the value of a random number with the elements of the *ith* row of the cumulative probability transition;
7. Repeat steps 5 and 6 until the required hourly wind power data is simulated.

2.2.3 Net Demand

To add the wind power generation into the Brazilian hydrothermal dispatch model, it is crucial to have all the data from the wind farms available. Consider that there are n wind farms on a certain database, each one of them with a certain installed capacity (IC_i, $i = 1, \dots, n$). The wind farm i share is calculate dividing the wind farm installed capacity by the wind power installed capacity considering all wind power producers.

$$Share_{i=} \frac{IC_i}{\sum_i IC_i} \varepsilon_t \tag{4}$$

For example, if a certain wind power generator starts its operation at day d, month m and year y, all the wind power generation simulated before this data must be discounted from $Share_i$.Concerning the capacity and availability factor, as there is no information about this matter for each wind farm, historical data for one-year monthly generation is used to calibrate the forecasted values. In other words, for a month m, o correction factor CF_m is calculated as following.

$$G_{h,d,m,y} = WSIM_{h,d,m,y} \times \left(1 - \sum_i Share_{i,h,d,m,y}\right) \times CF_m \quad (5)$$

To start the net demand calculation, data from hourly power demand forecasts are necessary. Due to the lack of official information about hourly load curves for Brazil, a standard load curve ($LP_{m,h}$) was conceived and used to transform the monthly power load forecasted ($ML_{m,y}$) (on section 2.1) into hourly power load data ($L_{h,d,m,y} = LP_{m,h} \times ML_{m,y}$.).

Once again, k-means clustering was applied to discrete wind power generation and transform the series into states ($LS_{h,d,m,y}$ and $GS_{h,d,m,y}$). In addition, the Markov Chain transition matrices were calculated, for each month, following the same steps presented on subsection 2.2.2. Then, the steady state probabilities associated with each load data and load generation data is estimate, for each month and year ($LSSP_{m,y}$ and $GSSP_{m,y}$).

As the net demand can be characterized as the difference between load and generation ($ND = L - G$), the last procedure in this methodology combines the load and generation model parameters to obtain states and probabilities for the net demand ($NDS_{m,y}$ and $NDSSP_{m,y}$) (Leite da Silva, Melo e Cunha, 1991).

In the last step of this method, expected values between states and the probability associated with each net demand are estimated, generating an amount of net demand for each month and year ($ND_{m,y} = \sum_w NDS_{m,y} \times NDSSP_{m,y}$, where w is the number of states of $NDS_{m,y}$).

3 RESULTS

3.1 Power Demand Forecasts

As already mentioned on subsection 2.1, the power demand forecast initiates with the monthly electricity consumption forecast scenarios conception for each subsystem and consumer classes, considering four years horizon.

To generate electricity consumption forecasts, the following data was used: electricity consumption per consumer class and subsystem, since January-2013. provided by Energy Research Office - EPE; income and GDP historical data; industrial production per sector; retail sales; temperature; rainfall; electricity tariffs and number of dwellings, per class and subsystem (provided by the Regulatory Agency - ANEEL); and number of business days.

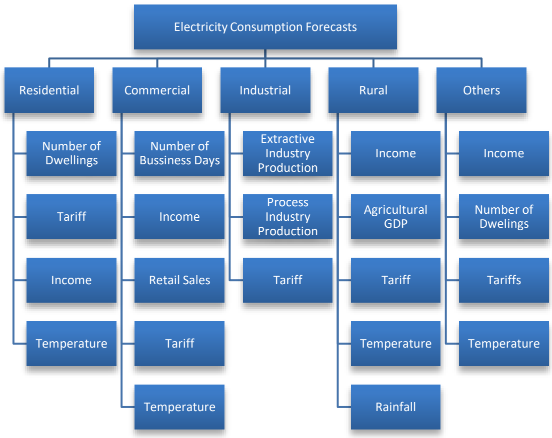


Figure 7: ADL Model Explanatory Variables.

The explanatory variables mentioned above are tested for each one of the models. Figure 7 presents the explanatory variables considered significant, for each consumer classes. In all consumer classes, tariff, as expected, was considered a significant variable to explain electricity consumption. Depending on the consumer classes, a different proxy represents income: industrial production for energy intensive sectors for the industrial sector; income itself for residential, others and commercial; and agricultural GDP for rural class. Also for Residential, commercial, rural and others, temperature plays an important role on electricity consumption forecasts. Especially for rural sector, rainfall was considered.

After adding losses and transforming it on power demand, the forecasts scenarios presented on Figure 8 were obtained. The load forecast scenarios presented on Figure 8 contains only data related with the northeast subsystem and is the load to be attended in the dispatch model. Figure 8 also presents the load to be attended considering the forecast provided by the System Operator, here named as NEWAVE. The forecasted period ranges from July/2017 until November/2021.

Table 1 presents power demand growth rates considering the System Operator official forecast (NEWAVE), the Energy Research Office – EPE power demand forecasts and the three scenarios build in this article. Through Table 1, it is possible to notice that System Operator forecasts (NEWAVE) and the Energy Research Office forecasts (PEN) are more optimist than the ones presented on the baseline scenario.

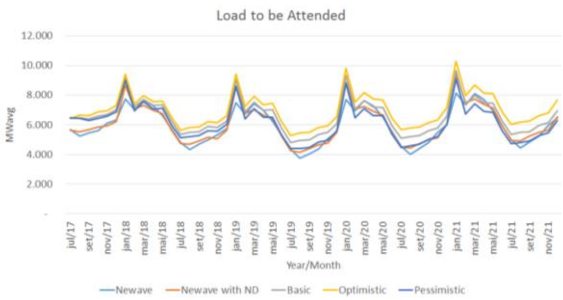


Figure 8: Load Forecasting: System Operator Forecast versus Alternative Scenarios.

Table 1: Power Demand Growth Rates.

Ano	NEWAVE	PEN	Optimist	Basic	Pessimist
2017	1,91%	1,52%	2,52%	2,47%	2,42%
2018	2,85%	3,49%	4,18%	2,55%	1,10%
2019	3,59%	3,59%	4,10%	3,25%	2,00%
2020	3,75%	3,77%	3,42%	3,03%	1,94%
2021	3,82%	3,80%	3,59%	2,89%	1,94%

Figure 9 presents the forecasting accuracy analysis, considering the System Operator official forecasts and the three scenarios build in this article. This analysis was made considering scenarios forecasts conceived by the authors in the last four years (11 times in total) as well as official forecasts made available by the system operator (NEWAVE).
It is possible to observe that, on average, the baseline scenario (the scenario with the highest probability of occurrence) presents the lowest MAPE followed by the pessimistic scenario and then the System Operator official forecasts (NEWAVE).

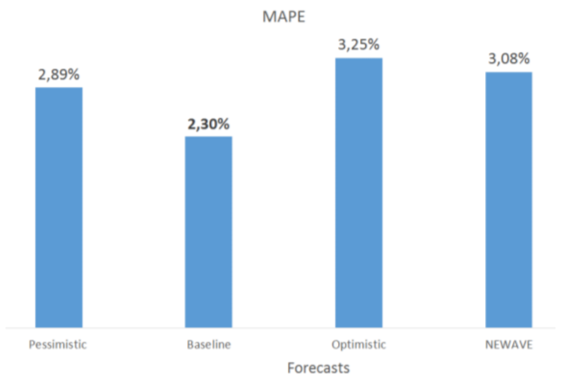


Figure 9: Load Forecasting - System Operator versus Alternative Scenarios.

Through this analysis, it is possible to notice that the baseline scenario obtained via ADL model perform better than the official model. The next step in the analysis is to use the demand load forecasts aligned with the simulated wind power generation to get estimations for energy storage and thermal generation forecasts.

3.2 Wind Power Generation

This subsection applies the method described on subsection 2.2.2 to simulate wind power generation on the northeast subsystem for the period between July/2017 and December/2021. The study uses 2016 as the base year, therefore all the daily wind speed extracted from Climate Forecast System Reanalysis - CFSR and hourly load curves (provided by the Syatem Operator - ONS) comprehends the period between 1st January and 31st December/2016. In July/2017, according to the Regulatory Authority - ANEEL, there were, in the northeast, 362 wind farms operating, 144 wind farms being constructed and 127 authorized to be constructed. Therefore, in total 597 wind farms are considered in the analysis, using the starting operation data to define its generation amount per month.
To transform the monthly power load forecasts into hourly power load forecasts the monthly load curves presented on Table 2 were used.

Table 2: Hourly Load Profile per Month.

	Jan	Fev	Mar	Abr	Mai	Jun	Jul	Ago	Set	Out	Nov	Dez
Hora 1	1.06	1.05	1.03	1.02	1.01	1.00	1.00	1.00	1.01	1.03	1.05	1.07
Hora 2	1.02	1.01	0.99	0.98	0.97	0.96	0.96	0.96	0.96	0.99	1.01	1.03
Hora 3	0.98	0.97	0.95	0.95	0.94	0.93	0.93	0.92	0.93	0.96	0.98	0.99
Hora 4	0.96	0.94	0.93	0.92	0.92	0.91	0.91	0.90	0.91	0.93	0.94	0.96
Hora 5	0.94	0.92	0.91	0.91	0.91	0.90	0.90	0.89	0.90	0.92	0.92	0.94
Hora 6	0.92	0.91	0.90	0.90	0.90	0.89	0.89	0.89	0.89	0.91	0.91	0.93
Hora 7	0.92	0.89	0.85	0.85	0.85	0.85	0.86	0.85	0.83	0.86	0.89	0.91
Hora 8	0.85	0.85	0.84	0.85	0.85	0.85	0.86	0.86	0.85	0.84	0.83	0.84
Hora 9	0.86	0.87	0.92	0.93	0.93	0.93	0.93	0.93	0.94	0.89	0.85	0.86
Hora 10	0.93	0.95	1.00	1.00	1.00	1.01	1.00	1.01	1.01	0.97	0.93	0.93
Hora 11	1.00	1.01	1.03	1.03	1.03	1.04	1.03	1.04	1.04	1.02	1.01	1.00
Hora 12	1.03	1.03	1.05	1.05	1.05	1.06	1.05	1.06	1.06	1.05	1.04	1.03
Hora 13	1.05	1.05	1.05	1.04	1.05	1.05	1.05	1.05	1.05	1.05	1.06	1.05
Hora 14	1.04	1.04	1.03	1.03	1.03	1.03	1.03	1.03	1.04	1.04	1.05	1.04
Hora 15	1.02	1.04	1.07	1.06	1.06	1.06	1.05	1.07	1.07	1.05	1.03	1.03
Hora 16	1.05	1.07	1.08	1.07	1.07	1.07	1.06	1.08	1.08	1.07	1.07	1.06
Hora 17	1.06	1.07	1.06	1.05	1.05	1.06	1.05	1.06	1.06	1.06	1.08	1.07
Hora 18	1.04	1.04	1.01	1.01	1.02	1.02	1.02	1.03	1.02	1.04	1.06	1.04
Hora 19	1.00	0.99	0.97	1.04	1.07	1.07	1.06	1.04	1.05	1.04	1.02	1.00
Hora 20	0.96	0.98	1.06	1.07	1.08	1.08	1.10	1.09	1.08	1.06	1.02	0.97
Hora 21	1.08	1.06	1.04	1.05	1.05	1.05	1.06	1.06	1.05	1.06	1.07	1.06
Hora 22	1.07	1.06	1.05	1.05	1.05	1.04	1.05	1.05	1.04	1.05	1.05	1.05
Hora 23	1.06	1.07	1.09	1.09	1.08	1.08	1.08	1.08	1.08	1.06	1.05	1.04
Hora 24	1.09	1.09	1.07	1.06	1.05	1.05	1.05	1.05	1.05	1.06	1.08	1.08

Figure 10 presents the wind power generation obtained after executing all the steps presented on subsection 2.2.2. The System Operator forecasts (NEWAVE) and the wind generation simulated in this article is shown on Figure 10 and it is possible to observe that, on average, wind power generation provided by the System Operator is higher than the one simulated, especially on peaks and valleys.

Besides of that, both have the same trend and behavior

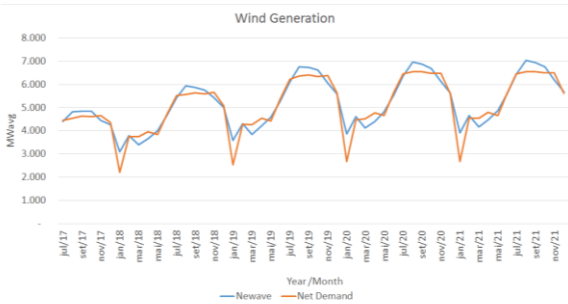


Figure 10: Wind Generation: System Operator versus Simulation.

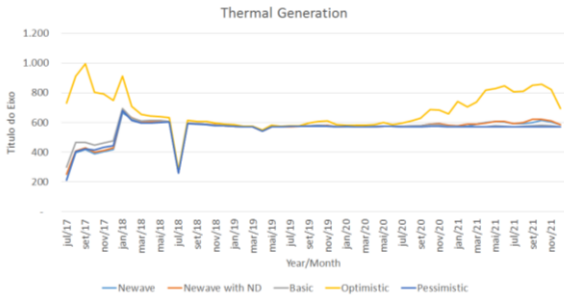


Figure 12: Thermal Generation.

The load to be attended (Figure 7) is higher on the basic scenario than on the System Operator Forecast (with wind power simulation abatement) and on System Operator Forecasts itself. The optimist scenario is the one with the highest load to be attended.

Considering the data from the load to be attended in all scenarios (Figure 7), it is possible to evaluate, using the hydrothermal dispatch model, which would be the system behavior according with the power demand forecasts and wind power generation simulated.

Figure 11 presents the Storage Energy and Figure 12 contains the Thermal Generation for each scenario conceived. From Figure 11 it is possible to notice that the energy stored considering the System Operator Forecasts is higher than the basic scenario and the optimist scenario, but lower than the pessimist scenario. Comparing the System Operator Forecasts (with wind power simulation abatement) and the System Operator Forecasts itself, it is possible to notice that the energy stored in this case is lower than in the traditional model.

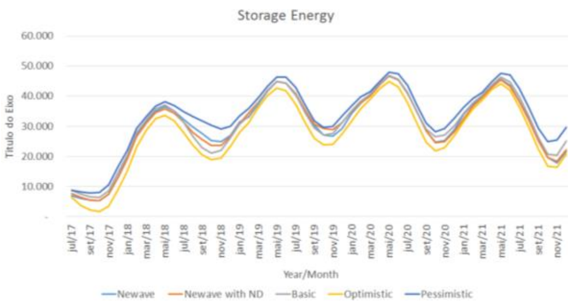


Figure 11: Energy Storage.

For the thermal generation, only the optimist scenario demands higher thermal generation. On average, the baseline scenario demands a little bit less thermal generation than the NEWAVE scenarios.

4 CONCLUSIONS

The study contains a nouvelle approach to introduce wind power generation on the Brazilian Dispatch model, using MCMC to simulate wind power generation instead of using the traditional historical monthly wind power generation. Additionally, additive distributed lags - ADL models were conceived to estimate power demand forecast per month, by subsystem. All the analysis in the article was done applying both approaches in the Brazilian northeast subsystem, considering de forecast period between July/2017 and December/2021. Concerning the power demand forecasts, one can notice that the baseline scenario provide more accurate forecasts than the System Operator forecasts, which has accuracy lower than the pessimist scenario. Changing the power demand forecasts for more accurate approaches would provide better price signals and dispatch signalizations to the system operator.

The introduction of wind power generation using stochastic simulation and therefore a new approach to estimate the net demand, showed little impact on the thermal energy generation, but generated considerable differences when it comes to the load to be attended and energy storage. For the future, the idea is to introduce probabilistic demand forecasts on the dispatch model and to make further improvements on the way wind power and solar energy would be considered on the dispatch model.

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