Statistical analysis of self-affinity of energy dispatch in power generation in the Northeast region of Brazil
Análise estatística de autoafinidade do despacho de energia na geração de energia na região nordeste do brasil

Received: 15-02-2024 | Accepted: 21-02-2024 | Published: 26-02-2024

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ABSTRACT
In this article, we study the fractal dynamics in time series of energy generation in the Northeast region of Brazil, considering a database used by the National Electric System Operator referring to semi-hourly information on the generation of various energy sources. Applying the DFA technique between the years 2020 and 2022, it was found that the dispatch of solar energy fluctuated in all years from superdiffusive behavior in the short term to persistent in the long term, whereas wind generation in all years varied from superdiffusive short-term to long-term subdiffusive. In all observation periods, there was a repeatability of the dispatch behavior of wind and solar sources, which can be explained by the fact that these sources always maintain a standard of availability for the energy matrix. When analyzing the behavior of solar generation, a greater predictability of energy availability was found, which can therefore be considered as a more viable source to make up for the lack of hydraulic energy. This analysis is based on historical time series numbers, not considering the costs of each energy source, environmental license situations, among other factors.

Keywords: Detrended Fluctuation Analysis (DFA); Analysis of long-range autocorrelations; Time series; Electric power dispatch; National Interconnected System;
RESUMO

Neste artigo, estudamos a dinâmica fractal em séries temporais de geração de energia na região Nordeste do Brasil, considerando uma base de dados utilizada pelo Operador Nacional do Sistema Elétrico referente a informações semi-horárias da geração de várias fontes de energia. Aplicando a técnica DFA entre os anos de 2020 e 2022, foi constatado que o despacho de energia solar flutuou em todos os anos do comportamento superdifusivo a curto termo para persistente a longo termo, já o de geração eólica em todos os anos, variou de superdifusivo a curto termo para subdifusivo a longo termo. Em todos os períodos de observação, houve uma repetibilidade do comportamento do despacho das fontes eólica e solar, o que pode se explicar por tais fontes de sempre manterem um padrão de disponibilidade para a matriz energética. Ao analisar o comportamento da geração solar foi constatado uma maior previsibilidade de disponibilidade de energia podendo assim, ser considerada como fonte mais viável para suprir a ausência da energia hidráulica. Esta análise se baseia em números históricos das séries temporais, não considerando os custos de cada fonte de energia, situações de licenças ambientais, entre outros fatores.

Palavras-chave: Detrended Fluctuation Analysis (DFA); Análise de autocorrelações de longo alcance; Séries temporais; Despacho de energia elétrica; Sistema Interligado Nacional;
INTRODUCTION

The installed capacity of electricity generation in Brazil is expanding year after year, while the dispatch (decision taken by the National Electric System Operator – ONS to authorize the best source of energy generation to be released at a given time, considering the security of the electricity system and operational restrictions) of generation sources depending on weather conditions. In Figure 1 we can follow the evolution of the installed capacity by generation sources in the National Interconnected System - SIN and projection until 2026.

In 2021, there was a moment of drought, where the lack of rainfall made it possible to increase the levels of generation from other energy sources. In 2022, we had a favorable hydrological regime, which resulted in a greater dispatch of hydroelectric plants and contributed to a reduction in the dispatch of fossil fuel thermoelectric plants. It is crucial to address the challenges associated with intermittency and infrastructure to ensure the sustainability and affordability of electricity in the Northeast Region, thus contributing to economic growth and the well-being of the population (Bradshaw, 2019).

**Figure 1**– Evolution of Installed Capacity by Energy Sources in the SIN (2013 to 2026).

Source: ONS (2023)

Data on both the demand and supply sides of generation from various sources of electricity are very important for the dispatch and exchange of energy between SIN subsystems in Brazil, as shown in Figure 2.
This synergy between energy demand and supply provides valuable information and has been obtained by ONS since January 2020 through the DESSEM (Dynamic Economic Model of the Energy Dispatch System) mathematical model, with the ability to perform detailed and real-time simulations of the electrical system (ONS, 2023). This allows system operators to assess the impact of variations in power generation and make informed decisions to ensure the stability and reliability of electricity supply. In the Northeast Region, where wind and solar generation are abundant, the ability to predict and manage the variability of these sources is essential to ensure a continuous energy supply.

Developed to simulate the functioning of the electricity market and the operation of the electricity system in real time, DESSEM plays a crucial role in the management and in the optimization of energy generation in a scenario of growing participation of renewable sources. This approach is essential to address the specific challenges introduced by the variability of wind and solar energy.

This work aims to perform a data analysis based on DESSEM information on the semi-hourly dispatch of energy in the Northeast of Brazil, through statistical methods based on the level of long-range self-affinity. To this end, the technique of non-trend fluctuation analysis (DFA) of the hydro, solar and wind generation sources between the
years 2020, 2021 and 2022 was used, providing a better understanding of the short and long-term behavior of the energy sources analyzed.

The present article is organized as follows: the second section describes the aspects of the method used in the study, the third section presents the numerical and qualitative results, while the fourth section presents the main conclusions.

METHODOLOGY

The trendless fluctuation analysis (DFA) (Peng et al., 1994) has been proposed to analyze the presence of long-range translation in non-stationary systems by means of polynomial fitting, which has been widely applied in non-stationary time series (Chen, et al., 2002; Kun et al., 2021). DFA is a derivation of the FA (Fluctuation Analysis) method that eliminates the trend of the time series at different scales and specifically analyzes the intrinsic fluctuations of the data (Chen, et al., 2002; Hu, et al. 2001).

This method provides a relationship between the fluctuation function, FDFA, and the temporal scale n. The DFA method has been very efficient in detecting long-range autocorrelations with long-tails, of the power law type and are quantified by a scale exponent (Zebende, 2011; Zebende et al., 2013; Zebende et al., 2023; Brito et al., 2018; Santos et al., 2018). The DFA method algorithm involves the following steps:

Step 1 - Considering a given signal u(i), where i = 1, ..., N, where N is the size (number of points) of the time series. The signal u(i) is summed, and thus we obtain:

\[ x(k) = \sum_{i=1}^{k} [u(i) - \langle u \rangle], \]

with \( \langle u \rangle \) being the mean value of u in the entire time series and with k = 1, ..., N, where N is the total number of points in the time series. At this point, the time series is integrated considering the equation below:

\[ \langle u \rangle = \frac{1}{N} \sum_{i=1}^{N} u(i) ; \]
Step 2 - The integrated signal \( x(k) \) is divided into boxes of equal size \( n \) (the timescale), and in some cases, it may also overlap. Each segment represents a part of the series that will be analyzed individually;

Step 3 - For each box of size \( n \), a polynomial adjustment of order \( l \) (usually \( l = 1 \) is used) is made at \( x(k) \), which will be the trend of the signal inside the box. The \( y \)-coordinate of the fit inside each box will be defined by \( x_n(k, l) \);

Step 4 - The integrated signal \( x(k) \) is "detrended", this by subtracting \( x_n(k, l) \) in each box (of size \( n \)), thus removing the local trend in each window, as shown in the equation below:

\[
f_{DFA}(n, l) = \frac{1}{n} \sum_{k=i}^{i+n} [x_k - x_n(k, l)]^2 ;
\]

Step 5 - For each time scale with \( (N) \) values, the FDFA\((n)\) fluctuation function calculated by:

\[
F_{DFA}(n) = \sqrt{\frac{1}{N} \sum_{i=1}^{N} [f_{DFA}(n, i)]^2} ;
\]

Step 6 – This calculation is repeated for all scales (interval sizes) to give the relationship between \( F(n) \) and the interval size \( n \). For a self-similar process \( F(n) \) tends to grow with the size of the interval, \( n \), by the power law, as deduced below:

\[
F_{DFA}(n) \propto n^{\alpha_{DFA}}.
\]

The slope of the line between \( \log F_{DFA}(n) \) e \( \log(n) \), figure above, determines the exponent (self-similarity parameter), \( \alpha \), which is related to the long-range autocorrelation function, see Table 1, of the original series with properties that indicate higher probabilities of persistence or anti-persistence of previous values (Santos et al., 2019).

<table>
<thead>
<tr>
<th>Exponent</th>
<th>Time Series Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>( 0 &lt; \alpha &lt; 0.5 )</td>
<td>The signal is anticorrelated or antipersistent</td>
</tr>
<tr>
<td>( 0.5 &lt; \alpha &lt; 1 )</td>
<td>Correlated, persistent behavior</td>
</tr>
</tbody>
</table>

Table 1 – Scale exponent values from DFA and time series type.
<table>
<thead>
<tr>
<th>Exponent</th>
<th>Time Series Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha \approx 0.5$</td>
<td>Uncorrelated, white noise, or no memory</td>
</tr>
<tr>
<td>$\alpha \approx 1.0$</td>
<td>Noise Behavior $1/f$ (Pink Noise)</td>
</tr>
<tr>
<td>$1 &lt; \alpha &lt; 1.5$</td>
<td>Sub-diffusive behavior</td>
</tr>
<tr>
<td>$\alpha \approx \frac{3}{2}$</td>
<td>Brownian Noise Behavior (Brown Noise)</td>
</tr>
<tr>
<td>$\alpha &gt; 1.5$</td>
<td>Super-diffusive behavior</td>
</tr>
</tbody>
</table>

Positive correlations in time series mean that an upward trend in the past may be followed by an upward trend in the future, thus a persistent signal. A negative correlation means that an increasing trend in the past can be followed by a decreasing trend in the future, this signal is called anti-persistent (Delignières et al., 2011; Podobnik et al., 2008; Eke et al., 2000).

With the use of DFA, the detection of false correlations that are of non-stationary origin in the studied series is avoided. The goal of the method is to eliminate the deterministic trends of the original series and study the data in a detrended way. (Peng et al., 1994).

For analysis, the DFA algorithm written in R language was used to evaluate the tabulated data of energy generation presented in time series, where we identified trends and seasonalities, as well as other patterns as a function of the time of day and aiming to better understand the behavior of this parameter and then draw some conclusions.

**PROPOSED PROCEDURE**

The basic procedure used in this work is the application of Detrended Fluctuation Analysis (DFA) methods of complex systems analysis, as described in the previous section, to investigate long-range auto-affinities in non-stationary time series among power generation dispatch data in the Northeast region of Brazil.
DATA

Since January 2020, the ONS has adopted the mathematical model (ONS DESSEM DATABASE, 2023) DESSEM to simulate the economic dispatch of electricity in real time, considering the safety of the electrical system and operation constraints, such as transmission limits and generation capacity of the SIN's plants.

The data refer to the supply records and forecast of energy consumption for a reference day in the semi-hourly periodicity of energy dispatch, in MWmed, from various generation sources.

RESULTS AND DISCUSSION

Based on the data collected from DESSEM for the full analysis period (2020 to 2022) of generation, each energy source was developed, with the original time series displayed below for examination and comparison of the results.

The time series of the dispatch of solar, wind, and hydro power generation in 2020, shown in MWmed for a time interval in days, are shown in Figures 3, 4, and 5, respectively. Furthermore, we looked at the time series for 2021 and 2022.

**Figure 3** – Hydropower Generation dispatch time series (2020).
The solar energy dispatch time series exhibits a distinctive trend because of the nocturnal period when there is no sun radiation. Figures 6, 7, and 8 for the year 2020 show, respectively, the graphical representation of the exponents (α)-DFA and the behavior of the wind, hydraulic, and solar energy dispatch series.
**Figure 6** – DFA of the hydraulic energy dispatch (2020).

**Figure 7** – DFA of wind energy dispatch (2020).
The behavior shown in Figures 4, 5, and 6 in 2020 is indicative of the presence of non-stationary or persistent long-range self-affinities ($\alpha$ between 1 and 1.5) for the dispatch of wind and hydraulic energy. These exponents of the DFA scale ($\alpha$), which are calculated from the slope coefficient of the corresponding lines of the graphs, are greater than 0.5 in the short- and long-term horizons. But the solar series exhibits long-range, persistent behavior ($\alpha>0.5$).

Analyzing the behavior of the time series, represented by the exponents in table 1, we can observe the uniformity in the behavior of the dispatch of hydraulic generation sources in all years, 2020, 2021 and 2022, changing from subdiffusive ($1<\alpha<1.5$) with higher intensity in the short term to subdiffusion with lower intensity, tending to 1 in the long term.

The dispatch of wind generation source in all the years analyzed ranged from superdiffusive ($\alpha$ between 1 and 1.5) in the short term to subdiffusive in the long term. Regarding the dispatch of solar generation source in all years, it ranged from superdiffusive in the short term to persistent in the long term.
In table 1, the first columns of each year represent the short term (short term - ST) and the next column the long term (long term - LT), with the crossover representing approximately 1 (one) day, or close to 48 observations.

Both solar and wind energy dispatches are superdiffusive ($\alpha$ between 1 and 1.5) during the day, which can be explained by climatic issues with a high gradient and a lack of characterization of energy storage generated to be dispatched at a time other than the moment of generation. Solar dispatch is the only one that becomes persistent ($0.5 < \alpha < 1$) over time, with values of 0.83, 0.89 and 0.78 for the years 2020, 2021 and 2022 respectively, being more predictable than the dispatch of wind energy. The latter goes from a situation of great variation to a situation of almost pink noise.

### Table 2 – DFA of the time series of the dispatches of energy sources analyzed.

<table>
<thead>
<tr>
<th>DFA</th>
<th>2020 (ST)</th>
<th>2020 (LT)</th>
<th>2021 (ST)</th>
<th>2021 (LT)</th>
<th>2022 (ST)</th>
<th>2022 (LT)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hydraulic</td>
<td>1.37±0.01</td>
<td>1.05±0.01</td>
<td>1.34±0.01</td>
<td>1.12±0.01</td>
<td>1.35±0.01</td>
<td>1.05±0.02</td>
</tr>
<tr>
<td>Wind</td>
<td>1.56±0.02</td>
<td>1.05±0.01</td>
<td>1.54±0.02</td>
<td>1.01±0.02</td>
<td>1.57±0.02</td>
<td>1.02±0.01</td>
</tr>
<tr>
<td>Solar</td>
<td>1.52±0.02</td>
<td>0.83±0.03</td>
<td>1.53±0.03</td>
<td>0.89±0.03</td>
<td>1.53±0.02</td>
<td>0.78±0.04</td>
</tr>
</tbody>
</table>

### CONCLUSIONS

In the course of the work, the original time series of energy dispatch of the Northeast region of Brazil coordinated by ONS were analyzed, considering the scenarios and simulations of the DESSEM model. Short- and long-range self-affinity analyses were performed by analyzing the time series using the DFA method, and the results obtained were useful to measure the levels of behavior of the generation sources.

As a first important result for the research we can mention particular characteristics that are very interesting in the Northeast region of Brazil, especially with solar energy having a persistent long-term behavior, that is, it can be predicted more easily, while wind energy shows superdiffusion in daily life, short-term behavior, but in the long term, the fluctuations reach practically the noise value, thus, solar energy has a higher stability of firm energy than wind energy.

Therefore, we can mention that solar generation has a greater predictability of energy availability and can be considered as a more viable source to supply the absence
of hydraulic energy. This analysis is based on historical numbers of the time series analyzed, not considering costs of implementation, maintenance, operation or other factors.

The statistical analysis of self-affinity in time series can be considered as an additional criterion for the decision model for simulations of scenarios of expansion of the installed capacity of the national electricity sector, considering solar energy as a source of generation in substitution for hydraulics, thus supporting the energy planning of expansion for the Northeast region.

For future work, it is feasible to analyze these and other energy sources in the other subsystems of the SIN, deepening the analysis of correlations between generation sources using other techniques such as Multifractal Detrended Cross-Correlation Analysis (MF-DCCA) and in relation to the need for import or export of energy between the Northeast and/or other subsystems.

REFERENCES


