PERSISTENCE IN SHOCKS OF ELECTRIC POWER SUPPLY CONTINUITY INDICATORS

Persistência aos choques nos indicadores de continuidade do fornecimento de energia elétrica

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Resumo: Os indicadores de continuidade do fornecimento de energia elétrica são utilizados para verificar a confiabilidade da distribuição de energia. Este artigo analisa a persistência aos choques nos indicadores de continuidade do fornecimento de energia elétrica dos conjuntos de unidades consumidoras de uma das maiores distribuidoras do setor elétrico brasileiro, a Celg-D. É utilizada uma das técnicas de long-range dependence em dados semanais para analisar o grau de persistência das séries em diferentes conjuntos. Os resultados indicam que o nível de persistência, medido em termos do parâmetro fracionário, mudou substancialmente de uma série para outra, dependendo do tipo, duração ou frequência e do conjunto elétrico envolvido. Na maioria das séries, a ordem de integração foi menor do que 1, indicando que, nesses casos, elas são reversão à média e convergem para um valor médio ao longo do tempo. Apesar de ser um estudo específico, este trabalho tem validade empírica, pois a sua contribuição está alicerçada em dois pilares: i) na metodologia aplicada ao entendimento dos indicadores de continuidade na análise da qualidade da energia fornecida; e ii) ao acesso aos microdados, o que permitiu resultados, até então, não observados na literatura.

Palavras-Chave: Confiabilidade; Celg; Microdados.

Abstract: Electric power supply continuity indicators are used to check the power distribution reliability. This paper analyses persistence in shocks of continuity indicators for one of the largest Brazilian power distributors, Celg-D. A long-term dependence technique was applied to weekly data to analyze the level of persistence in outage frequency and duration series for certain areas of coverage. The results indicate that the level of persistence, measured in terms of the fractional differential parameter, changed substantially from one series to another, depending on the type, duration or frequency, and on the area of coverage involved. In most series, the integration order was less than 1, indicating that, in these cases, they are mean reverting and converge towards a mean value over time. Despite being a specific study, this paper has empirical validity, because the contribution of this study is twofold: i) the methodology used to understand continuity indicators; and ii) access to microdata, producing results previously not observed in the literature.

Keywords: Reliability; Celg; Microdata.

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1 INTRODUCTION

The issue of power supply quality has been widely discussed in the literature, mainly after the expansion in the privatizing of companies throughout the world. Authors have discussed the frequency and duration of power outages highlighting the main determining factors and the damage caused. In this context, problems regarding the reliability and resilience of the electric power system have been addressed by LaCommare and Eto (2006), and LaCommare et al. (2018). Maliszewski et al. (2012), Chen et al. (2017) and Larsen et al. (2016) have also addressed these issues but considering extreme climate events that generate economic losses for consumers due to outages. Other authors have studied how better allocation, the use of smart technologies, and the installation of network protection equipment can reduce the time needed to restore power (see Hammarstron et al. (2016), López et al. (2016) e Pombo et al. (2015)).

Current literature has also focused on analysing time series on the service quality and continuity indicators. Factionary integration has become an alternative and viable modeling method for various time series. The main idea behind such a specification is that dependency between observations, which are increasingly distant in time, may be better captured in terms of a hyperbolic decay rate instead of an exponential rate associated with the autoregressive structure (GIL-ALANA, 2008). In other words, the presence of long memory is related to the persistence of autocorrelation in each series (APERGIS; TSOUMAS, 2011; 2012) and its memory in relation to shocks. Shocks are events that occur at a specific point in the series and which are not limited to said point. They are considered as having a temporary or short-term effect if, after successive periods, the series returns to its previous level of performance. On the other hand, the shock may have a persistent or long-term effect if the short-term effect produces and defines a new trend in the behavior of the series (BARROS et al., 2016).

The Celg Distribuição S.A. (Celg-D)[1] has been facing problems related to power distribution, mainly regarding its continuity indicators, DEC (Equivalent Duration of Interruption by Consumer Unit) and FEC (Equivalent Frequency of Interruption by Consumer Unit). As a result, the company holds one of the lowest national service continuity positions in a ranking created and divulged by the National Electric Power Agency (ANEEL) and is one of the Brazilian distributors that most compensates their consumers for interruptions in the power supply. Between 2014 and 2020 alone, for example, US$ 170 million was paid in compensation for surpassing the regulatory limits of the indicators, directly affecting the results of the company, and thus reducing returns for shareholders.

Given the difficulty that Celg-D face to revert the trend in their indicators, it is possible to work with the hypothesis that part of this trend contains long-term components, which characterizes a process of long memory, thus requiring greater effort by managers. In this case, the present study aims to analyze the persistence in shocks of power interruption duration and frequency series for the Celg-D areas of coverage. More specifically, we aim to test for the presence of long-term memory in the series, to verify the existence of structural breaks in the data, and to determine whether there is heterogeneity in the behavior of the series for different groups of consumers. A long-term dependence technique will be applied to weekly data to analyze the level of persistence in outage frequency and duration series.

The choice of this company is justified by the greater availability of disaggregated data on supply quality indicators. The other studies used aggregated data for the entire country or for large

1 *Celg Distribuição S.A.* (Celg-D) which, as of March, 2018 is *Enel Distribuição Goiás* (Enel-GO), located in the state of Goiás (in the midwestern region of Brazil, spanning 340 thousand , with 246 municipalities and with a population of 7 million inhabitants). *Enel Distribuição Goiás* is a company of the Enel Brasil Group – subsidiary of the Italian multinational S.p.A. – which won the bid for the privatizing of Celg Distribuição, sponsored by the Brazilian government and the National Economic and Social Development Bank (BNDES). Currently, the groups holds nearly 94.8% shareholding of the company. The privatizing process began in 2016 and ended in 2017, but only in March 2018 was the name changed from Celg-D to Enel-GO.

regions, while the present study had access to disaggregated data on the behavior of interruptions for groups of Celg consumers, defined as electrical sets[2], allowing the construction of weekly series on the phenomenon. This increases the frequency of the data and allows localized actions to be proposed, considering the heterogeneity existing within the state of Goiás: climate, relief, demographic density, presence of agriculture and livestock, etc. All these factors require that the distributor take different measures for locations with particular characteristics.

Therefore, this study is different than previous literature not only for analysing the behavior of interruption duration and frequency series, with a methodology considered more robust, but also for the database, which has yet to be utilized by the academy. The results obtained may also be highlighted, given that the level of persistence, measured in terms of the fractional differential parameter, changed substantially from one series to another, depending on the type, duration or frequency, and on the area of coverage involved. In most series, the integration order was less than 1, indicating that, in these cases, they are mean reverting and converge towards a mean value over time, and that the persistence in each is related to the time necessary for the series to return to its previous level of performance. Lastly, the analysis allows both the focusing of public and business policies, which may be used to support corporate and public management decision-making, to improve the continuity indicators and increase the well-being of the consumers.

This study is structured as follows: the following section provides a brief overview of the literature; section 3 describe the methodology and the data used in the study; section 4 outlines the empirical analysis and the policy implications; and lastly, we present our conclusions.

2 LITERATURE REVIEW

Several electric power companies are facing pressure to reduce costs and improve the quality of supply. Intensive technical development and capital investment have contributed to improving the reliability of generation and transmission systems, however, in most cases the high voltage distribution network remains primarily responsible for the causes of power supply interruptions (BRINT et al., 1998). The various political, economic and technical changes are putting pressure on the way distribution systems are built and operated (SHORT, 2014). In this scenario, some studies stand out when analyzing the continuity of electricity supply.

Some studies have focused on the analysis of problems regarding the reliability and resilience of the electric power system. LaCommare e Eto (2006) find that the majority of outage costs are borne by the commercial and industrial sectors, not the residential sector. In addition, costs tend to be driven by the frequency rather than the duration of reliability events. Momentary power interruptions, which are more frequent, have a greater impact on the total cost of interruptions than sustained interruptions, which are less frequent. The work by LaCommare et al. (2018) is predicated on the understanding that power interruptions have economic consequences. In this regard, the authors believe that it is useful to recognize that addressing the costs of power interruptions is actually a shared responsibility involving multiple entities – utility, regulator or oversight authority and local, state or even federal government.

Other studies also addressed the problems regarding the reliability and resilience of the electric power system but considering extreme climate events that generate economic losses for consumers due to outages. Maliszewski et al. (2012) claim that espite many studies on the vulnerability of infrastructure systems, the effect of interacting environmental and infrastructural conditions on the reliability of urban residential power distribution remains an understudied problem. Larsen et al. (2016) argue that utilities and regulators should consider planning for abnormal weather,

2 Areas of coverage are subdivisions of the distributors used by Aneel to evaluate continuity in the power supply. They are of various sizes, may span more than one municipality, and some municipalities contain more than one area.

because these deviations from long-term average weather conditions are clearly impacting the reliability of power systems. In this sense, Chen et al. (2017) presents an integrated solution based on a decision support tool that could assist utilities with decision making for distribution system restoration in response to extreme weather events.

Some authors have studied how better allocation, the use of smart technologies, and the installation of network protection equipment can reduce the time needed to restore power. Pombo et al. (2015) present a multi-objective planning approach for the reliability of electric distribution networks using a memetic optimization. The obtained results by the study show that this approach allows the utility to obtain the optimal type and location of the equipment's to achieve the best reliability with the lower cost. While López et al. (2016) presents a new methodology for the optimal allocation of switching devices in radial electrical distribution systems. A specialized greedy randomized adaptive search procedure algorithm defines the location of a number of switching devices in order to simultaneously improve the following optimization subproblems related to the use of the allocated switches: the optimal reconfiguration of electrical distribution systems; and the optimal service restoration of electrical distribution systems.

In Brazil, some studies have focused on the analysis of the continuity of electricity supply, tais como Steiner (2006), Hammarstron et al. (2016) e Lauro (2020). Through the use of Operations Research techniques, an Integer Programming Mathematical model and Floyd Algorithm, Steiner (2006) defined a method to determine in an optimized way, the number of teams needed by the served by the Portão office, located in Curitiba, PR, Brazil, as well as the optimized assignment for the teams to the sites in need, in order to offer efficient services to the users. While Pessanha et al. (2007) presents a new implementation of the yardstick competition that combines two Data Envelopment Analysis models to set the continuity standards for the electricity distribution utilities and their groups of consumption units.

Hammarstron et al. (2016) defend the installation of smart meters to reduce the time of fault location, since it can result in reducing the time of the occurrence service and total interruption time for the consumers achieved. Thus, there is impact on the system average interruption duration index, increasing system reliability. Lauro (2020) investigates whether environmental, institutional, structural and seasonal factors have an impact on the duration of power outages in the State of Goiás and whether there are differences between these impacts for the Metropolitan Region of Goiânia (REMG) and the interior of the state. The main results suggest that the investigated factors impact the quality of electrical energy, also pointing out significant differences between the duration of interruptions in the interior and in the REMG, being lower in this group.

3 METHODOLOGY

3.1 Data and object of study

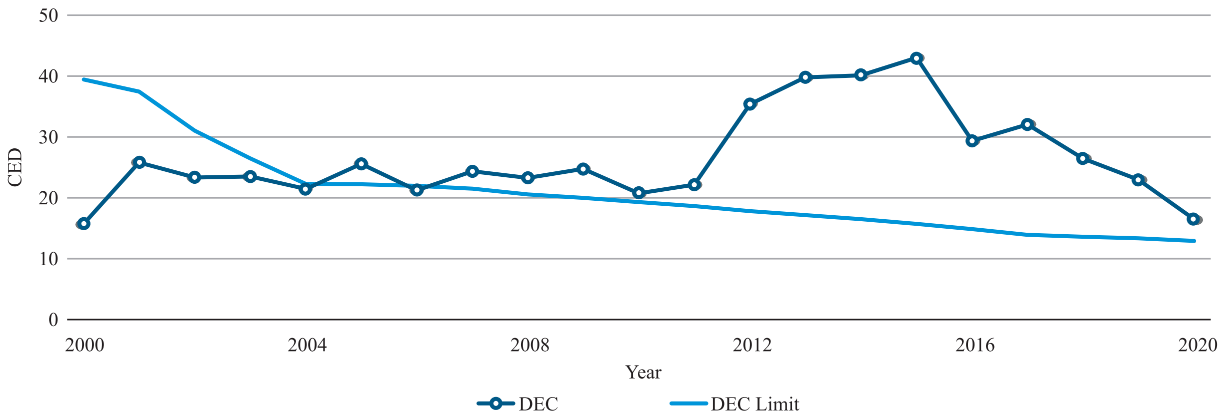
Celg-D is responsible for the sale of electric power to approximately 98.7% of the territory of the state of Goiás, 237 municipalities, covering nearly 2.9 million consumer units, over a distribution network of 200,800 kilometres (ENEL, 2018). The company has a comprehensive interruption data collection system. Every time a fault is detected in the system, related information is precisely registered in the database. If the duration surpasses the limit established by Aneel, which is 3 minutes, give or take any purges, this information will then be added to the company's continuity indicators.

In Brazil, both individual and collective continuity indicators are used. The first are determined in terms of money and consumer units, and the second, the DEC and FEC indicators, are performance indicators, which are measured according to areas of coverage.

DEC reflects the operational costs (OPEX) of the distributor, and FEC reflects both return on the investment (EBTIDA) and the purchase and maintenance of material and equipment, also known as Capital Expenditures (CAPEX). In 2017, for example, the Enel CAPEX and OPEX expenditures were, respectively, US$ 250 million and US$ 300 million. Both are directly related to the quality of the power supply.

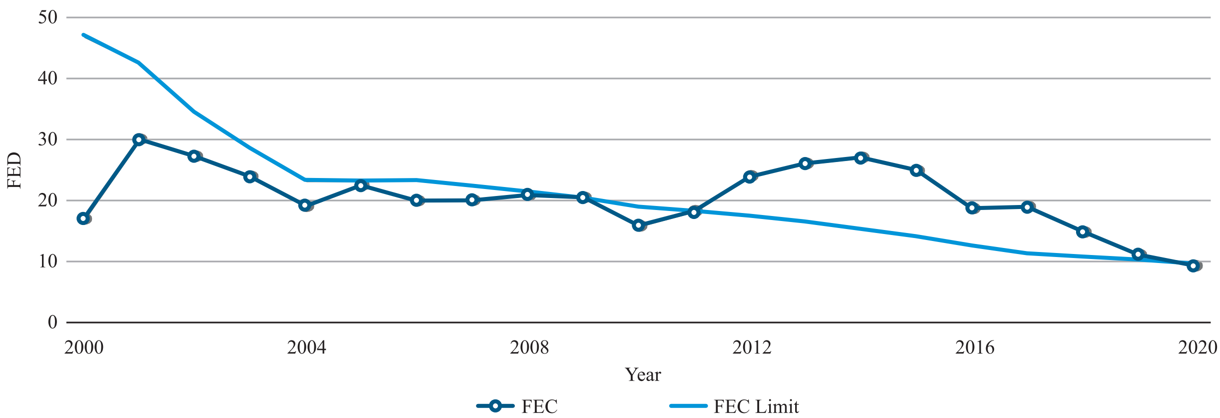
The Celg-D collective continuity indicator trends followed two different periods from 2000 to 2020 (Figure 1 and Figure 2). Between 2000 and 2003, the DEC and FEC indicators were below the regulatory limits, however, with the reform of the Brazilian electric power sector in 2003 and the stricter regulatory norms, there was a change in the behavior of values registered, mainly in the DEC values, which were close to the regulatory limits between 2004 and 2011. In 2011 there was another change, and values began surpassing the regulatory limit, and remained above the limit until 2019.

Figure 1 – Annual evolution of registered DEC and DEC Limits for Celg-D – 2000 to 2020



Source: Aneel (2021).

Figure 2 – Annual evolution of registered FECs and FEC limits for Celg-D – 2000 to 2020



Source: Aneel (2021).

With the sale of Celg-D to the *Grupo Enel Brasil* in 2016, the Annual Global Limits to be met for the indicators by the distributor are in Table 1. The surpassing of any of the indicator limits is considered a violation of the efficiency criterion. In the seventh column, we present the variation (in percentages) of the DEC and FEC limits that Enel-GO must comply with by 2022. A requirement of the acquisition contract, defined by Aneel, is that as of 2019 the downward trend in the indicators must be reverted, or the company will be subject to intervention by the regulatory agency or even lose the concession.

Table 1 – Annual Global Limits for the DEC and FEC indicators (2018 to 2022)

	2018	2019	2020	2021	2022	Δ18-22 (%)
DEC	37,48	30,33	21,53	14,11	12,18	-67,50
FEC	24,55	20,22	14,88	10,39	9,22	-62,44

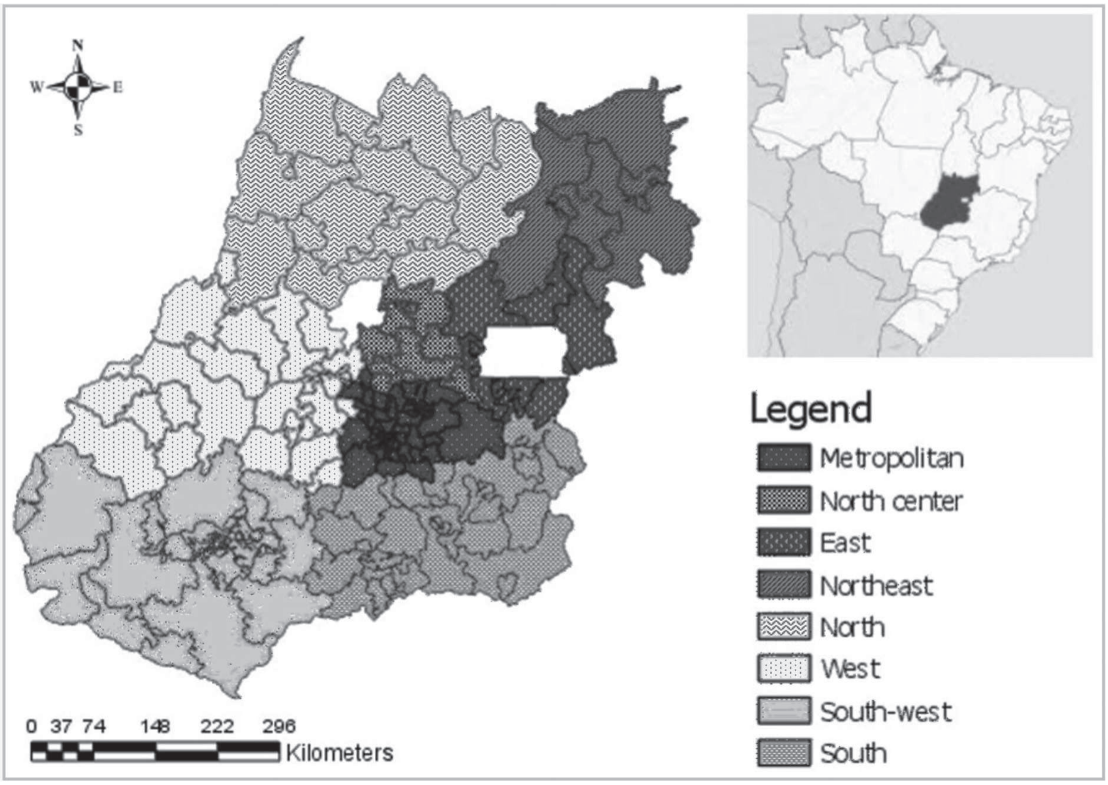
Source: Aneel (2017).

As highlighted above, Celg ranks among the worst nationally in service continuity (for providing a service of inferior quality) and is one of the distributors that most compensates their consumers, directly affecting the results of the company and generating losses to shareholders. It may be argued that the compensation values are low when compared to the investments needed to improve the service. However, what is being discussed here is the possibility that part of indicator trends have long-term components.

In this study, we used weekly data on the duration and frequency[3] of Celg-D power interruptions, for each one of the 148 areas of coverage, totalling 296 time series, between 2014 and 2016 (159 observations). We also used annual data on the compensations paid by the distributor for surpassing the limits established by Aneel for individual DIC and FIC indicators (second column of Table 2). The source of these data was the company itself, acquired through a R&D cooperation project, and were not readily available in a disaggregate manner[4].

Figure 3 presents the map of the state of Goiás, depicting the overall Celg-D concession area, the 148 areas of coverage, and the regions where they are located (the state was divided into 8 regions by the company in detriment of the observed heterogeneity).

Figure 3 – Map of the 148 areas of coverage (by Celg-D Region)



Source: prepared by the authors with data of Celg-D.

3 The average duration of events (in minutes) is the *proxy* for DEC, and the number of events per week is the *proxy* for FEC.

4 The econometric software used to perform the statistical procedures in this study was Regression Analysis of Time Series (RATS 9.2) and its complement, the Cointegration Analysis of Time Series (CATS).

3.2 MODEL

3.2.1 Different methods in related studies

In the energy time series literature, it is widely known that series may present trends, seasonalities, lack of linearity, fractal structures, and other such characteristics. Studies by Chen and Lee (2007), Narayan and Smyth (2007, 2008), Hsu et al. (2008), Maslyuk and Smyth (2009) and Mishra et al. (2009), for example, used a variety of unit root testing procedures based on the I(0)/I(1) dichotomy, i.e., stationary/stationary in the first differences, to study power consumption and production. Other studies, as carried out by Narayan et al. (2010), Apergis and Payne (2010), Aslan (2011), Aslan and Kum (2011), Hasanov and Telatar (2011), Ozturk and Aslan (2011) and Kula et al. (2012) used conventional unit root and stationarity tests to analyze the integration properties of various types of power consumption. However, the power of conventional unit root tests is lower when the process involves long memory (Fava and Alves 1998), for not being able to distinguish the I(1) processes from the fractional integration I(d) processes. It then becomes necessary to apply own methods to evaluate fractionally integrated series when long memory is suspected.

Various methodologies may be used to evaluate the long memory of a series (SOUZA et al., 2006). These include the classic R/S analysis of Hurst (1951) and Mandelbrot (1972), the modified R/S analysis of Lo (1989) (see Tabak and Cajueiro (2007), the fractional integration parameter estimation method proposed by Geweke and Porter-Hudak (1983), o teste LM de Robinson (1994), the semi-parametric by log-periodogram method of Robinson (1995b), the Gaussian semiparametric estimator of Robinson (1995a), and the V/S analysis, developed by Giraitis et al. (2003) and Cajueiro and Tabak (2005). This study resembles the studies conducted by Lean and Smyth (2009), Gil-Alana et al. (2010), Apergis and Tsoumas (2011, 2012), Barros et al. (2011, 2012, 2016) which used the fractional integration methodology to identify the level of persistence in the series, particularly the study of Barros et al. (2012) that used the method proposed by Robinson (1995a) to estimate the fractional parameter.

The Chart 1 shows different methods in related studies, it is observed that most studies used time series of energy consumption. Therefore, this study is different than previous literature not only for analyzing the behavior of interruption duration and frequency series, with a methodology considered more robust, but also for the database, which has yet to be utilized by the academy.

3.2.2 Fractionally Integrated

For the aims of this study, each series is denoted by y_t and their behavior is described by the following model:

$$y_t = \beta^T Z_t + x_t, \qquad t = 1, 2, \dots \qquad (1)$$

where β is the vector of unknown coefficients (k x 1), Z_t is a set of determinst terms which may include an intercept ($Z_t = 1$), an intercept with a linear time trend ($Z_t = (1, t)^T$), or any other type of determinist process, and where x_t are the regression errors.

Barros et al. (2012) point out that the time series x_t ($t = 1, 2, \dots$) is fractionally integrated to the d order, and follows a I (d) model represented by:

$$(1 - L)^d x_t = u_t, \qquad t = 1, 2, \dots \qquad (2)$$

where $(1-L)^d$ is the operator of the fractional difference, L is the lag operator (i.e., $Lx_t = x_{t-1}$), d is the process integration order, which may be any real number, and u_t is a stationary process I(0), with zero mean and $f_u(\lambda)$ spectrum.

Chart 1 – Different methods in related studies

Authors	Title of paper	Objective	Method	Results
Lean and Smyth (2009)	Long memory in US disaggregated petroleum consumption: evidence from univariate and multivariate LM tests for fractional integration	Test for long memory in disaggregated petroleum consumption in the United States.	Univariate and multivariate Lagrange multiplier (LM) tests for fractional integratio1n.	The multivariate test suggests that petroleum consumption in the commercial and industrial sectors is clearly fractionally integrated when allowing for short-run dynamics, and, as such, exhibits persistent effects, while petroleum consumption in the residential sector is a stationary process.
Gil-Alana et al. (2010)	Does energy consumption by the US electric power sector exhibit long memory behavior?	Determine whether various energy consumption measures by the US electric power sector exhibit long memory behavior.	The methodology employed is based on the Whittle function in the frequency domain along with a testing procedure developed by Robinson (1994).	The results indicate that each energy source consumed by the US electric power sector is highly persistent, displaying long memory along with autoregressive behavior and strong seasonal patterns. Furthermore, different policy initiatives will have differing effects on the long memory behavior of the US electric power sector.
Apergis and Tsoumas (2011)	Integration properties of disaggregated solar, geothermal and biomass energy consumption in the US	Investigating the fractional integration behavior of solar, geothermal and biomass sectoral energy consumption in the U.S. over the 1989–2009 period in the presence of structural breaks.	The methodology employed is based on Robinson's (1994) test statistic.	The results suggest that there are differences in the order of integration depending on both the type of energy and the sector involved. Moreover, the inclusion of structural breaks traced from the regulatory changes for solar, geothermal and biomass energy seem to affect the order of integration for each series.
Apergis and Tsoumas (2012)	Long memory and disaggregated energy consumption: Evidence from fossils, coal and electricity retail in the US	The goal is to extent the research by Lean and Smyth (2009) by investigating the fractional integration behavior of sectoral fossils, coal and electricity retail consumption in the U.S.	The methodology employed is based on Robinson's (1994) test statistic.	There is heterogeneity in the order of integration between disaggregated fossils, coal and electricity retail consumption and for the different sectors employed, which is affected by the inclusion of a break event. The order of integration was generally higher for the case of a break in the intercept than in the slope, with the latter being more plausible for all series.
Barros et al. (2011)	An analysis of oil production by OPEC countries: Persistence, breaks, and outliers	Examine the time series behavior of oil production for OPEC member countries within a fractional integration modelling framework.	The authors estimate *d* using a Whittle function in the frequency domain along with a testing procedure developed by Robinson (1994).	The results indicate there is mean reverting persistence in oil production with breaks identified in 10 out of the 13 countries examined. Thus, shocks affecting the structure of OPEC oil production will have persistent effects in the long run for all countries, and in some cases the effects are expected to be permanent.
Barros et al. (2012)	Evidence of long memory behavior in US renewable energy consumption	Examine the degrees of time persistence in U.S. total renewable energy consumption.	Long range dependence techniques. The authors also conducted a semi-parametric approach due to Robinson (1995a).	The results indicate that renewable energy consumption is better explained in terms of a long memory model that incorporates persistence components and seasonality. The degree of integration is above 0.5 but significantly below 1.0, suggesting nonstationarity with mean reverting behavior.
Barros et al. (2016)	Energy production in Brazil: Empirical facts based on persistence, seasonality and breaks	Investigate the statistical properties of the production of energy in Brazil.	Long range dependence techniques. The authors also employ a testing procedure developed by Robinson (1994)	The results indicate first that seasonality is an essential issue in modeling the persistence in energy production. Also, the persistence itself, measured in terms of the differencing parameter is relevant, with orders of integration in the series found to be positive though smaller than 1 and thus implying mean reversion.

Source: prepared by the authors.

The polynomial $(1-L)^d$ in the left side of Equation (2) may be expressed in terms of binomial expansion, for any real number d.

$$(1-L)^d = \sum_{j=0}^{\infty} \psi_j L^j = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \cdots, \tag{3}$$

In other terms,

$$(1-L)^d x_t = x_t - d x_{t-1} + \frac{d(d-1)}{2} x_{t-2} - \cdots \tag{4}$$

The parameter d plays a crucial role in the data analysis because it is an indicator of the level of dependence of the series. The higher the value of d, the higher the level of association between the observations that become increasingly more distant in temporal terms (BARROS et al., 2011, 2016).

If $d = 0$ in (2), the covariance of the stochastic process x_t is stationary. If $d = 1$, x_t is a non-stationary process with a unit root, i.e., the model contains a stochastic trend. Fractional integration arises when d assumes positive non-integer values, $0 < d < 1$. If d is restricted to the interval $0 < d < 0{,}5$, x_t is mean-reverting and continues being a stationary covariance process, but since the decay of the autocovariance function is slower than in the stationary case, I(0). If $0{,}5 \le d < 1$, x_t is non-stationary, but mean-reversion and the autocovariance function show greater persistence (APERGIS; TSOUMAS, 2011, 2012). However, if $d \ge 1$, x_t is non-stationary and non mean-reverting (GIL-ALANA, 2008).

Response to impulses are also affected by the magnitude of d, since the higher the value of d, the higher the responses. However, if $d < 1$, the series is mean-reverting, and temporary effect shocks disappear in the long term. On the other hand, if $d \ge 1$, the shocks will have permanent effects, unless strong policy measures are taken (BARROS et al., 2011).

In the context of fractional processes, the occasional neglecting of structural breaks may lead to the spurious discovery of long memory (GIL-ALANA, 2008). In this study, we examine the possibility of fractional integration in the presence of a single structural break at an unknown point within the sample. To do this, each one of the series, y_t, that presents a break, is represented as follows:

$$y_t = \beta_1^T + x_t; \qquad (1-L)^{d_1} x_t = u_t, \qquad t = 1, 2, \ldots, T_b \tag{5}$$

$$y_t = \beta_2^T + x_t \qquad (1-L)^{d_2} x_t = u_t, \qquad t = T_b + 1, \ldots, T \tag{6}$$

where the β's are the coefficients corresponding to the determinist terms, d_1 and d_2 are real numbers, u_t is a stationary process I(0), with mean zero, and spectrum $f_u(\lambda)$ and T_b is the unknown-point of the break.

As in Lebo and Box-Steffensmeier (2008), Gil-Alana (2008), and Barros et al. (2012), the methodology used in this study to estimate the fractional differentiation parameter is the method proposed by Robinson (1995a): the Gaussian Semiparametric Estimador (GSE) based on the Whittle function in the frequency domain. We also applied the test proposed by Andrews and Ploberger (1994), with the *p-value* assuming the approximations of Hansen (1997), which is recommended for a single structural break at an unknown point within the sample to identify the date of the break, T_b. Subsquently, new estimates of the paramenter were made in the presence of the break.

4 RESULTS AND DISCUSSION

We estimated the fractional parameter of the model given by Equations (1) and (2) for the 296 series. Disregarding the possibility of any structural changes, the third and 7th column of Table 2 presents the estimates for the Robinson (1995a) parameter for the duration and frequency series.

The duration series of all areas of coverage show estimates in the (0,1) interval. This suggests that they are fractionally integrated. Of the 148 series, 127 showed lower persistence (), with more expressive fluctuations than the other 21 series presenting higher persistence (). In other words, there is a greater probability of a high DEC indicator (duration series) be preceded by a lower indicator in the subsequent period and vice versa. The lower the persistence in the series, the higher this probability is.

The *Parque das Emas* area, belonging to the Southeast Region, presented the highest value for the parameter ($d = 0.609$), while the lowest value was for the *Aeroporto S3* area, $d = 0.098$, located the Goiânia Metropolitan Region (state capital). In the case of *Parque das Emas*, the company will have to conduct additional planning to revert the situation, because in addition to the area having a long memory duration series it is among those most highly compensated by the company for the DIC indicator.

For the frequency series, a large proportion of areas of coverage showed estimates in the (0, 1) interval, except for *Jatai S1*, whose parameter was greater than 1. This indicates a shock in the series which may have permanent effects unless strong policy measures are taken.

Of the 148 frequency series, 58 were persistent, but did not fluctuate as much as the non-persistent series, 89 series. The higher level of persistence, excluding the case of *Jatai S1* ($d = 1.433$), was for the *Uruacu* area, with a parameter value of 0.67, and the lowest value was the *Aeroporto S3* area, whose integration order was $d = 0.212$.

In order to facilitate spatial viewing of the level of persistence in the areas covered by the company, Figure 4 shows the results for the estimates of the duration and frequency series of the entire sample. The darker the color, the greater the persistence in the series.

The results for all areas of coverage indicate that, in general, the frequency series show greater persistence than the duration series, suggesting that better planned actions need to be adopted by the company to revert the trend in the continuity indicators of the areas of coverage that receive high compensations. On the other hand, the persistence analysis also highlights the economic and social problems faced by the state, where certain groups are given priority regarding power supply and maintenance.

In the last part of this paper, we use the Andrews and Ploberger (1994) test, with *p-valor* assuming the approximations of Hansen (1997), to identify a potential structural change in the series. Thus, each series, y_t, containing a break, assumes the model represented by Equations (5) and (6).

The results of the break test procedure for the duration and frequency series are shown in Table 2. The break point (T_b) values are listed in the 4th and 8th column. The 5th and 9th column shows the parameters before the break (d_1) and the 6th and 10th column after the break (d_2). Of the 296 series, breaks were detected in 116 duration series, in 111 frequency series, but no evidence of structural changes was found in the remaining series.

Table 2 – Fractional parameter estimates of the duration and frequency series, by area of coverage (2014 to 2016)

Electric Sets	DIC and FIC	Duration				Frequency			
		d	Structural Break	d_1	d_2	d	Structural Break	d_1	d_2
Rio Claro	US$ 1,616,894	0.446	2016:03:16	0.465	0.538	0.425	2015:01:07	0.514	0.461
Parque Das Emas	US$ 1,323,395	0.609	2016:03:02	0.657	0.618	0.551	2014:08:27	0.892	0.564
Pamplona	US$ 977,588	0.405	2016:03:16	0.388	0.287	0.297	2016:03:23	0.385	0.438

Electric Sets	DIC and FIC	Duration				Frequency			
		d	Structural Break	d_1	d_2	d	Structural Break	d_1	d_2
Cabriuva S2	US$ 922,549	0.427	2014:08:27	0.867	0.495	0.355			
Jatai S1	US$ 884,598	0.541				1.433			
Cristalina S1	US$ 845,442	0.381	2015:09:09	0.331	0.370	0.316	2014:09:10	0.377	0.366
Cachoeira Alta	US$ 796,204	0.415				0.482	2015:09:09	0.590	0.530
Marajoara	US$ 751,557	0.485	2015:09:09	0.477	0.307	0.477	2014:09:24	0.712	0.509
Sao Joao D Alianca	US$ 735,375	0.481				0.579			
Britania	US$ 721,176	0.374				0.592	2014:06:11	0.401	0.581
Padre Bernardo	US$ 710,144	0.457	2016:03:23	0.459	0.572	0.501	2014:10:22	0.761	0.514
Itiquira	US$ 662,860	0.497	2016:03:16	0.476	0.496	0.583	2014:10:08	0.635	0.448
Pires Do Rio S2	US$ 649,600	0.484	2016:03:23	0.589	0.223	0.607	2016:02:24	0.591	0.572
Cristalina S2	US$ 642,736	0.396	2015:10:28	0.266	0.258	0.512			
Sao Domingos	US$ 638,348	0.397	2014:06:11	0.507	0.482	0.628	2016:04:20	0.580	0.538
Porangatu	US$ 627,808	0.515	2016:03:23	0.993	0.374	0.610	2014:09:10	1.013	0.593
Santa Terezinha	US$ 601,226	0.592	2016:03:23	0.616	0.443	0.590	2016:04:27	0.577	0.479
Rio Dos Bois	US$ 582,936	0.484				0.438			
Inhumas S1	US$ 579,529	0.480	2016:02:24	0.375	0.284	0.461			
Cezarina	US$ 573,128	0.307	2015:04:29	0.314	0.388	0.398	2014:10:22	0.400	0.376
Santa Helena S1	US$ 567,001	0.351	2014:08:27	0.500	0.453	0.504			
Vianopolis	US$ 557,213	0.575	2016:03:16	0.522	0.513	0.569			
Acreuna	US$ 557,009	0.421	2016:03:23	0.494	0.188	0.465	2014:09:17	0.773	0.434
Aguas Lindas De Goias S2	US$ 541,060	0.388				0.532	2014:10:01	0.498	0.492
Uruacu	US$ 507,635	0.514	2016:04:06	0.545	0.488	0.670	2014:09:17	0.692	0.606
Carajas	US$ 507,428	0.371	2016:02:24	0.313	0.189	0.454	2014:09:24	0.364	0.414
Firminopolis S2	US$ 495,689	0.459	2016:03:30	0.498	0.450	0.431	2015:09:30	0.554	0.483
Itapuranga	US$ 493,710	0.477	2016:04:20	0.459	0.193	0.565			
Palmeiras	US$ 486,216	0.429	2016:03:16	0.448	0.298	0.490	2015:09:09	0.648	0.413
Catalao S1	US$ 483,964	0.512	2014:10:08	0.146	0.626	0.586	2015:10:28	0.532	0.520
Flores De Goias	US$ 458,103	0.465	2016:04:06	0.334	0.441	0.432	2015:10:21	0.510	0.472
Vicentinopolis	US$ 427,960	0.431	2016:03:23	0.464	0.541	0.427			
Itapaci	US$ 426,386	0.343	2016:03:16	0.420	0.370	0.393	2014:09:17	0.504	0.393
Ferroviario S1	US$ 423,257	0.256				0.481	2016:01:13	0.506	0.490
Iaciara S2	US$ 417,810	0.402	2016:03:23	0.409	0.572	0.586	2014:10:15	0.648	0.592
Sao Miguel Do Araguaia	US$ 417,799	0.494	2015:05:20	0.538	0.556	0.613	2016:04:27	0.613	0.375
Cepaigo S2	US$ 414,638	0.401	2016:03:02	0.461	0.310	0.474			
Trindade	US$ 411,524	0.482	2016:02:24	0.311	0.282	0.511	2014:09:17	0.830	0.448
Itaberai S1	US$ 410,210	0.514	2016:03:23	0.437	0.441	0.599	2015:05:06	0.484	0.605
Nova Crixas	US$ 401,695	0.391				0.540	2016:04:27	0.577	0.603
Sao Luiz Dos Montes Belos	US$ 400,046	0.529	2016:03:16	0.541	0.394	0.593	2015:10:28	0.643	0.617
Planaltina	US$ 399,184	0.556				0.425	2014:10:15	1.072	0.426
Mara Rosa	US$ 398,591	0.519	2016:03:16	0.598	0.498	0.637			
Anicuns	US$ 379,295	0.543				0.542	2014:10:15	0.749	0.543
Caiaponia	US$ 362,821	0.464	2016:03:23	0.419	0.660	0.544			
Goianesia S1	US$ 362,540	0.299	2014:10:22	0.301	0.271	0.508	2016:04:20	0.523	0.724
Itaberai S2	US$ 360,923	0.438	2016:03:23	0.515	0.355	0.471	2014:08:27	0.592	0.491
Jussara	US$ 344,333	0.480	2016:03:23	0.513	0.562	0.614	2014:10:15	0.823	0.556
Quirinopolis	US$ 341,972	0.371	2016:03:16	0.479	0.413	0.498			
Pacaembu	US$ 334,022	0.454	2015:10:28	0.520	0.324	0.472	2014:09:17	0.499	0.442

Electric Sets	DIC and FIC	Duration				Frequency			
		d	Structural Break	d_1	d_2	d	Structural Break	d_1	d_2
Goias	US$ 328,392	0.448	2016:03:30	0.472	0.131	0.520			
Daia S2	US$ 325,942	0.559	2016:03:23	0.521	0.553	0.597	2014:08:27	0.644	0.499
Guapo	US$ 325,429	0.410	2016:03:16	0.444	0.363	0.480	2016:05:04	0.452	0.337
Rio Verde S2	US$ 324,704	0.480				0.577	2014:09:17	0.467	0.520
Anhanguera	US$ 316,213	0.312	2016:03:30	0.431	0.308	0.284	2015:07:15	0.415	0.511
Real S1	US$ 315,981	0.293	2016:02:03	0.405	0.348	0.487	2014:09:24	0.817	0.196
Alexania	US$ 313,832	0.340				0.467	2014:09:17	0.487	0.596
Matrincha	US$ 311,222	0.501	2015:04:29	0.423	0.499	0.576	2014:09:10	0.737	0.619
Caldas Novas S1	US$ 310,954	0.485	2016:03:16	0.471	0.196	0.548	2014:09:17	0.575	0.506
Senador Canedo	US$ 310,931	0.416	2016:04:06	0.510	0.282	0.403	2014:09:24	0.502	0.341
Bom Jesus De Goias	US$ 296,535	0.425	2016:03:23	0.475	0.216	0.375			
Ipora	US$ 291,788	0.461	2016:03:23	0.444	0.664	0.603			
Barro Alto	US$ 281,234	0.455	2015:10:21	0.381	0.400	0.548	2015:09:16	0.642	0.557
Pontalina	US$ 278,816	0.409				0.498	2016:04:20	0.990	0.746
Mozarlandia	US$ 277,641	0.446	2016:04:20	0.427	0.452	0.609	2016:04:20	0.609	0.772
Daia S1	US$ 272,828	0.454	2016:04:06	0.565	0.376	0.370	2015:08:26	0.545	0.417
Independencia S1	US$ 272,026	0.349	2016:02:17	0.424	0.287	0.410	2014:09:24	0.598	0.391
Anapolis Universitario S2	US$ 253,062	0.477	2015:10:07	0.277	0.289	0.508	2014:09:17	0.744	0.559
Minacu	US$ 251,940	0.417				0.588	2014:09:24	0.583	0.509
Chapadao Do Ceu	US$ 250,391	0.373	2015:10:21	0.365	0.216	0.382			
Inhumas S2	US$ 244,131	0.500	2016:03:16	0.439	0.307	0.479	2014:08:27	0.677	0.423
Rio Verde S1	US$ 239,682	0.524	2016:03:30	0.565	0.440	0.496	2014:09:10	0.587	0.567
Corumba	US$ 238,739	0.505	2016:03:30	0.559	0.383	0.571			
Jaragua	US$ 237,091	0.443	2016:02:24	0.306	0.251	0.568	2014:10:15	0.759	0.530
Campinas S2	US$ 234,940	0.481	2015:12:30	0.268	0.277	0.275	2014:09:24	0.461	0.160
Serra Do Ouro	US$ 234,928	0.356	2015:04:22	0.351	0.289	0.447	2014:10:22	0.629	0.440
Independencia S2	US$ 234,178	0.354	2016:03:23	0.447	0.093	0.433	2014:09:24	0.493	0.495
Santa Helena S2	US$ 228,161	0.313				0.366			
Neropolis S2	US$ 212,957	0.418	2014:06:11	0.434	0.380	0.470			
Anapolis Universitario S1	US$ 208,821	0.487	2016:04:06	0.531	0.288	0.522	2014:10:15	0.319	0.399
Goianesia S2	US$ 206,228	0.427	2016:03:30	0.353	0.226	0.506	2014:09:24	0.573	0.466
Atlantico S1	US$ 205,156	0.409				0.429	2014:09:10	0.202	0.514
Itumbiara Nova	US$ 201,699	0.336	2016:03:16	0.303	0.223	0.379	2014:10:15	0.317	0.497
Campo Alegre De Goias	US$ 199,343	0.453	2016:03:23	0.592	0.258	0.503			
Goya S1	US$ 196,259	0.517				0.369	2014:09:24	0.201	0.355
Neropolis S1	US$ 192,778	0.374	2016:04:06	0.491	0.341	0.604	2014:08:20	1.084	0.443
Piracanjuba	US$ 186,076	0.338	2016:02:24	0.425	0.323	0.445			
Rubiataba	US$ 178,344	0.484	2016:04:06	0.552	0.633	0.465			
Jundiai S1	US$ 169,804	0.565	2016:04:20	0.648	0.558	0.395	2014:09:17	0.339	0.419
Goiania Leste S1	US$ 164,294	0.344	2016:02:24	0.353	0.396	0.340	2014:09:24	0.459	0.367
Cabriuva S1	US$ 163,892	0.271	2016:02:24	0.335	0.349	0.332	2014:08:27	0.787	0.373
Fab Cim Itau	US$ 163,146	0.407				0.438			
Aguas Lindas De Goias S1	US$ 161,000	0.366	2016:04:13	0.412	0.231	0.523	2014:09:24	0.576	0.485

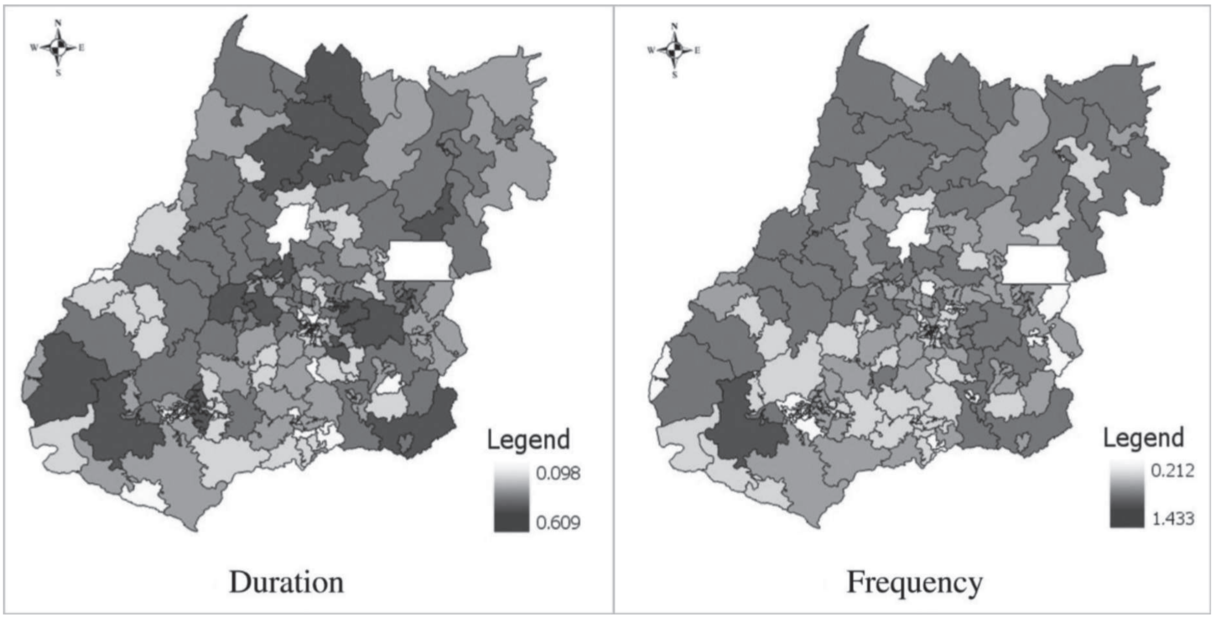
Electric Sets	DIC and FIC	Duration				Frequency			
		d	Structural Break	d_1	d_2	d	Structural Break	d_1	d_2
Campinas S1	US$ 159,964	0.247	2015:12:30	0.347	0.418	0.319	2014:09:10	0.572	0.261
Jatai S2	US$ 158,060	0.445	2016:03:16	0.389	0.428	0.550	2014:09:17	0.631	0.628
Ipameri	US$ 153,424	0.302	2016:03:30	0.434	0.028	0.423	2014:10:08	0.371	0.429
Edeia	US$ 147,874	0.337	2015:04:01	0.363	0.228	0.573	2016:06:22	0.564	0.574
Goiania Leste S2	US$ 143,600	0.357	2016:03:23	0.364	0.380	0.418	2014:09:10	0.468	0.400
Sao Francisco De Goias	US$ 138,132	0.426	2015:08:26	0.398	0.322	0.477	2016:04:13	0.457	0.546
Pires Do Rio S1	US$ 138,065	0.406	2016:02:24	0.560	0.447	0.503	2014:10:08	0.912	0.542
Bela Vista S1	US$ 133,018	0.566	2016:03:16	0.427	0.545	0.475			
Meia Ponte	US$ 130,212	0.389	2016:02:03	0.443	0.416	0.323	2014:10:15	0.252	0.227
Morrinhos	US$ 130,200	0.425	2016:03:09	0.425	0.335	0.431			
Niquelandia	US$ 127,893	0.412	2016:04:20	0.510	0.563	0.522	2016:04:27	0.546	0.536
Goiania Leste S3	US$ 127,752	0.355	2016:01:06	0.490	0.367	0.328	2014:09:24	0.718	0.264
Goiatuba S2	US$ 126,150	0.440	2016:03:30	0.453	0.275	0.440			
Cachoeira Dourada	US$ 125,743	0.302	2016:03:23	0.302	0.234	0.528			
Aragarcas	US$ 123,474	0.273				0.454	2014:09:03	0.290	0.463
Atlantico S2	US$ 122,427	0.283	2015:12:30	0.378	0.300	0.373	2014:09:24	0.635	0.386
Ferroviario S2	US$ 120,551	0.314	2016:03:16	0.297	0.221	0.223	2016:03:23	0.303	0.305
Piranhas	US$ 118,755	0.361	2016:03:30	0.417	0.405	0.434	2014:08:20	0.581	0.431
Itaja S1	US$ 115,941	0.379	2015:08:12	0.219	0.235	0.441	2015:09:09	0.599	0.245
Real S2	US$ 113,180	0.409	2014:08:27	0.884	0.273	0.461	2014:09:24	0.481	0.407
Catalao S2	US$ 106,834	0.460	2016:03:30	0.615	0.244	0.530	2014:09:24	0.283	0.485
Goya S2	US$ 98,105	0.346	2016:02:03	0.222	0.218	0.441	2014:09:24	0.475	0.447
Cepaigo S1	US$ 96,626	0.338				0.390	2015:08:05	0.028	0.153
Goianira	US$ 93,168	0.227	2016:01:27	0.281	0.168	0.343	2014:09:24	0.640	0.375
Jatai S3	US$ 88,473	0.422				0.410	2014:10:08	0.319	0.445
Rio Vermelho	US$ 86,608	0.543				0.538	2014:09:24	0.485	0.613
Aruana	US$ 84,268	0.397	2014:06:25	0.158	0.309	0.443			
Bela Vista S2	US$ 78,920	0.430	2016:03:23	0.486	0.387	0.545			
Jundiai S2	US$ 76,785	0.423	2015:08:26	0.135	0.137	0.346	2014:09:17	0.291	0.415
Santa Rita Do Araguaia	US$ 73,296	0.380				0.282	2014:10:08	0.286	0.321
Rochedo	US$ 70,839	0.199				0.393	2014:08:20	0.444	0.336
Goiatuba S1	US$ 69,561	0.274				0.381	2016:03:23	0.452	0.321
Itumbiara Velha S2	US$ 66,972	0.273	2014:08:13	0.061	0.363	0.460			
Aeroporto S1	US$ 65,702	0.303				0.377	2014:09:24	0.495	0.318
Aracu	US$ 64,786	0.421	2016:03:16	0.453	0.462	0.554	2015:03:25	0.357	0.561
Atlantico S3	US$ 64,290	0.366	2015:12:30	0.435	0.146	0.390	2014:08:27	0.302	0.385
Itaja S2	US$ 62,889	0.160				0.393	2015:09:09	0.432	0.417
Serra De Caldas	US$ 62,516	0.409	2016:04:06	0.549	0.231	0.582	2014:08:27	0.529	0.500
Caldas Novas S2	US$ 61,060	0.432	2016:03:09	0.555	0.265	0.341	2014:08:27	0.340	0.346
Aeroporto S3	US$ 57,969	0.098				0.212	2015:09:23	0.409	0.432
Bom Jardim	US$ 56,328	0.365	2016:03:23	0.441	0.582	0.507	2016:03:30	0.563	0.267

Electric Sets	DIC and FIC	Duration				Frequency			
		d	Structural Break	d_1	d_2	d	Structural Break	d_1	d_2
Novo Planalto	US$ 54,473	0.446	2016:05:04	0.519	0.242	0.472	2015:05:06	0.632	0.669
Urutai	US$ 52,334	0.253	2016:03:23	0.412	0.108	0.453			
Aeroporto S2	US$ 52,078	0.367	2014:08:20	0.533	0.209	0.330	2014:08:27	0.854	0.243
Arenopolis	US$ 51,529	0.351	2016:03:23	0.388	0.413	0.587			
Iaciara S1	US$ 50,255	0.447	2016:04:13	0.418	0.226	0.491			
Campinorte	US$ 49,934	0.378				0.514			
Firminopolis S1	US$ 48,585	0.491				0.420	2014:10:08	0.351	0.392
Cristianopolis	US$ 46,207	0.290	2016:04:06	0.289	0.178	0.556			
Itumbiara Velha S1	US$ 46,020	0.401	2016:01:06	0.325	0.334	0.352	2014:09:10	0.431	0.440
Ferroviario S3	US$ 42,936	0.343	2015:12:30	0.186	0.281	0.399	2014:06:25	0.241	0.417
Palestina	US$ 31,137	0.320	2016:03:16	0.372	0.415	0.407	2014:10:15	0.485	0.390
Petrolina	US$ 30,084	0.324				0.288	2016:02:03	0.558	0.331
Alto Buriti	US$ 25,546	0.275				0.417	2014:09:10	0.532	0.246
Paranaiba	US$ 14,845	0.324	2015:12:23	0.331	0.211	0.301	2014:09:10	0.590	0.260

Source: prepared by the authors.

Notes: *d* = fractional parameter of the entire sample; = fractional parameter before the break; = fractional parameter after the break.

Figure 4 – Persistence in the duration and frequency series of Celg-D coverage areas



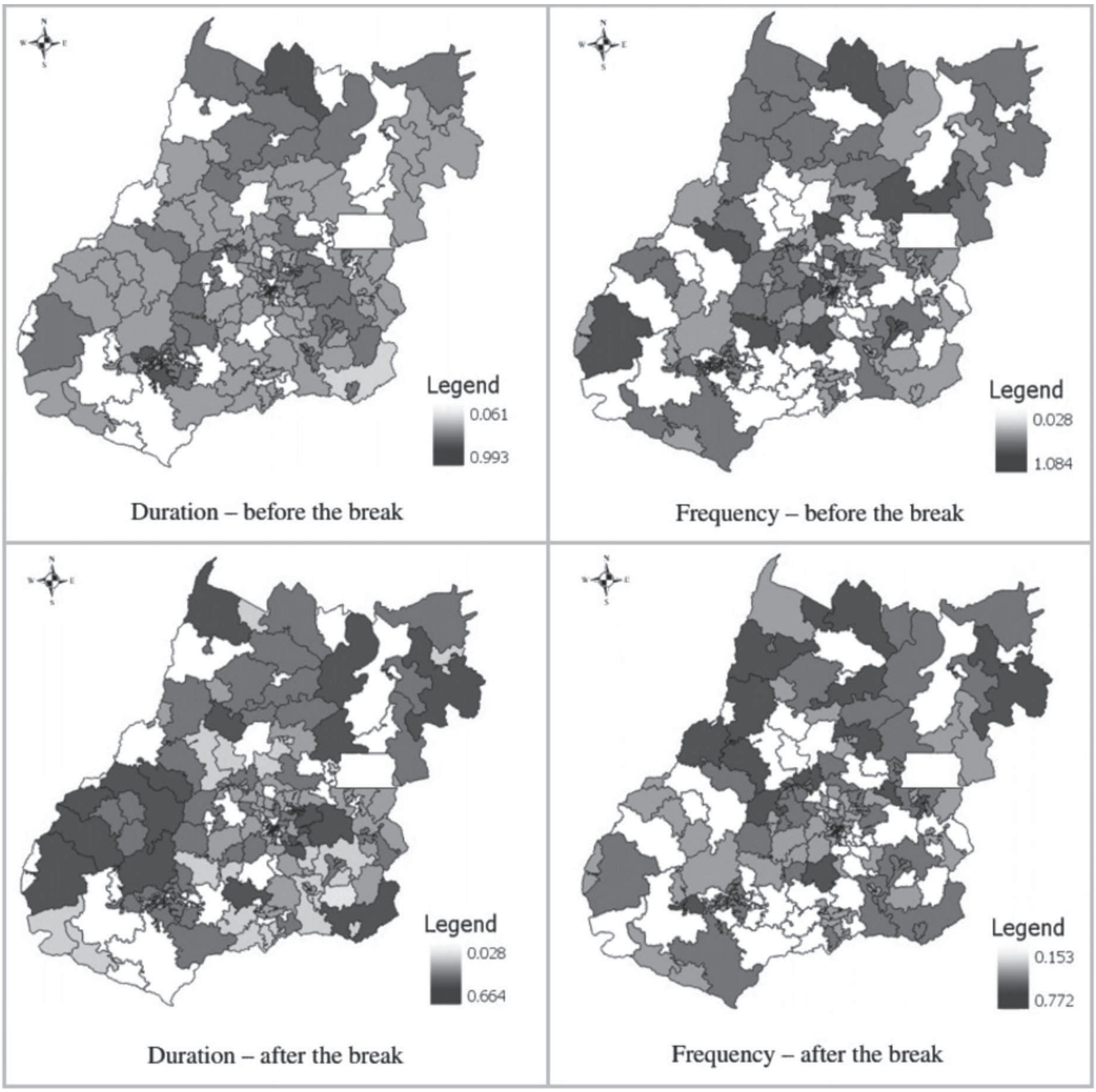
Source: prepared by the authors.

Figure 5 shows the spatial representation of the fractional parameter estimates, before and after the break, for the duration and frequency series. The areas in grey are those of series without breaks.

Before the break, the *Porangatu*, *Planaltina* and *Neropolis S1* areas presented frequency series with unit root. However, the results of the estimates of parameter , post-break, suggest that this trend is reverted. After a break, the level of persistence in certain series was altered. There was a reduction in the level of persistence in most of the duration and frequency series, in comparison with the previous period.

Considering the date of the break, this analysis is worthy of credit, since changes in the duration series generally took place in 2016 and were not only influenced by climatic factors, but also by pressure by Aneel on concessionaires for poor performance. However, most changes in the frequency series trends took place in 2014, because of investments made by the company.

Figure 5 – Persistence in the duration and frequency series, with structural breaks



Source: prepared by the authors.

Previous knowledge of the level of persistence in the series related to power supply is relevant for the effectiveness of the policy to be adopted over time (BARROS et al., 2012). Similarly, the results presented in this article show the importance of understanding in a disaggregated way the functioning of these series, with regards the type of series (frequency or duration of outages) as well as the geographical characteristics of consumers. In this sense, the analysis of disaggregated series by electric sets and a higher frequency can be shown as an important tool for decision-making on the type of investment to be made by the companies and control measures of regulatory agencies.

The analysis of persistence of the duration and frequency of interruptions series proves to be useful because the indicator reversion policies tend to produce more effective results in series with less persistence between observations, since random shocks tend to dissipate more rapidly than shocks in persistent series. In the persistent series, the indicators tend to take longer to respond to policies, requiring more planning and financial disbursements.

If, for example, a certain area of coverage has high rates for certain indicators (duration in the DEC case, and frequency in the FEC case), that surpass the limits established by regulatory agency, and the series of this same indicator presents a high level of persistence, this means that if the distributor maintains the actions of previous periods, the area of coverage will once again tend to have a high indicator. So, if the distributor wants to take action to improve the situation, these actions must be based on better planning, investments and time. In other words, random shocks may shift the indicator to levels that are distant from the pre-determined ones, unless strong policy measures are taken.

However, long memory may be considered a problem only in cases where compensations are high; on the other hand, long memory must be considered an advantage. This means that the value of the indicator in the current period is a result of a series of events that took place in the past and that these events will continue to influence future periods. Thus, if in the previous period the indicator was low, in the following period the value of this same indicator will also tend to be low.

For the specific case of the distributor analyzed in this study (Celg-D currently known as Enel--GO), the results found indicate that the frequency series generally presented a higher level of persistence that the duration series, which may reflect the existence of more complex problems in the distribution network, such as equipment or operational failures, which become more evident at certain times of the year, mainly during the rainy season in the state of Goiás. Given that the frequency indicator is more closely related to the company's CAPEX, it can be stated that over the years, all investments made by the company were not sufficient to improve the quality of the power supplied, and this affected the continuity indicator values. Better planning is needed by the concessionaire to address the problem of areas of coverage that have long-term memory series that generate sizable monetary losses.

The opening of the data by electrical sets also allows us to conclude that the problems of continuity and the difficulty in reversing them are directly related to geographical features. The persistence identified in the series may associated with Enel-GO's capacity to attend clients and address the problem across the territory. In Goiás there are four distinct situations that deserve special attention from the company: the populational density of the Metropolitan region; the social problem of the outlying areas of the Federal District; the Agro-industrial District of the city of Anápolis (DAIA); and the distances between towns in the interior of the state, where economic activity is based mainly on agriculture and livestock raising. They are distinct realities, that the simple analysis of aggregated data would not allow its identification and implications for the necessary actions.

Therefore, if Enel-GO decides to make certain investments to improve the quality of the product provided and to reduce the values of their indicators, it is recommendable that the company first direct its actions to those areas of coverage that receive the highest compensations, and that have series with less persistence, since these tend to produce results more rapidly. Subsequently, for areas where the highest compensations are paid and whose series present greater persistence, better planning is required to revert the problem.

For the regulatory agency, which also has access to disaggregated data, the information obtained seems to indicate the need to establish the limits of transgressions considering the geographic and social reality of each electrical set, and the difficulties of reverting an initial framework of high indicators. Within the Brazilian reality, Aneel periodically carries out reviews of its regulatory limits. Future revisions may use long-memory methods to analyze the condition and difficulty each distributor will have in improving its supply indicators, as well as establishing new evaluation criteria. Distributors with high persistence and high indicators may be, for example, worse ranked.

5 CONCLUSIONS

In this article we analyzed persistence in the power interruption duration and frequency series for the Celg-D areas of coverage. We sought to test for the presence of long-term memory in the series, verifying the existence of structural breaks in the data, identifying heterogeneity in the behavior of the series for different areas of coverage.

About heterogeneity in the behavior of the series, the results indicate that the level of persistence, measured in terms of the fractional differential parameter, changed substantially from one series to another, depending on the type, duration, frequency, and on the area of coverage involved.

In most series, the integration order was less than 1, indicating that, in these cases, they are mean reverting and converge towards a mean value over time, and that the persistence in each is related to the time necessary for the series to return to its previous level of performance, thus requiring active policies. As in Barros et al. (2016), persistence must be attributed to each series separately since different policy measures may be formulated based on the identified level of persistence.

When we consider the potential presence of structural breaks in the data, the integration order is altered, with the frequency series having the highest level of persistence in comparison with the duration series and, after the break, there is a reduction in the level of dependence in most series in comparison with the previous period.

Both the fractional integration analysis that considers the presence of a structural break and the one that does not consider this indicate that few of the areas of coverage presented persistent duration and/or frequency series, and the majority of areas of coverage that did present this are those that received the highest compensations. However, the areas of coverage that received the highest monetary compensations were not the only ones to received the highest compensations. Therefore, the hypothesis where part of the indicator trends have long-term components is not rejected in 24% of the areas of coverage that received the highest compensations for the DIC indicator, and in 40% of the areas of coverage that received the highest compensations for the FIC indicator.

What are the contributions of this study to the literature and electric power sector? The results can contribute to the improve the quality of the power supplied by Enel-GO, since the results may directly help the distributor make *ex-ante* decisions whether to adopt policies aimed at reducing its indicators, thus increasing the welfare of consumers. In addition, other distributors may adopt the methodology used in this study to analyze the behavior of their indicators and improve the quality of the power supplied. This paper is different from the rest and may stand out for the research problem it posed, for using a database not previously used in academic research, for using microdata provided by the company itself, for the methodology used to conduct the analysis of all 148 power coverage areas, and for finding original results.

Further studies may produce even more. The database used may allow more focused studies to be conducted, not only according to area of coverage, by also by type of consumer unit, either residential or non-residential. On the other hand, a spatial analysis of persistence in the series for different Celg-D coverage areas highlights the economic and social problems faced by the state, where power supply priority is given to certain groups, allowing us to assume that the highest compensations are concentrated in the poorest regions of the state. Furthermore, Celg-D continuity indicators and those of other distributors may be analyzed with the use of other methodologies to study seasonality and long-term memory of the series (for example, modified R/S and other types of fractional parameters), given that further research is needed in this area.

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