Rafael F. LOPES[1], Fabiano F. COSTA[1] , Antonio C. de C. LIMA[1]

Federal University of Bahia (1)

doi:10.15199/48.2015.12.05

Industry Energy Demand Forecast in Real Time via Singular Spectrum Analysis

Streszczenie. *W artykule zaproponowano metodę prognozowania popytu na podstawie analizy widma Singular (SSA).Metoda ma być wykorzystywane przez duże koncerny energetyczne i klientów do realizacji w czasie rzeczywistym i zapobiega piki przekroczenie zapotrzebowania mocy umownej za pomocą tego programu. Można ją stosować do zarządzania zapotrzebowania mocy elektrycznej w zakładach przemysłowych. Skuteczność metody jest potwierdzony korelację pomiędzy prognozowanym a faktycznym zużyciem energii.* ***Przewidywanie zapotrzebowania na energię w czasie rzeczywistym z wykorzystaniem metody SSA*** *.*

Summary*. This paper proposes a method for demand forecasting based on the Singular Spectrum Analysis (SSA). The method is to be used by large power utility's customers and to be implemented in real-time and prevents peaks from surpassing the contracted power demand with the utility. It can be applied as an auxiliary tool for management of electrical power demand in industrial plants. The effectiveness of the method is endorsed by the high correlation between the forecasted and actual time-series forecasted.*

Słowa kluczowe: Metoda SSA, prognozowanie zapotrzebowania na energię
Keywords: Singular Spectrum Analysis, Demand Side Management, Forecast

Introduction

The relationship between energy consumption and supply is a primary factor in the planning and operation of power systems. Brazil is experiencing major problems with the energy crisis into which it was placed. The lack of investment in energy supply is one of the determining factors. During the 1980s, these investments cost $10 billion on average every year. In recent years, however, these investments were reduced by half.

With problems such as lack of rain shows the reality of the lack of an efficient planning process in the country. The levels of reservoir in the Northeast and Southeast reservoirs have been recorded daily . This shows a need for the state to re-invest in this sector and that conditions are created for the private sector to also invest and make your more efficient consumption.

The problem of consumption efficiency misinformation is still prevalent mainly in small and medium-sized businesses. Many industries don't understand their accounts, for example; how much is spent and how much can be saved.

If the contracted demand is not exceeded, the energy dealers will not have to increase its own demand. This is a benefit to both parties. The energy dealers want to sell as much of the power they generate as possible and the consumer wants to make the most of their money .

The area of Energy Management can be seen as one of the main factors, since a large part of the production process depends on the consumption of electricity by its machinery and equipment to manufacture the final product. The electricity consumption is now one of the parameters used to see whether a country is developed, is developing or is underdeveloped.

A methodology that allows for the energy demand with some time in advance would help avoid overtaking in peak times thus producing more efficient consumption with less penalties/drawbacks/disadvantages [2].

The diversification and dynamics of production are variables that directly affect the hiring of electricity demand with a dealership. It is through the supply contract that the technical characteristics and the commercial terms of electricity supply are set to the value demand contracted every month [3].

The electricity bill should be divided into two parts: measured demand and measured consumption . The measured consumption refers to the energy consumed during the month in peak and off-peak hours, being billed separately. However, demand measurement refers to the increase in demand for active power. This is verified by measurement paid-in 15-minute intervals during the billing period in kilowatts (KW).

These measurements are made by electronic meters, necessary for the application of the tariff structure [3]. If the demand value measured is less than, equal to, or even 10% higher than the contracted demand of value then one pays the full contracted amount. If the demand value measurement is more than 10% over the contracted demand value, however, then you pay the contract value together with the fine for registered Overtake value, which is approximately three times the unit price of the kilowatt (kW) of contracted demand.

When the contracted demand value is greater than the demand value as the false impression one has of the electrical system of the company is well proportioned, it does not pay for exceeding the demand. However, an excess paid by contracting it in fact is not being consumed. This generates an additional cost, which is stipulated in the supply contract and goes unnoticed by the financial sector of the company for not coming broken in the electricity bill.

The development of statistical methods for analyzing data obtained in cases where the observations are dependent has shown tremendous growth in recent decades and in particular, the data from time series analysis, which is the case of the series presented here.

When working with time series, the most common goal is predicting future values. The need for accurate predictions of future events and their consequences, whether climatic, economic, epidemiological or of any nature, has led to steady development in the forecasting of techniques in a time series.

The classical statistical methods for a time series analysis are well documented. However, many of these methods require specialized knowledge for their correct application. Thus, the proper use of the classic models require checks of their assumptions. This requires effort and experience in exploratory data analysis. The Singular Spectrum Analysis (SSA, Singular Spectrum Analysis of the English), is presented as a relatively simple and powerful alternative that can be applied.

Methodology

SSA is a nonparametric method used in time series analysis and requires little prior knowledge of the series behavior. This technique investigates the behavior of time series through the decomposition and reconstruction of the components that characterize the stages of SSA [1].

The SSA method proves helpful in the series of analyses of the areas of meteorology, geophysics, physics, climatology, economics, health and many other fields of knowledge. This tool can be applied in short or long series, stationary or non-stationary series, noisy or not, or at any time with any number [4] structure [6].

It is noteworthy that the SSA perform of future values predictions, but the technique aims to identify and extract generator standards of the time series.

Fig. 1 shows the time series used in this study, whose data is referred to in the necessary energy demand in a month. Measurements were taken every 15 minutes and only on weekdays.

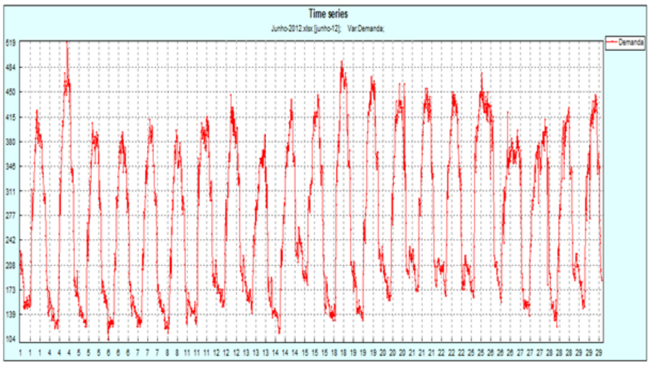

Fig. 1. Time series on energy demand (only on weekdays) in June 2013.

The SSA technique is based on two stages that complement each other: decomposition and reconstruction of the time series. Each stage consists of two steps that form the four steps of the technique: Embedding, Singular Value Decomposition (SVD), Grouping and Diagonal Averaging.

1- Decomposition

At the stage of decomposition, the original time series is decomposed into a sum of a few subsets so that each subset can be identified and interpreted as constituent components.

1.1 Embedding

Consider a one-dimensional time series and the real non-zero, $Y_t = Y_1,\dots,Y_N$; $t = 1,2,\dots,N$, where N is the number of observations over the investigated time interval. In this case, there are 96 readings per day, one every 15 minutes and 21 working days equivalent to a sample of 2016 data.

Initially, the original one-dimensional series is transformed into a multi-dimension L series, named “length of the window”. The length of the window is the only parameter of this step and represents the number of components in the series is decomposed. This parameter should be an integer between $2 \le L \le N-1$, and, according to theoretical results, the size L should be large enough, but not exceeding. A value for L divisible by 96, given that the number has been chosen daily intervals (96 intervals of 15 minutes one day) and as close as possible to half the number $(\frac{N}{2})$, as suggested by [5] and [6]. Specifically in this case, the value for L was 960.

The multi-dimensional time series is a sequence of vectors consisting of elements $_t$ of the set y, forms the matrix shown in expression (1), called “trajectory matrix”, the result of this first step [4] [6] [7].

$$(1) \qquad X_{LxK}=[X_1 \dots X_k] = \begin{bmatrix} Y_1 & Y_2 & \cdots & Y_k \\ Y_2 & Y_3 & \cdots & Y_{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ Y_L & Y_{L+1} & \cdots & Y_N \end{bmatrix}$$

Where K = N−L+1 is the number of vectors or subsets lagged in time. Therefore, based on the determined size of the window obtained in the decomposition step, it is delayed a set of 1057 vectors (K = 1057).

In general, the embedding step is regarded as mapping that transforms one-dimensional series Y_t, in a multidimensional X formed subsets by $X_1,\dots,X_K$; wherein $X_i = [Y_i,Y_{i+1},\dots,Y_{i+L-1}]^T$ and where $1 \le i \le K$.

1.2 - Singular Value Decomposition (SVD)

This Phase is carried out in the SVD decomposition of the trajectory matrix X into a sum of elementary matrices. Let S be the product of the trajectory matrix and its transpose, $S = XX^T$. In performing the SVD of the matrix S obtained by their eigenvalues, they can be ordered according to their magnitude ($\lambda_1 \ge \cdots \ge \lambda_L \ge 0$), and the corresponding eigenvectors $U_1,\dots,U_L$; orthogonal and normalized.

To be considered the transformation given by the expression (2):

$$(2) \qquad V_i = \frac{X^T U_i}{\sqrt{\lambda_i}}, (i = 1, \quad \dots \quad, d)$$

SVD trajectory matrix can be written as in expression (3):

$$(3) \qquad X = E_i + \quad \dots \quad + E_d = \sum_{i=1}^{d} E_i$$

where d denotes the number of distinct eigenvalues of the matrix S to zero and each $E_i = \sqrt{\lambda_i} U_i V_i^T$ represents a unit matrix rank, which is commonly named “elementary matrix”.

The triple ($\sqrt{\lambda_i} U_i V_i^T$) is known as the i-th eigenvector of the matrix X and $\sqrt{\lambda_i}$ your unique value as [4].

2 - Reconstruction

2.1 - Grouping

The grouping aims distinguish/differentiate the additive components of time series. This stage occurs at the junction of elementary matrices Ei into several groups. In other words, the grouping stage identifies the most correlated components and puts them in order in the same group.

Mathematically, the grouping step partitions the set of indices of the elementary matrices s expression (3) {1, ..., d}, into disjoint subsets $I_1,\dots,I_m$, which corresponds to the representation in the expression (4):

$$(4) \qquad X = E_{I_1} \quad + \cdots + \quad E_{I_m} = \sum_{p=1}^{m} E_{I_p};$$

where E_{I_1} ,..., E_{I_m} are known as resulting arrays. Each resulting matrix is obtained from the sum of elementary matrices in a particular set index I_p, as expression (5),

$$(5) \qquad E_{I_p} = \sum_{i \in I_p} E_i; \; p = 1, \quad \dots \quad, m.$$

Therefore, the result of this step is the representation of the trajectory matrix as a sum of resulting matrices (E_{I_1},..., E_{I_m}).

The choice of the sets $I_1,...,I_m$ is the second and final decision necessary for the implementation of SSA method. This choice is based on the property called "separability". The separability between sets can be measured by the weighted correlation. The weighted correlation between two subsets $Y_t^{(1)}$ and $Y_t^{(2)}$ can be expressed as in expression (6):

$$\rho_{12}^{(w)} = \frac{<Y_t^{(1)},Y_t^{(2)}>_w}{||Y_t^{(1)}||_w||Y_t^{(2)}||_w}; \tag{6}$$

where the norm of the ith subset is given by:

$$||Y_t^{(1)}||_w = \sqrt{< Y_t^{(i)}, Y_t^{(i)} >_w}; \tag{7}$$

with the inner product is defined by:

$$< Y_t^{(i)}, Y_t^{(j)} > = \sum_{c=1}^{N} w_c Y_c^{(i)} Y_c^{(j)}; i, j = 1,2; \tag{8}$$

where the weights w_c are represented by $w_c = \min\{c,L,N - c\}$, and it is assumed that $L \le \frac{N}{2}$.

2.2 - Diagonal Averaging

The process carried out in the last phase turns every matrix, resulting in an additive component of the original series. That is, each matrix decomposition is converted into a new series of size N. This makes it possible to obtain a one-dimensional series and is considered as an approximation of the original series.

The transformation of the resulting matrices in series occurs when applying a linear operator "Hankelization" (H). This operator acts on an arbitrary matrix such that it becomes a Hankel matrix, and therefore, a path matrix, and final in a series. In the context of the fourth stage, the operator M counts the medium along the parallel lines of the secondary diagonal matrices E_{I_p}, for p = 1,...,m.

Results and Discussion

Through applying the step of decomposing the series electrical energy demand data, we found the following results:

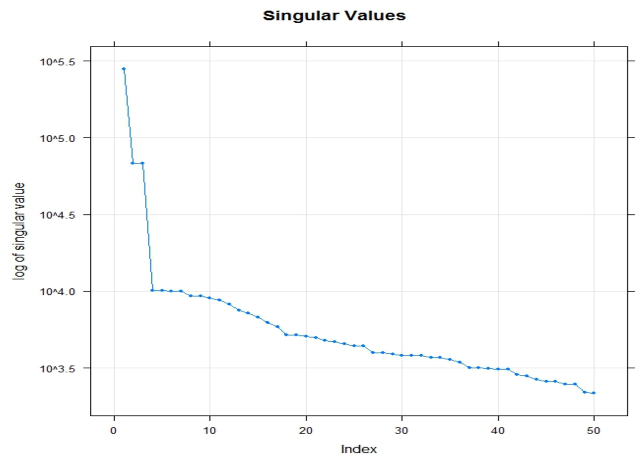

Fig. 2. Logarithm of the first 50 eigenvectors of the SVD.

In Fig. 2, one can observe that the unique value of the first eigenvector is considerably larger than the other singular value eigenvectors. Thus, it can be said that the eigenvector 1 is well separated from the other eigenvectors and is the main trend of the series. The eigenvectors 2 and 3 have very close singular values, forming a step on the graph and therefore representing a harmonic component. Based on this graph it can also be said that the eigenvectors, possibly 4, 5, 6 and 7 forming the lower step, also represent a harmonic component. As for the others, they still cannot claim to be noise.

In the graph of the average covariance between the eigenvectors, shown in Fig. 3, there is the periodic behavior of the covariance functions of the original series. The distance, in the axis X, among the largest covariance values, as well as among lower, is equal to 96 and is the main frequency of the series. The graph of covariance confirms the initial result of the frequency shown in the visual analysis of the original time series.

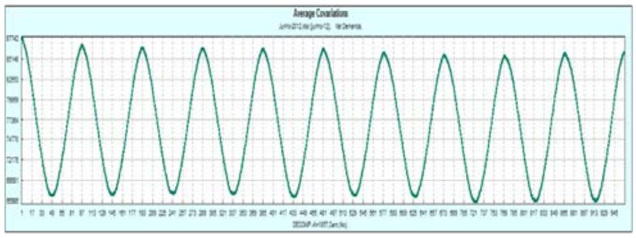

Fig. 3. Covariance average of eigenvectors.

Additional information regarding the frequency is given in the periodogram analysis, where we observe the extracted seasonal components of the time series. However, only one harmonic frequency component, equal to the periodogram, is distinguishable from 96 shown in Fig. 4 .

Fig. 4. Average periodogram of the time series.

Fig. 5. First singular eigenvectors in the matrix path SVD

In Fig. 5 the first nine natural eigenvectors of the matrix path SVD can be observed. Through this observation it can be seen that the component SSA 1 (which is associated with the unique eigenvector 1, SVD) is equal to 87.819%. Also based on the plot of eigenvalues and Figure

3 it can be concluded that the SSA component 1 was confirmed as the main trend and none of the other components, such as harmonics, were considered according to noise [4].

It can also be seen that from the second component of Fig. 6 a pattern of seasonality begins to be identified.

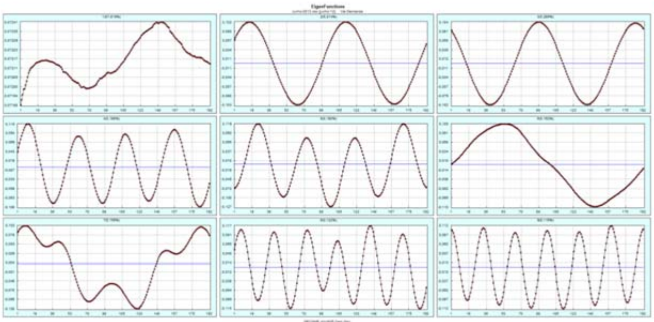

Fig. 6. Main components in the form of time series.

In Fig. 7 , there are the graphics (continuous) dispersion few pairs of singular eigenvectors of the matrix path SVD. Through its analysis one can identify which ordered pair of members is associated. Also, it helps identify which eigenvectors are considered trend, harmonic or noise [6].

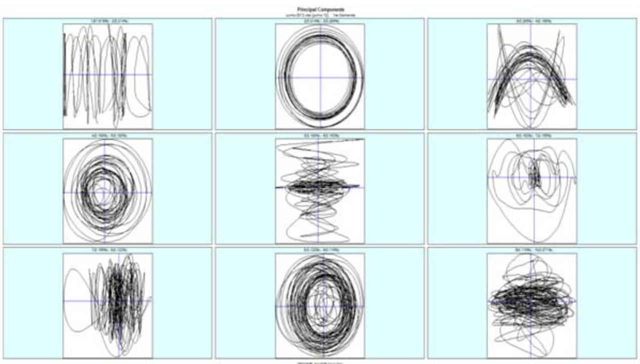

Fig. 7. Scatter charts (scatterplots) for the first couple of eigenvectors.

Secondly, Fig. 7 [4] notes that the graphics of the singular eigenvectors pairs, (2,3), (6,7) and (8,9) in the SVD analysis, show that there is, in each pair, no linear association between the eigenvectors that compose them. Therefore, they cannot be classified as noise. Furthermore, in these cases in particular, is it true that the eigenvectors that make up these second pairs [6] are considered harmonics because their diagrams show circles or regular polygons of n sides thus indicating that the data analyzed really has a periodic trend.

After the step of decomposition the reconstruction stage was started. Depending on the mix between the harmonic components, trend and noise, it was often difficult to decide which eigenvectors should be included in the reconstruction of the series. Therefore, the evaluation of the weighted correlation matrix was necessary. Looking at Fig. 8 , it can be noted that the pairs of eigenvectors which derived from the same trend component are highly correlated, such as the eigenvalues 2 and 3 (ρ = 1.000), and the harmonic component from the period is equal to 96, which are eigenvectors 4 and 5 (ρ = 0.964) and peer 6 and 7 (ρ = 0.970). The first eigenvector, which is the main trend in the series, does not correlate with any other eigenvector which also shows that the signal-to-noise separation was conducted efficiently. The eigenvectors 10 and 11 are correlated, although this correlation is not as high (ρ = 0.919) and the correlation between the other eigenvector harmonics.

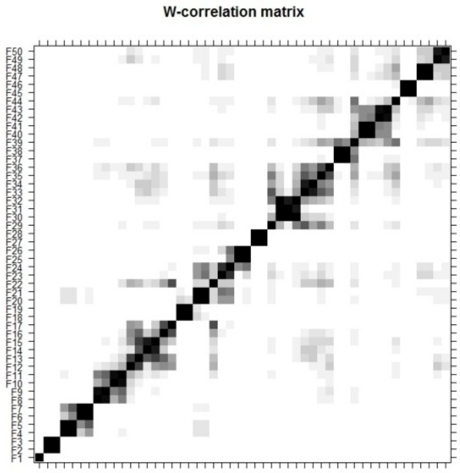

Fig. 8. Correlation Weighted Matrix.

As the singular values of the eigenvectors 7 and 8 are not very close, we chose to include these eigenvectors in the reconstruction of the series trend. Eigenvector 18 and the subsequent eigenvectors have different correlations with other eigenvectors, indicating similarities between the eigenvectors mixture. These eigenvectors were interpreted as originating from noise in the time series.

Grouping the trend and seasonality of the time series (1-17), it is possible to reconstruct the signal of the series, as can be seen in Fig. 9.

The highest residue found in the reconstruction stage was 118 kW. While much of the error can be attributed to noise present in the original series, it can be said that the error in reconstruction can also be due to extreme events and unpredictability .The absolute average error (MPE) and the mean relative error (RMS) were equal to 17.6 kW and 0.9%, respectively, and furthermore, the original series and the reconstructed series are significantly correlated (ρ = 0.9124; t = 38.8962, df = 550, p-value < 2.1 × 10-16). The absolute errors in the reconstruction step can be further seen in Fig. 9 .

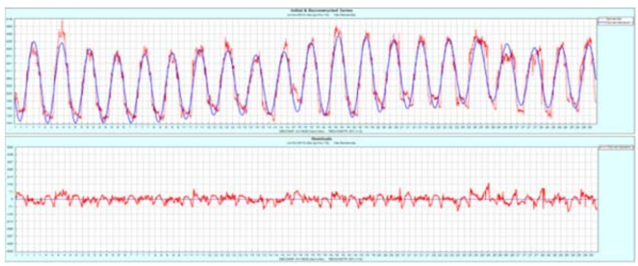

Fig. 9. Original Series x Rebuilt Series and Waste.

Recursive algorithm used to forecast

Let $Y_t = Y_1,...,Y_N$ the original series and $\tilde{Y}_t = \tilde{Y}_1 + \cdots + \tilde{Y}_N$ the reconstructed series as the second stage of SSA. The forecast of future values $Y^{\wedge}_{N+h}$ with h = 1, ..., M, is obtained from the following form of words:

(9) $$\hat{Y}_{N+h} = \sum_{p=1}^{L-1} a_p \hat{Y}_{(N+h)-p}; h = 1,\ldots, M.$$

Wherein, are the coefficients of the linear combination of L - 1 last terms of the reconstructed series.

It is noteworthy that the higher the number of steps ahead (h), the more dependant the predictions become on previous predictions. For the prediction consider at least an approximate value ($\tilde{Y}_j$) of the original series, we recommend using a horizon of at most M = L-1 according [8].

In summary, the numbers $\hat{Y}_{N+1},\ldots,\hat{Y}_{N+M}$, forming the M terms predicted by the applicant prediction algorithm based on SSA.

Based on the reconstructed series, the prediction was made for the subsequent step 96, Fig. 10 .

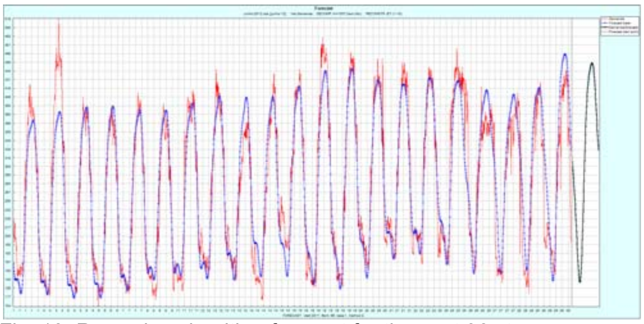

Fig. 10. Recursive algorithm forecast for the next 96 steps.

The Mean Absolute Error (MPE) and Eastern Relative (EMR) committed in the forecast were 109 kW and 0.85%, respectively, and remained as expected, given the errors in the analysis of this series. Furthermore, the predicted values were very similar to the values of the reconstructed series to the latest data.

Conclusion

This method allowed us to determine the trend characteristic of the series, extract seasonal components, and separate the components that represent the signal (information) of the noise. In the case of the data analyzed during the month of June in this study, the method was effective in extracting the trend component and seasonal components of the entire series. The series had at least a seasonal component for the period of 96 minutes. The analysis of eigenvectors, periodogram and covariance medium confirmed the seasonality due to the daily cycle characteristic of the industry.

Taking into account the magnitude of the errors and the correlation coefficient, it can be concluded that the reconstructed series with the first 10 and the extracted eigenvectors represented the behavior of the original series. In addition to revealing seasonal variations, another relevant fact regarding the robustness of the method is its ability to reveal trends whose behavior is nonlinear. The results show that spectral analysis is a useful technique when you want to extract information about the behavior of time series in order to reveal their trends and seasonal effects.

The SSA method can be applied as a tool for the management of monitoring programs, especially in the management of electrical demand where the data comes in real time. Since the sampling rate directly affects not only the cost of the monitoring system, but also information that can be obtained from the data available, there is a need to use statistical methods such as quantitative criterion for the choice of sampling intervals. The SSA method, as demonstrated in this study, can be a useful tool for recovering lost information, minimizing the cost of monitoring, and maximizing the quality of information derived from the collected data.

Using this method it was especially possible to predict the demand that exceeded the contracted peaks in almost all cases, thus reducing costs and maximizing efficiency of use.

Thanks

In the Support Foundation of Bahia State Research (FAPESB) for financial support.

REFERENCES

[1] Konrad Bojar, Trend extraction from noisy discrete signals by means of singular spectrum analysis and morphological despiking. *Przeglad Elektrotechniczny* ed. 06/2011 Page n. 241

[2] Mirosław Parol, Paweł Piotrowski, Long-term forecasting method of annual electrical energy demand in electric distribution companies. *Przeglad Elektrotechniczny* ed. 08/2010 Page n. 182.

[3] ANEEL – Agência Nacional de Energia Elétrica (Brasil). Resolução n°. 456, de 29 de novembro de 2000.Art. 2°, II. Available in*: <http://www.aneel.gov.br/cedoc/res2000456.pdf>*. Acesso em: 11 set. 2014.

[4] Golyandina N., Nekrutkin V., Zhigljavsky A., Analysis of time series structure: SSA and related techniques. *Chapman Hall/CRC*, New York; 2001.

[5] Golyandina N., Osipov E., The "Caterpillar"-SSA method for analysis of time series with missing values. *Journal of Statistical Planning and Inference*. n.137, 2642–2653, 2007.

[6] Hassani H., Singular Spectrum Analysis: Methodology and Comparison. *Journal of Data Science*, n.5, 239-257, 2007.

[7] Hassani H., Heravic S., Zhigljavsky A., Forecasting European industrial production with SSA. *International Journal of Forecasting*, n.25, 103-118, 2009.

[8] Esquivel R. M., Análise Espectral Singular: Modelagem de séries temporais através de estudos comparativos usando diferentes estratégias de previsão. 2012. 173 p. *Dissertação de Mestrado em Modelagem Computacional e Tecnologia Industrial,* CIMATEC/SENAI-BA, Salvador, 2012.

Authors: *Rafael Ferreira Lopes, Federal University of Bahia, Department of Electrical Engineering, Rua Aristidis Novis Nro. 2, 40210-630, Salvador-BA-Brazil, E-mail: galotinhodelta@gmail.com.*

Fabiano Fragoso Costa, Federal University of Bahia, Department of Electrical Engineering, Rua Aristidis Novis Nro. 2, 40210-630, Salvador-BA-Brazil, E-mail: ffcostabr@yahoo.com.br.

Antonio Cezar de Castro Lima, Federal University of Bahia, Department of Electrical Engineering, Rua Aristidis Novis Nro. 2, 40210-630, Salvador-BA-Brazil, E-mail: acdcl@ufba.br.