Abstract

This paper proposes the use of the Teager–Kaiser energy operator (TKEO) for the detection of a broken rotor bar (BRB) in a squirrel cage induction generator, which is used usually in wind energy systems. The TKEO is investigated using the non-stationary signals representation in the time/frequency domain by sensing the estimation of the instantaneous amplitudes and frequencies present on the stator of wind turbine. This situation of the rotor bar breaks is caused mainly by combinations of mechanical and electrical stresses, including vibration, pendulum, thermal and centrifugal and rarely it can appear due to the fabrication and the quality of the used material’s origins. Consequently, the case of a BRB may occur under these circumstances and it is a common fault which can occur in the rotor of the squirrel cage induction generator, it can be estimated to be around 20% among the eventual faults of this kind of machine. The necessary properties for the development of this representation based on the TKEO in time and frequency are presented, which can improve the diagnosis of the studied wind energy system. The obtained results of the presented method have been experimentally validated by robustness tests, which raise the effectiveness of the proposed approach, including a 4-kW induction generator for online rotor bar fault detection using the spectrum analyser and stator current sensors board designed especially for this experimental purpose.

Key Words

Induction generator, broken rotor bars, faults diagnosis, renewable energy, motor current signal analysis, Teager–Kaiser energy operator

1. Introduction

Recently, the diagnosis of the systems has experienced remarkable and significant progress in several industrial fields. By the emergence of new methods arising from artificial intelligences, future challenges include their development and applications. Among these methods, spectral analysis and signal processing are widely used because of their great ability to analyse physical phenomena and because of their flexibility of implementation in a real time. Indeed, spectral analysis often uses the acquisition of a mono-dimensional signal as a function of time, as a simple temporal representation, which does not always allow a complete analysis of the signal. This little generated spectral leakage poses a problem in the interpretation and readability of the signals to be analysed. In this context, this work proposes the use of the Teager–Kaiser energy operator (TKEO) for the detection of a wind turbine rotor defect to reduce the effects of the spectral leakage of the signals measured on the squirrel cage induction generator of this machine.

However, the idea of the use of an energy operator was proposed by Teager in 1980 in [1] where he gave observations on the flow of oral air during phonation, subsequently Maragos et al. [2] in 1993 made energy separation in signal modulations with application to speech analysis, in 1994 Alexandros and Maragos [3] proposed a comparison of the energy operator and the Hilbert transform approaching signal and demodulation of speech. In 2016, Deepan et al. [4] determined the phase derivatives from a single fringe model using the Teager Hilbert Huang transformation, Abdel-Ouahab et al. [5] in 2008 proposed a defect detection strategy based on an energy operator and in 2005 Dimitrios et al. [6] determined the Teager energy operator (TEO) coefficients for a robust speech recognition system. However, other works have been carried out in this field validating the approach of the use of energy operator to reduce the effects of spectral leakage in the measured signals.

These spectral leakage effects are undesirable in the signal analysis stage that are present if the periodic signal is not sampled by an integer number of periods. On the other side, it is well known that the discrete Fourier transform will have non-zero components at frequencies
other than the initial frequency. It may also have folding if the signal contains harmonics of frequencies higher than half of the sampling rate. To reduce these effects of folding, a higher rate sampling frequency is required to obtain an error smaller than 5% in the first harmonics. This can minimize spectral leakage effects, which should be ideally sampled for an integer number of periods to reduce spectral spacing. Therefore, the TKEO is proposed to solve the leak problem and to estimate the energy of a harmonic system. The estimated instantaneous energy makes it possible to demodulate the signal by calculating its instantaneous amplitude and its instantaneous supply frequency, this operator uses the real signals during the spectral analysis of the current.

In this work, the TKEO based on the length of the window is applied to the wind turbine rotor defect detection to reduce the effects of spectral leakage of the signals measured on the squirrel cage induction generator. The obtained performances are compared with the square energy operator approach. This new operator makes it possible to measure the interaction between two complex measured signals of the short-term energy and the additive noise and makes it possible to calculate the delay time between these two signals to find solutions to the problems of its estimation.

2. Teager–Kaiser Approach

The TKEO was proposed by Teager in 1980 and subsequently approved by Kaiser for the estimation of frequencies harmonics of unamortized linear energy in a speech processing system, where the modulation plays an important role [7]–[9]. On the other side, it has been applied in several applications such as in communications studies to the representation of the instantaneous frequency of transient signals. In energy supply analysis, the energy operator is used for the detection of the three-phase power supply oscillations; in the electrical engineering field, especially for bearings failures diagnostics [10], [11], [20]–[33].

2.1 Continuous Time Representation

The method of the TEO is oriented towards the demodulation of multi-component signals (amplitude modulation/ frequency modulation). Several works have been developed in this direction with comparative studies [8], [12]–[14]. Kaiser proposed a very simple and fast algorithm to estimate the energy, as the restriction related to the bandwidth of the signal (narrowband signal) is respected [7]. One of the first applications of this operator is the detection of modulations (AM/FM) of the formants by estimating the product of their amplitude and their frequency. This demodulation method, initially dedicated to speech signals, has been extended to the entire class of narrowband signals for other industrial applications in diagnosis and control based on the signal analysis. The representation of this estimate in continuous time of the signal \( y(t) = A \cos(\omega t + \varphi) \) is given by the following equation:

\[
\psi(y(t)) = \dot{y}(t)^2 - x(t) \ddot{y}(t)
\]  

where \( \dot{y}(t) = \frac{dy(t)}{dt} \), \( \ddot{y}(t) = \frac{d^2y(t)}{dt^2} \) are the first and the second derivatives of \( y(t) \) and \( \psi(y(t)) \) is the instantaneous energy operator of \( y(t) \).

If (1) is applied to the actual values of the signal \( y(t) \), we obtain the following result:

\[
\psi(y(t)) = (-A \omega \sin(\omega t + \varphi))^2 \\
- (A \cos(\omega t + \varphi)) (-A \omega^2 \cos(\omega t + \varphi)) \\
= A^2 \omega^2 \left[ (\sin(\omega t + \varphi))^2 + (\cos(\omega t + \varphi))^2 \right] \\
\psi(y(t)) = A^2 \omega^2
\]  

(2)

In addition, if the TKEO is applied to the first derivative of \( y(t) \), the following expression is obtained:

\[
\psi(\dot{y}(t)) = A^2 \omega^4
\]

(3)

By combining (2) and (3), the amplitude \( A \) and the frequency \( \omega \) can be calculated by the following equation:

\[
|A| = \frac{\psi(y(t))}{\sqrt{\psi(\dot{y}(t))}} \\
\omega = \sqrt{\frac{\psi(\dot{y}(t))}{\psi(y(t))}}
\]

(4)

The amplitude and its frequency estimated by (4) make it possible to demodulate the signal and give an estimation with rich information.

2.2 Discrete-Time Representation

The discrete temporal representation of the signal, which can be determined by sampling the continuous signal with the sampling frequency \( f_S \), is given by the following equation:

\[
y[n] = y(nT_s) = A \cos(\omega nT_s + \varphi)
\]

(5)

with \( T_s = 1/f_s, n = 0, 1, 2, \ldots \)

Using the approximation of the derivatives backwards, (1) becomes the following:

\[
\psi(y[n]) = \left( \frac{y[n] - y[n-1]}{T_s} \right)^2 \\
- y[n] \cdot \frac{y[n] - 2y[n-1] + y[n-2]}{T_s^2} \\
= \frac{1}{T_s^2} \left( y[n-1]^2 - y[n] \cdot y[n-2] \right)
\]

(6)

Equation (6) can be written in the following centred form:

\[
\psi(y[n]) = y[n]^2 - y[n-1]y[n+1]
\]

(7)
The solution of (7) is given as follows:

\[ |\hat{A}| = \frac{2\psi(y[n])}{\sqrt{\psi(y[n+1] - y[n-1])}} \]  

(8)

\[ \hat{\omega} = \frac{1}{T_s} \arcsin \left( \frac{\psi(y[n+1] - y[n-1])}{4\psi(y[n])} \right) \]

The parameters of (8) are the variables of the discrete-time energy separation algorithm (DESA), this algorithm is used in the estimation of frequencies (AM/FM) as given by (5).

### 2.3 Signal Estimation in Current Generator using the Teager–Kaiser Energy Operator

The stator current in a normal generator supplied by a sinusoidal voltages power system is purely sinusoidal, as given by the following equation:

\[ i_{\text{Normal}}(t) = I_m \cos(\omega t) = I_m \cos(2\pi ft) \]  

(9)

with the frequency \( f \) being defined in the interval 50–60 Hz.

The use of TKEO for the phase current gives a constant value which can be presented by the following equation:

\[ \psi(i_{\text{Normal}}(t)) = I_m^2 \omega^2 \]  

(10)

In the situation of periodical perturbations caused by a broken bar, mixed eccentricity or bearing faults, the amplitude of the stator current is modulated by the fundamental frequency \( f_0 \), which allows to obtain the characteristic of the defect. The stator current of normal generator under risk of these defects, based on the healthy current presented in (9), can be characterized as follows [1]:

\[ i_{\text{Defect}}(t) = i_{\text{Normal}}(t)[1 + \beta \cos(\omega_0 t)] \]

\[ = I_m \cos(\omega t) + \frac{\beta I_m}{2} [\cos((\omega - \omega_0)t) + \cos((\omega + \omega_0)t)] \]  

(11)

Equation (11) shows the presence of the defective components in the form of spectral lines characteristic of the lateral band around the fundamental component. According to [15], the modulation index \( \beta \) is expressed as follows:

\[ \beta \approx \frac{n_b}{N_b} \]  

(12)

where \( \omega_0 = 2\pi f_0 \), \( N_b \) is the rotor bars number, \( n_b \) is the broken rotor bars (BRBs) number.

The amplitude of the fault frequency is small compared with the amplitude of the reference frequency, with \( \beta \ll 1 \) given in (11). This component corresponding to a broken bar is in the range 35–45 db less than that of reference.

Using the TKEO to the stator current in the defective generator represented by (11), their variables are multiplied by \( \beta^2 \), then this equation becomes:

\[ \psi(i_{\text{Defect}}(t)) = I_m^2 \omega^2 + \frac{1}{2} I_m^2 (4\omega^2 + \omega_0^2) \beta \cos(\omega_0 t) + \frac{1}{2} I_m^2 \omega_0^2 \beta \cos((2\omega - \omega_0)t) + \cos((2\omega + \omega_0)t) \]  

(13)

From this equation, the following remarks are given:

- A fixed term, due to the fundamental supply frequency.
- The second fluctuate at the fault frequency.
- The last two sideband terms appear nearly twice the fundamental frequency.

### 2.4 Teager–Kaiser Energy Operator Investigations

It is obvious that the leading term in the TKEO demodulated current is the fixed term or the DC term which corresponds to the fundamental supplied current this term is presenting the mean value of the function presented in (13). Therefore, this term can be eliminated simply by subtracting from (13) its principal value. In this paper, the suggested detection method relies on the processing of new signal \( i_{TK}(t) \), which is derived mainly from the current signal \( i(t) \) through its TKEO, as follows:

\[ i_{TK}(t) = \frac{\psi(i(t)) - \bar{\psi}(i(t))}{\psi(i(t))} \]  

(14)

where \( i_{TK}(t) \) is the normalized AC component of the function \( \psi(i(t)) \), by dividing it by the DC component \( \bar{\psi}(i(t)) \).

For the condition of normal generator \( i_{TK,\text{Normal}}(t) = 0 \), because \( \psi(i(t)) = \bar{\psi}(i(t)) \), whereas, based on (13) and (14), for the condition of defect generator, the diagnostic signal \( i_{TK,\text{Defect}}(t) \) is given as follows:

\[ i_{TK,\text{Defect}}(t) = \left( 4 + \left( \frac{\omega_0}{\omega} \right)^2 \right) \beta \frac{1}{2} \cos(\omega_0 t) + \left( \frac{\omega_0}{\omega} \right)^2 \frac{\beta}{2} \cos((2\omega - \omega_0)t) + \cos((2\omega + \omega_0)t) \]  

(15)

From (15), the diagnostic signal \( i_{TK,\text{Defect}}(t) \) corresponds to the defect generator. At the characteristic frequency of the defect \( \omega_0 \), the component is not affected by the leakage of the fundamental harmonic, compared with the results of the classical spectral analysis, so that it can be used to characterize the existing and the severity of the defect, so it can be used to identify the severity of the defect. Also, a twice similar sideband components around the fundamental current frequency are imposed by the power supply, which can be used for more evaluation of the fault detection.

Like the main component has been eliminated in the diagnostic function \( i_{TK}(t) \), the fault frequencies can be seen in the spectrum of \( i_{TK}(t) \) more easily than using
the spectrum of the current signal $i(t)$. This reality also subscribes to get better accuracy of automated diagnostic systems, which depends on the appearance of peaks that are near to the theoretical frequencies of the defect.

Motor current signal analysis (MCSA) process was investigated in this work, using the TKEO, this process contains three steps:

- **Step 1:** The TKEO algorithm given in (7) is used to the captured current $i(t)$, after this, the detecting signal $i_{TK}(t)$ is obtained by using (13).
- **Step 2:** The signal $i_{TK}(t)$ is processed by the fast Fourier transform (FFT) to obtain its spectrum.
- **Step 3:** The obtained $i_{TK}(t)$ spectrum in step 2 is analysed and evaluated for detecting the possible fault characteristics.

Practically, the spectrum assessment is implemented based on (15), the main faulty signal component corresponding to the fault frequency is presented as follows:

$$i_{TK,Defect,main}(t) = \left(4 + \left(\frac{\omega_0}{\omega}\right)^2\right) \frac{\beta}{2} \cos(\omega_0 t)$$  \hspace{1cm} (16)

At $f_o$, the spectral component offers a great peak than the other two components, with frequencies $2f \pm f_0$. It can be concluded that this resulting component gives a better signal-to-noise ratio (SNR) relative to the main component presented in (11) in comparison with the same component obtained by the classical MCSA technique. Indeed, there is a rising operator of $4 + (w/w_0)^2 = 4 + (f_0/f)^2$ between the same main components presented in (7) and (13).

### 2.5 Frequencies of Rotor Boken Bars

The broken bar fault frequencies are given by the following expression [16], [17]:

$$f_{bb} = (1 \pm 2s)f$$  \hspace{1cm} (17)

where $s$ is the slip, $f$ is the supply frequency and $f_{bb}$ is the BRB frequency.

The least frequency sideband is related to the BRB defect, but the higher sideband frequency is related to the angular speed oscillation caused by the rotor fault, it was explained that the broken bar frequencies are included in the sideband frequencies as follows [16], [17]:

$$f_{bb} = (1 \pm 2ks)f$$  \hspace{1cm} (18)

where $k = 1, 2, 3, \ldots$ is the number of sideband jumps.

In this work, more attention is given to the first two current components presented in (20) with $k = 1$. Where the amplitudes of the remaining frequencies decay too fast and are practically more difficult to be detected. The expressions in (17) and in (18) show also that the fault-related frequencies are extremely sensitive to the rotor slip. Consequently, for low-load condition where the slip has small values, these two components are near to the fundamental frequency. Furthermore and even using high-resolution methods, their discrimination from the fundamental components presents more additional difficulties.

3. **Experimental Results**

3.1 **Test Bench**

The sensors board is designed by using three current sensors LA-55P to ensure the real-time generator stator current measurements. On the other side, three voltage sensors LV-25M are used to ensure the voltage measurements. The measured signals are concurrently sampled via channels of a 16-bit, 200-kHz PCI data acquisition (DAQ) card and stored into the PC. The Matlab software was used for the analysis of the obtained data at a sampling frequency of 10 kHz.

The suggested technique has been verified experimentally in a PC-based diagnostic system on three similar generators. The comparative analysis is performed for the signals that are obtained experimentally in the laboratory from three identical generators 4kW, the first one is normal, the second has only one broken bar and the third with two broken bars. In all these cases, the generators are coupled to a wind turbine, which acts as a mechanical source, in the same time this generator is coupled to a tachymeter to ensure the real-time measurement of the speed. This experiment analysis is based on the comparison between the results obtained from the model of the two generators with broken bars (faulty case) and with the model of a normal generator (healthy case).

3.2 **Motor Current Signal Analysis Results**

After sampling the stator phase current for the three cases, it is analysed by applying the traditional MCSA based on the power spectral density (PSD) estimation. A zoom window of the generator phase current $i(t)$ spectrum using the classical approach around the fundamental frequency for each studied case is presented in Figure 2.

Tables 1 and 2 summarize the generators conditions of the three experimental tests for the verification of the suggested technique. At the same time, the frequencies of the sideband components related to the rotor defect are presented.

From Figure 2, it is shown obviously that as the number of the BRBs increases, the magnitude of the characteristic sidebands, the distance between the sidebands and the supply frequency component are increased as well. The sideband components’ characteristic of the broken bar condition is distinguishable in the tests performed under the load condition for 1 BRB ($s = 2.5\%$) and for 2 BRBs ($s = 2.6\%$). For the condition of normal generator ($s = 2.2\%$), a low-amplitude components near the natural fault frequencies appear in Figure 2(a). The presence of these two components is due mainly to the process of aluminium alloy injection of the rotor bars during fabrication which results in some degree of irregularity in the cross-section of the rotor bars. This intrinsic asymmetry in the rotor circuit leads to small differences in the resistance of rotor bars, which can be considered as a kind of fault; however, its effect is neglected practically.

The spectrum modulus of the phase current under one and two BRB is shown in Figure 2(b) and in Figure 2(c),
respectively. We can see that the frequency components $(1 \pm 2ks)f$ are clear in the magnitude spectrum of the phase current. To be sure that the frequencies $(1 \pm 2ks)f$ presented in this spectrum are due to the presence of a damaged rotor bar, a comparison with the spectrum of the stator current of the healthy rotor generator is performed. This processing assists to prove the reality that the occurrence of a broken bar in the rotor leads to the appearance of picks at the stator current spectrum at the frequencies $(1 \pm 2ks)f$.

It is noticed also that there are clear peaks of the spectrum at frequencies $(1 \pm 2ks)f$ that are due mainly to the existing of one or more BRB. So, it is possible to set the diagnosis of squirrel cage generator by analysing the spectrum of the particular peaks presented at the stator current spectrum.

To ensure a rotor fault diagnosis without using a comparison with a reference (reference obtained from a normal functioning), the last decision, that is, “Is the rotor healthy or not?” should be done only from the processing signal which permit to use the presented technique for lower or higher power machines. On the other side, all the induction generators have a few asymmetry of construction that can induce a frequency component $(1-2ks)f$ in the stator current spectrum. Sometimes, the oscillation speed creates this component which is illustrated in Figure 2(b), is sufficient to create an additional component of frequency $(1+2ks)f$ which appears at the same frequency spectrum as it is clearly shown in Figure 2. However, induction generator builders guarantee that the machines have a little asymmetry because it could be the main cause of defects. The phase current spectrum is studied, especially the components with the frequency peak at $(1+2ks)f$.

### 3.3 Teager–Kaiser Energy Operator Results

The suggested technique depends on the analysis of the variation of $i_{TK}(t)$, the generator currents data have been previously transformed using the TKEO, then after that they have been analysed based on PSD estimation. The spectrums $i_{TK}(t)$ of each generator, among the three cases that are presented in Tables 1 and 2, and Figure 2, are shown furthermore in Figures 3 and 4 for two different frequency ranges of 0–10 Hz and of 90–110 Hz, respectively.

Figure 3 illustrates the frequency spectrum of the signal $i_{TK}(t)$ presented in (13) within the frequency range of 0—10 Hz, under the condition of a normal generator as shown in Figure 3(a), a low amplitude of the components $f_0 = 2skf$ can be observed with the same demonstration mentioned in Section 3.2, and for the case of a faulty generator with one and two broken bars, the components $f_0 = 2skf$ have important amplitudes in comparison to the component presented in Figure 3(a), which are clearly shown in Figure 3(b) and (c), respectively. The spectrum analysis of the proposed current signal $i_{TK}(t)$ with the frequency range 90–110 Hz is illustrated in Figure 4, the
components $2f \pm f_0$ with a difference of $2\beta < 1$ have amplitudes lower than those obtained in the first term corresponding to the components $f_0 = 2skf$ as mentioned previously in (17) for all cases of the three generators.

Actually, the presented technique distinguishes accurately the frequency associated with the BRB defect, coverage the medium range of load conditions. The leakage from the main frequency component has been removed from these spectra. Moreover, the aim frequency is detected in the spectra of the suggested signal $i_{TK}(t)$ exactly at its predictable value $f_0 = 2skf$ and $2f \pm f_0$, in place of sidebands of the fundamental current component, as in the MCSA.

4. Results and Discussion

The TKEO is an easy algorithm, tentatively centralized and able, with suitable signal restrictions of accuracy, to track the instantaneous magnitude and the instantaneous frequency of the signal. At the same time, DESA-2 presents a few computational complexity, which has proved that in case of signal with constant magnitude and linear phase, there are no approximation errors. As declared in Section 3.3, the DESA-2 algorithm can just amount to frequencies up to one-fourth of the sampling frequency of the data, so it is a disadvantage of this technique. For the special situation of the studied stator current data in this paper, the sampling frequency of 10 kHz has demonstrated to be very low for the estimation of the frequency bandwidths of the data that were most sensitive to damage, as shown in Figures 2 and 3.

Through the Hilbert transform study that has been previously presented in [1], [17], [18], [16], [20], [34], [35], this transform is fully not local, and all the samples are required to be calculated with Hilbert transform at each point. The calculation of the Hilbert transform of a
Figure 3. Spectrum of $i_{TK}(t)$ based on the TKEO in frequency range 0–10 Hz: (a) normal generator; (b) defective generator (1 BRB); and (c) defective generator (2 BRBs).

The purpose of this study is to use a recent signal processing method for the condition monitoring of a SCIG-wind turbine BRB. The TKEO is an energy tracking

defects presented on the rotor, and also appropriate for real-time implementations.

The sampled current requires the analysis of direct and inverse FFT, with a computational cost $O(N \log N)$, where $N$ is the number of samples. This method has not a great computation complexity that are existing in other methods, and it is able to distinguish the kind and the number of

Figure 4. Spectrum of $i_{TK}(t)$ based on the TKEO in frequency range 90–110 Hz: (a) normal generator; (b) defective generator (1 BRB); and (c) defective generator (2 BRBs).
algorithm, combined with the DESA-2, it can be used to estimate the instantaneous frequency and the amplitude envelope of a signal. It was shown that the TKEO has the advantages of high-resolution and low-computational requirements as an algorithm in comparison with other algorithms such as Hilbert transform algorithm and DESA-2, but it has the disadvantage of inability to estimate frequencies higher than one-fourth of the sampling frequency. In the case of the signal processing of the SCIG-wind turbine stator current data, the datasets used were taken at a sampling frequency of 10 kHz which has not been proved to be satisfactorily high enough. Despite the fact that in this particular case, the TKEO failed to estimate specific frequency components of the signal that were important for the condition monitoring of the BRB, this method can be used successfully, with the condition that the measurements should be taken at sampling frequencies that can satisfy the algorithm’s needs or by using different approximation methods for estimating the instantaneous frequency, resulting in the appropriate trigonometrically expressions, for example, methods similar to the DESA-1 algorithm can be used to accomplish the good performance of the TKEO and to overcome the drawbacks faced during its application under the aforementioned conditions and situations. In this case, the TKEO could be a good alternative to other time–frequency methods, offering higher resolution and much lower computational complexity.

5. Conclusion

In this work, the TKEO has been used as a stator current signal pre-treatment, with the main objective to ensure its accurate demodulation and the suppression of the fundamental component before the application of the PSD estimation, with an extremely low-computational cost. In this direction, the defect components can be simply and accurately detected within the consequent spectra, also in critical conditions in which the classical MCSA method may be unsuccessful. Another useful characteristic of TKEO, which is related to its conduct when processing impulsive data, is introduced. The TKEO can be applied as a post-treatment of the spectrum used for fault detection. For this situation, it represents as a nonlinear, signal-dependent filter and amplifier. So, in the proposed method, the TKEO is used not just as a pre-processor for demodulating the defect signal before its spectral analysis, and as a post-processor for increasing the SNR of the resultant spectra. The suggested technique has been proved mathematically and it has been verified in a PC-based diagnostic system under induction generators with BRB that have been used to implement the experience verification of the suggested technique.

References


and fault detection of electrical machines.

A. Bouzida, O. Touhami, R. Ibitrour, A. Belouchrani, X. Boqiang, L. Heming, and S. Liling, Sensitive and reliable


M.Q. Duong, F. Grimaccia, S. Leva, M. Mussetta, and D. Camarena-Martinez, C.A. Perez-Ramirez, M. Valtierra-

A.C. Bovik, J.P. Havlicek, M.D. Desai, and D.S. Harding, Image demodulation using mul-


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