On the novel approach to the On Load Tap Changer (OLTC) diagnostics based on the observation of fractal properties of recorded vibration fingerprints

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Abstract— **On Load Tap Changer contacts are the only movable, and thus the most sensitive part of the power transformer. Over time several diagnostic methods for condition assessment of these contacts have been developed. Some of them are based on invasive procedures, such as dynamic resistance measurement, while others are less invasive, such as those based on observation of the vibration fingerprints. Fractal geometry is an interesting way of describing non-regular shapes, whose rapid development began in the late seventies. The aim of this paper is to investigate the possibility of applying fractal geometry to OLTC vibration fingerprints for the purpose of extracting useful diagnostic materials.**

Keywords—OLTC; diagnostics; vibration; fractal dimension;

I. Introduction

Movement of the OLTC contacts causes vibration of its chamber. The most intensive vibrations are usually sensed on the OLTC cover, and a vibration sensor (accelerometer) can be used to record these vibration fingerprints. The question is how to process these signals in order to draw conclusions about the state of the observed contacts. To be able to apply algorithms that are based on artificial intelligence and which will be able to answer the given question, the common approach is to extract some numerical values from the recorded signals. The problem is that these fingerprints usually express high complexity, which makes it very difficult to perform this extraction in the time domain. As these are also highly non-stationary signals, in theory, analysis in the frequency domain is not the best approach. Regardless of that, some authors have successfully used this approach, applying frequency analysis on the parts of the recorded signals where they can be considered more or less stationary [1][2]. On the other hand, a very popular method is also analysis in the time-frequency domain. Such an approach is mostly used to extract moments in time in which the new/dominant frequency content appears. These methods are usually based on the time-frequency Wavelet approach [3][4][5], or similar methods such as empirical mode decomposition (EMD) [6], etc. Also, non-linear methods were used in some previous works, such as [7], where Lyapunov exponents are used for OLTC contact condition assessment. Most researchers have concluded that for analysis of OLTC vibration signals it is enough to observe frequencies up to several tens of kHz. In addition, in previous works, some preprocessing strategies were used, such as the application of some filtration methods or extraction of the signal envelope. Such methods are helping in reducing signal complexity before application of the developed extraction method. This paper will also investigate if such preprocessing strategies can be useful for the proposed method based on fractal properties of the recorded vibration fingerprints.

II. Signal Preprocessing

Since extraction of the signal envelope is the most commonly used approach as a signal preprocessing strategy, we present here some basic information about this methodology. By definition, the signal envelope represents a smooth curve outlining its extremes. The goal is to compromise between reducing recorded data set complexity from the one hand, and the loss of the useful diagnostic material from the other. If this compromise can be achieved, it is desirable to use this procedure, since usually such an approach simplifies the next step – extraction of the desired numerical parameters.

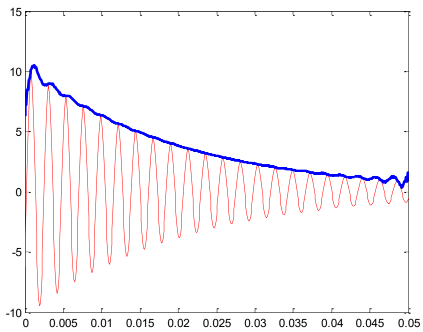

Fig. 1. Oscillatory signal (red) and its envelope (blue)

Several standard methods can be used for signal envelope extraction: Hilbert transformation, squaring signal and usage of low pass filter, application of Teager operator - which estimates current signal energy, etc. However, in this paper we will discuss the possibility of using the Hilbert transformation. In literature this transformation is introduced through several approaches. One of the most popular is the one that uses a convolution integral [8]:

<u>Def.</u> The Hilbert transform of a real-valued function x(t) extending over the range $-\infty < t < +\infty$ is a real-valued function $\hat{x}(t)$ defined by:

$$\hat{x}(t) = \mathcal{H}\big(x(t)\big) = \int_{-\infty}^{+\infty} \frac{x(u)}{\pi(t-u)} du \tag{1}$$

So, it represents convolution of function x(t) with function $y(t) = 1/\pi t$:

$$\hat{x}(t) = x(t) * (\frac{1}{\pi \cdot t}) \tag{2}$$

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Hilbert transform is used for the signal envelope extraction. For that purpose analytical function z(t) is formed, where:

$$z(t) = x(t) + j\hat{x}(t) \quad (3)$$

The last term can also be written in the following form:

$$z(t) = A(t)e^{j\Theta(t)} \quad (4)$$

Where, A(t) is called the envelope, and $\Theta(t)$ is called the instantaneous phase signal of x(t). Considering this, it is obvious that the signal envelope can be extracted through:

$$A(t) = [x^2(t) + \hat{x}^2(t)]^{1/2} \quad (5)$$

III. FRACTAL GEOMETRY

A. Introduction

In his essay [7], Benoit B. Mandelbrot, an author whose almost entire scientific work was related to researching fractal geometry, and who was also responsible for the name of the fractal (derived from Latin, fractal -> fractus -> latin Fanger - "to break": to create irregular fragments), observes that shapes created by nature do not fully follow Euclidean form, on which standard geometry is based. According to Mandelbrot, the behavior of nature might not even be characterized by a higher level of complexity compared to standard geometry. Therefore, nature behavior represents the whole new level of complexity. Such thoughts have led him to leave the Euclidean form, in search for a new ways of describing natural phenomena. For the purpose of fairness, it is worth noting that the Mandelbrot's work was not isolated in this field and is a continuation of previous achievements (Hausdorff, Besicovitch, Richardson, etc.). However, it can be stated that the Mandelbrot has first formalized these forms and set strong foundations for further development in this interesting field. In the mentioned essay, Mandelbrot states that the concept of fractals is the best to be left without any definitions (in his earlier essay [10] from 1977, even he did not use any). As a main reason for such approach stands the fact that any definition would not be able to fully embrace all the sets that one would like to see in such description. A parallel can be drawn with the complex numbers, whose definition failed to exclude the real numbers.

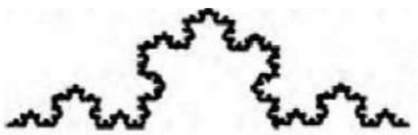

Fig. 2. Koch curve , k=4

However, one way to define fractal form is through the concept of self-similarity, which is one of the fundamental properties of fractal objects. Therefore, according to Mandelbrot, concept of self-similarity informally can be introduced through the following observation: *when each piece of a shape is geometrically similar to the whole, both the shape and the cascade that generate it are called self-similar.* But, such definition is often misunderstood. Self-similar shapes are perceived as beautiful, almost artistic forms, and they definitely have fractal characteristics and are also called fractal forms. However, one should be aware of existence of two forms of self-similarity, standard and fractal. As an example of standard self-similarity, we can take any portion of a straight line and it will resemble the whole, but further detail will not be revealed. Very often the Koch curve, showed in Fig. 2, is taken as a representative example of a self-similar fractal object.

Despite, the concept of the fractal induced by Mandelbrot refers to a much broader concept which exceeds the idea of self-similarity. This concept can be strongly related with the term fractal dimension (FD), which will be introduced below.

B. Fractal dimension

In his work, Mandelbrot focuses on two dimensions - topological D_T, which is more intuitive, since in n dimensional Euclidean space R^n this dimension corresponds to its dimension n, and another called the Hausdorff-Besicovitch, dimension D, which was initially defined by Hausdorff in 1919, and brought into the final form by Besicovitch, and later named the fractal dimension. D_T is always an integer, while D does not have to be one. A fractal can also be defined as an object for which the Hausdorff-Besicovitch dimension exceeds its topological dimension. Mandelbrot also states that each set with non-integer value D is a fractal. If these shapes are defined in Euclidian space ($E<\infty$), they are usually called Euclidian fractals. However, there is a problem even with this definition and it refers to the border cases. For instance, a curve that has D=1 can still be called a fractal or non-fractal object. Since fractal geometry has already been the subject of different studies over the last 40 years, the aim of this paper is not to go too deep into mathematical definitions and the structural description of fractals, but rather to introduce the reader with some basic concepts before they are applied to specific problems. A purely mathematical approach in this case could obscure the essencecover the essence, thus, we believe that a less formal description can contribute more to this purpose. Here, the concept of fractals will be introduced through the illustration used in [11]: "Consider an object. One has to take an element of this object. One has to surround it with a sphere of a given radius R and count the amount of R object elements inside the sphere. The measure of R can be arbitrary. Here, of importance is only the dependence of D on the sphere radius after averaging over the element of time and its origin. This definition takes into account the fact that the relevant dimension of an object depends on the spatial scale. A fundamental characteristic of fractal objects is that their measured metric properties, such as length or area, are a function of the scale of measurement.*"*

Sometimes, this illustration may be insufficient to fully understanding the concept of fractals. Therefore, they can be introduced through a more plastic approach, used in Mandelbrot's work, which is actually a continuation of research of the Richardson effect described in 1969, in his posthumously published paper [12], in which he expressed very strange observations in estimating the length of the border between Spain and Portugal, or Belgium and the Netherlands. The differences in the measured border lengths, conducted by government agencies of different countries, show deviations of up to 20%. Mandelbrot observes that the basis of this deviation lies in the arbitrary selection of the scale ε that was used for the purpose of these measurements. Later, it turned out that there is a link between the scale ε, and length L, which can be described by the following relation:

$$L(\varepsilon) = K^{\varepsilon(1-D)} \quad (6)$$

Where K is a constant, and D is described as fractal dimension observed fractal structure (boundaries). It turns out that fractal dimension D introduced this way does not correspond to anything in the standard geometry.

Such an observation can also be applied to self-similar objects. If we take a set A in Euclidean n-dimensional space, then the definition of the self-similarity could be rephrased in the following formulation: A is self-similar if A represents the union of N non-overlapping copies of itself, where each copy is scaled according to the ratio r in all coordinates. Mandelbrot defined the fractal dimension of such a set through the next equation:

$$D = \frac{logN}{\log(\frac{1}{r})} \tag{7}$$

This equation actually represents the similarity dimension of the observed set A. For instance, it is (relatively) easy to prove that for the Koch cure its Hausedorff dimension is actually equal to its similarity dimension. Such proof can be found in [13]. It should be noted that in many cases it is very difficult to calculate the fractal dimension defined this way, so usually some estimation methods are used for its evaluation. Today, many computer algorithms have been developed to estimate the fractal dimension of a certain form.

It turns out that a large number of phenomena in the real world have fractal properties. OLTC vibration fingerprint is a very complex form, which can be perceived as a fractal object. Our assumption is that its fractal dimension is also a carrier of useful diagnostic information.

C. Higuchi algorithm

In 1988, T. Higuchi in [14], described the algorithm for estimating the fractal dimension of the set of points (t, f(t)) of some function f defined over the unit interval.

Higuchi observed a finite set of time series observations taken at a regular interval:

$$X(1), X(2), X(3), \dots, X(N) \tag{8}$$

and constructed a new time series, X_k^m, defined as follows:

$$X_k^m: X(m), X(m+k), X(m+2k), \dots, X\left(m + \left[\frac{N-m}{k}\right] \cdot k\right) \tag{9}$$

where m=1,2,...,k.

If the curve length for the interval k is defined as:

$$L_m(k) = \left\{ \sum_{i=1}^{\left[\frac{N-m}{k}\right]} (|X(m+ik) - X(m+(i-1)\cdot k)|) \cdot NF \right\} / k \tag{10}$$

Where $NF = \frac{N-1}{\left[\frac{N-m}{k}\right] \cdot k}$ represents normalisation factor in the observed subinterval, then total cuve length can be calclulated from:

$$< L(k) >= \sum_{m=1}^{k} L_m(k) \tag{11}$$

According to Higuchi, if:

$$< L(k) > \propto k^{-D} \tag{12}$$

then D represents the fractal dimension of the observed curve.

Accuracy and calculation time of the proposed algorihtm will obviously depend on paramter k_{max} which defines the maximal length of the observed subinterval.

Before Higuchi, Burlaga and Klein in [15] defined the so called BK method for FD estimation. Higuchi pointed out that his algorithm is more accurate than BK's algorithm, since the BK method is based on the operation of averaging the time series prior to calculating the curve length. Several other algorithms have also been developed, such as Katz [16] or Petrosian [17]. A nice comparative analysis on the performance of these algorithms is given in [18]. When estimating FD with one of these algorithms, one should also be aware of their limitations regarding the available amount of data and numerical or experimental noise sensitivity.

IV. Proposed Diagnostic Method

A. Introduction

By reviewing previously published papers on OLTC diagnostics from vibration signals, we have learned that several authors as the most important diagnostic parameters idenify: the number of vibration bursts in the observed signal, time distances between these bursts and their amplitudes. However, these parameters are often very hard to extract, since real signals are highly non-stationary and also contaminated by external noise.

Let us assume that it is possible to isolate several interesting zones (time intervals) in the observed vibration fingerprint, such as those caused by OLTC contact movement or mechanical spring discharging.

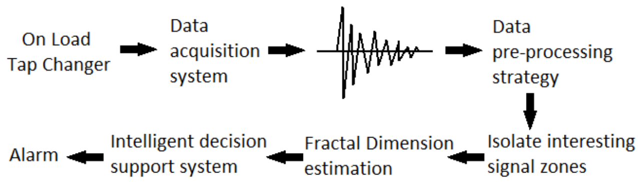

Fig. 3. Schematic representation of the proposed diagnostic system

Then, we propose separate observation of signal fractal properties in each of these intervals separately. Such a procedure would allow the extraction of several numerical values that would represent the level of signal complexity in each interval. Our assumption is that mechanical degradation over time could be observed by looking at changes in these numerical values. In that case, a diagnostic system based on artificial intelligence would be able to monitor these degradations and issue an alarm in case anything suspicious appears. Such a system would have to be designed so its decision-making process is based on the embedded a priori knowledge gained through the previously conducted experiments. This approach would allow not only detection of possible failures, but also detection of the early stages of the degradation of the state of the observed object. Therefore, the proposed system could be schematically represented in Fig. 3.

Unfortunately, the development of such system would require a lot of time. In the moment of writing this paper we were not able to conduct the necessary amount of experiments the results of which would serve as a foundation of such a system. That is the reason why we decided on a slightly different approach: verification of the proposed method on the syntactical data set, and comparison of vibration fingerprints of different tap positions. The first one should use as a proof that degradation of the synthetic signal can be observed by the FD, and the second one as proof that real vibration fingerprint manifest fractal properties, and that through the FD we can distinguish transitions between the different tap positions under various measuring conditions.

B. Method verification on synthetically generated signals

In [19], the authors have modeled OLTC vibration fingerprint through the sum of the damped sinusoidal components. Thus, the synthetic signal, that approximates acceleration signal caused by OLTC contact movement from one to another tap position, was induced through the next equation:

$$a(t) = \sum_{i=1}^{n} A_i e^{-\alpha_i (t-t_{0i})} \cos(\omega_i (t - t_{0i})) \quad (13)$$

Also, the tree time intervals in the vibration fingerprint have been identified. These intervals can be associated with different mechanical and electrical events that occur during OLTC operation: interval (a) contacts friction and the electric arc, (b) relates to unloading of the spring, and (c) corresponds to the system accommodation time. The authors concluded that at least 3 sinusoidal components were needed for a reliable signal reconstruction. Power spectral density was used for identification of the dominant frequencies, while RLS (Recursive Least Squares) algorithm was used for identification of other parameters. These parameters were used for comparison between new and old contacts, or good and improper ones. Based on the given results in [19] we have reconstructed each of these intervals for new and old contacts and generated syntactical signals which will be used for testing the proposed diagnostic technique based on signal fractal properties.

TABLE I. SELECTED PARAMETER VALUES FOR SYNTACTICAL SIGNAL RECONSTRUCTION

f_1=200 Hz	**New contacts**	**Old contacts**
A_i	Higher, selected: 0.05	Lower, seleted: 0.04
α_i	Lower, selected 17	Higher, selected: 21
t_i	Lower, Selected: $8*10^{-3}$	Higher, selected: $10*10^{-3}$
f_1=440 Hz	**New contacts**	**Old contacts**
A_i	Higher than 0.02, selected: 0.03	Lower than 0.015, selected: 0.01
α_i	No difference, selected: 22	No difference, selected: 22
t_i	No difference, selected: $8*10^{-3}$	No difference, selected: $8*10^{-3}$
f_1=740 Hz	**New contacts**	**Old contacts**
A_i	Higher, selected: 0.1	Lower, selected: 0.01
α_i	Higher, selected: 35	Lower, selected: 25
t_i	Higher, selected: $11*10^{-3}$	Lower, selected: $6*10^{-3}$

Due to limited space we have decided to only show analysis in the interval (a) that was characterized as the interval which carries the most useful diagnostic information. Signal length in this interval is around 20ms. Selected values are presented in Table 1. Based on this, reconstructed signals for the new and old contacts are shown in Fig. 4.

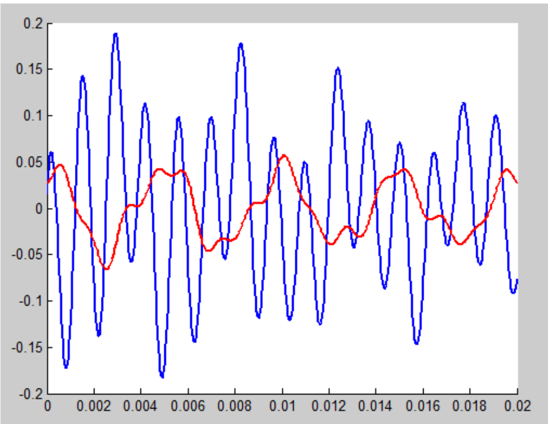

Fig. 4. Reconstructed signals: (blue) new contacts, (red) old contacts

The highest frequency that appears in the signal is 1kHz. Since the diagnostic system is usually based on some kind of digitizer, it is necessary to determine the optimal sampling rate. Parameter k_{max} for calculation of FD using Highuchi algorithm should also be determined. In that case all calculation will be conducted with the same parameters which will allow data comparison. Theoretically, at least 2kHz is needed for reliable 1kHz signal reconstruction. On the other hand, the length of interval (a) is only 20ms, which means that with a 2kHz sampling rate, the available number of samples is only 40. That is the main reason why we are proposing at least a 5kHz sampling rate. To determine k_{max}, and its dependency on the sampling rate, we have selected several sampling rates which are integer multiples of the lowest proposed frequency ($n \cdot 5$ kHz, n=1,2,...,6). Higuchi algoritm implemented in Matlab software package was used for calculating FD on reconstructed signal for new and old OLTC contacts for different values of k_{max} and different sampling rates (represented by different colors). Fig. 5. shows the dependency of differences between estimated FD for new and old OLTC contacts from parameter k_{max}/n.

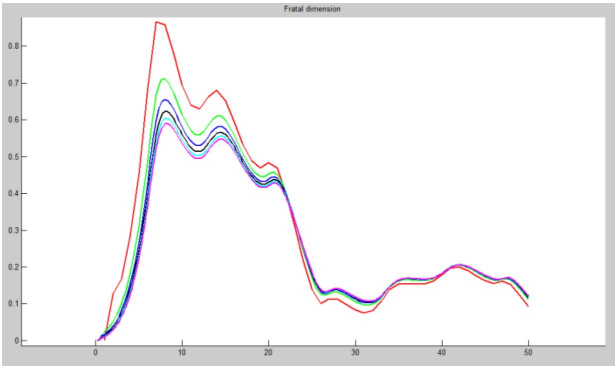

Fig. 5. Differences between estimated FD's for new and old contacts

Based on this we can conclude that k_{max} should rise as sampling frequency (number of samples) rises. On the other hand, the biggest differences are obtained for $k_{max} = n \cdot 7$, while, generally speaking, steady state is obtained for $k_{max} \geq n \cdot 25$, where n represents the selected multiple of the proposed minimum sampling rate of 5 kHz. Such an observation can be connected with the lowest frequency that appears in the signal. For instance, at a sampling rate of 5kHz, the period of the lowest interesting frequency component (200Hz) is 5ms, which at this sampling rate represents 25 samples. For $k_{max} = n \cdot 25$, calculated differences in estimated FDs for vibration signals of old and new contacts are around 0.1. Still, as parameter k_{max} rises, oscillations in these differences can be observed. These oscillations can be explained by the available amount of data, limited by the observed interval (a), whose time length is only 20ms. Even though the goal is to maximize differences in the estimated FDs, so deviations could be easily spotted, we cannot rely on the value $k_{max} = n \cdot 7$ where these differences are obviously maximal, since this could produce unstable results. That is the reason why we are proposing a sampling rate of 10 kHz, and $k_{max} = 60$, which seems a good compromise between the amount of the needed diagnostic data from one side and deviations in estimated FD from the other. Fig. 6. (blue) shows the deviation of differences of FD estimates for new and old contacts in the contact aging process, where aging was simulated through slow changes in sinusoidal parameters that were used for the signal reconstruction. This simulation was performed through the linear deviations of these parameters with each new iteration. A total of 100 iterations was selected. However, it should be noted that the real signal probably will not deviate this way, but such simulation can be useful in understanding the proposed method. Fig. 6. clearly shows that the contact aging process can be monitored through monitoring differences in estimated FDs. Since the real signals are also always effected by some external or measurement noise, to test the method's resistance to these influences, white Gaussian noise, with a selected value of 20dB for signal-to-noise ratio, was added to the reconstructed synthetic signals. Fig. 6. (red) shows how this noise affects the obtained results.

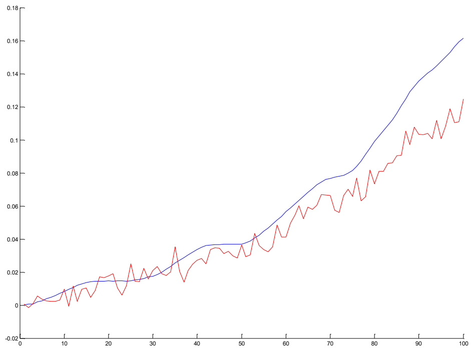

Fig. 6. Simulation of contact aging process

In both cases, due the contact aging process, the differences between estimated signal fractal dimensions are increasing, which leads to the conclusion that the proposed method could be used by the diagnostic procedure, either independently or as an addition to other methods. The increase in the differences between FD estimates can be explained by the reduction of the complexity of vibration fingerprints in the contacts aging process. The advantage of such an approach is obvious because it provides only one numerical parameter per observed signal zone whose degradation should be observed. Yet, for now we have only discussed the contact aging process. The next step is to investigate if the same logic could be applied for failure detection.

Since the signal envelope extraction through application of Hilbert transform was the most used preprocessing method in related works, we wanted to see if this method could also be useful for the proposed procedure. For every iteration, the envelope of the reconstructed signal was first extracted, after which differences between fractal dimensions of new and old contacts were calculated. Fig. 7. shows these differences for 100 iterations, which represent the contact aging process.

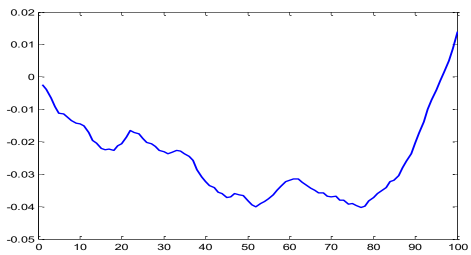

Fig. 7. Simulation of contact aging process with envelope extraction

It is obvious that envelope extraction simplifies observed forms, which leads to reduced complexity, but also causes reduced differences for the calculated FDs. Further, the contact aging process in this case is not represented by a monotone increasing curve as it was in the previous case. To conclude, it is obvious that such simplification is not desirable for the proposed method.

V. REAL OBJECT TESTING

Unfortunately, in the moment of writing this paper we were not able to conduct verification of the proposed method on the OLTC contacts whose condition is a priori known. Simply, for such verification we would need to have access to several real-life objects, whose condition is already known or predetermined by applying some other diagnostic method. Such verification would also require many experiments to be conducted and a lot of data to be gathered in the field. Our intention is to do that in the near future.

Anyhow, we managed to conduct several experiments on a real test object, where we recorded OLTC vibration fingerprints for contact transition between several different tap positions. For that purpose, an industrial accelerometer, with a measuring range of ±50g, and sensitivity of 100mV/g was used. Signals were sampled at a 10 kHz sampling rate.

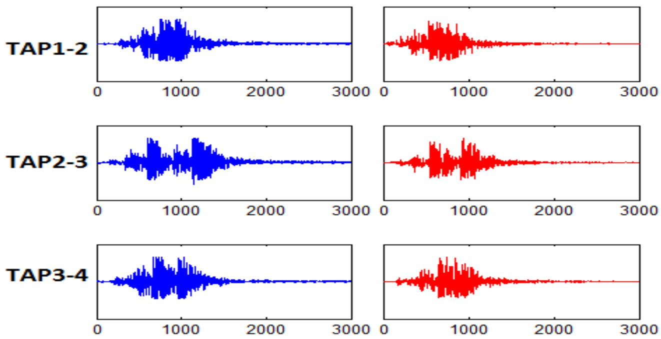

Fig. 8. Vibration fingerprints for TAP positions 1-4 with different accelerometer mounting methods

One of the problems with vibration diagnostics technique [20] in general lies in the repeatability of test conditions, especially with (offline) methods that require sensor reinstallation for each new measuring procedure. Signals can be affected by many factors: installation point, nearby noise in the given time interval or even by the sensor installation method. Some commonly used accelerometer mounting methods are based on permanent magnet or usage of mounting wax. Unfortunately, these different installation methods can affect accelerometer performance and bandwidth, which can lead to different frequency content in the obtained signals.

Both of these installation methods have been used in conducted experiments. For every measurement, a sensor was installed at the same measuring point. Fig. 8. shows obtained vibration fingerprints with a sensor installed with the help of a magnet (red) or Petro mounting wax (blue). As can be seen from the given figure, obtained vibration fingerprints with different measuring methods are very similar to each other. However, when looked closely enough, differences can be noticed, and it can be seen that the fingerprint recorded with an accelerometer mounted by wax is "richer", especially with higher frequency content. The goal of this experiment was to investigate how Higuchi algorithm will handle these samples, and if calculated FD can help to distinguish different tap positions. For this purpose, k_{max} was chosen in a range of 1000 to 1500 and FD was estimated with the help of Higuchi algorithm. Fig.9 (right) shows estimated values for different records. Considering this, it can be noted that estimated FD for different mounting methods follow the same pattern as k_{max} rises. However, a small offset between them is noticeable, which can be explained with different frequency content in signals.

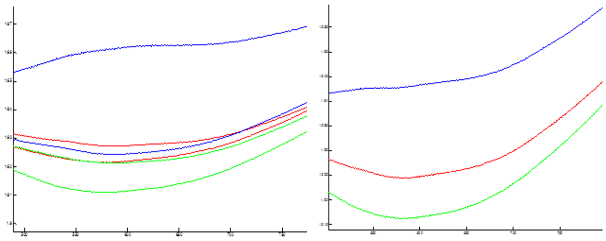

Fig. 9. Comparison vibration fingerprints for different TAP positions

Obviously, regardless of the chosen sensor mounting method, using FD estimate, it is possible to distinguish different TAP positions. Fig. 9 (left) demonstrates this better. Diagrams on the figure represent average values of estimated FD for different measuring methods. One should take into account that these TAP positions are quite similar to each other. That is the reasons why differences between estimated FDs are also not so big, but are still noticeable (at the second decimal point).

VI. Conclusions

OLTC vibration fingerprint is a very complex form that expresses fractal proprieties. Fractal dimension is an important parameter that characterizes fractal objects and reveals the level of their complexity. However, FD is usually estimated through usage of some algorithm. By using Higuchi algorithm applied on the syntactical data set, which was used for simulation of the OLTC aging process, we have successfully showed that the FD estimate can be used for tracking OLTC degradation over time. Our assumption is that this parameter could also be useful in OLTC condition assessment and detection of early failure stages. Also, it has been shown that reducing signal complexity is not a desirable preprocessing strategy for FD estimation, since it also reduces observed differences. Due to a limited amount of available verification data, we decided to test Higuchi algorithm by comparing vibration fingerprints of different TAP positions for two different sensor mounting methods. Obtained results show that with even different frequency content, which is the result of the influence of the sensor mounting method, FD can be used to distinguish these TAP positions.

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