IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received May 2, 2019, accepted June 10, 2019, date of publication June 19, 2019, date of current version July 12, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2923809

Vibro-Acoustic Methods in the Condition Assessment of Power Transformers: A Survey

ADNAN SECIC[1,2], (Student Member, IEEE), MATEJ KRPAN[2], (Student Member, IEEE), AND IGOR KUZLE[2], (Senior Member, IEEE)
[1]DV Power, 181 25 Lidingö, Sweden
[2]Faculty of Electrical Engineering and Computing, Department of Energy and Power Systems, University of Zagreb, 10000 Zagreb, Croatia

Corresponding author: Adnan Secic (adnan@dv-power.com)

This work was supported by the Croatian Science Foundation under project WINDLIPS—WIND Energy Integration in Low Inertia Power System under Grant HRZZ-PAR-02-2017-03.

ABSTRACT It has been over two decades since the publication of pioneer works about the power transformer diagnostics based on monitoring of their acoustic fingerprints. Since then, there has been great progress in this field and the methods used are as complex as ever. Any unnecessary intervention on a power transformer implies its temporary disconnection from the power grid. The inability to supply electricity to the customer means not only financial loss for the utility but also generates a non-material loss, e.g., the loss of reputation to the customer. Faster, more accurate, more reliable, and less invasive diagnosis is the main reason behind development and improvement in this field. The main goal of this paper is to categorize and review state-of-the art of vibro-acoustic diagnostic methods for power transformers. This paper opens with a brief note about continuous condition monitoring, after which we overview the causes of transformer vibrations as well as the collection and preprocessing of diagnostic data. Then, we review and categorize works related to the acoustic condition assessment of power transformers considering both: feature extraction in the time, frequency, time-frequency domain, and mathematical modeling and system identification of dynamic systems.

INDEX TERMS Power transformers, power system faults, power system reliability, fault diagnosis, maintenance, acoustic emission, acoustic signal processing, acoustic measurements, acoustic sensors, vibrations.

NOMENCLATURE

AE	Acoustic emission.
BREMD	Band Restricted Empirical Mode Decomposition.
BSS	Blind Source Separation.
CWT/DWT	Continuous/Discrete Wavelet Transform.
DC	Direct current.
DFT	Discrete Fourier Transform.
EMD	Empirical Mode Decomposition.
EEMD	Ensemble EMD.
FFT	Fast Fourier Transform.
HHT	Hilbert-Huang Transform.
HSA	Hilbert Spectral Analysis.
HF	High frequency.
HV	High(er) voltage.
ICA	Independent Component Analysis.
LF	Low frequency.
LV	Low(er) voltage.
MFEMD	Multiple Frequency EMD.
OLTC	On-load tap changer.
PCA	Principal Component Analysis.
PD	Partial discharge.
PWT	Probabilistic Wavelet Transform.
RMS	Root Mean Square.
SNR	Signal-to-noise ratio.
SOMs	Self-Organising Maps.
STFT	Short-Time Fourier Transform.
TEO	Teager Energy Operator.
TIFROM-BSS	Time-frequency ratio of mixtures — Blind Source Separation.
UHF	Ultra high frequency.

The associate editor coordinating the review of this manuscript and approving it for publication was Shunfeng Cheng.

I. INTRODUCTION

Preventive maintenance of machinery and other objects is becoming more and more suppressed by continuous monitoring. Such trends are not only noticeable in engineering, but in other areas as well, e.g. medicine: there are more and more systems that provide continuous monitoring of single human organs and, consequently, early detection of diseases. There are many reasons for this: on the one hand, rapid development of technology enables continuous data monitoring, big data storage, faster, more complex and more reliable data analysis; development of complex monitoring systems and their interconnection allows the formation of data clusters which describe certain physical phenomena as a result of mechanical, thermal, electromagnetic or other types of processes inside or outside the observed object. On the other hand, sensors are getting smaller and less power intensive, e.g. the development of sensors based on micro-electro-mechanical systems (MEMS sensors). Furthermore, easier and faster access to stored data enables an intelligent approach to condition assessment because it can now be based on previously gained experiences and allows the application of artificial intelligence or machine learning. In doing so, obtained data can be grouped in the appropriate clusters based on the same object design characteristics which leads to the formation of databases that can be used in experimental frameworks for further development of diagnostic methods.

Thus far, this approach has been proven to be reasonable and justified. The requirements for improved system uptime, reliability and availability of the future smart grid calls for the shift from time-based or condition-based maintenance towards the maintenance based on continuous online monitoring of the equipment operating conditions [1]. Increased requirements also point to the need of the ability of such monitoring solutions to inform about potential failure even before it happens as well as provide ongoing maintenance recommendations. An excellent paper on transition from offline to online transformer winding deformation diagnostics is one from Bagheri *et al.* [2], where they classify winding deformations, give an overview of both offline and online methods and then address practical problems of their implementation.

A continuous online monitoring system has to meet several goals. One of the most important goals is that the applied methods should not interfere with the normal operation of the monitored object. Also, they should not require any special mode of operation. Many published papers on this subject (and this seems like a trend in the modern diagnostic approach) are about the analysis of acoustic signals. This is quite logical because the collection of such data sets generally represents a non-invasive method.

One can state that the most sensitive part of a power transformer is the on-load tap changer (OLTC). This conclusion stems from several surveys carried out on the national and international level that studied the reliability of power transformers. First survey conducted by CIGRÉ published in 1983 [3] analysed data from 13 countries. Data has shown that about 41% of failures were due to the OLTC (Fig. 1). Given that the OLTC contacts are the only movable part of the transformer and that every mechanical movement is accompanied by occurrences such as friction which cause wear & tear and ultimately damage to the contacts, it is no wonder that OLTC is a very common cause of failure. Besides OLTC, common causes of failures on power transformers are short circuits and deformations of its windings. According to the aforementioned study, core, windings and OLTC failures constitute 63% of all observed failures. Some newer compiled failure statistics [4] (transformer failure data from 22 countries) show progress in the reliability of the OLTC (27%), but there is still a high percentage of failures connected to windings (40%) and core (3.4%) (see Fig. 1). This is precisely the reason why this paper focuses on vibro-acoustic diagnostic methods for these three parts of the transformer.

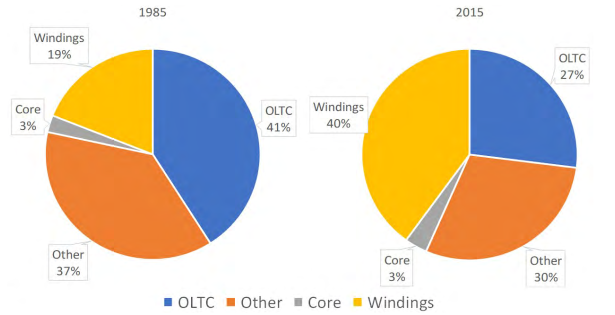

FIGURE 1. Power transformer failure location analysis from 1983 report [3] and 2015 report [4] .

Precisely speaking, vibro-acoustic methods should also include acoustic methods related to partial discharge (PD) detection. Partial discharge causes occasional breakdowns in electrical insulation. PD activity causes several physical effects including optical (light), thermal, chemical, electromagnetic and other phenomena. Such breakdowns in turn also cause the appearance of the acoustic waves that can be monitored by appropriate sensors placed on the tank of the transformer. However, issues related to PD are beyond the scope of this paper.

Rest of the paper is structured as follows: in section II a brief overview of causes behind transformer vibrations is given; in section III, diagnostic data collection and preprocessing are discussed; sections IV and V are the focus of the work and here the literature on vibro-acoustic methods for condition assessment of power transformers is surveyed. In section VI, the surveyed literature is summarised in a table format and taxonomy is provided. Section VII concludes this paper. In the end, in Section VIII, we provide a glimpse towards future.

II. CAUSES OF TRANSFORMER VIBRATIONS

Main cause of transformer core vibrations is magnetostriction-a property of ferromagnetic material to change its shape under the influence of a magnetic field. Magnetostrictive stress vs. magnetic induction curve of iron can be approximated with a quadratic formula (Fig. 2) since the magnetostrictive stress is proportional to the square of the magnetic induction [5]–[7]. Thus, it also correlated to the square of the applied voltage. On the other hand, current through the transformer windings induces axial, radial and combined Lorentz forces which try

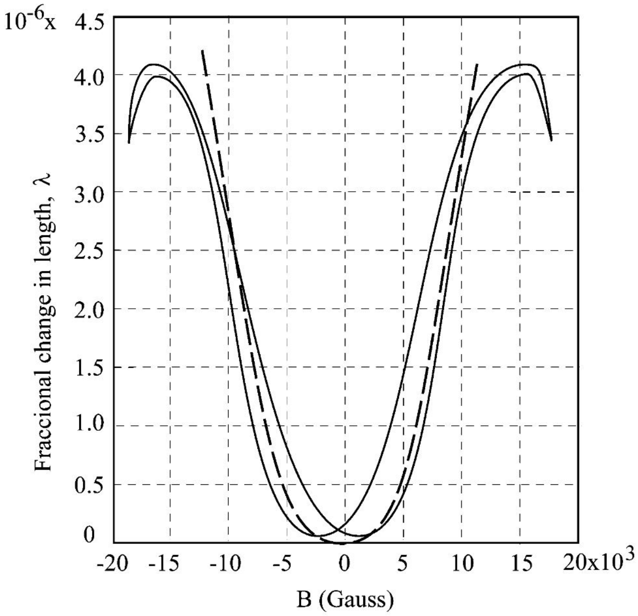

FIGURE 2. Iron magnetostriction as a function of induction–taken from [6] .

to compress and stretch the windings, respectively [5]–[7]. Lorentz forces are proportional to the square of the current. Voltages and currents are mutually dependent and since they cause transformer core and windings vibrations, respectively, bulk of the works in this field treat the problem of diagnosing these two vibrations simultaneously.

Transformer core and windings vibrations propagate through the transformer oil and reach the transformer housing which will also, in turn, start vibrating. The viscosity of transformer oil as well as any rigid structures (reflection) affect the propagation of vibrations towards the chassis. Therefore, all these issues must be taken into account when choosing the appropriate sensors and points for sensor placement to perform the measurements.

Motion of the OLTC contacts will cause vibrations that can be sensed on the OLTC housing. Ageing of the contacts or early occurrence of a defect (deformation) cause changes in the vibration pattern. Therefore, by analysing these signals it is possible to establish a diagnostic method which can be used to evaluate the condition of the OLTC contacts, without disassembling its chamber. It is possible to detect faults in the OLTC tap selector and the diverter switch by means of vibration measurements.

III. DIAGNOSTIC DATA COLLECTION AND PREPROCESSING

A. DIAGNOSTIC DATA COLLECTION

In the majority of the surveyed literature, the authors used commercial accelerometers for recording vibration signals. These sensors typically have a limited linear frequency bandwidth as well as a resonance bandwidth with the corresponding resonance frequency. The frequency of observed phenomena should be adjusted to the bandwidth of the sensor. It is important to note that the mounting method of the sensor to the object can directly affect the accelerometer's HF operating range, e.g. the characteristics of M608A11 commercial accelerometer provided in the manufacturer documentation (Fig. 3).

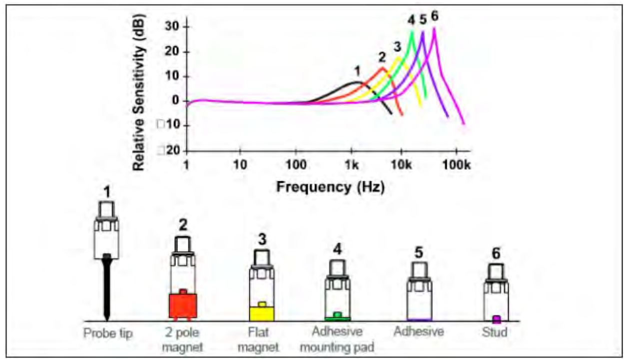

FIGURE 3. Effects of mounting configurations on high-frequency response for commercial accelerometer M608A11 [8].

Thus, for accurate diagnostics, it is crucial to choose not only the appropriate sensors but also to pay attention to the mounting method and how it affects the sensor's frequency response. Furthermore, the ability to synchronise measurements when multiple sensors are used is also crucial. Additionally, different physical phenomena can manifest themselves in the acquired signals and, as will be shown later, a lot of authors employed auxiliary measurements in their acquisition systems (e.g. OLTC motor current, temperature, OLTC motor rotor angle in [9]). The location of the sensors is also very important and in many papers authors sought the optimal sensor location by trying to maximise signal-to-noise ratio (SNR) or by mounting the sensor as close to the source of vibrations as possible. Since the sensors are mounted on HV objects, additional precautions in the form of electrical insulation can be taken if necessary. For example, Sanz-Bobi *et al.* [10] covered every electrical contact with silicone and every sensor cable was inserted in a fibreglass envelope to address the insulation and electromagnetic issues for the sensors installed inside a transformer.

Hydro-Québec's experiences in OLTC diagnostics have been reported in [11]. They used a vibro-acoustic sensor mounted on the OLTC tank as close as possible to the OLTC diverter switch. OLTC motor current was used for triggering the tap change measurement. Field experience showed that the vibro-acoustic signature is significantly affected by ambient temperature, and it was reported that a switching time of a healthy OLTC is increased by 26 ms at ambient temperature of -11°C compared to the ambient temperature of 27°C and that this could be erroneously interpreted as a faulty condition. The recorded signature was compensated for the temperature using first-order time-realignment technique [12]. Alongside accelerometers and OLTC motor current measurements, Brikci *et al.* [13] also used a high-speed camera to record OLTC movement and dynamic resistance measurements.

To summarise, the following issues must be addressed in order to conduct quality diagnostics of a power transformer:

- sensor mounting method;
- synchronisation of measurements if multiple sensors are utilised;
- prediction and understanding of underlying physical phenomena which can be manifested in the collected signals;
- sensor location;
- sensor insulation.

Experimental results demonstrate that for the proper diagnostics of transformer core and windings based on vibro-acoustic measurements it is usually enough to observe the frequency spectrum in the range up to 1 kHz [14], [15], although harmonics up to 2 kHz were observed in [16] and [17]. On the other hand, OLTC diagnostics require observation of a higher frequency range-up to 10 kHz [18], although some authors [19]–[21] observed a much higher frequency spectra (even up to several hundreds of kHz) in order to be able to apply some digital filtration techniques, or to be able to observe not only acoustic events of the mechanical origin, but also other events, e.g. emergence of electric arc or events related to PD activity. PD analysis is usually performed in the UHF spectrum (300 MHz–1 GHz). However, during the process of PD inside the transformer tank, some part of the electrical energy from the PD pulse (about 1–5%) is converted to the mechanical energy, which results in the emission of the acoustic wave [22]. This fact is used by acoustic emission partial discharge monitoring methods, where emitted waves are captured by piezo-electric sensors mounted on the external wall of the transformer tank. The dominant frequencies observed of recorded PD signals typically lie in the range of 70 kHz to 180 kHz [23], which are quite higher when compared to the signals generated by transformer vibrations or OLTC operation. Besides accelerometers, some researchers also used other types of sensors such as hydrophone [19] or strain gauge sensors [24].

In [25], a 2 mm thick fibre-optics vibration sensor was successfully installed in the gap between the windings of a power transformer to measure axial vibration. The sensor accurately registered vibration frequencies between 5 Hz and 1000 Hz. Kung *et al.* noted that by splicing a single mode fibre to the Fabry-Perot cavity, the whole fibre acts as a vibration sensor and can function without a "diving board".

An interesting study was conducted in [19] where the authors compared samples that were gathered simultaneously from several sensor types mounted in/on the OLTC. Besides the standard accelerometer, a hydrophone and a wide-band contact transducer were used as well. Power density spectrum analysis showed a number of differences between these signals. The signal recorded with the hydrophone contained frequencies with the largest share in the band 0–50 kHz and such a signal is not reliable for establishing diagnostics because the transducer is very sensitive to electromagnetic interference in that frequency range due to the current through OLTC's contacts. On the other hand, a signal acquired with a wide-band transducer, that contains frequency components in the range 10 kHz–500 kHz is the best choice for OLTC diagnostics as it also allows analysis of acoustic emission (AE) signals during current flow and electrical discharges when higher frequency components are present. However, time domain plot shows that hydrophone captures events that are not so evident in the signal gathered with contact sensor types. Also, by using a hydrophone immersed in oil it is possible to avoid contact problems demonstrated in Fig. 3. Beltle and Tenbohlen [26] also used a hydrophone immersed in transformer oil and an accelerometer mounted on the transformer's tank. Although the hydrophone shows better SNR compared to the accelerometer, the inaccessibility of insulation oil as a medium in which the hydrophone should be immersed makes this sensor less attractive compared to the contact sensor types. Signal acquired with an accelerometer contains low frequencies in the range 0–10 kHz and thus it only allows analysis of AE signals of the mechanical origin. However, the accelerometer is the most commonly used type of sensor in the vibro-acoustic OLTC diagnostics.

Finally, accelerometer output is usually a voltage signal that contains some unwanted frequency content. That is the reason why this signal needs to be passed through a series of high pass and low-pass hardware or software filter. Filter designer should pay special attention to the accelerometer resonant frequency, at which its' maximum sensitivity is achieved. These sensors require external supply and their output signal is usually measured in mV so proper gain is also required in the signal acquisition stage.

B. DIAGNOSTIC DATA PREPROCESSING

In the data preprocessing stage, the goal is to transform recorded data in order to facilitate further analysis and comparison. Diagnostic data are usually collected from multiple sensors. Therefore, one should take into account that acquired signals should be synchronised. This leads to the conclusion that the acquisition system should be designed so that it includes reliable trigger sources. Normalisation of the collected data is also very important, as it allows easier comparison. Data preprocessing stage can be roughly divided into the following sequence of steps:

1) Removing DC offset.
2) Normalising the amplitude.
3) Isolating the individual events.
4) Resampling the signals.
5) Synchronization of signals.
6) Signal envelope extraction.

DC offset can be removed through a high-pass filter or by subtracting the mean value of the signal from each sample. (1) normalises the recorded signal to obtain unit amplitudes:

$$x_n[k] = \frac{x[k]}{\max\{|\mathbf{x}|\}}; \quad k \in \{1, \ldots, N\}, \tag{1}$$

where $\mathbf{x}$, $x[k]$, $x_n[k]$ are the recorded signal amplitude array of N samples, amplitude of the k^{th} sample and the normalised amplitude of the k^{th} sample, respectively. If the recorded signal contains multiple events, e.g. switching between different tap positions in OLTC, then it useful to split the recording into multiple signals each corresponding to a certain tap transition, i.e. one signal for transition from tap 0 to tap 1, one signal for transition from tap 1 to tap 2, etc.

If different recording systems with different sampling frequencies have been used, in order to compare the two signals, it is necessary to resample them to a common sampling frequency. One common method of resampling is by using a rational conversion factor L/M which first increases the sampling frequency L times and then reduces the sampling frequency M times. L/M is basically a ratio between the two sampling frequencies. From signal theory, it is known that each of the above steps has to be complemented by an appropriate filter: interpolation filter and anti-aliasing filter. Block diagram of such a resampling technique for small rational factors is shown in Fig. 4 [27], where L and M are the upsampling and downsampling blocks, respectively. $H_I(z)$ and $H_d(z)$ are interpolation and anti-aliasing filters, respectively. F_{in} and F_{out} are the sampling rate of input and output signal, respectively.

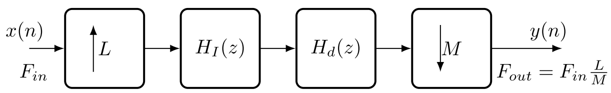

FIGURE 4. Resampling with a rational conversion factor [27] .

Since both H_I and H_d filters are cascaded and operate at the same sampling frequency, both of these low-pass filters can be combined into a single low-pass filter $H(z)$ with the stopband edge frequency equal to (2):

$$\omega_s T = \max\left\{\frac{\pi}{L}, \frac{\pi}{M}\right\}. \tag{2}$$

In order to completely synchronise two signals, a discrete cross-correlation method can be used (3). Cross-correlation is a measure of similarity of two functions and is similar to a convolution of two functions.

$$(x_1 * x_2)[n] := \sum_{-\infty}^{\infty} x_1^*[m]x_2[m+n], \tag{3}$$

where x_1^* is a complex-conjugate of x_1 and m is a discrete time-shift.

High complexity and nonlinearity is observed in the results shown in numerous papers dealing with OLTC diagnostics. That is the main reason why researchers attempt to simplify these signals while at the same time trying to keep as much useful diagnostic material as they can. The most common approach is the extraction of the signal envelope from the analysed vibration fingerprint. There are several methods that allow one to do that. Most commonly used method is the Hilbert transform [28]. Other noted methods include signal squaring with low pass filtering, usage of TEO, RMS envelope or Peak envelope using spline interpolation over local maxima separated by at least N samples.

The complete OLTC operation for one tap transition usually takes around a few seconds, while the most interesting diagnostic interval, the one correlated with the OLTC diverter switch operation, usually takes much less (from 40 ms to 250 ms). As this is a very short period of time, and by taking into consideration OLTC position in relation to other elements of the substation, in most cases it is not necessary to take into account the impact of other machines on the collected vibration signals. However, it should be noted that in the case of audio-based diagnostics, challenges arise with transformer energising because the audio signals will become contaminated by the noise produced by the transformer and related equipment. The same applies to the analysis of the vibration or audio signals gathered from a transformer tank. The interval in which these data are collected is usually much longer and signals can be affected by other machinery. Such cases include switching on/off oil pumps, cooling systems, OLTC, etc. All these occurrences impact diagnostic signals and special care should be taken here.

C. DATA ANALYSIS AND DECISION STAGE

According to the surveyed literature, two basic approaches are used in this stage:

- the extraction of relevant features from the gathered data set and decision making process based on observing their values in:
  - time domain;
  - frequency domain;
  - time-frequency domain;
- mathematical modelling and system identification followed by the decision-making process based on the selected model.

Therefore, in the following sections these approaches are analysed separately: for both the OLTC and core/windings diagnostics. Table 1 shows a summary of different methods used for vibroacoustic condition assessment and their applications.

IV. EXTRACTION OF RELEVANT FEATURES

The extraction of relevant features leads to reduced data dimensionality. It is often necessary to use some kind of decision making process in order to classify the data based on the extracted features. Methods such as PCA can also lead to the additional data dimensionality reduction. Sejdic *et al.* [29] have organised feature extraction and decision making using signal processing techniques according to Fig. 5.

Here, a classification of feature extraction methods in three subgroups has been made, depending on the domain in which the collected data are analysed. The reader will notice that various signal processing techniques (e.g. Wavelet and Fourier transforms, TEO, HHT, etc.) are often used in the surveyed literature and therefore they are often mentioned throughout this text. No special introduction to these techniques will be written because it is beyond the scope of this paper, however the reader is referred to the following literature [28], [30]–[34] or any other signal processing textbook.

TABLE 1. Comparison of used methods for vibro-acoustic condition assessment.

Feature extraction	Used methods	Application
Time domain	Low pass and high pass filtration, signal energy estimation, fractal dimension	Early works, signal smoothing and filtering for simplification and feature extraction—mostly on OLTC
Frequency domain	Fast Fourier Transform (FFT)	Feature extraction mostly based on the highest signal harmonics and their relations. Special attention paid to coupling effects between nearby AC and HVDC transmission lines and their impact on transformer vibrations.
Time-frequency domain	STFT, DWT, CWT, Hilbert spectrum, EMD, BSS	Mostly used for the analysis of the vibration signals recorded on the OLTC due to their high non-stationary behavior. Source separation technique used for extraction of the useful source signal.
Mathematical modelling and system identification	Grey box model, ARX model, Hammerstein and Hammerstein-Wiener model, Chaos theory	Mathematical model parameter identification and comparison of the model outputs with the signals obtained from the real system.

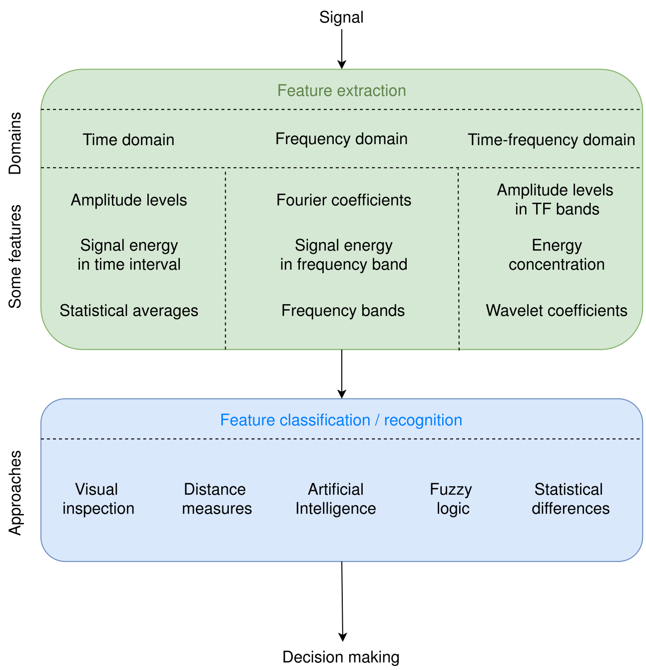

FIGURE 5. Signal processing techniques for feature extraction and decision making [29].

A. TIME DOMAIN

The length of recorded signals from OLTC, as well as their shape, allows extraction of some diagnostic features by observing these signals only in the time domain. On the other hand, signals recorded from the transformer tank usually require some kind of transformation which allows easier feature extraction.

1) OLTC

The first experiences in this field were described in [35]–[38]. In addition to the OLTC vibration signals, the motor current was also recorded which was used for triggering the recording device. What was perceived here is that mechanical and electrical events manifest themselves through signals in completely different frequency bands—electrical events, such as the appearance of an electric arc, are associated with higher frequencies, while mechanical events, such as friction and synchronisation problems, are associated with lower frequencies. High complexity of the acoustic fingerprint was noted, so the authors resorted to envelope extraction using the Hilbert transform. To separate electrical and mechanical events, this transform was performed on two different data sets separated. It was suggested that the decision stage should be based on the comparison between new and previously obtained records (online testing) or on the comparison of records without any OLTC load (offline testing). Combination of both methods was suggested as the best practice. It is possible to draw some conclusions this way, but this method requires experienced and knowledgeable testing personnel, which is usually not the case in the field. It is precisely why such requirements have led to the further evolution of the diagnostic methods towards smarter systems that would enable easier detection of potential issues.

DWT and TEO were used in [39]–[41] for envelope extraction to reduce complexity after collecting the vibration fingerprint. Properties derived from the auto-correlation function were used as input parameters for Self-Organising Maps (SOMs), which is a type of an artificial neural network used to classify and organise data. Experience showed that vibration fingerprint varies for each OLTC tap position and SOMs automatically classify the data according to their similarities. A priori knowledge was used to train the SOMs to carry out this automatic data classification. This principle implies that a large number of tests should be carried out on the objects that are in the healthy as well as those in the faulty state. Moreover, for objects that are in the faulty state, one should have a priori knowledge about the type of defect present. Five different OLTC conditions were observed that were used as classifiers in the SOMs:

- normal condition;
- weak springs;
- worn moving contacts;
- worn moving and fixed contacts;
- weak springs plus worn contacts.

Moreover, it was noticed that an alteration of OLTC condition is most often a gradual process rather than a sudden change. Crossing the defined threshold value of OLTC condition criterion activates an alarm that something is wrong. The main purpose of the design was to avoid false alarms. This design was successfully tested on a system that was in operation for three years at the time.

In [42], experiments were conducted on a transformer that was removed from the operation, so the authors were able to record vibration fingerprints for all 10 OLTC tap positions. Hilbert transform and a low-pass filter with a cut-off frequency based on Kolmogorov's complexity measure were used for signal envelope extraction. As there was no reference vibration fingerprint for the tested OLTC, one way to perform diagnostics is to compare different tap positions. The goal is to find a tap position that is most correlated with all the others. Finding such a position allows the comparison of the vibration fingerprint for each individual tap positions with that one. By doing so, the authors concluded that there are some differences between tap positions caused by their frequent use. This approach can be used to perform diagnostics in cases when measurement history is not available. However, it should also be noted that some OLTC tap positions are used more than others, which also implies that their wear will be more pronounced and all this will cause the differences between their vibration fingerprints.

Secic and Kuzle [43] proposed a diagnostic method based on signal fractal properties. Higuchi's algorithm was used on a signal envelope of a simulated OLTC vibration model from [44] to estimate the fractal dimension of the signal. By changing the model parameters, contact ageing was simulated and the results showed increasing differences between the estimated fractal dimension of a new and old OLTC contacts. This method can be used for diagnosing contact degradation and to distinguish between different mounting methods. However, no validation on OLTC contacts whose condition is a priori known has been conducted nor was the proposed algorithm tested for OLTC failure detection.

2) CORE/WINDINGS

A diagnostic technique based on time domain analysis of vibration stationarity was proposed in [45]. Vibration stationarity analysis is based on recurrence plot analysis where recurrence means a time in which the trajectory returns to a location it has visited before. System determinism is chosen as the transformer health criterion which is defined as the ratio of recurrence points that form diagonal structures to all recurrence points. The authors state that the system determinism value of a healthy transformer should be close to 1.

B. FREQUENCY DOMAIN

Vibration fingerprints obtained from OLTC display a non-stationary character and very high complexity. Frequency analysis therefore may not be the best tool for the analysis of these processes. Nevertheless, several authors have approached the problem from this perspective.

1) OLTC

In the frequency domain analysis of vibro-acoustic fingerprints of an OLTC, three papers have been found which differ in the type of decision making process utilized for the detection of the OLTC condition.

Rastgoufard *et al.* [24] observed sufficient differences between contacts in good and bad condition by observing the frequency spectrum of vibration signals recorded by strain gauge sensors mounted on the main drive arm of OLTC. Automatic detection of the OLTC condition was achieved with unsupervised fuzzy logic.

Bhuyan *et al.* [46] measured the dynamic resistance of OLTC contacts alongside the OLTC vibration fingerprint. The authors manually identified five different regions in the frequency spectrum using FFT which are separately used to distinguish contacts in good and bad shape, and contacts with increased electrical arcing. They showed that it is possible to recognise arcing and various defects in a single phase tap changer.

Hussain *et al.* [47] measured the OLTC motor current alongside the OLTC vibration fingerprint. An automatic expert diagnostic system was designed based on these signals and a knowledge database based on field experience. The main purpose of this system is to solve complex problems through reasoning based on a set of rules which minimises errors that can be caused by human factors in the decision making process.

2) CORE/WINDINGS

Significantly more papers deal with transformer core/windings vibration analysis in the frequency domain [10], [16], [17], [48]–[55]. Here, their conclusions and contributions are summarised.

Core/windings vibrations appear at multiple frequencies up to several kHz and the magnitudes of those frequency components are dependant on the external temperature. These frequencies appear as even, odd and rational multiples of the fundamental frequency and generally the most dominant components are 100 Hz and its integer multiples. Vibrations are highly correlated with the transformer loading and 100 Hz, 200 Hz and 300 Hz components are most sensitive to the loading of the transformer. Vibrations with frequencies <100 Hz are usually the product of cooling systems and oil pumps operation. Core vibrations caused by magnetostriction are non-linearly proportional to the applied voltage while the winding vibrations are non-linearly proportional to the current. Munir *et al.* [48] reported the dependency of vibrations to the square of the current, while Aidi *et al.* [52] found that the nonlinear properties of the insulation between the windings make the relation closer to the cubic representation. To separate the core (magnetostriction) and windings (Lorentz forces) vibrations it is best to do the measurements under no-load and under normal loading conditions [17] because the vibrations under normal loading are caused by both of those phenomena. Guo *et al.* [53] showed that even multiples of fundamental frequency harmonics appear under fastened core and odd multiples under slack core. Odd harmonics appear both under fastened and loose windings, but the intensity is different between the two cases.

Some guidelines regarding the core/windings vibration measurements were also defined in several papers [16], [17], [52]:

- reduction of the external noise can be achieved by: insulation between the sensor shell and the transformer's tank, shielding of the transmission cables and grounding of the measurement system;
- noise from the power supply lines can influence the measurements;
- measurement points should have a high correlation with the load current to better reflect vibration characteristics of the windings;
- when arranging the measurement points, one should take into account the structural features and flat surfaces of the transformer for better signals;
- stiffeners or other complex structures should be avoided;
- the sum of first four harmonics, the total harmonic distortion and the ratio between the amplitudes of the 50 Hz and 100 Hz harmonic are sufficient to establish good diagnostics and the estimation of the remaining service life of the transformer;
- best mounting position is at the top of the transformer oil tank with auxiliary measurement point at the side of the tank.

Li *et al.* [56] tackled the issues concerning laboratory testing due to the restrictions on the available power in the laboratory, but also the inability to dissipate large amounts of energy. They suggested a setup consisting of a current limiting resistor, a voltage regulator and a universal transformer whose LV side is connected to the LV side of the tested transformer.

Hong *et al.* [45] presented several health metrics based on DFT decomposition in the frequency domain.

As it was mentioned earlier in this paper, mounting method of an accelerometer impacts its frequency response. Additionally, the accelerometer is in direct contact with a high voltage objects and therefore it must be properly shielded from electromagnetic interference. This is why Zheng *et al.* [57] used a laser Doppler vibrometer to study the vibration of the windings. Four cases were studied: normal operating condition, different clamping pressures, loose insulation blocks and loose core clamping. Several conclusions have been drawn:

- radial vibration pattern of a healthy transformer is approximately bilaterally symmetric, while the radial vibration pattern of a transformer with faulty windings becomes asymmetric;
- looseness of winding clamping pressures or insulation block looseness are manifested as a change in vibration patterns at dominant frequencies;
- looseness in core clamping pressure doesn't affect the vibration pattern as much so the spatial variance cannot be used to determine the severity of the core looseness, but it is still detectable by observing the winding vibration distribution.

Very interesting observations were given in [26], [54], and [55]. These papers analyse the impact of geomagnetically induced currents and coupling effects between nearby AC and HVDC transmission lines on transformer vibrations. The Sun emits solar wind, which is basically low-density plasma that consists mostly of electrons, protons and alpha particles. These charged particles travel through the earth's atmosphere, causing variations in the intensity of the electrical field and creating a DC that can flow through the transformer's neutral. A similar effect is created by surrounding single-pole HVDC systems with the earth as a return conductor. The flow of DC causes increased magnetostriction, and may also lead to saturation of the transformer. Increased magnetostriction causes an increase of vibration intensity and additional losses through the occurrence of higher harmonics and reduction of reactive power. The conclusions of these studies are the following:

- 50 Hz component is present in the measured signal in the case when there is a DC flowing through the transformer neutral. This component is not present when there is no neutral current;
- amplitudes of the second and fourth harmonics increase as the DC increases;
- the shape and the intensity of the vibration fingerprint is significantly influenced by the DC;
- frequency analysis has shown shifting of the dominant harmonic and appearance of higher harmonics when the DC exists;
- authors propose monitoring additional inputs for condition assessment of the transformer: transformer load and DC through neutral.

C. TIME-FREQUENCY DOMAIN

This approach is mostly used in the analysis of the vibration signals gained from the OLTC that show high non-stationary behaviour. By observing such signals, one can state that Fourier analysis is not the best processing technique, not even the STFT, which by the introduction of the time window localises the Fourier transform of function $f(t)$ around the instant of time $t = u$ where the function can be considered stationary. Because of the character of the recorded signal, the used time window should be very narrow in order to consider this process stationary around the point $t = u$. The problem lies in the unavoidable Heisenberg uncertainty principle, which associates the width of the time window with the maximal width of the window in the frequency domain. The narrowing of the time window inevitably leads to the expansion of this window in the frequency domain, and to greater uncertainty in defining the frequency content or the complete loss of information (presence of a lower frequency). On the other hand, a too wide time window leads to a loss in precision. This is the reason why wavelet transform is used, in which the time window length is based on the appropriate frequency. This approach allows for an increase of the resolution while still satisfying the Heisenberg uncertainty principle. The selection of the optimal mother wavelet (kernel wavelet) plays a great role in the application of the wavelet transform. Several developed methods are based on the similarity of the observed signal and the mother wavelet. However, some studies show that such an approach is not always optimal. This is why several other techniques have been developed in order to get to the best solution, e.g. second generation Wavelets [58], which avoid eventual problems regarding the selection of the mother wavelet.

1) OLTC

CWT was used in [59]–[63] for the feature extraction from the OLTC vibration fingerprint. Kang and Birtwhistle [40] did a field evaluation over a period of three years with SOMs for data classification. They identified the establishment of reference vibration fingerprint as a practical problem in order to apply the monitoring system on a different OLTC. Viereck and Saveliev [63] showed several time-frequency images of the OLTC switching operation where different phenomena were clearly marked such as: preselector and diverter switch operation; transformer buzzing and 50 Hz disturbances of an energised transformer; impact of sensor mounting method; tap selector squeaking anomaly.

DWT was used in [18] and [64]–[68]. Based on the research conducted in [64] and [65], several accomplishments were pointed out by the authors:

- ability to differ between new and old (used) contacts;
- distinguishing vibration fingerprints of different tap positions;
- distinguishing between the following types of failures: loose contact springs, broken contact bar, worn out tap selector contacts and damaged tap selector contacts.

Filho and de Almeida [66] used SOMs for data classification to group data into 6 different clusters based on the wear level, faulty condition, etc. The main advantage of this method is that it provides information on the gradual degradation of the contacts condition, and that such info can be used by an online monitoring system.

In [68], besides OLTC vibration, a high frequency current transducer was used for measurement of the arcing signal for improved diagnostics. This signal was used as an additional diagnostic information that helps to clearly identify events in the OLTC switching operation that are manifested in the vibration fingerprint. Modified form of wavelet transform, called Probabilistic Wavelet Transform (PWT) [69] was used for segmenting arcing signals and noise.

Besides the obviously popular wavelet transform, several papers were found in which time-frequency domain was used but in which the authors approached the matter differently [9], [20], [21], [70]–[73]—the following methods or their combinations have been used or mentioned: EMD, Hilbert Transform, HHT, HSA, EEMD, BREMD, MFEMD. These methods were used to tackle the problems of highly non-stationary nature of the signals and to improve the precision of the diagnostics. CWT, DWT and STFT have also been used in [20], [21], [71], and [72] for the extraction of the diagnostic material. Li *et al.* [73] reported the shortcomings of the existing vibro-acoustic diagnostic methods when electrical faults without obvious mechanical vibration are being diagnosed, such as contact terminals fault and contact resistance anomaly. They proposed a method based on measuring the current waveform of an OLTC, for which they state it contains rich diagnostic information. Two faulty OLTCs have been analysed and their time-frequency spectrum shows rich frequency content compared to a healthy OLTC whose waveform is mainly composed of 50 Hz component.

FIGURE 6. Field setup of condenser microphones for recording the OLTC audio signature.

So far, all the surveyed research used accelerometers or AE sensors which require direct contact with the transformer or must be put inside the tank in the case of hydrophones. From our experience, the audio-based diagnostics is a relatively unresearched area which in our opinion is worth exploring. A method of recording the audio signal of the OLTC using an array of condenser microphones (Fig. 6) was tested in [74]–[76]. These papers deal with the extraction of the useful diagnostic material from a mixture of different audio signals and correlating audio signature with a vibration signature. Fast Independent Component Analysis Blind Source Separation (FastICA-BSS) was used to separate the useful diagnostic material from the surrounding noise. Some distortion in the estimated signal is unavoidable, and the real question is if this distortion will prevent diagnostic information extraction method in performing its task and how much it will affect the results. Using proper data extraction techniques and comparing original and estimated signals or using the OLTC reference audio fingerprint recorded in the de-energised state are some ways to tackle this issue.

2) CORE/WINDINGS

Classical ICA-based BSS recovers the different physical sources of a system given a set of external measurements assuming statistical independence of the sources. However, sources of transformer vibrations are highly correlated due to the mutual dependence of voltage (core) and current (windings). Therefore, Jing *et al.* [77] proposed a modified BSS algorithm named TIFROM-BSS (Time-frequency ratio of mixtures—blind source separation) which was used to separate the core and windings vibrations.

HHT was also used in [78] and [79], but in these papers it was applied on vibration signals obtained from the transformer tank. Xiong and Ji [78] concluded that for healthy

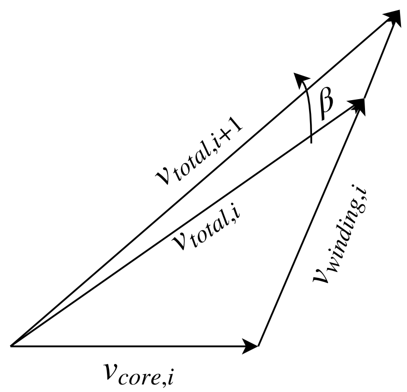

FIGURE 7. Fundamental frequency vibration variation between two samples [88].

transformers dominant frequencies in the Hilbert spectrum are 100 Hz, 200 Hz and 400 Hz, while for defected transformers the intensity of LF and HF components is amplified and for medium frequencies (oscillations around 400 Hz) it is decreased. These differences increase as the transformer defect is greater—the looser the core's clamp bolt is, the greater the frequency and energy content. In [79], before implementation of HHT, Wavelet Packet Decomposition (WPD) was used to minimise noise influence and to remove unwanted components from the signal. HHT is much more effective when it is preceded by WPD since in that case it is much easier to spot dominant frequencies and their time distribution. Hilbert spectrum showed dominant frequencies that are integer multiples of fundamental system frequency (50 Hz). Basically, the time-frequency domain approach shows similar frequency content to the one in papers in which the authors used pure frequency approach. However, this method probably has an advantage over the pure frequency approach as the time dependent frequency content can be observed along with the load variations in time.

In [80], a transient method was proposed in which the vibration signals are collected during switching the transformer from offline to idle mode. Aside normal operating condition, three more cases were studied: core with loose screws fixing the upper yoke, core with loose screws fixing both upper and lower yokes and core with loose screws fixing both yokes with simultaneous reduction of HV windings' clamping pressure. The advantages of this method are: immunity to loading current magnitude, significant independence between the vibro-acoustic signals and the type, power and construction technology of the transformer, elimination of disturbances from oil and air circulation appliances, insignificant influence of transducer mounting position. The downside of this method is that the transformer must be out of service, but this time is only around 10 minutes compared to several hours needed for offline diagnostics. The aforementioned defects can be easily discerned in the time-frequency spectrogram since each defect has idiosyncratic amplitudes and dominant harmonics.

V. MATHEMATICAL MODELLING AND SYSTEM IDENTIFICATION

Dynamic model of a system can be created either by knowing the physical description of the system or through a technique called system identification by using a predefined model structure (linear, nonlinear, time-variant/invariant, black box, grey box) and observed data (i.e. measurements of input and output signals). System identification is a widely used technique in online condition monitoring systems.

The condition monitoring system uses this model through the simulation process to generate reference outputs that can be compared to the outputs of the real system, under the same input conditions. If the identification procedure was carried out correctly and the model parameters match the real system, then high deviation between output of the mathematical model and real system should trigger alarm activation because this means that for some reason the system is not behaving the way it is supposed to. For basic overview of system identification, the reader is referred to [81]–[84].

A. OLTC

In [44] and [85], OLTC vibration fingerprint was modelled as a second-order spring-damper system (4):

$$m\frac{d^2x(t)}{dt^2} + c\frac{dx(t)}{dt} + kx(t) = 0, \tag{4}$$

where, $x(t)$, m, c and k are the linear displacement, mass, damping factor and spring constant, respectively. System exhibits an underdamped behaviour and a sum of three underdamped sine waves was used to approximate the vibration signals (5):

$$a(t) = \sum_{i=1}^{3} A_i e^{-\alpha_i(t-t_{0i})} \cos(\omega_i(t - t_{0i})), \tag{5}$$

where $a(t)$, A_i, α_i, t_{0i} are the vibration signal estimate, amplitude, damping coefficient and time delay (phase shift), respectively. The authors reported that using less than 3 sine waves is not precise enough and for more than 3, the algorithm becomes too slow without significant improvements

TABLE 2. Categorisation of the vibro-acoustic diagnostic techniques.

*	OLTC	Core/windings
Time domain	[11]–[13], [24], [35]–[43], [47], [76]	[2], [14], [26], [45], [50]–[52], [54], [55], [91]
Frequency domain	[24], [46], [47], [85], [96]	[2], [10], [14], [16], [17], [25], [26], [45], [48]–[57], [91], [97], [98]
Time-frequency domain	[9], [18]–[21], [59]–[68], [70]–[75], [99]	[2], [15], [77]–[80], [100]
System identification	[44], [86], [87], [101]	[6], [7], [88]–[90], [92]–[95], [102]

TABLE 3. Taxonomy of the OLTC diagnostics literature.

Reference	Year	Contribution	Feature extraction	Feature classification / recognition
[35]–[39]	1996–2000	Some of the earliest published papers on OLTC diagnostics based on observation of vibration fingerprints. It was observed that electrical and mechanical events are reflected in different frequency areas.	Time domain	Visual inspection
[40], [41]	2001	Usage of SOMs neural network for OLTC diagnostics	Auto-corellation	SOMs
[12]	2001	U.S. Patent for vibro-acoustic signature treatment process including the time-realignment technique for compensation of signal deviations that result from the aging process, temperature variations, etc.	Time deviation	Software supported comparison with the reference signature
[59]–[61]	2001–2003	Diagnostic data feature extraction method based on CWT. Field evaluations of data classification using SOMs.	CWT / Auto correlation	SOMs / Visual inspection
[24]	2002	Several diagnostic parameters in time and frequency domain and data clusters for unsupervised fuzzy clustering algorithms for online OLTC monitoring.	Amplitude levels	Fuzzy clustering
[64]	2005	An OLTC vibration fingerprint feature extraction method based on the energy ratio between the DWT approximation and detail coefficients.	DWT / Energy concentration	Visual inspection
[44], [85]	2005	Mathematical modelling of the OLTC vibration signal. Estimation of the parameters using a genetic algorithm or Prony's analysis.	Mathematical modelling	Visual inspection
[62]	2008	Portable LabVIEW-based virtual instrument for monitoring OLTC elements with CWT-based feature extraction.	CWT	Visual inspection
[66]	2008	Unsupervised learning technique based on SOMs and DWT-based feature extraction.	DWT	SOMs
[18], [65]	2009–2010	Methods for OLTC and OLTC tap selector condition assessment based on observing characteristic vibration bursts.	Amplitudes and time distances between vibration bursts	Distance measures
[20]	2011	Analysis of AE signals generated by the electric arc in OLTC in time-frequency domain.	STFT / WT / DWT	Visual inspection
[11]	2012	Field experience showing that temperature impacts OLTC vibro-acoustic signature and that rain can have a significant impact on $\tan \delta$ measurements.	Time domain	Visual inspection
[21], [71]	2012–2013	Experimental verification of an OLTC vibration-based diagnostic method based on time-frequency analysis of the recorded signals.	STFT	Visual inspection
[19]	2012	Performance comparison of different sensor types for capturing the AE signals.	STFT / Energy concentration	Visual inspection
[96]	2012	Fault diagnostics based on the Hidden Markov Model.	Frequency domain	Hidden Markov Model
[67]	2013	Analysis of AE signal energy and frequency range of a healthy OLTC	DWT / Energy concentration	Distance measures
[86], [87], [101]	2014–2017	OLTC condition diagnostic methods based on chaos theory	Chaos theory	Visual inspection / Fuzzy clustering
[46]	2014	Condition monitoring method based on dynamic resistance measurement and acoustic signature of OLTC	FFT	Visual inspection
[47]	2015	MATLAB based expert system based on observation of current and vibration waveforms for condition assessment of power circuit breakers and OLTCs.	Time domain and FFT	Database supported expert system
[13]	2015	Experimental proof of the correlation between OLTC dynamic resistance curve and the vibration signatures.	time domain and dynamic resistance measurement	Visual inspection
[42]	2015	Condition diagnostic method when historical data is not available.	Correlation coefficients	Similarity based on obtained numerical values
[63]	2016	Effects of accelerometer mounting method on vibration fingerprints	CWT and time domain	Distance measures
[70]	2016	Improved EMD method called MFEMD for more precise diagnostics	HSA	Similarity based on Lorentz Information Measure
[72]	2016	Diagnostic method based on time-frequency analysis of the recorded signals and experimental validation.	STFT	Visual inspection
[9]	2016	Software framework for online monitoring system based on a wireless sensor network and the measurements of vibrations, motor current and rotation angle of OLTC main drive shaft.	EMD / FFT	Visual inspection
[68]	2017	Improved vibration-based monitoring method based on the arcing measurement.	PWT	Visual inspection
[43]	2017	OLTC diagnostics method based on the fractal properties of the vibration fingerprints.	Fractal dimension	Distance measures
[74]–[76]	2018	Audio-based diagnostics method using microphone arrays	BSS / Mathematical modelling / Correlation	Visual inspection / Correlation
[99]	2018	Diagnostics method based on mean energy of the gray-scaled time-frequency images of the vibration signals.	CWT	Comparison of the energy-mean of the TF images

in precision. Following signal preprocessing, estimated parameters were amplitude, damping coefficient and the phase shift with minimisation of mean square error as the criterion (objective function). Genetic algorithm was used for optimisation of the criterion in [44] while Prony's analysis was used in [85]. Both of these methods have a low computational cost. However, it is noted in [85] that some contacts operate only a few times during their life cycle and in such cases Prony's method may not be able to establish good diagnostics.

Chaos theory was used for OLTC diagnostics in both [86] and [87] for distinguishing contacts with weak spring condition from those in good condition. For practical application, external influences such as temperature and load variations will affect the results, and they should also be taken into account.

TABLE 4. Taxonomy of the transformer core/windings diagnostics literature.

Reference	Year	Contribution	Feature extraction	Feature classification / recognition
[10]	1997	One of the first published papers that investigates the possibility of developing an online monitoring system of a power transformer based on vibration analysis.	Frequency domain	Visual inspection
[49]	2000	Diagnostic method that allows reliable evaluation of the residual clamping pressures in core and windings.	Frequency domain	Visual inspection
[16]	2001	Guidelines for selecting the appropriate sensors to eliminate electromagnetic interference in a test environment.	Frequency domain	Visual inspection
[17]	2004	Vibration analysis under load and no-load. Definition of several diagnostic indices which can be used for automatic decision making.	Several diagnostic indices	Numerical comparison
[6], [7], [88]	2005–2006	Tank vibration model that links fundamental vibration component with the transformer's current, voltage and temperature.	System identification	Comparison of the estimated and measured outputs
[50]	2006	A method that can separate fundamental frequency components of the core and winding vibrations under loaded transformer condition.	Time domain / Frequency domain	Correlation
[78]	2006	HHT-based condition monitoring method.	HHT	Visual inspection
[26], [54], [55]	2008–2012	Experimental analysis of the impact of direct current through the transformer neutral on transformer vibrations. Experimental proof of correlation between vibration harmonics and loading.	Time domain / frequency domain	Visual inspection
[51]	2008	Test setup for recording vibration signals using a multi-sensor approach.	Time domain / frequency domain	Visual inspection
[15], [79]	2009	Feature extraction method that combines the WPT and HHT.	WPT / HHT	Visual inspection
[94]	2012	Transformer core vibrations model for the development of vibration suppression measures.	System identification	Comparison of the simulated and measured outputs
[80]	2012	Method for analysing the transformer vibrations based on measurement acquisition during the transition of the transformer from offline to idle mode.	STFT	Visual inspection
[52]	2012	Theoretical and experimental analysis to determine the best position for installing the accelerometer on the transformer tank that will best reflect the state of transformer windings.	Time domain / frequency domain	Correlation
[48]	2012	Experimentally show that vibration harmonics are multiples of fundamental frequency and that they are proportional to the square of the load current. This correlation can indicate transformer health.	Frequency domain	Visual inspection
[89], [90]	2013–2015	The Hammerstein-Wiener model for parameter identification of tank vibration model.	System identification	Comparison of the estimated and the measured outputs
[14]	2013	Experimentally showed the correlation between the transformer's top-oil temperature and vibration amplitude. The authors have also investigated the dependency of the amplitude of some vibration harmonics on the load conditions over time.	Time domain / frequency domain	Correlation
[53]	2014	Simulation and experimental results led to the conclusion that the optimum mounting point for the vibration sensor is at the top of the oil tank. Slackness of the iron core and the windings are possible to discern from the vibration frequency spectrum.	Frequency domain	Visual inspection
[56]	2014	Vibration-based transformer winding simulation test method applicable for laboratory tests that takes into consideration the limited lab power capacity and the inability to dissipate large amounts of energy in the lab.	Frequency domain	Visual inspection
[77]	2014	An algorithm for separating the core and windings vibrations	TIFROM BSS	Visual inspection
[98]	2014	Feasibility study for monitoring transformers using an optical fiber system.	Chromatic analysis	Visual inspection
[57]	2015	A contactless method for measuring transformer vibrations based on the laser Doppler technique.	Frequency domain	Visual inspection
[91]	2015	Winding condition assessment method based on PCA and simple geometric relation between two close vibration samples	Time domain / frequency domain	Correlation
[92], [93], [95]	2016–2017	Core and winding vibration model using finite element modelling	System identification	Finite element modelling
[25]	2016	Vibration measurement method based on a thin fibre-optic sensor that can fit between the windings.	Frequency domain	-
[45]	2016	Four complementary and experimentally validated vibration-based diagnostic techniques.	Time domain / frequency domain	Distance measures
[100]	2017	Experimentally validated vibration-based diagnostic method for detection of loosening and loss of rigidity of the mechanical structure of the core.	STFT / CWT / DWT	Visual inspection
[97]	2018	Vibration-based Internet-of-Things system for monitoring the mechanical integrity of the power transformer.	FFT	Distance measures
[102]	2018	A real-time vibration-based model for prediction of transformer inter-turn short circuit fault and detection of over- and under-excitation	System identification	Absolute and relative errors

B. CORE/WINDINGS

Construction of a numerical model based on aforementioned spring damper concept was used to monitor tank vibrations in [6], [7], [89]. Basically, the used model was quite simple—it was constructed as the sum of the vibrations caused by the transformer core (proportional to applied voltage squared) and windings (proportional to load current squared). An additional variable was used to take into account temperature influence. The mathematical model is shown as (6):

$$v_{tank,100} = (\alpha + \beta\theta_{to})i_{50}^2 + (\gamma + \delta\theta_{to})u_{50}^2, \tag{6}$$

where $v_{tank,100}$, i_{50}, u_{50} are the complex variables that represent the tank vibration model at 100 Hz frequency, transformer current and voltage fundamental frequency components, respectively. α, β, γ, δ are transformer geometry-specific complex parameters obtained from measurements. θ_{to} is the temperature measured at the top of the oil.

For other potential sources of vibrations, such as oil pumps and fans that don't work in continuous mode of operation, a different set of model parameters can be used in order to describe the system when such elements are turned on because they shift the dominant frequencies in the frequency spectrum of the recorded signal. The proposed model was experimentally validated on a real system in [7]. A deformation of the transformer winding lead to a significant increase in model error.

Jing *et al.* [90] and Hong *et al.* [91] use standard Hammerstein-Wiener model type for nonlinear systems. These models are often used for systems where the input-output relationship can be decomposed into serial connection of static nonlinear input-output blocks and a dynamic linear block. Identification of the model parameters in [91] was done with a neural network. By using a neural network, it is possible to have less a priori knowledge of the system and that nonlinearity does not need to be predefined.

Winding condition assessment based on principal component analysis was proposed in [45] and [88] using the mathematical model of transformer core/winding vibrations from [6], [7]. Total vibration depends on the power factor between the fundamental voltage and current [45], [88], [89], thus the currents and voltages must be treated as complex variables. In practice, if the power factor angle fluctuation is less than 0.02 radians, the transformer current is the only factor that contributes to the total winding variation. Therefore, two close samples of transformer vibrations can be used to separate the winding vibration from the total vibration. This principle is illustrated in Fig. 7, where $v_{\text{total},i}$, $v_{\text{core},i}$, $v_{\text{winding},i}$ are the total vibration signal, core and winding vibration signals of sample i, respectively. The winding vibration variation from sample i to sample $i+1$ is denoted with Δv_w and β is the phase angle between the total vibration signals i and $i+1$. Winding vibration variation can then be expressed as (7):

$$\Delta v_w = \sqrt{v_{\text{total},i}^2 + v_{\text{total},i+1}^2 - 2v_{\text{total},i}v_{\text{total},i+1}\cos\beta}. \quad (7)$$

Works [92]–[95] deal with the electromagnetic vibration noise analysis of core and windings of a power transformer using finite element modelling. Additionally, Hu *et al.* [92] and Bouayed *et al.* [93] combined electromagnetic field analysis with mechanical field analysis and acoustic analysis. FFT analysis of the electromagnetic forces has shown that the most prominent harmonics are again 100 and 200 Hz, respectively. Furthermore, the core magnetostriction depends only on the magnetic induction and that the frequency of core magnetostriction is twice as that of the magnetic induction, i.e. twice the fundamental grid frequency.

VI. SUMMARY

Surveyed literature is categorised in Table 2 according to the type of analysis (time domain, frequency domain, time-frequency domain or mathematical modelling and system identification) and according to the observed transformer element (OLTC or core/windings). Note that some works also fall into multiple categories when more than one analysis technique has been used. Taxonomies of the OLTC and core/windings diagnostic techniques are given in Table 3 and Table 4, respectively.

VII. CONCLUDING REMARKS

This paper provides an overview of the current state-of-the-art in vibro-acoustic condition monitoring of power transformers with the focus on OLTC and transformers' winding/core diagnostics which are three elements that are responsible for over 70% of the all transformer failures according to the international statistics.

Non-invasive diagnostics are superior over the classical approach as it doesn't interfere with the regular operation of the object being tested. This opens a possibility of implementation of the continuous monitoring systems that will provide insights into the health condition of the monitored equipment at any moment, or inform about potential failure before it even happens. It can also provide the ongoing maintenance recommendations. In this sense, the logical choice is the capturing and analysis of the audio and vibrating signals produced by the tested object during its regular mode of operation. For that reason, this paper paid special attention to recent advancements in audio and vibration signal processing techniques and decision making processes whose complexity, but also the reliability is increasing with the advancements in research and development.

Audio/vibration-based diagnostics can contribute to the safety of test personnel and to the reduction of the labour costs. If these methods really prove effective, they will be welcomed by the utilities. However, it cannot be said that there is no resistance in adapting these methods in the field. The nature of this resistance can sometimes be rational. For instance, some utilities are not ready for big investments in the condition monitoring systems, but will rather turn to the short term solutions which can include engagement of the external consultants for one-time condition assessment of their currently installed equipment. Sometimes, these reasons can also be totally irrational. Engineers who are used to one way of thinking are often reluctant to change their habits. When asked about his opinion on online monitoring systems, the head of the test department in one of the big utilities in USA (with 20+ years of experience in diagnostics and testing) gave an interesting answer: *"I don't want to spend my time testing a monster that tests the monster"*, showing the complete distrust in the continuous monitoring systems, their communication channels, and the decision processes based on the artificial intelligence. He also believes that the human factor and its experience are still inevitable in terms of making decisions. Likewise, field engineers are just accustomed to the on-site diagnostics that can provide instant information about the need to conduct maintenance and the instant info on the possibility of re-commissioning after the maintenance procedure. From all of the above, it's easy to conclude that online monitoring systems will not be able to suppress classic diagnostic methods for a long time. However, the two approaches to the object condition assessment do not necessarily have to compete with each other. They may also complement each other, which will eventually lead to greater reliability and lower the risk of possible failures.

The combination of invasive and non-invasive diagnostic methods is already used, even in the offline monitoring approach. A typical example is the simultaneous measurement of the OLTC dynamic resistance and the vibration signals which is already implemented in some solutions. The last option for utilities is always disassembling the tested object. Therefore, any confirmation that leads to a better understanding of the health of the tested object is always welcomed. In terms of offline condition assessment, the goal is to spend as little time as possible in the test field. For that reason, in case of an offline test, we believe that the audio-based diagnostics can contribute to a faster test setup, as it doesn't require any connection with the object being tested. In addition to avoiding problems that may result from poor contact of the sensor with the test object, audio-based diagnostics allow greater location possibilities and even the possibility of recording the signals from a certain distance. We also believe that audio-based diagnostics could also enable "easily portable" recording systems that could be used for collecting the diagnostic material only for a certain period of time from one object during its regular exploitation after which the recording system can be easily transferred to another location. This can be seen as a much cheaper alternative to permanently installed monitoring systems. However, there are still some challenges in audio-based diagnostics that need to be overcome. These challenges are reflected in the unavoidable influence of the machine environment which is reflected through a mixture of the useful diagnostic material with surrounding sounds. However, the rapid development of the source separation techniques is promising and will certainly contribute to the application of these methods in the future.

Every diagnostic procedure must be followed by a good understanding of the physical processes that are taking place both within and around the test object. Good diagnostics imply not only the analysis of the signals, feature extraction and their classification, but also the understanding why something happens at a certain point in time and what could cause such phenomena. Therefore, simulation models that describe physical processes can greatly help in their understanding. Various computer programs that allow these kinds of simulations evolve daily and greatly facilitate this task. The obvious development of the signal processing techniques is reflected in the analysis of the acoustic signals in transformers' condition assessment. The evolution of these techniques allows the extraction of the features from signals that express a highly non-stationary behaviour. The same applies to future classification and pattern recognition methods. The obvious problem is the lack of the relevant fingerprints for different transformer/OLTC types. One way to increase the reliability of the already developed diagnostic methods and the future developments is to establish the relevant acoustic signature database that could be used by researchers and the utilities. That way the performance comparison between different methods could lead to the adaptation of the most reliable techniques. This obviously requires collaboration between the researchers and the industry.

VIII. WHAT DOES THE FUTURE HOLD?

We can not talk about the future without mentioning the fifth generation (5G) cellular network technology that provides broadband access. Wireless data transfer at speeds exceeding 1 Gbps at very low latency rates opens up a whole new spectrum of possibilities. 5G will also have a big impact on machinery diagnostics. Although there is already a possibility of rapid transmission of large amounts of data and their storage in the cloud, 5G will simply standardise the approach and impose itself as an unavoidable factor in many fields. Greater connectivity and data access from various remote locations will allow experts to share their experiences and revolutionise the diagnostic process.

For this reason, methods of collecting data which will not interfere with the regular operation of the transformer, OLTC or any other test object, such as those based on audio and vibration signal measurements, will become more and more interesting. Obviously, with the amount of the data being collected, big data and cloud computing are the technologies that will dominate the next decade in the field of diagnostics. The artificial intelligence will also become an inevitable factor in decision-making processes. Rapid development and progress of neural networks and deep learning comes at the right moment and will definitely have a big impact on future developments.

In any case, one interesting and exciting period is ahead of us.

REFERENCES

[1] G. J. Paoletti and G. Herman, "Monitoring of electrical equipment failure indicators and zero-planned outages: Past, present and future maintenance practices," in *Proc. Ind. Appl. Soc. 60th Annu. Petroleum Chem. Ind. Conf.*, Sep. 2013, pp. 1–9.

[2] M. Bagheri, M. S. Naderi, and T. Blackburn, "Advanced transformer winding deformation diagnosis: Moving from off-line to on-line," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 19, no. 6, pp. 1860–1870, Dec. 2012.

[3] Working Group 12.05, "An international survey on failures in large power transformers in service," CIGRÉ, Paris, France, Tech. Rep. ELT_088_1, 1983. [Online]. Available: https://e-cigre.org/publication/ELT_088_1-an-international-survey-on-failures-in-large-power-transformers

[4] Working Group A2.37, "Transformer reliability survey," CIGRÉ, Paris, France, Tech. Rep. 642, 2015. [Online]. Available: https://e-cigre.org/publication/642-transformer-reliability-survey

[5] A. Belahcen, "Magnetoelasticity, magnetic forces and magnetostriction in electrical machines," Ph.D. dissertation, Dept. Elect. Commun. Eng., Helsinki Univ. Technol., Espoo, Finland, 2004.

[6] B. Garcia, J. C. Burgos, and A. M. Alonso, "Transformer tank vibration modeling as a method of detecting winding deformations-part I: Theoretical foundation," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 157–163, Jan. 2006.

[7] B. Garcia, J. C. Burgos, and A. M. Alonso, "Transformer tank vibration modeling as a method of detecting winding deformations-part II: Experimental verification," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 164–169, Jan. 2006.

[8] A. Collet and M. Källman, "Pipe vibrations measurements," Energiforsk, Stockholm, Sweden, Tech. Rep. 2017:351, Feb. 2017.

[9] J. Liu, G. Wang, T. Zhao, L. Shi, and L. Zhang, "The research of OLTC on-line detection system based on embedded and wireless sensor networks," in *Proc. IEEE Int. Conf. High Voltage Eng. Appl. (ICHVE)*, Sep. 2016, pp. 1–4.

[10] M. A. Sanz-Bobi, A. Garcia-Cerrada, R. Palacios, J. Villar, J. Rolan, and B. Moran, "Experiences learned from the on-line internal monitoring of the behaviour of a transformer," in *Proc. IEEE Int. Electr. Mach. Drives Conf. Rec.*, May 1997, pp. TC3/11.1–TC3/11.3.

[11] P. Picher, S. Riendeau, M. Gauvin, F. Léonard, L. Dupont, J. Goulet, and C. Rajotte, "New technologies for monitoring transformer tap-changers and bushings and their integration into a modern IT infrastructure," in *Proc. CIGRE Symp.*, Aug. 2012, pp. 1–9.

[12] F. Léoçnard, M. Foata, and C. Rajotte, "Vibro-acoustic signature treatment process in high-voltage electromechanical switching system," U.S. Patent 6 215 408 B1, Apr. 10, 2001.

[13] F. Brikci, P.-A. Giguére, M. Soares, and C. Tardif, "The vibro-acoustic method as fast diagnostic tool on load tap changers through the simultaneous analysis of vibration, dynamic resistance and high speed camera recordings," in *Proc. CIGRÉ Condition Monitor., Diagnosis Maintenance*, Oct. 2015, pp. 1–9.

[14] M. Beltle and S. Tenbohlen, "Vibration analysis of power transformers," in *Proc. 18th Int. Symp. High Voltage Eng.*, Aug. 2013, pp. 1816–1821.

[15] S. Wu, W. Huang, F. Kong, Q. Wu, F. Zhou, R. Zhang, and Z. Wand, "Extracting power transformer vibration features by a time-scale-frequency analysis method," *J. Electromagn. Anal. Appl.*, vol. 2, pp. 31–38, Jan. 2010.

[16] J. Shengchang, S. Ping, L. Yanming, X. Dake, and C. Junling, "The vibration measuring system for monitoring core and winding condition of power transformer," in *Proc. Int. Symp. Elect. Insulating Mater.*, Nov. 2001, pp. 849–852.

[17] C. Bartoletti, M. Desiderio, D. D. Carlo, G. Fazio, F. Muzi, G. Sacerdoti, and F. Salvatori, "Vibro-acoustic techniques to diagnose power transformers," *IEEE Trans. Power Del.*, vol. 19, no. 1, pp. 221–229, Jan. 2004.

[18] E. Rivas, J. C. Burgos, and J. C. Garcia-Prada, "Condition assessment of power OLTC by vibration analysis using wavelet transform," *IEEE Trans. Power Del.*, vol. 24, no. 2, pp. 687–694, Apr. 2009.

[19] A. Cichoń and S. Borucki, "Diagnostics of technical condition on load tap changers by acoustic emission method using different types of measuring transducers," in *Proc. Int. Conf. High Voltage Eng. Appl.*, Sep. 2012, pp. 621–624.

[20] A. Cichoń, T. Borucki, T. Boczar, and D. Zmarzly, "Characteristic of acoustic emission signals generated by electric arc in on load tap changer," in *Proc. Int. Symp. Electr. Insulating Mater.*, Sep. 2011, pp. 437–439.

[21] A. Cichoń, P. Frącz, T. Boczar, and D. Zmarzły, "Detection of defects in on-load tap-changers using acoustic emission method," in *Proc. IEEE Int. Symp. Elect. Insul.*, Jun. 2012, pp. 184–188.

[22] W. Sikorski and W. Ziomek, "Detection, recognition and location of partial discharge sources using acoustic emission method," in *Acoustic Emission*, W. Sikorski, Ed. Rijeka, Croatia: IntechOpen, 2012, ch. 3.

[23] Z. Deheng, T. Kexiong, and J. Xianhe, "The study of acoustic emission method for detection of partial discharge in power transformer," in *Proc. 2nd Int. Conf. Properties Appl. Dielectric Mater.*, Sep. 1988, pp. 614–617 vol.2.

[24] P. Rastgoufard, F. Petry, B. Thumm, and M. Montgomery, "Application of fuzzy logic pattern recognition in load tap changer transformer maintenance," in *Proc. Annu. Meeting North Amer. Fuzzy Inf. Process. Soc.*, Jun. 2002, pp. 389–394.

[25] P. Kung, R. Idsinga, J. B. Fu, H. C. V. Durand, C. S. Yang, and M. I. Comanici, "Online detection of windings distortion in power transformers by direct vibration measurement using a thin fiber optics sensor," in *Proc. IEEE Elect. Insul. Conf. (EIC)*, Jun. 2016, pp. 576–578.

[26] M. Beltle and S. Tenbohlen, "Usability of vibration measurement for power transformer diagnosis and monitoring," in *Proc. IEEE Int. Conf. Condition Monitor. Diagnosis*, Sep. 2012, pp. 281–284.

[27] M. Abbas, "On the implementation of integer and non-integer sampling rate conversion," Ph.D. dissertation, Dept. Elect. Eng., Linköping Univ., Linköping, Sweden, 2012.

[28] J. S. Bendat and A. G. Piersol, *Random Data: Analysis and Measurement Procedures*, 4th ed. Hoboken, NJ, USA: Wiley, 2010.

[29] E. Sejdić, I. Djurović, and J. Jiang, "Time–frequency feature representation using energy concentration: An overview of recent advances," *Digit. Signal Process.*, vol. 19, no. 1, pp. 153–183, Jan. 2009. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S105120040800002X

[30] E. Kvedalen, "Signal processing using the teager energy operator and other nonlinear operators," Ph.D. dissertation, Dept. Inform., Univ. Oslo, Oslo, Norway, May 2003.

[31] A. N. Akansu, W. A. Serdijn, and I. W. Selesnick, "Emerging applications of wavelets: A review," *Phys. Commun.*, vol. 3, no. 1, pp. 1–18, Mar. 2010. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S1874490709000482

[32] L. Chun-Lin, "A tutorial of the wavelet transform," Dept. Elect. Eng., Nat. Taiwan Univ., Taipei, Taiwan, 2010.

[33] MathWorks. *Continuous and Discrete Wavelet Transforms*. Accessed: Jun. 13, 2018. [Online]. Available: https://www.mathworks.com/help/wavelet/gs/continuous-and-discrete-wavelet-transforms.html

[34] T. Strohmer. *Local Time-Frequency Analysis and Short Time Fourier Transform UC Davis*. Accessed:Jun. 14, 2018. [Online]. Available: https://www.math.ucdavis.edu/ strohmer/research/gabor/gaborintro/node3.html

[35] T. Bengtsson, H. Kols, L. Martinsson, B. Stenestam, M. Foata, F. Léonard, C. Rajotte, and J. Aubin, "Acoustic diagnosis of tap changers," CIGRÉ, Paris, France, Tech. Rep. 12-101, 1996.

[36] M. Foata, T. Bengtsson, H. Kols, L. Martinsson, B. Stenestam, F. Léonard, C. Rajotte, and J. Aubin, "On-line acoustic monitoring of tap changers," in *Proc. EPRI V Substation Equip. Diag. Conf.*, Feb. 1997, pp. 1–6.

[37] P. Kang and D. Birtwhistle, "Analysis, application of condition monitoring and diagnostic techniques for on load tap changers," in *Proc. Australas. Univ. Power Eng. Conf.*, 1997, pp. 1–6.

[38] M. Foata, R. Beauchemin, and C. Rajotte, "On-line testing of on-load tap changers with a portable acoustic system," in *Proc. IEEE 9th Int. Conf. Transmiss. Distrib. Construct.*, Oct. 2000, pp. 293–298.

[39] P. Kang, D. Birtwhistle, J. Daley, and D. McCulloch, "Noninvasive on-line condition monitoring of on load tap changers," in *Proc. IEEE Power Eng. Soc. Winter Meeting. Conf. Proc.*, vol. 3, Jan. 2000, pp. 2223–2228.

[40] P. Kang and D. Birtwhistle, "Condition monitoring of power transformer on-load tap-changers. I. Automatic condition diagnostics," *IEE Proc. Gener., Transmiss. Distrib.*, vol. 148, no. 4, pp. 301–306, Jul. 2001.

[41] P. Kang and D. Birtwhistle, "Condition monitoring of power transformer on-load tap-changers. II. Detection of ageing from vibration signatures," *IEE Proc. Gener., Transmiss. Distrib.*, vol. 148, no. 4, pp. 307–311, Jul. 2001.

[42] J. Seo, H. Ma, and T. K. Saha, "Vibration measurement and signal processing for condition assessment of OLTC of transformer," in *Proc. IEEE PES Asia–Pacific Power Energy Eng. Conf. (APPEEC)*, Nov. 2015, pp. 1–5.

[43] A. Secic and I. Kuzle, "On the novel approach to the on load tap changer (OLTC) diagnostics based on the observation of fractal properties of recorded vibration fingerprints," in *Proc. 17th Int. Conf. Smart Technol.*, Jul. 2017, pp. 720–725.

[44] E. F. Simas F, L. A. L. de Almeida, and A. C. de C. Lima, "Vibration monitoring of on-load tap changers using a genetic algorithm," in *Proc. IEEE Instrum. Meas. Technol. Conf.*, vol. 3, May 2005, pp. 2288–2293.

[45] K. Hong, H. Huang, Y. Fu, and J. Zhou, "A vibration measurement system for health monitoring of power transformers," *Measurement*, vol. 93, pp. 135–147, Nov. 2016.

[46] R. Bhuyan, A. R. Mor, P. Morshuis, G. C. Montanari, and W. Erinkveld, "Analysis of the arcing process in on-load tap changers by measuring the acoustic signature," in *Proc. IEEE Elect. Insul. Conf. (EIC)*, Jun. 2014, pp. 193–197.

[47] A. Hussain, S.-J. Lee, M.-S. Choi, and F. Brikci, "An expert system for acoustic diagnosis of power circuit breakers and on-load tap changers," *Expert Syst. Appl.*, vol. 42, no. 24, pp. 9426–9433, Dec. 2015.

[48] B. S. Munir, J. J. Smit, and I. G. M. R. Rinaldi, "Diagnosing winding and core condition of power transformer by vibration signal analysis," in *Proc. IEEE Int. Conf. Condition Monit. Diagnosis*, Sep. 2012, pp. 429–432.

[49] Z. Berler, A. Golubev, V. Rusov, V. Tsvetkov, and C. Patterson, "Vibro-acoustic method of transformer clamping pressure monitoring," in *Proc. IEEE Int. Symp. Elect. Insul.*, Apr. 2000, pp. 263–266.

[50] J. Shengchang, L. Yongfen, and L. Yanming, "Research on extraction technique of transformer core fundamental frequency vibration based on OLCM," *IEEE Trans. Power Del.*, vol. 21, no. 4, pp. 1981–1988, Oct. 2006.

[51] S. A. Rikardo, C. B. Bambang, C. Sumaryadi, T. D. Yulian, S. E. Arief, and S. F. I. Kharil, "Vibration monitoring on power transformer," in *Proc. Int. Conf. Condition Monit. Diagnosis*, Apr. 2008, pp. 1015–1016.

[52] L. Aidi, W. Zebo, H. Hai, Z. Jianping, and W. Jinhui, "Study of vibration sensitive areas on 500kV power transformer tank," in *Proc. IEEE 10th Int. Conf. Ind. Inform.*, Jul. 2012, pp. 891–896.

[53] S. Guo, K. Long, Z. Hao, J. Ma, H. Yang, and J. Gan, "The STUDY on vibration detection and diagnosis FOR distribution transformer in operation," in *Proc. China Int. Conf. Electr. Distrib. (CICED)*, Sep. 2014, pp. 983–987.

[54] H. Ma, J. He, B. Zhang, R. Zeng, S. Chen, and L. Cao, "Experimental study on DC biasing impact on transformer's vibration and sound," in *Proc. IEEE Int. Symp. Electromagn. Compat.*, Aug. 2008, pp. 1–4.

[55] J. He, Z. Yu, R. Zeng, and B. Zhang, "Vibration and audible noise characteristics of AC transformer caused by HVDC system under monopole operation," *IEEE Trans. Power Del.*, vol. 27, no. 4, pp. 1835–1842, Oct. 2012.

[56] K. Li, H. Xu, Y. Li, Y. Zhou, H. Ma, J. Liu, and J. Gong, "Simulation test method for vibration monitoring research on winding looseness of power transformer," in *Proc. Int. Conf. Power Syst. Technol.*, Oct. 2014, pp. 1602–1608.

[57] J. Zheng, J. Pan, and H. Huang, "An experimental study of winding vibration of a single-phase power transformer using a laser Doppler vibrometer," *Appl. Acoust.*, vol. 87, pp. 30–37, Jan. 2015.

[58] W. Sweldens, "The lifting scheme: A construction of second generation wavelets," *SIAM J. Math. Anal.*, vol. 29, no. 2, pp. 511–546, 1998.

[59] P. Kang and D. Birtwhistle, "Condition assessment of power transformer on-load tap-changers using wavelet analysis," *IEEE Trans. Power Del.*, vol. 16, no. 3, pp. 394–400, Jul. 2001.

[60] P. Kang and D. Birtwhistle, "Condition assessment of power transformer onload tap changers using wavelet analysis and self-organizing map: Field evaluation," *IEEE Trans. Power Del.*, vol. 18, no. 1, pp. 78–84, Jan. 2003.

[61] P. Kang and D. Birtwhistle, "Characterisation of vibration signals using continuous wavelet transform for condition assessment of on-load tap-changers," *Mech. Syst. Signal Process.*, vol. 17, no. 3, pp. 561–577, May 2003. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0888327002915256

[62] F. Poza, P. Marino, S. Otero, and V. Pastoriza, "Instrumentation system for industrial transformers," in *Proc. 10th Int. Conf. Control, Autom., Robot. Vis.*, Dec. 2008, pp. 1929–1933.

[63] K. Viereck and A. Saveliev, "Acoustic tap-changer analyses using continuous wavelet transformation," in *Proc. IEEE/PES Transmiss. Distrib. Conf. Expo. (T&D)*, May 2016, pp. 1–5.

[64] L. A. L. de Almeida, M. Fontana, F. A. Wegelin, and L. Ferreira, "A new approach for condition assessment of on-load tap-changers using discrete-wavelet transform," in *Proc. IEEE Instrum. Meas. Technol. Conf. Proc.*, vol. 1, May 2005, pp. 653–656.

[65] E. Rivas, J. C. Burgos, J. C. Garcia-Prada, "Vibration analysis using envelope wavelet for detecting faults in the OLTC tap selector," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1629–1636, Jul. 2010.

[66] E. F. S. Filho and L. A. L. de Almeida, "Self-organized classification of on-load tap changers acoustic signatures," in *Proc. IEEE Instrum. Meas. Technol. Conf.*, May 2008, pp. 1051–1056.

[67] T. B. Shanker, H. N. Nagamani, and G. S. Punekar, "Acoustic emission signal analysis of on-load tap changer (OLTC)," in *Proc. IEEE 1st Int. Conf. Condition Assessment Techn. Elect. Syst. (CATCON)*, Dec. 2013, pp. 347–352.

[68] J. Seo, H. Ma, and T. K. Saha, "A joint vibration and arcing measurement system for online condition monitoring of onload tap changer of the power transformer," *IEEE Trans. Power Del.*, vol. 32, no. 2, pp. 1031–1038, Apr. 2017.

[69] J. Seo, H. Ma, and T. Saha, "Probabilistic wavelet transform for partial discharge measurement of transformer," *IEEE Trans. Dielectr. Electr. Insul.*, vol. 22, no. 2, pp. 1105–1117, Apr. 2015.

[70] R. Duan and F. Wang, "Fault diagnosis of on-load tap-changer in converter transformer based on time–requency vibration analysis," *IEEE Trans. Ind. Electron.*, vol. 63, no. 6, pp. 3815–3823, Jun. 2016.

[71] A. Cichoń, S. Borucki, and T. Boczar, "Diagnosis of the non-concurrent operation of the on-load tap changer contacts by the acoustic emission method," *Arch. Acoust.*, vol. 36, no. 4, pp. 823–830, Dec. 2013. [Online]. Available: http://acoustics.ippt.gov.pl/index.php/aa/article/view/146

[72] H. Majchrzak, A. Cichoń, and S. Borucki, "Application of the acoustic emission method for diagnosis in on-load tap changer," *Arch. Acoust.*, vol. 42, no. 1, pp. 29–35, 2016. [Online]. Available: http://acoustics.ippt.gov.pl/index.php/aa/article/view/1713

[73] Z. Li, Q. Li, Z. Wu, J. Yu, and R. Zheng, "A fault diagnosis method for on load tap changer of aerospace power grid based on the current detection," *IEEE Access*, vol. 6, pp. 24148–24156, 2018.

[74] A. Secic, K. Jambrosic, and I. Kuzle, "Blind source separation as an extraction tool of the useful diagnostic material in on load tap changer audio based diagnostics," in *Proc. IEEE PES Innov. Smart Grid Technol. Conf. Eur.*, Oct. 2018, pp. 1–6.

[75] A. Secic, N. Hlupić, and I. Kuzle, "Using a non-linear least square curve fitting method for better understanding of ICA algorithm capabilities in audio based OLTC diagnostic," in *Proc. Medit. Conf. Power Gener., Transmiss., Distrib. Energy Convers.*, Nov. 2018, pp. 1–6.

[76] A. Secic and I. Kuzle, "Audio-based on-load tap changer diagnostics: Correlation of sound and vibration fingerprints," in *Proc. Int. Symp. Ind. Electron.*, Nov. 2018, pp. 1–6.

[77] J. Zheng, H. Huang, K. Hong, J. Zhou, J. Liu, and Y. Zhou, "Blind source separation of vibration signals for fault diagnosis of power transformers," in *Proc. ICIEA*, Hangzhou, China, Jun. 2014, pp. 412–417.

[78] W. Xiong and R. Ji, "Nonlinear time series analysis of transformer's core vibration," in *Proc. 6th World Congr. Intell. Control Automat.*, vol. 2, Jun. 2006, pp. 5493–5496.

[79] S. Wu, W. Huang, F. Kong, Q. Wu, and P. Zhu, "Vibration features extraction of power transformer using an time-scale-frequency analysis method based on WPT and HHT," in *Proc. IEEE 6th Int. Power Electron. Motion Control Conf.*, May 2009, pp. 2577–2581.

[80] S. Borucki, "Diagnosis of technical condition of power transformers based on the analysis of vibroacoustic signals measured in transient operating conditions," *IEEE Trans. Power Del.*, vol. 27, no. 2, pp. 670–676, Apr. 2012.

[81] J. Swevers. *Introduction to System Identification*. Accessed: Jun. 14, 2018. [Online]. Available: https://people.mech.kuleuven.be/ jswevers/h04x3a/lecture_c2_c3.pdf

[82] L. Ljung, *System Identification: Theory for User*, 2nd ed. Upper Saddle River, NJ, USA: Prentice Hall, 1999.

[83] D. Chinarro, *System Engineering Applied to Fuenmayor Karst Aquifer (San Julian de Banzo, Huesca) and Collins Glacier (King George Island, Antarctica)*, 1st ed. New York, NY, USA: Springer, 2014.

[84] MathWorks. *System Identification Overview*. Accessed: Jun. 14, 2018. [Online]. Available: https://www.mathworks.com/help/ident/gs/about-system-identification.html

[85] E. A. Wegelin, R. S. Magalhaes, L. A. L. de Almeida, and M. Fontana, "Condition monitoring of power transformers using acoustic signal Prony's analysis," in *Proc. IEEE Instrum. Meas. Technol. Conf. Proc.*, vol. 2, May 2005, pp. 1384–1387.

[86] X. Zhou and F. H. Wang, "Research on chaotic dynamic characteristics of onload tap changers," in *Proc. IEEE PES Gen. Meeting Conf. Expo.*, Jul. 2014, pp. 1–5.

[87] R. Duan and F. Wang, "Mechanical condition monitoring of on-load tap-changers using chaos theory amp; fuzzy c-means algorithm," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2015, pp. 1–5.

[88] K. Hong, H. Huang, and J. Zhou, "Winding condition assessment of power transformers based on vibration correlation," *IEEE Trans. Power Del.*, vol. 30, no. 4, pp. 1735–1742, Aug. 2015.

[89] B. García, J. C. Burgos, and Á. M. Alonso, "Winding deformations detection in power transformers by tank vibrations monitoring," *Electr. Power Syst. Res.*, vol. 74, no. 1, pp. 129–138, 2005.

[90] B. Luo, F. H. Wang, and Z. J. Jin, "A tank vibration model for online monitoring of power transformer," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2013, pp. 1–5.

[91] Z. Jing, H. Hai, and P. Jie, "A hammerstein-type Fourier neural network-based identification with application to transformer vibration system modelling," in *Proc. IEEE 10th Conf. Ind. Electron. Appl. (ICIEA)*, Jun. 2015, pp. 1974–1979.

[92] J. Hu, D. Liu, Q. Liao, Y. Yan, and S. Liang, "Electromagnetic vibration noise analysis of transformer windings and core," *IET Electr. Power Appl.*, vol. 10, no. 4, pp. 251–257, Apr. 2016. [Online]. Available: http://digital-library.theiet.org/content/journals/10.1049/iet-epa.2015.0309

[93] K. Bouayed, L. Mebarek, V. Lanfranchi, J.-D. Chazot, R. Marechal, and M.-A. Hamdi, "Noise and vibration of a power transformer under an electrical excitation," *Appl. Acoust.*, vol. 128, pp. 64–70, Dec. 2017.

[94] Q. Li, X. Wang, L. Zhang, J. Lou, and L. Zou, "Modelling methodology for transformer core vibrations based on the magnetostrictive properties," *IET Electr. Power Appl.*, vol. 6, no. 9, pp. 604–610, Nov. 2012.

[95] J. Marks, S. Vitolina, and R. Liepniece, "Modelling of vibrations caused by magnetostriction in magnetic core of large power transformers," in *Proc. IEEE 58th Int. Sci. Conf. Power Elect. Eng. Riga Tech. Univ. (RTUCON)*, Oct. 2017, pp. 1–5.

[96] Q. Li, T. Zhao, L. Zhang, and J. Lou, "Mechanical fault diagnostics of onload tap changer within power transformers based on hidden Markov model," *IEEE Trans. Power Del.*, vol. 27, no. 2, pp. 596–601, Apr. 2012.

[97] N. Mussin, A. Suleimen, T. Akhmenov, N. Amanzholov, V. Nurmanova, M. Bagheri, M. Naderi, and O. Abedinia, "Transformer active part fault assessment using Internet of Things," in *Proc. 2nd Int. Conf. Comput. Netw. Commun.*, Sep. 2018, pp. 169–174.

[98] A. G. Deakin, J. W. Spencer, D. H. Smith, D. Jones, N. Johnson, and G. R. Jones, "Chromatic optoacoustic monitoring of transformers and their onload tap changers," *IEEE Trans. Power Del.*, vol. 29, no. 1, pp. 207–214, Feb. 2014.

[99] Z. Liu, X. Xia, S. Ji, Y. Shi, F. Zhang, Y. Fu, and Z. Jiang, "Fault diagnosis of OLTC based on time-frequency image analysis of vibration signal," in *Proc. Condition Monitor. Diagnosis (CMD)*, Sep. 2018, pp. 1–6.

[100] S. Borucki, A. Cichoń, H. Majchrzak, and D. Zmarzły, "Evaluation of the technical condition of the active part of the high power transformer based on measurements and analysis of vibroacoustic signals," *Arch. Acoust.*, vol. 42, no. 2, pp. 313–320, 2016. [Online]. Available: http://acoustics.ippt.gov.pl/index.php/aa/article/view/1816

[101] Y. Zheng, W. He, F. Wang, and S. Li, "Vibration monitoring of converter transformer onload tap-changer using phase space reconstruction and poincare section," in *Proc. 4th Int. Conf. Electr. Power Equip. Switching Technol. (ICEPE-ST)*, Oct. 2017, pp. 365–369.

[102] M. Bagheri, A. Zollanvari, and S. Nezhivenko, "Transformer fault condition prognosis using vibration signals over cloud environment," *IEEE Access.*, vol. 6, pp. 9862–9874, 2018.

ADNAN SECIC (S'17) received the bachelor's and master's degrees in automatic control and electronics from the Faculty of Electrical Engineering, University of Sarajevo, in 2008 and 2014, respectively. He is currently pursuing the Ph.D. degree in electrical engineering with the Department of Energy and Power Systems, Faculty of Electrical Engineering and Computing, University of Zagreb. Since 2008, he has been with DV Power, Sweden, where he is currently an R&D Engineer. His research interests include invasive and noninvasive methods for condition assessment of power system equipment, with the focus on high voltage circuit breakers, transformers, and on-load tap changers.

MATEJ KRPAN (S'17) received the bachelor's and master's degrees in electrical power engineering from the Faculty of Electrical Engineering and Computing, University of Zagreb, in 2014 and 2016, respectively. He is currently pursuing the Ph.D. degree in electrical engineering with the Department of Energy and Power Systems, Faculty of Electrical Engineering and Computing, University of Zagreb.

His research interests include power system dynamics, stability and control, the integration of large-scale renewable energy sources, and grid frequency support from wind power plants and power system inertia.

IGOR KUZLE (S'94–M'97–SM'04) is currently a Full Professor and the Head of the Department of Energy and Power Systems, Faculty of Electrical Engineering and Computing, University of Zagreb. His current research interests include problems in electric power systems dynamics and control, unit commitment, maintenance of electrical equipment, power system analysis, smart grids, and the integration of renewable energy sources.

He was the Project Leader of more than 60 technical projects for industry and electric power companies. He published three books and more than 200 journals and conference papers including technical studies for utilities and private companies. He serves in ten international journals as a Member of Editorial Board or an Associate Editor.