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De-noising of time-domain spectroscopy data for reliable assessment of power transformer insulation

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Abstract: Polarisation–depolarisation current (PDC) measurement and its analysis is a popular technique for assessing the condition of transformer insulation. Owing to the low magnitude of PDC, recording noise-free PDC data from in-situ power transformers is a challenge. Once the relaxation current data get affected by noise, it becomes difficult to formulate insulation model (as recorded data loses its characteristic shape). This further makes the data difficult to analyse and predict insulation condition. In this study, two de-noising techniques are discussed (one is based on Wavelet Transform while the other is based on Stockwell Transform) for eliminating low-frequency non-stationary noise from recorded PDC data. Comparison between these two techniques suggests de-noising using Stockwell Transform is advantageous over wavelet analysis. The proposed methodology is first tested on data recorded from the sample prepared in the laboratory and then on data measured from real-life in-service power transformer.

1 Introduction

The diagnosis of insulation used in power transformer has always been a point of interest among utilities. During normal operation, the desirable properties of insulation get reduced due to moistening and ageing [1]. Existing literature [1–5] reported that time-domain spectroscopy-based technique and its analysis (using the insulation model) provides a good way for insulation diagnosis. Among available time-domain based techniques, analysis of polarisation–depolarisation current (PDC) data is popular among utilities. Oil–paper insulation (OPI) contains different dipole groups, each having different relaxation time constants [1]. After the application of dc step voltage, these dipole groups get aligned in the direction of the applied field and generates a current called polarisation current. As per existing literature [2], polarisation current follows a monotonically decreasing profile and this polarisation current can be modelled by adding several exponential decay functions given in (1) [2]

$$\varphi(t) = \sum_{i=1}^{n} K_i \exp(-t/\tau_i) \tag{1}$$

In (1), τ_i and K_i represent the time constant and amplitude of the ith exponential decay function, respectively, while n represents the total number of exponential functions required to model the recorded dielectric response function with a satisfactory level of accuracy.

The magnitude of polarisation current is usually low (from nA to μA [3]) and hence, there is a high possibility that noise might affect the recorded PDC data especially during field measurement. During field measurement, it came to notice that both high and low-frequency noise affect the recorded time-domain data. Available literature shows that other energised equipment and additional circuitry present in the vicinity of the unit being tested tend to contribute to noise [3]. Consequently, available equipment used for PDC recording also employs appropriate filtering which is capable of rejecting high-frequency field noise [6]. However, it is difficult to design a filter for the detection and elimination of low-frequency non-stationary noise from polarisation current owing to its low magnitude. Low-frequency non-stationary noise is usually created by slow varying environmental conditions. As per information provided by the utilities, low-frequency noise affected data measurement tends to be concurrent with a variation of environmental conditions. For instance, slow-variation in ambient temperature is quite common during field measurement. It is generally assumed that owing to the presence of large bulk oil volume recorded data does not appreciably affect by temperature oscillations. Temperature variations combined with a finite thermal time constant of oil [7] can be one of the sources of such low-frequency noise in polarisation current. Other sources may include human error, the effect of residual energy [8], and variation in humidity [4]. It is worth mentioning here that the resultant noise profile reflects the cumulative effect of all the above-mentioned noise sources.

This low-frequency non-stationary noise influences the measured relaxation current data and provides inaccurate information regarding insulation condition. Existing literature shows that insulation model formulation and its analysis depends on the monotonically decreasing profile of PDC data [1, 5]. If such low-frequency noise affects the monotonically decreasing profile of relaxation current, it becomes no longer possible to formulate an insulation model using such affected data.

PDC measurement being an offline measurement technique is generally performed after providing the equipment sufficient post-shutdown cooling time. Furthermore, the measurement time PDC data can continue for hours depending on the condition of the concerned insulation system. Utilities normally favour methods that need reduced equipment shut down time for testing purposes. It can be understood from the above discussion that in case the low-frequency noise makes the measured PDC data un-analysable, the whole measurement process needs to be repeated. This, in turn, increases the shut down time of the unit. Hence, it will be beneficial from the utility point of view to have a suitable de-noising technique that is capable of filtering out the low-frequency noise from the recorded relaxation current data. This will ensure not only an accurate diagnosis but will also reduce overall shut down time.

It is reported by researchers that the presence of non-stationary aperiodic noise in PDC data due to environmental conditions is a common problem [5–7, 9]. Dey *et al.* [6] reported that it is possible to remove high-frequency noise from relaxation current using hybrid filtering scheme. However, removal of low-frequency noise is still a problematic task. For this work, all data related to

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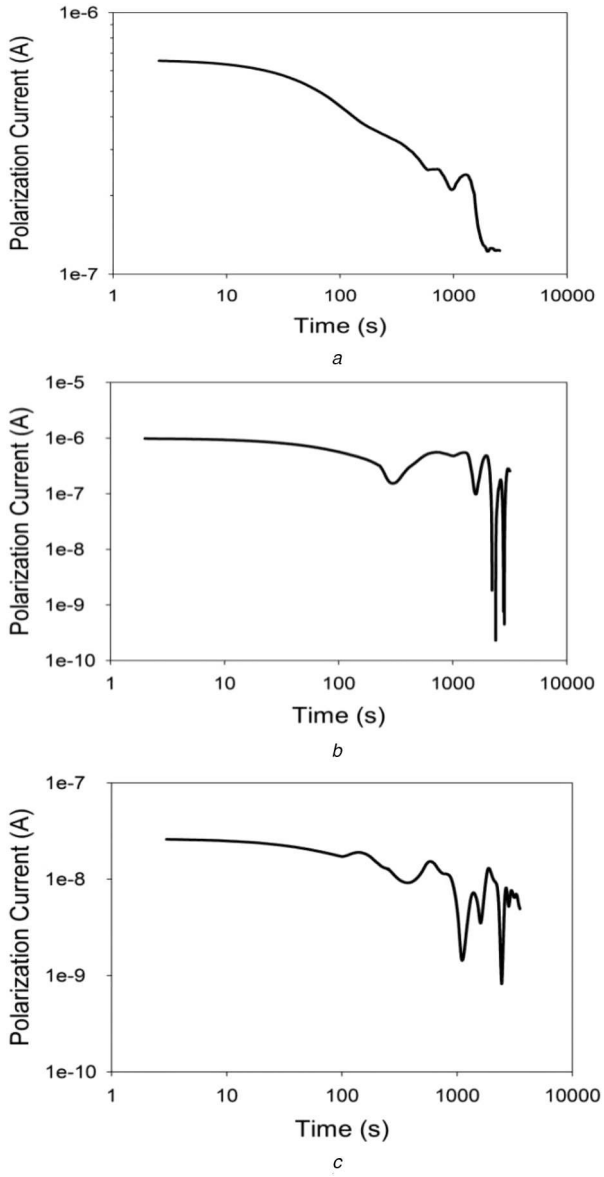

Fig. 1 *Polarisation current measured from* ***(a)*** Trafo1 (power rating 420 kV, 200 MVA) real-life transformer Trafo1, ***(b)*** Trafo2 (power rating 765 kV, 200 MVA), ***(c)*** Trafo3 (power rating 400 kV, 240 MVA)

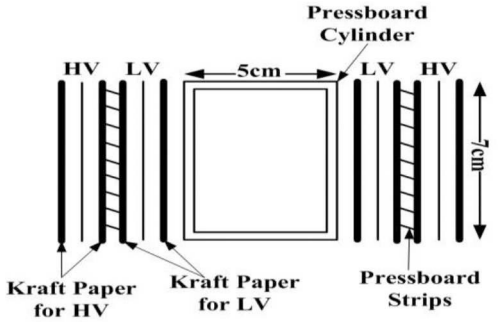

Fig. 2 *Schematic diagram of the sample*

transformers were made available to the user from the utilities. The authors were informed that the utilities used a Keithley Electrometer (model no 6517B) based equipment for measuring PDC data. The equipment comes equipped with a low pass IIR filter with cut-off frequency of 0.2 Hz [6]. This implies that non-stationary noise (with a frequency <0.2 Hz) can affect the measured polarisation current data. Figs. 1*a–c* show such low-frequency noise affected polarisation current recorded from few power transformers. At present utilities tend to discard such noise affected data as they cannot be analysed using available non-invasive diagnosis methods [1, 2]. As a result, utilities resort to multiple measurements. This is both time-consuming and inefficient in nature. Not to mention this risks introduction of other problems like the effect of residual dipole energy [8]. Though it is a common issue encountered during field measurement, almost no literature is available which addresses de-noising of such low-frequency noise from the recorded dielectric response. In this paper, two de-noising techniques are discussed, one is based on Wavelet Transform [10–12] while the other is based on Stockwell Transform [13].

Further, a comparative analysis is also provided based on the performance of both the above-mentioned techniques. Both techniques are found to be capable of removing the effect of low-frequency non-stationary noise from polarisation current. However, analysis based on Wavelet Transform is observed to be computationally more intensive and hence a time-consuming process. Available literature shows that optimum mother wavelet for de-noising purposes needs to be identified using either qualitative or quantitative approaches. This involves either the computation of signal entropy or visually identifying common features between the signal and the mother wavelet. Furthermore, the optimum level of decomposition also needs to be identified at which the maximum effectiveness of de-noising is achieved [14–16]. On the other hand, Stockwell Transform (S-Transform) does not have such requirements for analysing non-stationary signals.

It is understood that the de-noising scheme should be such that it does not change the original profile of the polarisation current. The performance of both the techniques has been first tested on laboratory sample data with synthetic noise and thereafter on data measured from in-service equipment. In [17], the authors of this paper presented a neural network-based methodology to estimate the entire profile of polarisation current using only 600 s of measurement data. It is understood that the method reported in [17] is applicable only when the influence of noise in polarisation current data, within 600 s, is not predominant. During field measurement, this is often not the case (as illustrated in Figs. 1*a–c*). Hence, the requirement of an effective denoising technique cannot be ignored.

2 Sample fabrication

In order to analyse the performance of the proposed de-noising methods, the test sample was constructed in the laboratory. The sample was prepared in such a way that it emulates the OPI that is used in power transformers. The preparation of the sample is similar to that reported in the literature [5]. Low voltage (LV) and high voltage (HV) winding within the sample were emulated using two copper foils. The copper foils were placed between two layers of 2 mil Kraft papers. Thereafter, this arrangement was wrapped around a pressboard cylinder (constructed using a 2 mm thick pressboard) as shown in Fig. 2). In order to emulate oil ducts between HV and LV winding pressboard strips (around ten numbers) were placed between HV and LV windings. Post-construction, moisture that was absorbed by raw materials (Kraft paper, pressboard) used during sample preparation was removed by heating it in a temperature-controlled hot air oven at 90°C for more than 120 h in presence of silica gel. The effectiveness of the sample drying process was also verified using a vacuum oven (Rivotek make vacuum oven; model no. 6701 0002). After this de-moisturisation process, the samples were left in an open environment to absorb a pre-determined amount of moisture content. During the phase of moisture absorption, the weight of each sample was continuously checked using a precise weighing machine (resolution of 10 µg). This was done to get information about the amount of moisture absorbed by the sample. Once the sample had absorbed the pre-determined value of moisture, it was immersed in 1.5 l of transformer oil for impregnation. It is worth mentioning here that the impregnation was carried out in a complete vacuum (with the help of Rivotek make vacuum oven; model no. 6701 0002) at 30°C. This was done so that no moisture from the surrounding atmosphere gets absorbed by the oil during the impregnation process.

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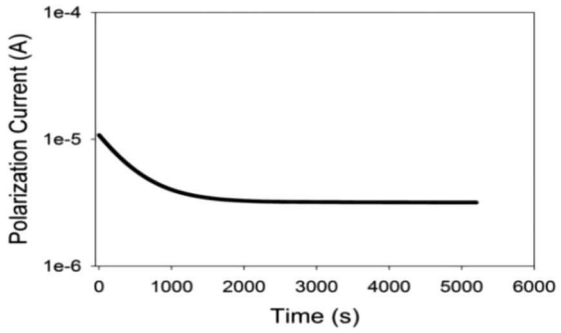

Fig. 3 *Polarisation current recorded from the sample*

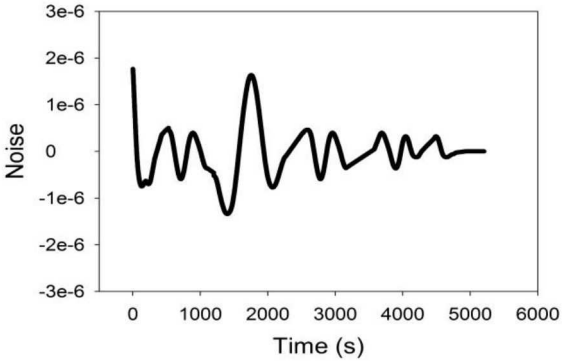

Fig. 4 *Profile of synthetic noise affected the polarisation current*

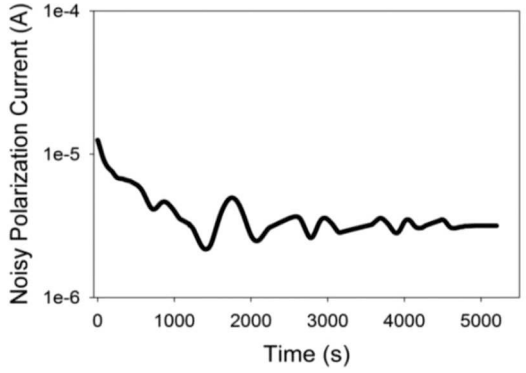

Fig. 5 *Polarisation current recorded from the sample affected with synthetic noise*

PDC data from the constructed sample were recorded using a setup that is developed at HT Laboratory, Jadavpur University [5]. The setup uses a KEITHLEY 6517B Electrometer as the main measurement module. Fig. 3) shows the profile of the polarisation current that was recorded from a laboratory sample.

It can be clearly observed from Fig. 3 that polarisation current measured from the sample is not affected by any type of noise. A synthetic non-stationary noise was introduced in measured relaxation current (shown in Fig. 4). Fig. 5 shows the resultant polarisation current affected by non-stationary noise. Here, the non-stationary noise profile chosen is exemplary in nature.

3 Wavelet analysis: brief theory

Technique based on Wavelet analysis is widely used in signal processing for data compression and de-noising applications [10–12]. This method can easily be applied to non-stationary signals as it has the ability to provide better time-frequency representation compared to Fourier Transform (FT) [11, 14–16]. It is a known fact that time-frequency localisation is necessary for getting time information of spectral components. Using Wavelet Transform it is possible to achieve this time-frequency localisation which makes it suitable to deal with a non-stationary signal [14, 15]. A wavelet is a wave ($\psi(t)$) that exists for a very short duration and has zero average value [15, 16] provided it satisfies the conditions given in (2) and (3)

$$\int_{-\infty}^{\infty} |\psi(t)|^2 \, \mathrm{d}t < \infty \tag{2}$$

$$\int_{-\infty}^{\infty} |\psi(t)| \, \mathrm{d}t = 0 \tag{3}$$

Continuous Wavelet Transform (CWT) is obtained by multiplying the main signal $x(t)$ with a scaled and shifted version of mother wavelet function $\psi(t)$ and shown in (4) [16]

$$W_{a,b} = \int_{-\infty}^{\infty} x(t)\psi(a,b,t) \, \mathrm{d}t \tag{4}$$

where $W_{A,b}$ denotes the coefficients of wavelet while a is scaling parameter. The value of $a > 1$ represents the stretching of wavelet and corresponds to lower frequencies. While $a < 1$ means compression of wavelet and corresponds to higher frequencies. In (4), factor b represents the translation parameter and decides the position of mother wavelet with respect to the concerned signal. As per the available literature, CWT analysis produces a large number of wavelet coefficients that are not used for de-noising purposes [15, 16]. Hence, researchers generally choose Discrete Wavelet Transform (DWT) over CWT in which scale and time are based on a power of two thus reducing the overall number of coefficients generated and memory requirement.

In DWT, the first level of decomposition results in the signal getting divided into two components, one is approximate and another is a detailed coefficient. Approximate coefficients correspond to high scale which represents low-frequency components while detailed coefficients correspond to high-frequency components [16]. The concerned signal is decomposed up to a certain level according to the property of DWT called Multi-resolution Signal Analysis [15]. For de-noising purposes, the signal is reconstructed back using either approximation or detailed coefficients depending on the type of noise.

3.1 Selection of decomposition level and suitable mother wavelet

Literature shows that maximum decomposition level ($\mathrm{DL_{max}}$) for a given signal is given by (5) [15, 16]

$$\mathrm{DL_{max}} = \log_2 N \tag{5}$$

where N signifies the number of samples present in the concerned signal. According to literature, the number of decomposition levels of the signal should not exceed $\mathrm{DL_{max}}$ [15, 16]. The value of $\mathrm{DL_{max}}$ is found to be 12 for the polarisation current data collected from the laboratory sample. For this work, the decomposition of signal for de-noising purpose depends on the lower frequency component which is required to be removed from the signal [16, 18]. After carrying out the necessary investigation, it is found that approximate coefficients at tenth level provide satisfactory results for de-noising polarisation current (shown in Fig. 6). It is also observed that if the decomposition level is further increased, then distortion starts to appear in the de-noised waveform. There are large numbers of mother wavelets such as Haar, Daubechies, biorthogonal, and Symlet. In order to have better results, selection of mother wavelet is an important task. It is reported in [15, 16] that there are mainly two approaches (qualitative and quantitative) available for the selection of mother wavelet [15].

In the qualitative approach, a suitable mother wavelet is selected by observing the resemblance between the wavelet and concerned signal [15]. However, practically it is difficult to select a mother wavelet by visual observation, especially if the data length is large. Hence, the researcher recommended the quantitative approach to justify the resemblance between the signal of interest and the mother wavelet [15]. According to this approach, the

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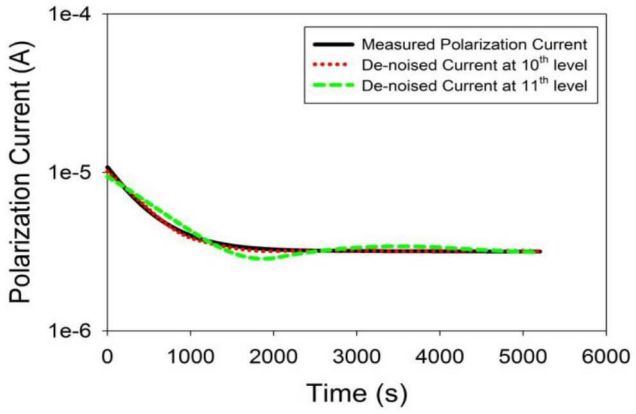

Fig. 6 *Sample original polarisation current and de-noised polarisation current (obtained using approximate coefficient at 10th and 11th level of decomposition)*

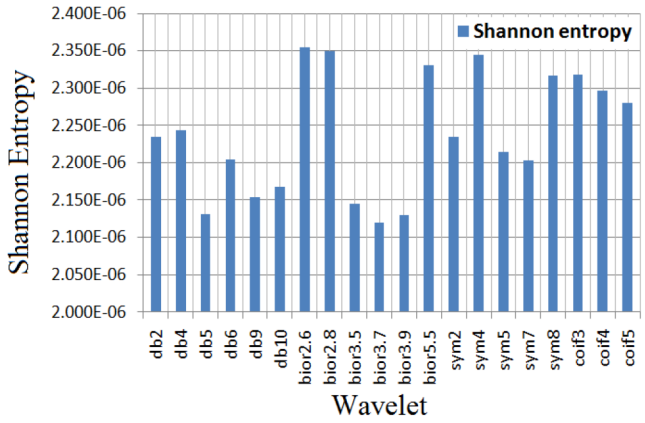

Fig. 7 *Shannon entropy of wavelet coefficients for various wavelets at 10th level of decomposition for Trafo1*

selection of mother wavelet can be done on the basis of Minimum Shannon Entropy Criterion [14, 15]. In this approach, the mother wavelet that minimises the value of Shannon entropy of wavelet coefficients is better suited for selection as a mother wavelet.

Fig. 6 shows the original polarisation current (without noise) along with the de-noised signal (reconstructed using approximate coefficient obtained after 11th level of decomposition). Such distortion in de-noised signal (obtained from 11th level of decomposition) is observed for a large number of mother wavelets that were tested in this work. Hence, here the maximum decomposition level is selected to be 10. Fig. 7 shows the value of Shannon Entropy obtained corresponding to some of the mother wavelets tried in this work at the 10th level of decomposition. Data illustrated in Fig. 7 shows that the minimum value of Shannon Entropy corresponds to the *'bior3.7'*. Hence, *'bior3.7'* is selected for de-noising polarisation current recorded from the sample. During field measurement, the profile of noise present in PDC data cannot be pre-determined. Depending on the profile of noise present, a wavelet (other than *bior3.7*) might be better suited for de-noising purposes. This makes de-noising using Wavelet Transform difficult. The algorithm to identify the best-suited wavelet for a given data is given in the next section.

3.2 Procedure for de-noising of signal using wavelet transform

It is well known that polarisation current maintains a monotonically decreasing profile which settles down to a constant value [1, 2]. Any oscillating component that affects this characteristic profile should be considered as noise. These oscillating components which introduce noise must be sensitive to the detail coefficients of DWT. Steps that are used for de-noising the noise affected polarisation current are given as follows:

Step 1: Estimate the maximum Decomposition level (DL_{max}) using (5).
Step 2: Select a given wavelet $\Psi_{i=1}$ from the set $\{\Psi_i\} = (\Psi_1; \Psi_2; .... \Psi_{max_wave})$ containing all possible wavelets.
Step 3: Decompose the noisy signal upto max level DL_{max} using Ψ_i.
Step 4: For each level, L_j; $j = 1, 2, \ldots, DL_{max}$, follows step 5 to step 8.
Step 5: Reconstruct the signal using approximate coefficients at level L_j.
Step 6: Check if the signal obtained in Step 5 is stepped in nature by inspecting the derivative of the reconstructed signal. If the signal does not have a stepped nature, goto step 8.
Step 7: Assign *Shannon Entropy* value SE(i, j) corresponding to wavelet Ψ_i and L_j level to a pre-defined high value; increment level L_j to L_{j+1} and goto step 5.
Step 8: Evaluate the effectiveness of de-noising at level L_j

- Use Haar wavelet to obtain first level decomposition coefficients of the reconstructed signal.
- Compute First Level Decomposed Signal (FLDS) [19] using obtained coefficients.
- Evaluate Direction Change Mark (DCM) [19] from FLDS.
- Calculate and store a number of peaks *peak(i, j)* in DCM vector corresponding to level L_j and wavelet Ψ_i.
- Evaluate and store *Shannon Entropy* value corresponding to wavelet Ψ_i and L_j level *SE*(i, j).

Step 9: Identify the level L_k such that $peak(i, L_k) = \min\{peak(i, j)\}$; $j = 1, 2, \ldots, DL_{max}$ for the wavelet Ψ_i.
Step 10: Assign all *SE(i, j)*; $j = 1, 2, \ldots, DL_{max}$ and $j \neq k$ values to a pre-defined high number.
Step 11: If $L_j = DL_{max}$ and $\Psi_i \neq \Psi_{max_wave}$ select the next wavelet $\Psi_{i=i+1}$ from the list $\{\Psi_i\}$ and goto step 3.
Step 12: If $L_j = DL_{max}$ and $\Psi_i = \Psi_{max_wave}$ identify the optimum wavelet Ψ_{ow} and level L_{ol} for which $SE(ow, ol) = \min\{SE(i, j)\}$; $i = 1, 2, \ldots, max_wave$; $j = 1, 2, \ldots, DL_{max}$.
Step 13: De-noise the noisy signal by reconstructing the wave using wavelet Ψ_{ow} and approximate coefficient obtained at level L_{ol}.
Step 14: Formulate insulation model and evaluate performance parameters for validation purposes.

De-noising is said to be successful once the de-noised signal matches with initial measured data (which is not affected by noise). In the case of real-life power transformers, direct validation is not possible due to the absence of noise-free data. Hence, indirect validation is performed here by matching performance parameters that are generally measured by utilities. Estimation of these parameters should also be possible using the insulation model parameter which can be formulated using de-noised data [5, 20]. If the insulation sensitive parameters using de-noised current matches with the measured parameter, it can be opined that de-noising is successful.

The value of %tanδ at a given frequency ω can be estimated using the relation given in (6) [2]

$$\tan\delta(\omega) = \frac{(1/\omega R_0) + \sum_{i=1}^{n} \omega R_i C_i^2/(1 + (\omega R_i C_i)^2)}{C_0 + \sum_{i=1}^{n} C_i/(1 + (\omega R_i C_i)^2)} \quad (6)$$

where R_i and C_i represent the branch parameters of ith branch of Insulation model while C_0 and R_0 denote geometric capacitance and dc insulation resistance, respectively. However, ensuring the accuracy of (6) in estimating %tanδ values at high frequencies necessitate measurement of polarisation current data immediately after the application of charging voltage. In the case of a laboratory sample, the measurement was carried out in a controlled noise-free environment on a scaled-down model. Hence, it was possible to

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Table 1 Comparison of insulation sensitive parameters for laboratory sample

Performance parameters	Computed from		%error	Coefficient of determination R^2 (between measured and de-noised data)
	Original polarisation current	De-noised polarisation current		
% pm	3.0	2.60	13.33	0.9938
PI	2.34	2.36	0.85	
DAR	1.18	1.16	1.69	

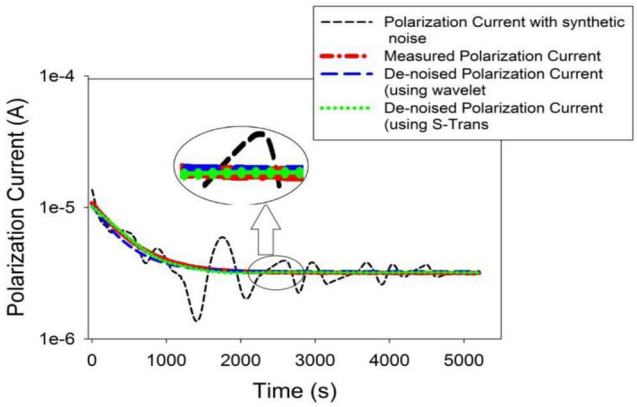

Fig. 8 *Comparison of de-noised current using wavelet analysis and S-Transform with original (before noise addition) and noisy polarisation current for sample*

record the data during the first few seconds (as illustrated in Fig. 3). Such measurement is usually not possible during field measurement [2] (as illustrated in Figs. 1*a*–*c*). As a result, the application of (6) and subsequent comparison %tanδ values to test de-noising effectiveness cannot be considered for real-life transformers. Hence, in the case of laboratory samples, Polarisation Index (PI) [8], dielectric absorption ratio (DAR) [8] and %pm are compared. Table 1 shows the result of such a comparison. Table 1 also presents the coefficient of determination value obtained between measured and de-noised signal.

As per the available literature, a well-defined relation exists between %pm and Transfer Function zero Z_1 [20]. As per [5, 17] the value of %pm can be estimated using (7)

$$\%\text{pm} = k_1 + k_2 \times \ln(|Z_1|) \tag{7}$$

where k_1 and k_2 are constants and the value of these constants are reported [5] as 1.718 and 0.418, respectively. In (7), Z_1 represents the highest magnitude of zero obtained from the transfer function of the insulation model. It is reported in [5] that these values of k_1 and k_2 are valid only for a real-life in-service transformer. It is difficult to emulate all the complexities that exist in actual OPI in scaled-down laboratory samples. Hence, in order to use (7) for laboratory samples, the value of constants k_1 and k_2 are recalculated using the methodology reported in [5]. The estimated value of constants k_2 and k_1 for test samples prepared in the laboratory are found to be 1.2959 and 2.6399, respectively. Table 1 shows the comparison between performance parameters estimated using originally measured and de-noised polarisation current.

It can be observed from Table 1 that insulation sensitive parameters like %pm, PI, DAR calculated using measured (before noise addition) and de-noised polarisation current are close. Hence, it can be opined that the Wavelet Transform-based technique is capable of de-noising the polarisation current data recorded from the laboratory sample. The main disadvantage of Wavelet Transform-based method is that it requires the implementation of a computationally intensive iterative process.

4 Stockwell analysis: brief theory

In the case of de-noising, available literature suggest that *S* transform has certain advantages over wavelet analysis [21–23]. S-Transform is a time-frequency localisation method that combines the elements of short-time FT (STFT) and Wavelet Transform [21, 22]. It is the extension of CWT and overcomes its disadvantages [13]. It is based on localising the Gaussian window and supplies the frequency-dependent resolution as well as the multi-resolution strategy of the wavelets. The S-Transform is defined as [19, 20]

$$S(\tau, f) = \text{STFT}(\tau, f) = \int_{-\infty}^{\infty} x(t) \frac{|f|}{\sqrt{2\Pi}} \frac{\mathrm{e}^{-(t-\tau)^2 f^2}}{2} \mathrm{e}^{-\mathrm{j}2\Pi f t}\, \mathrm{d}t \tag{8}$$

In (8), τ and f denote the time of spectral localisation and Fourier frequency, respectively. The width of the Gaussian window is given by (9) [13]

$$\alpha(f) = T = 1/|f| \tag{9}$$

If the window width of S-Transform is made wider in the time domain, it provides better frequency resolution at lower frequency region. On the other hand, if the window width is made narrow, better time resolution can be obtained at a high-frequency region. Depending on the independent components (frequency and time), the amplitude of signal varies in different regions of the spectrum. S-Transform shows linearity property which can be represented by (10)

$$\text{ST}(\text{signal} + \text{noise}) = \text{ST}(\text{signal}) + \text{ST}(\text{noise}) \tag{10}$$

In Stockwell spectrum, the coefficients corresponding to different frequencies (except at $f = 0$ which corresponds to the average of the signal) represent the non-stationary noise present in the monotonically decreasing polarisation current. Owing to the linearity property of S-Transform, the profile of the noise can be obtained by taking the inverse S-Transform of the spectrum that represents noise. Thereafter, the de-noised signal is obtained by subtracting the noise profile from originally measured noisy data. The steps that are followed for de-noising of polarisation current are given as follows:

Step 1: Apply S-Transform (ST) to the measured noisy data.
Step 2: Replace the coefficients of Stockwell spectrum corresponding to $f = 0$ with zero.
Step 3: Apply Inverse Stockwell Transform on the modified spectrum.
Step 4: Signal obtained in *Step 3* is subtracted from the measured data.
Step 5: Formulate the insulation model and evaluate performance parameters for validation purposes.

Fig. 8 illustrates the de-noise signal for laboratory sample obtained using S-Transform and Wavelet Transform-based de-noising methodology. In order to improve readability, the original signal (not affected by noise) is also shown in Fig. 8. It can be observed from Fig. 8 that de-noised current almost matches with measured data (not affected by noise).

Fig. 8 shows that de-noised signal using S-Transform and Wavelet Transform almost matches with that measured polarisation current data (shown by red colour). Furthermore, Fig. 8 shows that reliable de-noising is possible with S-Transform without going into the iterative method used for the implementation of wavelet analysis. Table 2 shows the performance parameters obtained from measured data and de-noised data (using S-Transform). On comparing Tables 1 and 2, it can be observed that for denoising synthetic noise affected data (shown in Fig. 5), S-Transform based methodology is more effective.

The above-mentioned two denoising schemes are implemented by writing script in MATLAB 2014 using a desktop computer having Core i5, 8th Generation processor, 8 GB RAM. It was observed that the processing time required for de-noising of sample response using Wavelet Transform-based methodology is 2.1 s,

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Table 2 Comparison of insulation sensitive parameters for laboratory sample

Performance parameters	Evaluated from		%error	Coefficient of determination R^2 (between measured and de-noised data)
	Original polarisation current	De-noised polarisation current		
% pm	3.0	2.78	7.33	0.9962
PI	2.34	2.35	0.42	
DAR	1.18	1.17	0.84	

Unit Name	Measured			Calculated		
	%tanδ	%pm	PI	%tanδ	%pm	PI
Using Wavelet Transform based methodology						
Trafo1	0.30	0.60	2.67	0.28	0.54	2.58
Trafo2	0.42	1.30	2.32	0.39	1.23	2.23
Trafo3	0.48	1.60	2.19	0.44	1.51	2.08
Using S-Transform based methodology						
Trafo1	0.30	0.60	2.67	0.29	0.55	2.60
Trafo2	0.42	1.30	2.32	0.39	1.25	2.26
Trafo3	0.48	1.60	2.19	0.45	1.52	2.10

Fig. 9 *Comparison of insulation sensitive performance parameters of real-life transformers*

while in the case of S-Transform based methodology the processing time was found to be 0.09 s. Hence, it can be opined that the S-Transform based de-noising scheme provides effective results (for sample response affected with synthetic noise) in less amount of time. However, this does not prove S-Transform based technique to be superior. This is because the main aim of this paper is de-noising of noise affected polarisation current data recorded from real-life power transformers. Analysis of field data comes with several unique challenges like the unavailability of data for the first few seconds. In addition, the signal (without the effect of noise) also remains unavailable during field measurement. This creates difficulty in the computation of the determination coefficient (R^2). Hence, in the following section, the effectiveness of the two methods (Wavelet Transform-based method and S-Transform based method) is studied for data shown in Figs. 1*a–c*.

5 Application on data collected from in-service transformer

After successful application on laboratory sample, these de-noising techniques are applied to data collected from three in-service power transformers. The noise affected data considered for testing the de-noising method are shown in Fig. 1*a–c*. It is practically not possible to formulate the insulation model using the noise affected polarisation current [1, 5]. Hence, in such a situation it is difficult to assess the insulation condition.

As informed earlier, polarisation current that is not affected by noise is not available to validate the accuracy of de-noised data. Furthermore, during field measurement of PDC data from real-life transformers, polarisation current for the first few seconds are generally not recorded. Hence, it is not possible to calculate frequency-dependent performance parameters (especially at high frequency) for validation purposes. However, indirect validation can be carried out by comparing the measured and calculated values of performance parameters. As the main aim behind having an effective de-noising scheme is to ensure effective insulation diagnosis using noisy data, such indirect validation seems reasonable. The calculated values of performance parameters are obtained using either the de-noised data or from the insulation model. It is worth mentioning here that *PI, DAR* for *Trafo1, Trafo2* and *Trafo3* were measured using Megger MIT515. While %tanδ and %pm were measured using Megger IDAX 300.

The performance parameters considered for transformers include %tanδ, %pm, PI and DAR. PI and DAR were evaluated directly from the de-noised signal. Estimation of %tanδ and %pm was carried out using insulation model parameters. First, the transfer function of the insulation model is identified. Thereafter, zero (having the highest magnitude) Z_1 is obtained from it. Finally, Z_1 is used to evaluate the value of % tanδ and %pm using (11) and (12) [17, 20]

$$\%\tan\delta = 0.4423 + 0.0457 \times \ln(|Z_1|) \tag{11}$$

$$\%\text{pm} = 1.718 + 0.418 \times \ln(|Z_1|) \tag{12}$$

It is worth mentioning here that %tanδ at 50 Hz obtained through (11) is not directly obtained from time-domain PDC data (after applying some transformation technique). It is a well-known fact that polarisation current profile depends on the ageing and condition of the concerned insulation. Further, it is reported in [5, 20] that the transfer function zero, Z_1 (having the highest magnitude) is a geometry independent insulation sensitive performance parameter. As %tanδ at 50 Hz is also affected by insulation condition [2], the relation between the two parameters was explored by Baral and Chakravorti [20] and was subsequently reported in [20]. As the relationship given in (11) [20] is derived using data collected entirely from power transformers, it is assumed that the relationship between Z_1 and %tanδ [20] is also applicable to data considered in this paper. Equation (11) further makes it possible to compare %tanδ (for testing de-noising accuracy) even though measurement data corresponding to the first few seconds remain unavailable for the tested transformers.

A comparison between calculated (using de-noised data) and measured values of insulation sensitive parameters are reported in Fig. 9. It is clear from Fig. 9 that calculated values of the performance parameters are close to that of the measured ones. Figs. 10*a–c* show the performance of both S-Transform and Wavelet Transform-based de-noising techniques. Fig. 9 shows the comparison between measured and computed (de-noised data using S-Transform) value of performance parameters.

It can be observed from Fig. 9 that the value of performance parameters estimated using the de-noised signal is close to measured values. It is clear from Fig. 10 and the data presented in Fig. 9 that de-noised data using S-Transform provides almost similar results as obtained from wavelet analysis. Results reported in Fig. 9 show that S-Transform provides almost the same level of accuracy as provided by Wavelet Transform based. However, it should be mentioned here that in the case of Wavelet Transform-based methodology, the optimum decomposition level and the wavelet name are likely to vary depending on the profile of the noise. In order to illustrate this point, the optimum level and the wavelet name identified using the algorithm (mentioned in Section 3.2) for the data shown in Fig. 1 is presented in Table 3.

On the other hand, S-Transform based technique is simple and non-iterative in nature. This enables the S-Transform based technique less time-consuming. Table 4 shows the time required

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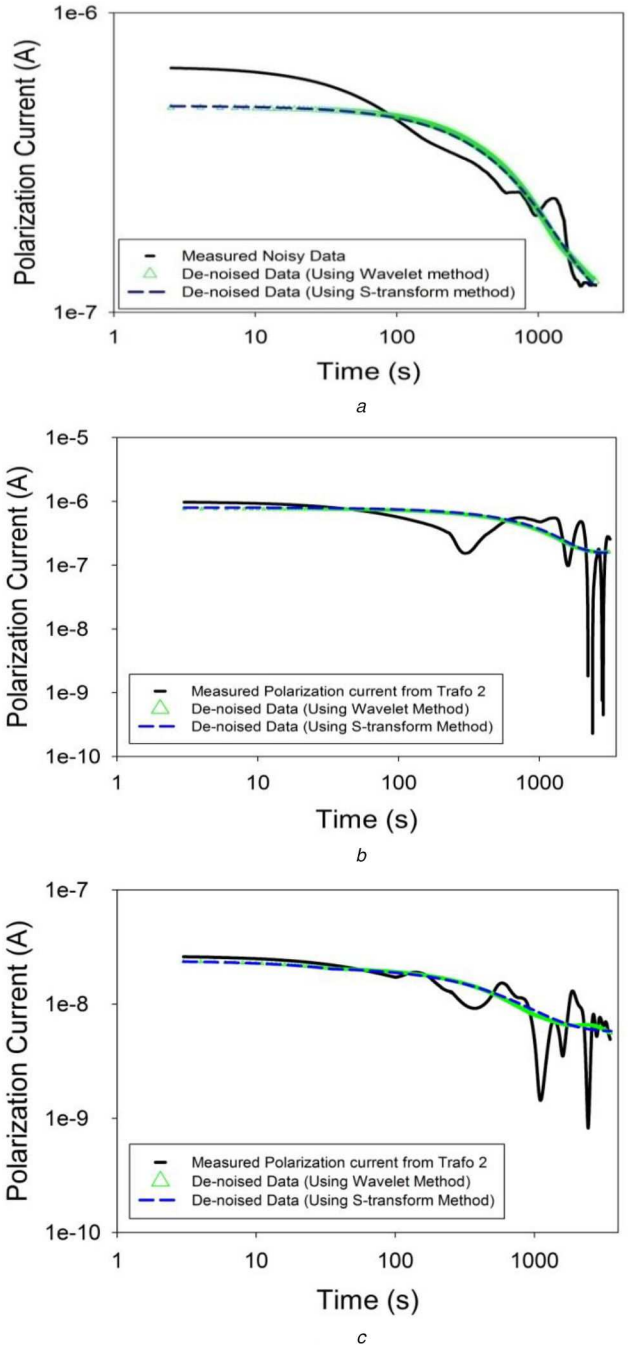

Fig. 10 *Noisy and de-noised polarisation current (using wavelet and S-Transform) for*
(a) Trafo1 of rating 200 MVA, 420 kV, ***(b)*** Trafo2 of rating 200 MVA, 765 kV, ***(c)*** Trafo3 of rating 240 MVA, 400 kV

Table 3 Optimum decomposition level and mother wavelet for de-noising transformer response

Unit name	Duration of signal, s	DL_{max}	Optimum level	Optimum wavelet
Trafo1	2551	12	10	bior3.7
Trafo2	3170	14	11	bior3.3
Trafo3	3503	14	10	Sym5

for de-noising the polarisation current shown in Fig. 1 using wavelet and S-Transform based technique.

It is worth mentioning here that the sampling frequency of data measurement using 6517B-based PDC recording equipment [5] can be controlled. After analysing the data provided by the utilities, it is observed that the sampling frequency tends to vary between 1 and 5 Hz. If a high sampling frequency is chosen or the duration of data

Table 4 Operating time of wavelet and S-transform based de-noising methodologies

Unit name	Type of method used	Total time required, s
Trafo1	wavelet transform-based method	1.94
Trafo2		3.3
Trafo3		3.8
Trafo1	Stockwell transform-based method	0.04
Trafo2		0.09
Trafo3		0.13

measurement is increased, it will increase the value of DL_{max} which in turn is going to further increase the computation time of Wavelet Transform-based methodology. Such an increase in operating time will be much less pronounced for the S-Transform based technique as it does not follow an iterative approach. This is also apparent from the data presented in Table 4.

6 Conclusions

Two de-noising techniques, one based on Wavelet Transform and other based on S-Transform are discussed in this paper. Based on the findings reported in this paper, the following conclusions can be made:

- Both wavelet and Stockwell Transform-based techniques are effective in de-noising low-frequency noise affected polarisation current data.
- The Wavelet Transform-based method is computationally intensive and is an iterative process. Hence, takes a longer time to operate.
- S-Transform based method provides the same level of de-noising accuracy, without going through any computationally intensive iterative process. Hence, takes much less time (as compared to Wavelet Transform-based technique) to operate.
- The proposed Stockwell transform-based de-noising technique is tested on data collected from a real-life power transformer.

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