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Incipient Equipment Failure Assessment and Avoidance through Robust Detection Technique

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Abstract

Key contributor to normal power grid operations is optimal working of the various power grid equipment/apparatus. Non-optimal operation of any of this equipment causes power quality problems which can pose great risk to the stability of the grid. Damaged or partially damaged equipment leaves characteristic signatures in the form of current and voltage waveform distortions. Detecting and localizing such signal distortions would contribute to grid reliability as the damaged equipment could be replaced in time before it can cause further damage. This paper proposes a Distortion Detection Technique (DDT) based on second-difference approach. This distortion detection technique has very low memory requirements and can be easily implemented on decentralized systems. The paper investigates the performance of this technique and evaluates it with case studies involving different kind of equipment failures simulated on Real Time Digital Simulator (RTDS).

1 Introduction

The reliable operation of a power system is dependent on the reliable operations of the several smaller apparatus, devices and components which all together constitute the power system. Any physical apparatus, device or component, which is a part of the power system, can be broadly classified as an equipment of the power system. Underperformance of any of these equipment can lead to unnecessary losses and other harmful effects like harmonics, noise, ferro-resonance etc. [1]. If left unchecked, harmful effects of failing equipment can even cascade to a large-scale blackout. With the passage of time, the equipment experiences a wide variety of stresses which includes mechanical stresses, electrical stresses, thermal cycles etc. [1]. These stresses lead to slow degradation of the equipment, which ultimately leads to its failure after a certain frame of time. Adverse weather conditions are another major contributor to equipment damage. Majority of the power system equipment have continuous work cycle and are installed in the exterior which makes them vulnerable to damage. Hence, the reliable working operation of a power system calls for strict vigil and periodic maintenance of different equipment's. There is also an important element of cost factor. It is much more advisable to replace failing equipment in time rather than risk the operations of the entire power grid. Risking operations of the entire grid would prove to be extremely costly to rectify and cause added inconvenience to the customers.

In this paper, a Distortion Detection Technique (DDT) based on second-difference approach is proposed. DDT is a new approach developed by the authors in the field of grid monitoring and protection. It has been applied in detection of High Impedance Faults (HIF) with successful results [2]. HIF is generally hard to detect by conventional protection schemes but with the implementation of DDT, HIF detection becomes much easier. In this paper, we apply DDT to equipment damage detection. Equipment damage is generally hard to

detect as they have a slow degradation process with a timeline stretching from few months to several years. However, they leave signatures of their degradation in form of distortions of the signals they are monitoring. Higher the degradation, more distorted is the signals. DDT aims to detect and analyse these distortions to identify failing equipment so that corrective actions can be taken before the power grid is affected.

DDT leverages the fact that a stable AC power system would have pure sinusoidal voltage and current waveforms. DDT aims to act during the pre-failure period to identify equipment damage. A pre-failure period can be defined as a time interval between the normal operating conditions of the grid and its subsequent collapse [3]. In this period the grid, though stable, is enduring more stress than normal. The time interval of the pre-failure period is the window of opportunity where the measured waveforms can be analysed to detect and classify a potentially harmful event for the grid.

There have been several studies where waveform analytics has been used to improve the reliability of the grid. In [4] non-technical losses have been detected using artificial intelligence while in [5] and [6] wavelet transformations have been used to detect and classify power quality problems. Texas A&M University has developed a tool in [3] where equipment damage is addressed through advanced situational awareness of the power grid. The tool however relies on massive databases of equipment failure and issues recorded by the Distribution System Operator (DSO's) over the years, which makes the commercial applicability of the tool costly and time-consuming. There has been Advanced Metering Initiatives [7] and Distribution Management Systems [8], where smart meters have been deployed to capture the customer energy usage pattern and record information of events at specific intervals. However these systems don't go beyond and are mainly used for billing and related activities. DDT on the other hand does online monitoring of the waveforms and does not depend on previously recorded databases. It is a robust yet lightweight technique which is

much faster than memory consuming processes like wavelet transformations.

DDT relies on difference based approach for detection of the distortions in the electrical waveforms measured from the grid. DDT forms the core of a larger algorithm that further processes the detected distortions in order to classify the nature of the event (harmful/not harmful) causing the distortion. The classification information is relayed to the operator who can then take appropriate actions to maintain the reliability of the grid. The detection technique leverages the sinusoid nature of voltage and current waveforms in the AC grid as explained in the subsequent sections. The mathematical backbone of the technique is a simple yet robust difference based approach which does not require large memory or huge computing power. A similar difference based waveform analytics approach has been used for current transformer saturation detection and compensation in [9].

In this paper, we validate the DDT and the associated algorithm by conducting simulations in the Real Time Digital Simulator (RTDS). In our first experiment we simulate a failing transformer and demonstrate how we detect it. In our second experiment, we mimic a set of real life events leading to failure of a device as detailed in [3]. The second experiment aims to demonstrate credibility of DDT by showing its applicability in real life equipment damage events.

The paper has been structured as follows: Section 2 discusses the mathematics behind DDT. Section 3 describes in detail the principle of the entire algorithm including the classification criteria. Section 4 presents and discusses the simulation results obtained. Finally, Section 5 presents the conclusions.

2 DDT as Difference Function

This section explains the DDT in detail and the mathematical principle behind it. The latter part of this section describes how DDT forms a part of a larger algorithm which governs how detection, analysis and classification of the distorted waveforms help in identification of a possible equipment failure. The setup is similar as explained in [2], but here a low pass filter has been added to improve performance against harmonics. Having proved its applicability in case of HIF, the main idea of this paper is to show the effectiveness of DDT against incipient equipment damage.

2.1 Distortion Detection Technique as Difference Function

The current and voltage waveforms in an AC power system are sinusoid and can be described as complex exponentials using Euler formula as seen in (1)

$$e^{j\omega t} = \cos \omega t + j \sin \omega t \quad (1)$$

Here ω is the angular frequency (*in radians per second*), t is time (*seconds*) and j is the imaginary unit.

The distinct characteristics of exponential functions are that the rate of increase or decrease of an exponential function is proportional to the value of the function at that instant. Another interesting characteristic of a complex exponential function is that they are not infinitely increasing or decreasing.

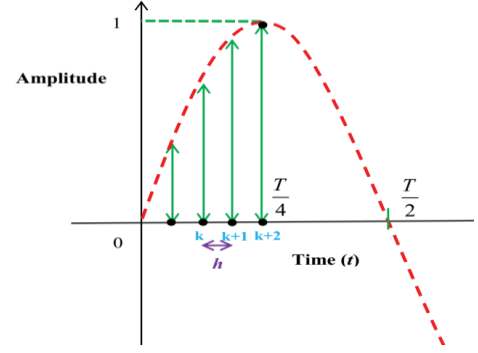


Figure 1 Sampled Signal $f[k]$

These characteristics of the complex exponential functions are used for devising the difference based DDT. The DDT proposed in this paper uses the first difference instead of continuous differentials since the signals that are being processed are sampled voltages and currents of the power grid.

The sampled signal $f[k]$, as shown in Fig. 1 is a general representation of any voltage or current signal measured from the grid. Assuming the signal as a sine wave of period T , which can be sampled at N samples per cycle, the samples could be denoted as: $n..k, k+1, k+2..n+N$. The samples are equally spaced in time-domain at an interval of length h , such that:

$$T = h \cdot N \quad (2)$$

Let $g[k]$ be the difference of the sample values at sample k and $k+1$, the first difference at k can be written as:

$$g[k] = \frac{f[k] - f[k-1]}{h} \quad (3)$$

Similarly at $k+1$:

$$g[k+1] = \frac{f[k+1] - f[k]}{h} \quad (4)$$

Now, for a pure sine wave, using (3) and (4), it can be written that:

$$g[k] > g[k+1], k \in \left\{n, n + \frac{T}{4}\right\} \cup \left\{n + \frac{T}{2}, n + \frac{3T}{4}\right\} \quad (5)$$

$$g[k] < g[k+1], k \in \left\{n + \frac{T}{4}, n + \frac{T}{2}\right\} \cup \left\{n + \frac{3T}{4}, n + T\right\} \quad (6)$$

Hence if $f[k]$ is a pure sine wave, (5) and (6) will always hold true. In case, (5) or (6) are violated, the violation will be recorded as a distortion. The violation will be interpreted as a distortion as for that instant, $f[k]$, would cease to be a pure sine wave. These simple yet distinct mathematical principles form the backbone of DDT.

3 DDT Implementation Algorithm

3.1 Distortion Detection Technique Implementation

In this subsection, we can discuss the DDT implementation in detail. DDT forms the main part of an overarching algorithm. The algorithm flowchart can be seen in Fig. 2.

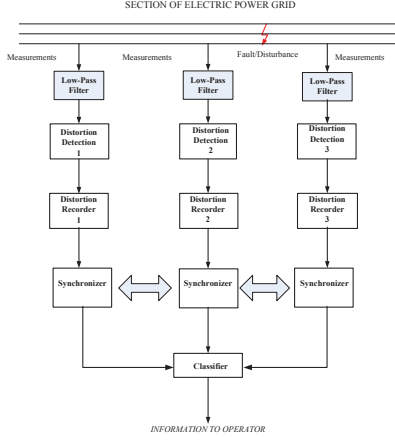


Figure 2 Distortion Detection Technique Implementation Algorithm flowchart

The electrical AC current and voltage waveform measurements are taken from the grid and analysed in steps as described below:

3.1.1 Low Pass Filter: The first step is to pass the waveforms through a low pass filter with the cut-off frequency being the fundamental frequency. This filter performs satisfactorily the frequency rejection above the first harmonic in order to avoid false flags by the technique.

3.1.2 Distortion Detection: The mathematics governing the Distortion Detection technique has been explained in the previous section. The main objective of this block is to implement the distortion detection technique. The input to this block is current or voltage waveform $f[k]$, measured with a sampling rate R from a particular node in the grid. Whenever this block detects violation of (5) or (6), a flag is raised and distortion reported. The output of this block is (d, t) , where d indicates the occurrence of the distortion at time t . We can define d as, $d = 1$ if distortion is detected and $d = 0$, if distortion is not detected. The output of this block serves as an input to the Distortion Recorder block.

3.1.3 Distortion Recorder: The objective of this block is to store the distortion occurrence data from Distortion Detection block in a data set of a specified length as explained below. This data set is called Memory Buffer. The input to this block is (d, t) . The input data is collected and processed by N sample window as it moves along the entire waveform. The size of the window is user-dependent and could vary from one measuring device to another. If we have m measuring devices such that $i = 1, 2, 3 \dots m$, then the memory buffer W_i in the time interval of (a_i, b_i) can be represented as:

$$W_i = \{(d_f, t_f) | d_f \in \{0, 1\}, t_f \in (a_i, b_i), f = (1, 2, 3 \dots N)\} \quad (7)$$

The memory buffer W_i contains the instants of occurrence and non-occurrence of distortions in a fixed length of time interval (a_i, b_i) . Eq. (7) is the output from the distortion recorder block and serves as an input to the synchronizer block.

3.1.4 Synchroniser: The synchronizer block helps in aligning all the reported distortions such that a correct classification can be achieved. The occurrence of a disturbance at a certain point in the grid will not have the same impact over the entire section of the grid. Same distortion can cause some measurement devices to report numerous and frequent distortion levels, some lower and some may not report any distortion at all. Also, the measurement devices may not have uniform sampling rates.

One of the pre-requisites for accurate analysis is that all the data collected should be synchronized. If not, it will cause false flag error leading to wrong results. Hence, for synchronization, comparison and further analysis of the distortion detection data we need a window of fixed time interval to collect all reporting's from different measurement devices during that time interval. The device with the highest sampling rate will report maximum distortion detection data in that fixed time interval compared to other measurement devices. The design of the smallest time interval for a single data recording of the window should be small enough to record reporting's from the measurement device of the highest sampling rate. Hence, the measurement device with the highest sampling rate forms the base reference for other measurement devices with lower sampling rates and consequently lower reporting rate of the distortion data. Henceforth, the design of the base window is governed by the measurement device of the highest sampling rate. The base window A can be represented as:

$$A = (a_{base}, b_{base}) = \cap_{i=1}^n (a_i, b_i) \quad (8)$$

The curtailed memory buffer \bar{W}_i , within the size limits of the base window can be represented as:

$$\bar{W}_i = \{w_i = (d_f, t_f) | w_i \text{ and } t_f \in (a_{base}, b_{base}) \text{ and } d_f \in \{0, 1\}\} \quad (9)$$

The last processing step of this block is to sum the values of the distortion occurrences d_f in \bar{W}_i . We can write:

$$C_i = \sum_{p=1}^{|\bar{W}_i|} d_p \quad (10)$$

Thus, (10) is the output from each synchronizer block sent to the classifier.

3.1.5 Classifier: As the name suggests, the main objective of this block is to classify events and present the output to the

operator. The classifier classifies the event as either ‘not harmful’ or ‘potentially harmful’. The classifier performs two main functions to classify any event causing distortion. The two functions are analysis of the reported distortions per measuring device and analysis of the reported distortions over the entire set of measuring devices:

The first function is to check the number of distortions occurring in each curtailed memory buffer \bar{W}_i . The value of C_i for each synchronizer block is compared against a threshold (th_i). If $C_i > th_i$, a flag is raised, else the classifier doesn’t process it further. The value of the threshold is user dependent and is based on the sampling rate of the waveforms. A major parameter for threshold value selection in our case study was comparison between the number of distorted samples recorded during a non-harmful event like switching actions and a harmful event like incipient equipment damage, HIF etc. A normal switching event might result in a small distortion of signal but the impact will be reflected on one or two samples and it will not repeat itself. Such an event will not exceed the threshold and trigger a warning unnecessarily. However a disturbance leading to a fault or an equipment failure would result in numerous and repeated distortions throughout the waveform, due to which the threshold limit value would be exceeded multiple times and a warning would be triggered.

The other function of the classifier block is to check the distortions reported from the waveforms recorded by all the measuring devices in a certain section of the grid. As the input to the classifier has already been synchronized, it is easier for classifier to compare the reported distortions across different devices in the same interval. A relatively stable switching event might not produce distortions in each section of the grid but a fault inducing disturbance would affect the entire grid and would produce distortions in all sections of the grid. The comparison of reported threshold violations over the entire measurement set ensures that false positives are minimized.

4 Simulation Results

4.1 Failing Transformer

In the simulation setup seen in Fig. 3, IEEE-9 bus system has been simulated in RTDS [10]. The measurement points (mp 1, mp 2, mp 3) record the waveforms at three different points. Transformers in a power system are very critical. They are costly and time-consuming to replace. One of the most common failures in the transformer is slow deformation of the insulation and the winding material with usage and time, which in turn directly affects the leakage inductance [11-12]. The failure of the transformer T1 in our case study has been simulated by varying leakage inductance value with time. The variation of leakage inductance values over time

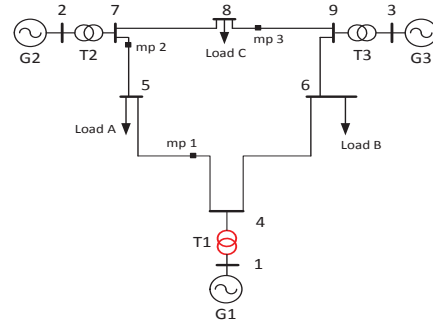


Figure 3 IEEE 9 bus system simulation setup (failing transformer)

intervals is done to mimic slow degradation of a device in real time. The change in waveforms at each interval is recorded and analysed by DDT.

The waveforms are recorded when the equipment damage is simulated to be at 30% and 60% respectively. During the time frame (0.035 - 0.045)s there are hardly any distortions

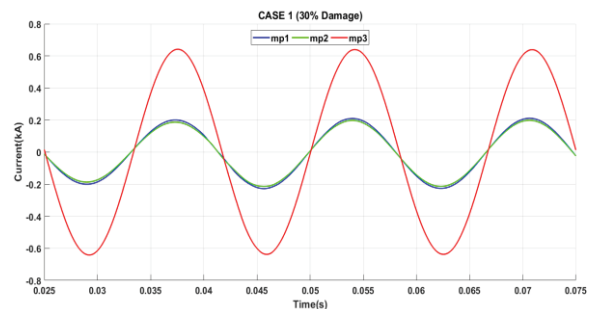


Figure 4 Current Waveforms at different measurement points for 30% damage

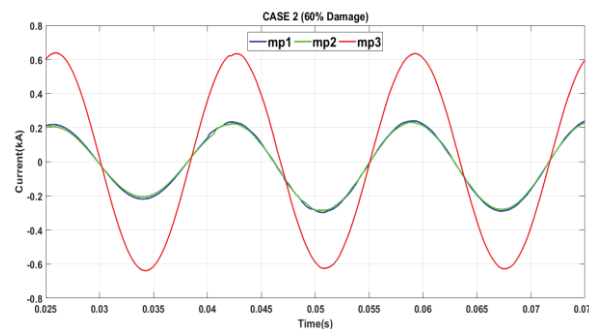


Figure 5 Current Waveforms at different measurement points for 60% damage

visible even though there are some magnitude change in Fig. 4, while in Fig. 5, for the same time frame there are visible distortions as the equipment is more than 50% damaged. However, when DDT is applied to the waveforms of both the cases, distortions at multiple samples are detected. A summary of the results are presented in Table I. The common reporting of the distortions help us to correctly identify a major event (incipient fault, equipment damage etc.) affecting several sections of a grid.

Table 1 Distortion Detection at different measurement points

Equipment Damage	mp1 (distorted samples)	mp2 (distorted samples)	mp3 (distorted samples)	Common Reporting's
1 st Interval (30% damage)	12	9	4	4
2 nd Interval (60% damage)	17	12	10	9

4.2 Circuit Breaker Failure (simulation of real-life event)

The second experiment conducted is based on switch and capacitor failure in an IEEE 9 bus system. At bus 8 a grounded Y capacitor bank was connected to protect the system from surge voltages and reduce triple and other harmonic currents. The parameters of the capacitor bank are 230KV, 60Hz and 0.5 μ F per phase as seen in Fig. 6.

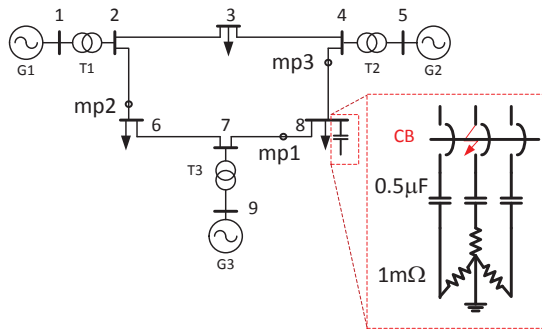


Figure 6 IEEE 9 bus with Switch and Capacitor Malfunction

The system works without any problem for a long time until a fault in the proximity of bus 8 occurs. During the fault the protection operation sequence works fine with relay trip action and reclosing actions working according to the protection scheme. After the fault clearance, the main circuit breaker (CB) exhibits an unusual behaviour. The breaker starts to switch on and off every 1.5mins, until the capacitor is damaged and has lost around 20% of its capacitance. The slight damage to the device leads to more unusual behaviour. The switching becomes more frequent in nature and takes place every 20s till the capacitor is damaged to a loss of 40% of its capacitance. The device gets damaged further which in turn made the switching problem increase to a recurring frequency of every 10s. This damage reduced the capacitance of the capacitor bank to 50% of its original capacitance. Eventually, as a result of extensive damage and malfunctioning capacitor bank, the CB opens and remains disconnected.

The full simulation of the above described chain of events was conducted on RTDS, where the CB behaviour was simulated through Batch Mode Operation using a script to change the characteristics of the capacitor bank. The waveforms at various measuring points were recorded and analysed. The entire simulation was run for 5mins to record

the waveforms. In Fig. 7 (a-i), (b-i), (c-i), a 10s extract is shown for all the three cases of switching of circuit breaker connected to three capacitor bank. The minute distortions at the instant of switching are not clearly visible in those waveforms. Fig. 7 (a-ii), (b-ii), (c-ii) shows the zoomed-in section of the distorted parts (encircled) of the waveforms. The distortions are now clearly visible for each of the three cases. These waveforms are continuously analysed by DDT. The distortions recorded are time stamped which helps in knowing the instant of distortion. The distortions are processed by the algorithm as discussed in section 3. The results are documented in Table 2 where the reported distortions for each measuring point for each case of switching are listed. The distortions listed in Table 2 are for the time frame when switching happens. We can observe that as the device damage increases, we detect more and frequent distortions. The common reporting's column contains the number of common distortions (distortions at the same time) recorded across all the measurement points. This helps to eliminate false reporting's due to inaccuracy or malfunction. The amount of common reporting's also help to assess the extent and severity of equipment damage. The classification is categorized as either 'not harmful' or 'potentially harmful'.

The disturbances created by the CB are nearly undetectable for the nearest commercial relays but the DDT discussed in this paper successfully detects it. DDT can help raise an alarm which could be useful for the utilities to replace faulty equipment before it leads to an outage. The flicker produced by the capacitor bank faulty switching can also damage the nearby customers or induce an outage leading to huge losses for both electricity providers and consumers but the application of the DDT can help in curbing these losses too. Overall, DDT and the associated classification algorithm can help utilities in identifying and replace damaged equipment's where conventional methods generally fail.

Table 2 Distortion Detection at different measurement points

Case Study	mp1 (distorted samples)	mp2 (distorted samples)	mp3 (distorted samples)	Common Reporting's
CASE I (switching every 1.5 mins) (6.97-7.05)s	57	54	41	35
CASE II (switching every 1.5 mins) (6.97-7.05)s	77	72	65	41
CASE III (switching every 1.5 mins) (6.97-7.05)s	117	107	102	67

5 Conclusions

In this paper the application of Distortion Detection Technique is shown in the case of incipient equipment damage. Real life equipment failure example was simulated in the lab and DDT successfully detects it. DDT is a lightweight yet robust tool which proves its performance where conventional methods fail. The frequency and intensity

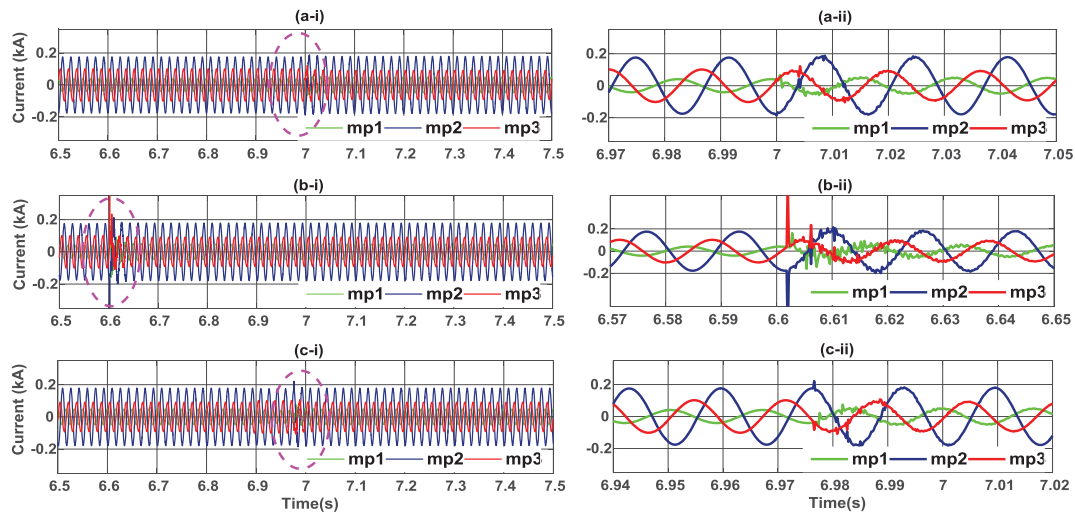


Figure 7 Measured currents at mp1, mp2 and mp3. Case I (a-i) switching at 1.5s and (a-ii) zoomed view. Case II (b-i) switching every 20 seconds and (b-ii) zoomed view. Case III (c-i) switching every 10 seconds and (c-ii) zoomed view.

of the distortions vary according to the proximity of the measurement point to the place of failure. Hence, future work will involve devising technique, which can help to locate the exact spot of equipment failure, which will further help in saving time and resources.

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