



Ground-Fault Detection based on Statistical Parameters of Wavelet Transform for Unit-Connected Generator

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Abstract: Majority of electric faults are ground faults. The severity of a single line to ground fault must be minimized. The ability to classify the type of fault plays a great role in the protection of a power system. This paper presents an approach of applying discrete wavelet transform to single ground fault detection in different locations at a unit-connected generator. In this paper, current waveform was decomposed through wavelet analysis into various approximations and details. A new statistical approach, which includes the feature extraction of statistical parameters at each type of single line to ground fault, is characteristic in nature, and was used for the detection of single line to ground faults. The simulation of the unit-connected generator was carried out using the Sim-Power System Blockset of MATLAB. The statistical analysis involved calculating the *mean*, *mode*, *median*, *range*, and *standard deviation* values of wavelet detail coefficients. The results indicated that the proposed algorithm was accurate enough to detect a single line to ground fault for a unit-connected generator.

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1. Introduction

Small current ground-fault (GF) detection has been a major concern in protective relaying for a long time. Relaying engineers and researchers often face the challenge of developing the most suitable technique that can detect faults with reasonable reliability to secure the run of a power system (Omar *et al.*, 2003). Reference (IEEE, 2006; Das, 1999) describe a step up transformer at an electric power station can be categorized either as a unit-connected generator configuration, a unit-connected generator configuration with generator breaker, a cross-compound generator or a generator involving a unit transformer. A GF on the transmission line or busbar can affect the system configuration of the generator.

Several methods have been reported for generator GF protection (Sultan *et al.*, 2012). These methods have been developed based on conventional method, third harmonic method, sub-harmonic injection method and numerical protection method. Fault detection and classification algorithms based on Wavelet Transform (WT) and artificial neural network was proposed in (Silva *et al.*, 2006; Zhengyou *et al.*, 2011).

Various feature extraction methods based on WT have been used for the detection and classification of fault. Fault classification algorithm

based on energy and wavelet entropy in transmission have been proposed in (Zhengyou *et al.*, 2011; Safty *et al.*, 2009) Reference (Pittner *et al.*, 1999; Rao *et al.*, 2007; Rahman *et al.*, 2007) describe the feature extraction method based on fast WT, a fault index and wavelet power for use to detect stator fault in the synchronous generator. Extraction of a statistical parameters as fault detection has been used for fault detection in previous studies, but only used *standard deviation*, *kurtosis* and *skewness* (Baqui *et al.*, 2011). Meanwhile, the statistical feature parameters include *kurtosis*, *skewness*, *crest factor*, *clearance factor*, *shape factor*, *impulse factor*, *variance*, *square root amplitude* value and *absolute mean amplitude* value to fault diagnosis in rotating machine as described in reference (Chagqin *et al.*, 2013). The new approach as proposed in this paper includes tendency and dispersion of statistical parameters on single-line to ground (SLG) fault detection.

The novel method for GF detection uses tendency and dispersion of statistical parameters, which involve calculating the *mean*, *mode*, *median*, *range* and *standard deviation* values of detail wavelet coefficients, which are included in the analysis in this paper. In the experiment, the GF signals were computed by using Discrete Wavelet Transform (DWT). The ground-fault detection was carried out

through the analysis of value of *mean*, *mode*, *median*, *range* and *standard deviation* of the current wavelet coefficients, included the detail and approximate of wavelet coefficients to distinguish SLG fault.

2. Statistical parameters extraction method based wavelet transform.

A WT is a powerful tool for feature extraction of the transient signals. WT has been applied in many researches for feature extraction of transient fault signals. The differences among modification of this method are: different types of mother wavelet, various numbers of decomposition level, and state of calculating the energy or entropy features (Ekici *et al.*, 2008). There are many types of mother wavelets, such as Symlets, Coiflets, Haar, Daubechies. The optimal choice of the mother wavelet is crucial for a successful wavelet transform application. The optimum wavelet for extracting signal information is defined as capability to generate as many coefficient as possible to represent the characteristic of signals (Megahed *et al.*, 2008).

In this study, DWT was used for feature extraction, which decomposes original, typically non-stationary signal into low frequency signals called approximations and high frequency signals called detail, with different levels or scales of resolution. At each level, approximation signal is obtained by convolving signal with low pass filter (LPF) followed by dyadic decimation, whereas detail signals is obtained by convolving signal with high pass filter (HPF) by dyadic decimation. The DWT was calculated by using the following equation (Kim *et al.*, 2002):

$$DWT(m, n) = \frac{1}{\sqrt{a_0^m}} \sum_k x(k) g(a_0^{-m}n - b_0k) \quad (1)$$

where “ $g(k)$ ” is the mother wavelet, “ $x(k)$ ” is the signal input and a, b are the scaling and translation parameters.

DWT was implemented by using HPF and LPF filter respectively (Polikar, 1999), defined as:

$$y_{high}[k] = \sum_n x[n] \cdot g[2k - n] \quad \dots (2)$$

$$y_{low}[n] = \sum_k x[k] \cdot h[2k - n] \quad \dots (3)$$

where “ $y_{high}(k)$ ” is the output from the HPF called detail and “ $y_{low}(n)$ ” is the output from the LPF called approximation.

In this study, for feature extraction process, the coefficient features of wavelet such as *Mean*, *Median*, *Mode*, *Range* and *Standard Deviation* had to be calculated. Mean is defined as the [average](#), while *median* is a [number](#). This number has the property that it divides a set of observed values in two equal halves, so that half of the values are below it, and half is above. The *mode* of a set of data is the one that occurs most. *Standard deviation* is a number used to tell how measurements for a group are spread out from the average or expected value.

3. Proposed Algorithm

The proposed of the SLG fault detection algorithm consists of three steps. The first step of the detection module was to get the current samples from Matlab Simulink simulation (Matlab, 2012). The next step, fault signals were then computed by DWT. The fault detection was carried out through feature extraction analysis of statistical parameters in the current wavelet coefficients, included the detail and approximate of wavelet detail coefficients. Finally, the SLG fault detection algorithm is summarized by the following rules:

1. Identifying the current signal for each phase
2. Calculating the signal using DWT to get signal of detail coefficients.
3. Identifying the statistical parameters of wavelet coefficient (including *Mean* (M), *Mode* (MD), *Median* (Md), *Range* (R) and *Standard deviation* (STD)).
4. Criteria for SLG fault must be fulfilled based on two conditions:
 - *Range* (R) and *Standard deviation* (STD) of feature extraction larger than R and STD of the other phase of feature extraction
 - *Mode* (MD) of feature extraction smaller than MD of the other phase of feature extraction

4. Simulation Result and Analysis

A simplified unit-connected generator with generator breaker for SLG fault simulation is shown on Figure 1. The proposed simulation of GF was applied at three locations (terminal generator (Point-1), the primary side of a transformer (Point-2) and the secondary side of a transformer (Point-3).

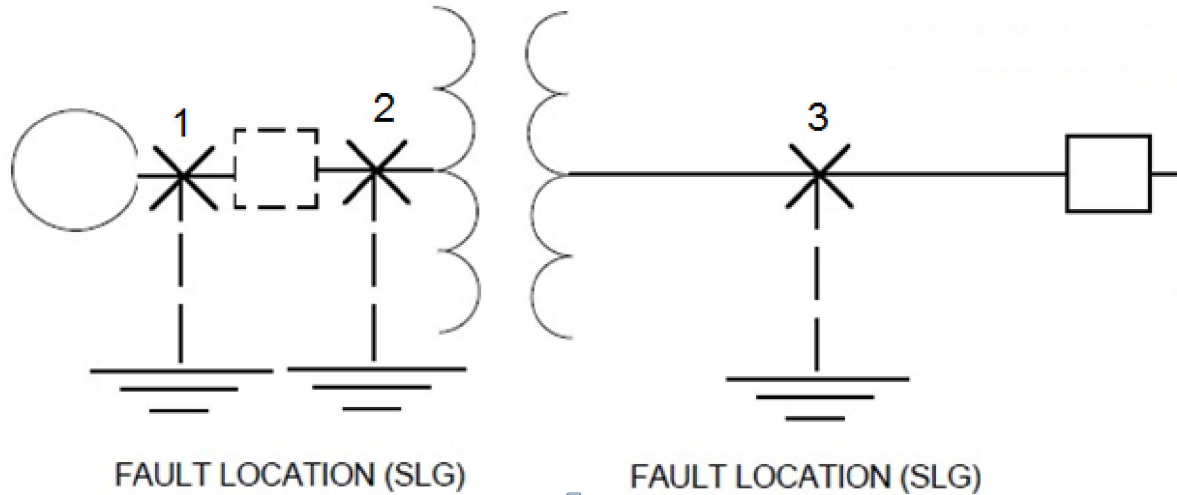


Figure 1. Fault location for simplified unit generator-transformer

The simplified power system models for GF simulation are shown in Figure 2. Via Matlab Simulink, three-phase source (mask) type was used to model the AC synchronous generator; while the three-phase transformer (two-winding) model was used as step-up transformer. The SLG fault was set to occur at 0.0167 until 0.0833 sec. Simulation was carried out at various fault locations. Fault current was taken from the generator bus.

The output results were then de-noised and compressed using daubechies (db) 4 and Detail Level 2 from the wavelet toolbox available in Matlab software. They were chosen because of their symmetric condition, hence should be very desirable property in signal processing application for the linear phase response. In general, it is expected that when an SLG fault occurs, the measured terminal current waveform should contain significant transient components.

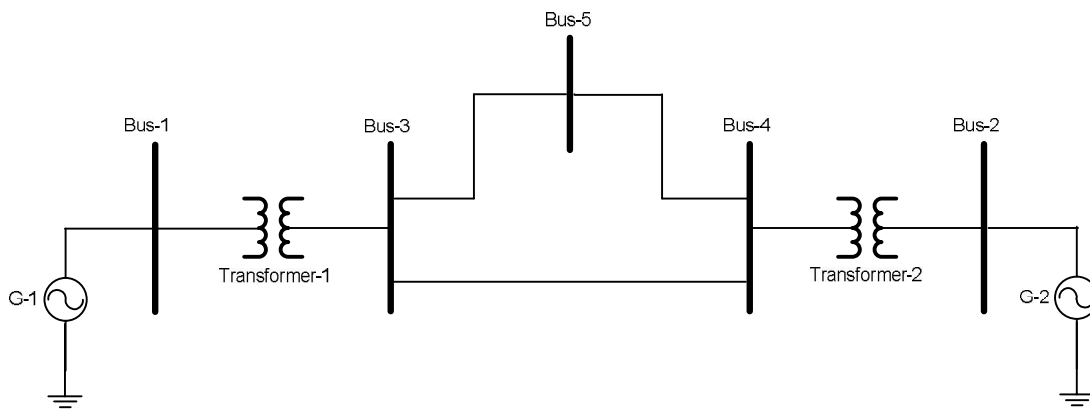


Figure 2. Simplified power system model for ground fault simulation

4.1 Normal Condition

The three-phase current signals at normal condition and their detail coefficient are shown in Figure 3a and 3b, respectively. Figure 3b shows that in normal condition, the detail coefficients of these

signals were near zero (3×10^{-6}). The *Mean, mode, median, range* and *standard deviation* of a current Detail-1 (D1) of DWT coefficient in normal operation are presented in Table 1.

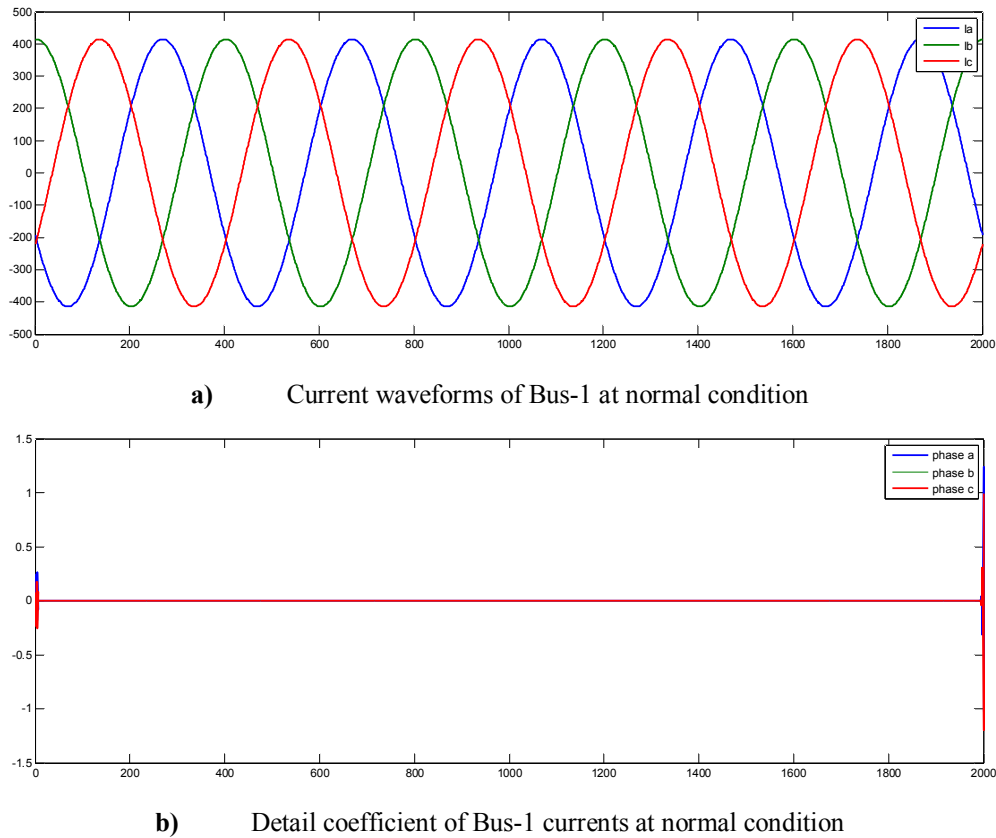


Figure 3. Current waveform with detail coefficient of Bus-1 at normal condition

Table 1. Statistical parameters of current detail coefficient data in normal condition

	Mean	Mode	Median	Range	Standard dev.
Current of phase-a	-0.000000035	-1.0232	-0.000000022	2.267595	0.038252
Current of phase-b	0.000000074	-0.0412	0.000000011	0.075019	0.001326
Current of phase-c	-0.000000040	-1.2024	0.000000059	2.191098	0.036913

Table 1 shows that based on the proposed method, the higher values of *range* and *standard deviation* parameter were 2.267595 and 0.038252, respectively, but the value of a *mode* parameters in phase-a was -1.0232. This value was higher than the *mode* values of other phases. Thus, under normal conditions, the proposed algorithm had successfully distinguished the non-occurrence of SLG fault.

4.2 SLG fault

In the simulation, SLG fault current was found to occur at phase-a, phase-b and phase-c. The current waveform at Bus-1 during SLG fault in phase-b at Point-1, Point-2 and Point-3 (refer to Figure-2) as shown in Figure 4, 5 and 6 respectively.

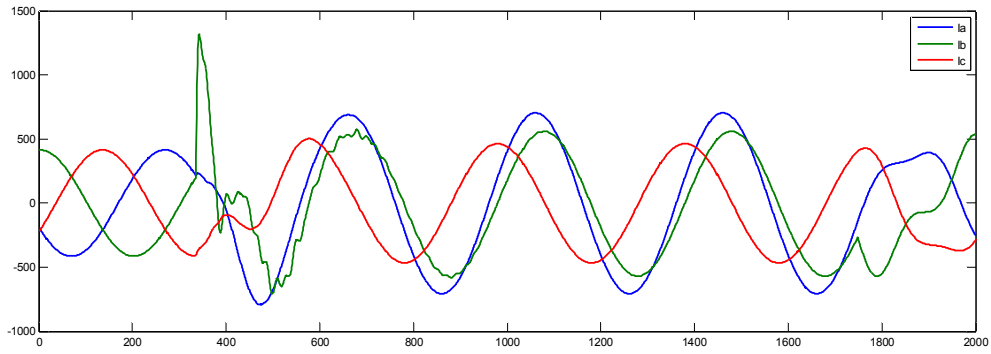


Figure 4. Current waveform at Bus-1 for during SLG Fault (phase b) at Point-1

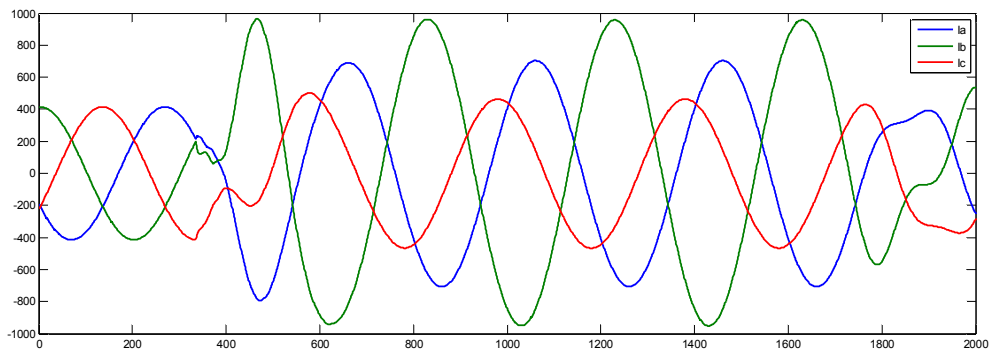


Figure 5. Current waveform at Bus-1 during SLG Fault (phase-b) at Point-2

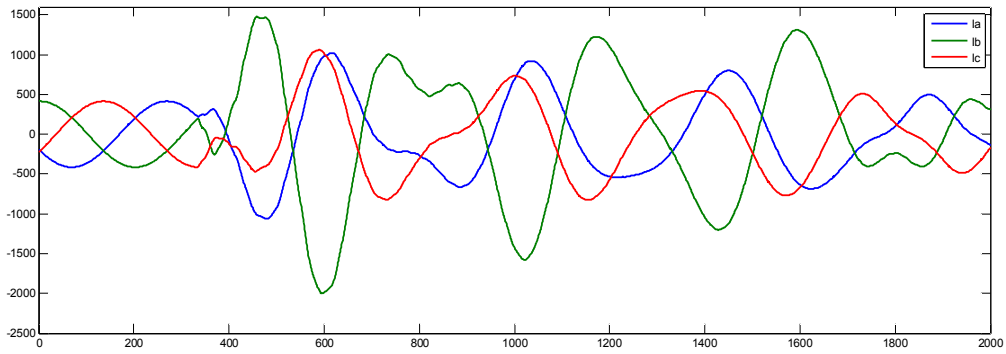


Figure 6. Current waveform at Bus-1 during SLG Fault (phase-b) at Point-3

With application of WT with daubechis (db) 4 and Detail Level 2, the detail outputs for SLG

fault at different fault location are illustrated in Figure 7, 8 and 9 respectively.

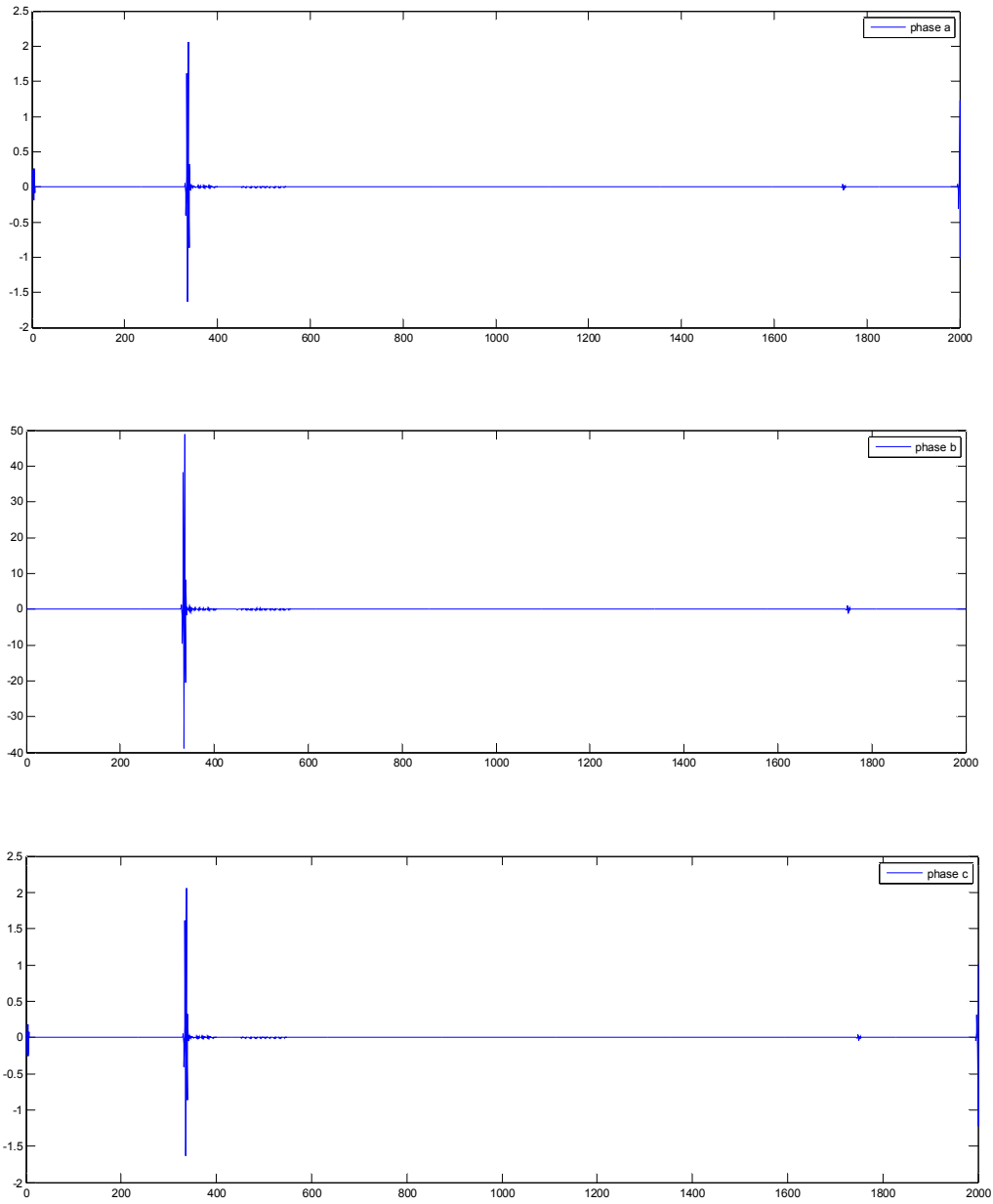


Figure 7. D1 current of DWT output for SLG-Fault (phase b) at Point-1.

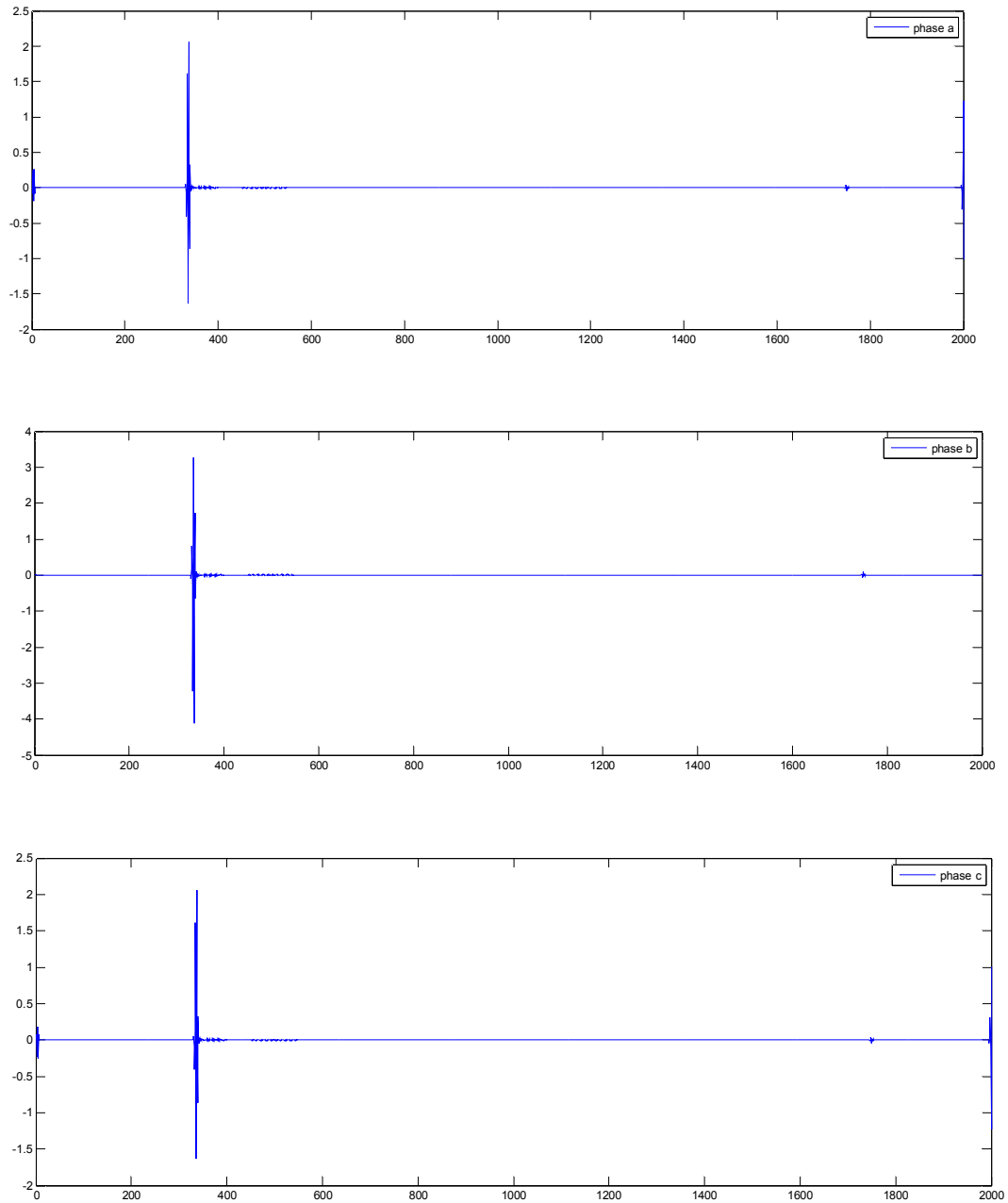


Figure 8. D1 current of DWT output at Bus-1 during SLG fault(phase b) at Point-2.

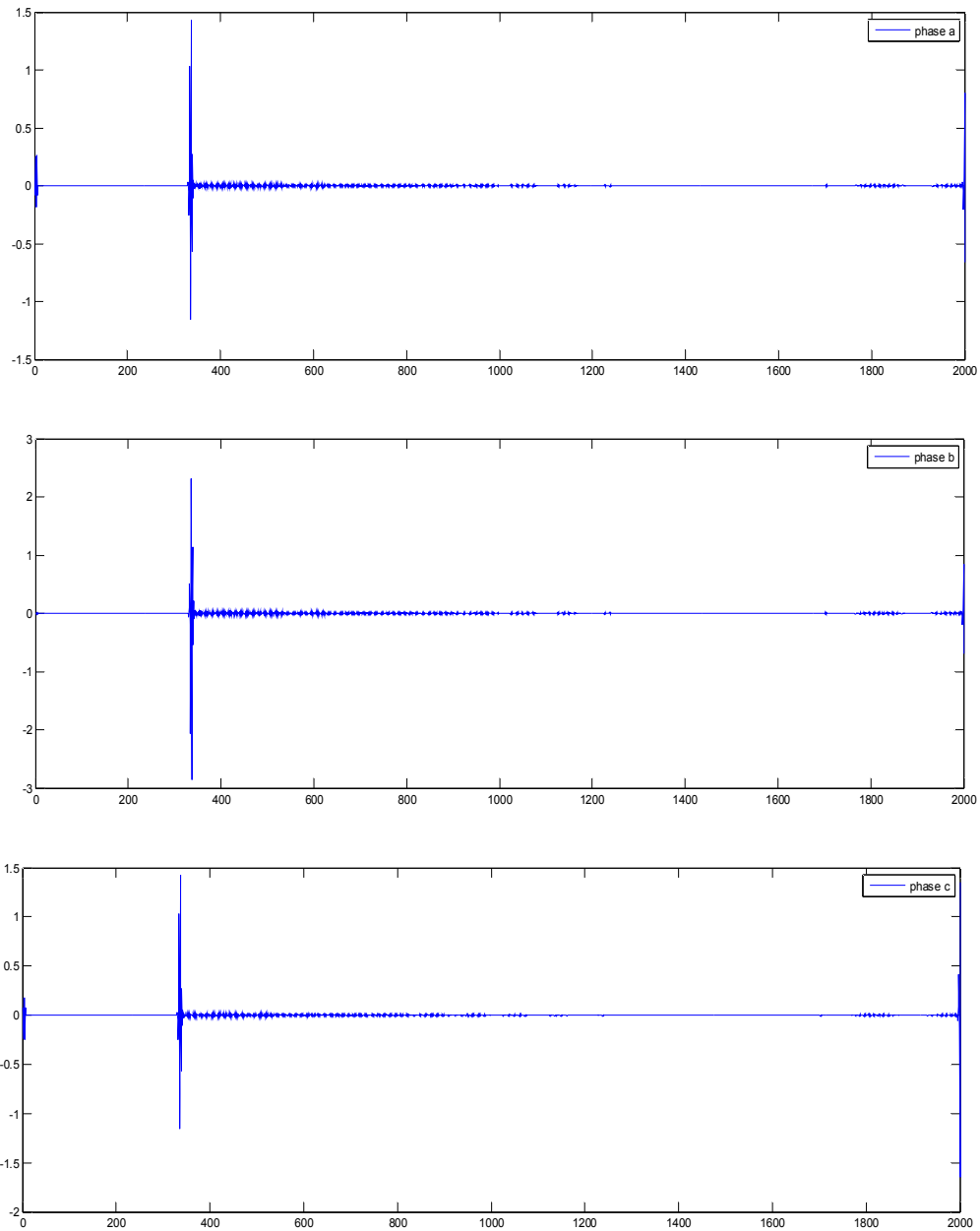


Figure 9. D1 current of DWT output at Bus-1 during SLG fault (phase-b) at Point-3.

Based on the daubechies wavelet detail as shown in Figure 7, 8 and 9, it was obviously seen that during SLG fault, the value of current D1 for the faulty phase was greater than the other phases. By using the statistical parameters approach, the quantities of each phase during SLG fault could be

clearly identified. The analysis results of the current detail coefficient data during SLG fault are shown in Figure 7, 8 and 9 for various phase and fault location, while the calculation results can be seen in Table 2, Table 3 and Table 4, respectively.

Table 2. Statistical parameters of current detail coefficient data during SL-G fault (phase a) at various fault locations.

	Mean	Mode	Median	Range	Standard dev.
Current of phase-a (Point-1)	0.0000021	-48.9700	0.000000044	87.69345	1.861055
Current of phase-b (Point-1)	-0.0000010	-2.0629	0.000000020	3.692284	0.078764
Current of phase-c (Point-1)	-0.0000011	-2.0628	0.000000147	3.692257	0.089552
Current of phase-a (Point-2)	0.0000021	-3.2467	-0.000000251	7.3631	0.16478
Current of phase-b (Point-2)	-0.0000010	-2.0628	-0.000000018	3.6920	0.07876
Current of phase-c (Point-2)	-0.0000011	-2.0627	0.000000156	3.6920	0.08955
Current of phase-a (Point-3)	0.0000052	-2.2912	0.000000408	5.1347	0.1285
Current of phase-b (Point-3)	-0.0000025	-1.8014	-0.000000177	2.5608	0.05600
Current of phase-c (Point-3)	-0.0000027	-1.8014	-0.000000223	3.2824	0.075586

Table 3. Statistical parameters of current detail coefficient data during SL-G fault (phase b) at various fault location

	Mean	Mode	Median	Range	Standard dev.
Current of phase-a (Point-1)	0.0000000153	-1.63742	-0.000000191	3.70236	0.087044
Current of phase-b (Point-1)	-0.0000000253	-38.8994	0.000000646	87.89727	1.86161
Current of phase-c (Point-1)	0.0000000102	-1.63743	0.000000216	3.702389	0.086896
Current of phase-a (Point-2)	0.0000000153	-1.63728	0.000000043	3.702119	0.087044
Current of phase-b (Point-2)	-0.0000000252	-4.12041	0.000000164	7.382957	0.156777
Current of phase-c (Point-2)	0.0000000101	-1.6373	0.000000217	3.702148	0.086894
Current of phase-a (Point-3)	-0.0000008705	-1.15827	0.000000032	2.586638	0.059034
Current of phase-b (Point-3)	0.0000017463	-2.86559	-0.000000029	5.186201	0.109369
Current of phase-c (Point-3)	-0.0000008758	-1.64518	0.000000212	3.073563	0.072668

Table 4. Statistical parameters of current detail coefficient data during SL-G fault (phase c) at various fault location

	Mean	Mode	Median	Range	Standard dev.
Current of phase-a (Point-1)	0.0000000218	-1.08262	-0.00000013	2.398562	0.040546
Current of phase-b (Point-1)	0.0000001308	-0.12711	-0.00000009	0.261286	0.004533
Current of phase-c (Point-1)	-0.0000001522	-3.09001	0.00000036	6.385261	0.11418
Current of phase-a (Point-2)	0.0000000220	-1.08268	-0.00000012	2.398691	0.040548
Current of phase-b (Point-2)	0.0000001308	-0.12714	-0.00000007	0.26136	0.004533
Current of phase-c (Point-2)	-0.0000001530	-1.34701	0.00000013	2.455833	0.042028
Current of phase-a (Point-3)	-0.0000037986	-0.30132	-0.00000001	0.666299	0.014985
Current of phase-b (Point-3)	-0.0000036896	-0.09223	-0.00000047	1.679436	0.027292
Current of phase-c (Point-3)	0.0000074878	-0.45578	0.00000052	1.013064	0.019212

By applying the proposed method, the SLG faults in phase-a at point-1 (Table 2) produced higher values of *range* and *standard deviation* parameter, at 87.69345 and 1.861055 respectively. The value of *mode* parameter in phase-a at point-1 was -48.9700. This value was smaller than the *mode* value of other phases. This conditions was similar for phase-b and phase-c though at different fault location (Table 3 and Table 4). Therefore, the proposed algorithm had successfully distinguished SLG fault at various phases and fault locations.

By using statistical parameters, it was observed that SLG fault at different phase and fault location (refer to Table 2, Table 3 and Table 4) produced *range* and *standard deviation* values for the faulty phase greater than the other phases. For the *mode* value, the amount of faulty phase was smaller than the un-faulty phase. However, the *mean* and *median* parameters were unable to distinguish SLG fault.

5. Conclusion

This paper has presented a novel approach for SLG fault detection at the unit-connected generator. In this study, analysis of statistical parameters had been successfully applied to distinguish SLG fault. The statistical parameters involved calculating the *mean*,

mode, *median*, *range* and *standard deviation* values of DWT detail. Parameters including *range*, *standard deviation* and *mode* are available to detect the ground faults, while the *mean* and *median* parameters were unable to distinguish SLG fault.

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