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Multi-Resolution Analysis Based Line to Ground Fault Discrimination in Standalone Wind Energy Conversion System in harmonic environment

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Abstract

This paper aims to identify line to ground (LG) fault, in a standalone Wind Energy Conversion System (WECS), monitoring the load current spectrums. Firstly, an isolated WECS has been built in simulated environment. The load side currents at normal and at LG fault have been recorded and analyzed to determine the frequency content of the signal and the magnitude for each harmonics present in the system both at normal and at fault. Secondly MRA based DWT analysis has been pursued. Significant difference between normal and fault conditions have been observed in these values. Later, optimization has been done with respect to DWT levels and statistical parameters for fault identification. Based on optimization, an algorithm has been developed for fault assessment. The algorithm has been validated with the data obtained from a practical stand-alone WECS, which gives satisfactory results. Thus this monitoring technique can be suitable for effective LG fault detection in standalone WECS.

Key words

Level Optimization, Line to ground fault, MRA based DWT analysis, Parametric Optimization, Practical validation.

1. Introduction

Globally wind energy has become a mainstream energy source and an important player in the world's energy market, which now contributes to the energy mix in more than 70 countries across the globe. To retain operational quality of wind energy systems, it is of utmost importance to provide predictive and preventive maintenances to the Wind Energy Conversion System (WECS). Numerous analyses have been seen in literature for providing maintenance to these sorts of systems. A standalone WECS unsymmetrical fault analysis has been done monitoring the pattern of MRA of DWT coefficient Skewness and Kurtosis values [1]. Wind Turbine aerodynamic asymmetry, rotor furl imbalance, blade imbalance, nacelle-yaw imbalance can be monitored using artificial neural network based empirical mode decomposition algorithm in Simulink, FAST and TurbSim [2]. Low speed synchronous generator electrical and mechanical faults can be identified using wavelet transform based spectral analysis [3]. Typical sensor fault in a variable speed wind energy conversion system can be detected using filter residual signal based monitoring strategy [4]. Empirical mode decomposition method can be used for extracting fault features from the vibrating signal of Wind turbines, wherein trained fusion based classifier can be used to disintegrate the faults [5]. Stator inter-turn fault in an excited synchronous generator and permanent magnet synchronous generator can be detected using stator current signature analysis, monitoring the harmonic frequencies generated in the system at fault [6]. Generator temperature prediction and fault identification can be pursued for wind turbine using unscented Kalman filter based approach [7]. Gear condition indicator can be used to detect gear damage during non-stationary load and speed operating conditions in wind turbines [8]. ATP-EMTP travelling wave based fault detection has been seen to be done in offshore wind power plants, for fault identification in the power cables burned deep into the sea bottom [9]. A method has been seen for injecting both positive and negative sequence currents by wind turbines during asymmetrical fault, which improves the grid performance in comparison to conventional systems [10]. Anomaly detection technique used in SCADA system can be used for online fault detection in WECS [11]. A multi-criteria decision making framework using analytic hierarchy process (AHP) can be used for fault detection in WTGs [12]. A dynamic model based approach has been seen to quantify the severity of upstream mechanical equipment faults in WTGs [13]. None of the assessments observed, except [1] deals with the unsymmetrical fault identification in standalone or grid interconnected WECS, monitoring the Multi-resolution analysis based Discrete Wavelet Transform (MRA of DWT) coefficients, Skewness, Kurtosis values.

This is an extended analysis and practical validation of [1] and the motivation of this paper, is thus to deal with the line to ground fault detection in standalone WECS, monitoring the MRA of DWT decomposition level coefficient's Skewness, Kurtosis and RMS values. Firstly an isolated WECS has been developed in simulation environment [1]. The current signature of the load side has been tracked and analyzed to determine the magnitude of the individual harmonic frequencies present in the signal at normal and at fault. Demonstrating the disadvantage of only harmonic content monitoring in fault detection, the proposed technique has been applied and accordingly feature extraction has been done to distinguish the LG fault in the network. To practically authenticate the proposed fault diagnosis, data has been collected at normal and at fault from field study and analyzed using the proposed fault diagnosis technique, with satisfactory outcome.

2. Harmonic Detection in the simulated system

The load current signature of the developed system [1] has been captured and the harmonic frequencies present in the system both at normal and at single line to ground fault has been assessed using Discrete Fourier Transform (DFT) [14]. The magnitude for each harmonics present in the system at normal and at fault has been determined. The DFT analysis and the magnitude of harmonics at normal and fault have been presented in Table 1. In Table 1, "*F*" denotes the frequency content of the signal.

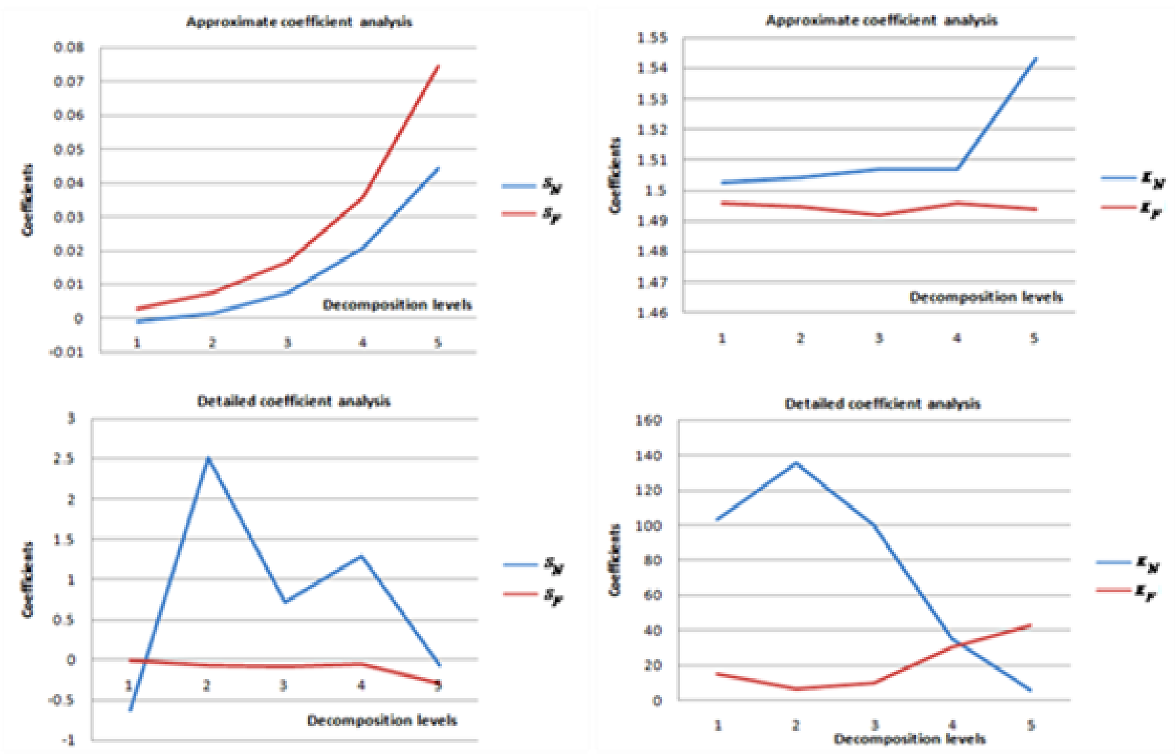
Table 1. Harmonic Assessment of load side current

Normal		Fault	
F (Hz)	Magnitude (dB)	F (Hz)	Magnitude (dB)
50	47.03	50	20.71
78	36.287	117	42.45
156	25.13	234	35.07
234	19.82	351.5	30.41
312.5	13.66	468.5	28.61
390.5	13.42	585.5	26.33
468.5	12.16	703	25.35
546.5	7.71	820	23.64
625	8.44	937.5	22.61
703	8.45	1054.5	21.54
781.25	4.59	1171.5	20.78

Thus by monitoring the values of Table 1, it is clear that for LG fault in a system, different harmonics with dissimilar magnitudes are generated in a system in comparison to healthy condition and thus monitoring these parameters fault can be assessed in a system. But specific type of fault identification in a system cannot be done using this technique. Thus a new technique of unsymmetrical fault analysis has been proposed in the succeeding sections.

3. LG Fault identification in simulated system

The load current, of the simulated system, has been collected both at normal and at LG fault in the bus. Both the tracked current signature has been analyzed using Multi-Resolution Analysis of Discrete Wavelet Transform (MRA of DWT) [15] algorithm. Here Daubechies 20 mother wavelet has been chosen and 5 decomposition levels have been taken into consideration depending on the nature of signal obtained. The approximate and detailed coefficient values have been analyzed computing the Skewness, Kurtosis and RMS [16-18] values of the coefficients. Monitoring the nature of the statistical coefficients, no concrete conclusion about the inception of fault in the system can be assessed. Thus for more specific identification, Skewness, Kurtosis and RMS value based analysis has been done. Depending on the values obtained, features have been extracted for LG fault identification in a system, monitoring the Skewness, Kurtosis and RMS values of the decomposition level coefficients as presented in Fig. (s) 2-3.



(a) (b)

Fig. 2. Feature extraction monitoring (a) Skewness (b) Kurtosis of approximate and detailed coefficients

Fig. 2 (a) shows that, with increase in DWT decomposition level, the Skewness of approximate coefficients gradually increases but the nature obtained is not exactly linear. Also the Skewness values are greater for LG fault in the system in comparison to healthy condition of the network and highest deviation in the coefficient values occur at 5th level of DWT decomposition. Observation from Fig. 2 (a) also reveals that, at healthy condition, the Skewness of detailed coefficients varies in zigzag nature and the Skewness values are greater in comparison to data at fault. However the data at fault has been seen to be decreasing with the increase of number of decomposition levels. However, the highest deviation in the values occurs at 2nd level of DWT decomposition. Monitoring Fig. 2 (b) it is clear that with increase in number of decomposition levels, the Kurtosis of the approximate coefficients at healthy condition gradually increases up-to 4th level but abruptly increases in 5th level of decomposition. But in Fig. 2 (b) for fault, the Kurtosis of the approximate coefficient values remain more or less same for 1st two decomposition levels, decreases for 3rd level, and increases for 4th level which has been seen to decrease again for 5th level. Thus the nature is zigzag and the highest deviation occurs at level 5. Again in Fig. 2 (b), the healthy Kurtosis of the detailed coefficient values increase for 2nd decomposition level and then gradually decrease for increase in number of decomposition levels. The data at fault for Kurtosis of the detailed coefficient decreases for 2nd level of decomposition remains more or less same for 3rd level of decomposition and gradually increases for increase in decomposition levels. Here the highest deviations between healthy and faulty conditions occur at 2nd level.

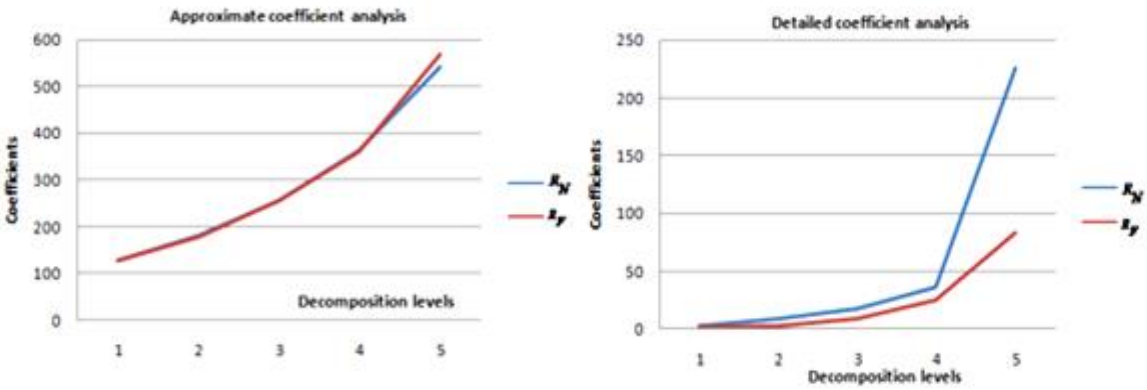


Fig. 3. Feature extraction monitoring RMS of approximate and detailed coefficients

Observations from Fig. 3 reveal that at healthy and faulty conditions, the RMS of approximate coefficients, are more or less similar to each other and seem to linearly increase with the increase in number of decomposition levels. The highest deviation between the data at normal and fault occurs at 5th level. Fig. 3 also reveals that the RMS of detailed coefficients for healthy condition is greater than that at fault and the values gradually increase with the increase in number of decomposition levels. However here also the nature obtained is not exactly linear and the highest deviation occurs at 5th level. Depending on the natures obtained, optimization has been done as presented in succeeding section.

4. **Optimization**

4.1. Level Optimization

The natures obtained in Fig. (s) 2-3 have been assessed and features have been extracted for maximum deviation assessment as presented in Table 2. In Table 2, $\delta S_{(NF)A}$, $\delta S_{(NF)D}$ denotes the deviation in Skewness values for approximate and detailed coefficients between normal and fault conditions respectively. $\delta K_{(NF)A}$, $\delta K_{(NF)D}$ denotes the deviation in Kurtosis values for approximate and detailed coefficients between normal and fault conditions respectively. $\delta R_{(NF)A}$, $\delta R_{(NF)D}$ denotes the deviation in RMS values for approximate and detailed coefficients between normal and fault conditions respectively. Monitoring Table 2, it has been observed that, $\delta S_{(NF)A}$, $\delta S_{(NF)D}$, $\delta K_{(NF)A}$, $\delta K_{(NF)D}$, $\delta R_{(NF)A}$, $\delta R_{(NF)D}$ values are maximum at 5th, 2nd, 5th, 2nd, 5th, 5th levels of DWT decomposition respectively.

Table 2. Maximum deviation analysis from extracted features

Deviation	Value	Highest deviation level	Remarks
$\delta S_{(NF)A}$	$S_N - S_F$ =-0.03	5th	$S_F > S_N$
$\delta S_{(NF)D}$	$S_N - S_F$ =2.59	2nd	$S_N > S_F$
$\delta K_{(NF)A}$	$K_N - K_F$ =0.05	5th	$K_N > K_F$
$\delta K_{(NF)D}$	$K_N - K_F$ =128.9	2nd	$K_N > K_F$
$\delta R_{(NF)A}$	$R_N - R_F$ =-25.43	5th	$R_F > R_N$
$\delta R_{(NF)D}$	$R_N - R_F$ =142.8	5th	$R_N > R_F$

4.2. Parametric Optimization

Monitoring Table 2, it has been inferred that the deviation in Skewness values of approximate coefficient is negative and hence the data at fault condition is greater than that at normal. The deviation in Skewness values of detailed coefficient is positive as a result of which the data at normal is greater than that at fault. The deviation in Kurtosis values of both approximate and detailed coefficient is positive and hence the data at normal is greater than that at fault. Again for RMS values of approximate coefficients, the data at fault is greater than at normal, since the deviation in the value has been obtained to be negative and for detailed coefficients, the data at normal is greater than the data at fault, as the deviation has been seen to be positive. However, monitoring all parameters in Table 2, it has been observed that, the deviation in RMS value of detailed coefficients is greatest and the deviation in Kurtosis value of detailed coefficients is also very high. Thus these two features can be used as a best fit solution to identify the LG fault in the system since the deviation between normal and fault conditions for both of the cases is very high.

4.3. Algorithm for LG fault detection

Depending on the results obtained from Table 2 and optimization done, an algorithm has been developed for LG fault identification in stand-alone WECS. The algorithm has been presented below:

Step 1: Record load current.

Step 2: Depending on the wave nature choose the mostly suitable mother wavelet and number of decomposition levels.

Step 3: Perform MRA based DWT analysis.

Step 4: Determine deviations as presented in Table 2.

Step 5: Compare deviation and assess fault.

To practically authenticate this algorithm, data from a practical WECS has been collected at normal and fault, as presented in succeeding sections.

5. Validation

5.1. Practical system under analysis

An industrial standalone WECS has been considered. The network uses a 440 V, 300 kVA synchronous machine, a wind turbine driving a 440 V, 300 kVA induction generator, a domestic load (10kW), a commercial load (25kW). In this system, data has been collected both for normal and for single line to ground fault at load bus of the network.

5.2. Harmonic Identification and percentage harmonic distortion calculation with respect to fundamental frequency

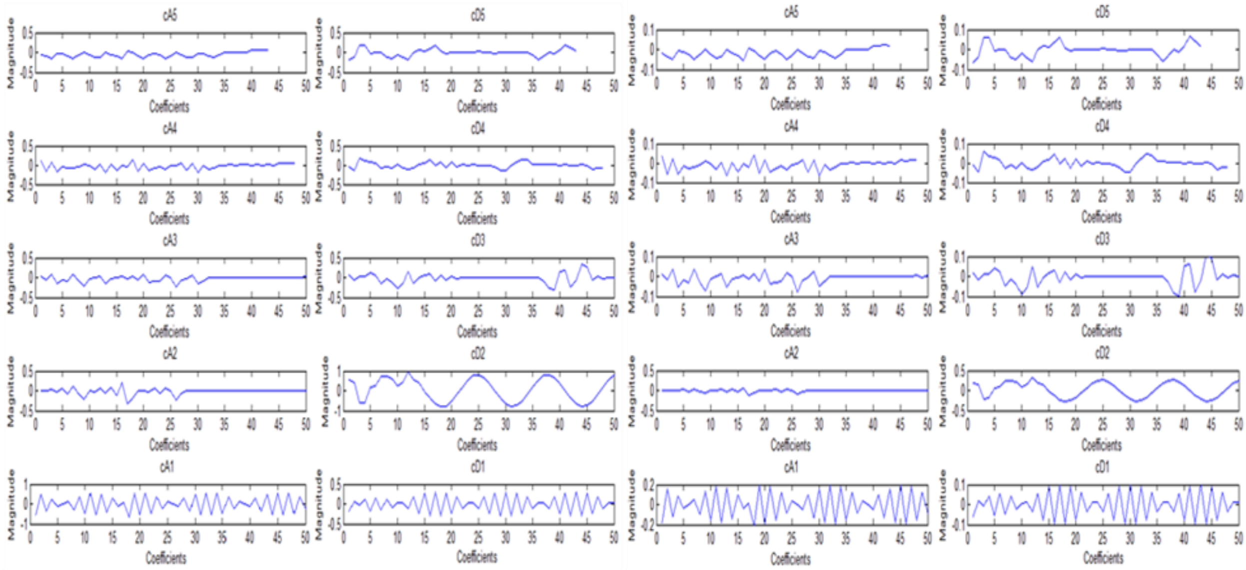
The load current signature of the system developed in laboratory has been captured and the harmonic frequencies present in the system both at normal and at single line to ground fault has been assessed using DFT. The magnitude of each harmonics present in the system at normal and at fault has been determined. The DFT analysis and the magnitude of each harmonic present at normal and fault has been presented in Table 3. Thus by monitoring the values of Table 3, it is clear that for LG fault in a system, different harmonics with dissimilar magnitudes are generated in a system in comparison to healthy condition and thus monitoring these parameters, fault can be assessed in a system. Comparing with Table 1, in Table 3 it has also been observed that there is a difference between the harmonic frequencies present in the simulated and practical system both for normal and fault conditions of the network. Again specific type of fault identification in a system cannot be done using this technique. Thus to validate the algorithm developed in Section 4.3, experimental analysis has been pursued in succeeding sections.

Table 3. Harmonic Assessment of load side current

Normal		Fault	
F (Hz)	Magnitude (dB)	F (Hz)	Magnitude (dB)
50	322.01	50	312.47
132.5	322.71	125	313.16
265.5	321.8	250	312.34
398	314.8	375	305.34
531	310.9	500	301.41
664	312.3	625	302.84
796.5	314.4	750	304.9
929.5	311.6	875	302.1
1062.5	308.5	1000	298.9
1195	315.2	1125	305.6
1328	311.6	1250	302.1

5.3. Line to Ground fault analysis in practical system

The current spectrum of the system at operating condition has been recorded both at healthy and at single line to ground fault in the system. These signals have been analyzed using the developed MRA of DWT algorithm, wherein the deviation in Skewness, Kurtosis and RMS values have been calculated for the chosen levels as per algorithm specified in Section 4.3. The DWT decomposition levels and the approximate and detailed coefficients, for normal and fault conditions, have been presented in Fig. 4. Monitoring Fig. 4 (a) it is clear that the coefficient values are changing in zigzag pattern and in each decomposition level, the change in the coefficient value is clearly visible. Similar nature of the coefficients has been observed for Fig. 4 (b). But it is worth mentioning that, for Fig. 4 (b) the magnitude of the coefficients is lesser in comparison to that at healthy condition, which is clear from individual coefficient monitoring. Depending on the deviations obtained from this analysis, assessment has been done for LG fault identification in the system. The results obtained after assessing the highest deviation has been presented in Table 4.



(a) (b)

Fig. 4. Approximate and Detailed coefficients of DWT decomposition levels of rectifier input current at (a) healthy (b) LG fault condition

Table 4. Deviation in extracted features and percentage difference with optimized results

Deviation at specified level	Value	% difference in deviation values compared to Table 2
$\delta S_{(NF)A}$ at 5th level	$S_N - S_F = -0.0302$	-0.67
$\delta S_{(NF)D}$ at 2nd level	$S_N - S_F = 2.62$	-1.15
$\delta K_{(NF)A}$ at 5th level	$K_N - K_F = 0.051$	-1.96
$\delta K_{(NF)D}$ at 2nd level	$K_N - K_F = 128.88$	-0.02

$\delta R_{(NF)A_{at\,5th\,level}}$	R_N - R_F =-25.9	-1.8
$\delta R_{(NF)D_{at\,5th\,level}}$	R_N - R_F =142.77	-0.02

6. Discussion

Assessment from Table 4 has been pursued and it has been concluded that the percentage deviation in the values obtained in Table 4 in comparison to that in Table 2 is lowest for the detailed coefficient Kurtosis and RMS values. Rest of the values has comparatively higher percentage deviations with respect to that specified in Table 2. Also the deviation in RMS value of detailed coefficient is greatest followed by the deviation in Kurtosis value of detailed coefficients. The results of the case study in Table 2 have thus been seen to closely match with that presented in Table 4 and thus the algorithm presented in Section 4. 3 have been validated. Thus Kurtosis and RMS value of detailed coefficients can be effectively used for fault identification with least operating error in a system. In this paper analysis has been shown for the acquired current spectrum of the Red-phase only.

7. Conclusion

This paper describes the shortfall of only harmonic magnitude analysis for LG fault identification in a system and presents a new technique for LG fault identification in stand-alone WECS, monitoring the Kurtosis and RMS values of the MRA based DWT coefficients for optimized levels. Features have been extracted from the deviation in the Skewness, Kurtosis and RMS values of MRA based DWT coefficients at normal and at fault. Depending on the maximum deviation of the coefficients from normal at fault, level and parametric optimizations have been done to identify the best fit solution for LG fault identification in a system. Validation of the work has been done in an industrial stand-alone WECS and the two results have been cross-checked. The percentage error between the results obtained from both the assessments has been seen to be below 2%. Thus, it can be concluded that, this analysis can be fruitfully applied for LG fault identification in a stand-alone Wind Energy Conversion System with least operational error. However this analysis has also been extended for other fault identification in traction systems and transmission and distribution systems with more or less similar results.

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