DIAGNOSIS OF INCIPIENT FAULTS USING WAVELET PACKET DECOMPOSITION IN SYNCHRONOUS GENERATORS

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Abstract— This paper presents incipient fault diagnosis of synchronous generators using wavelet packet decomposition. Proper incipient fault detection techniques are required for synchronous generators because of their utilization in generating stations, petrochemical industries. Three phase currents are acquired from generator during fault condition. These currents are decomposed into approximate and detail signals to find energy of approximate signal and maximum energy of detail signals to diagnose the behavior of fault. Simulation results in MATLAB/SIMULINK are presented for various faults and for normal condition to find difference in energy ratio during healthy condition and faulty condition.

Keywords— Wavelet, Incipient fault, WPD, MCSA, Energy Ratio.

I. INTRODUCTION

Generating capacity improvement to meet load demand and continuous power are having much importance because of growing energy demand and sensitive loads. For power generation synchronous generators are commonly used because of their well construction, robustness [1]. Due to heavy stresses on electromechanical conversion systems synchronous generators are very prone to incipient faults on stator windings, rotor windings and bearings.

Diagnosis of these incipient faults in synchronous generators leads to increase in downtime period for scheduling of maintenance [2]. These incipient faults reduce life span of synchronous generators. Efficient and less time consuming diagnosis of incipient fault is necessary in case of large generators which are used in generating stations, chemical industries and so on [3].

By detecting faults in generators early will prevent cost failures, reduces maintenance cost and downtime periods. Condition monitoring and signal processing are considered as important for fault diagnosis [4]. By acquiring signals from generators using sensors and applying effective signal processing technique on these signals fault diagnosis can be done. Important task of the diagnosis is to differentiate normal operating condition and faulty condition. Indication of incipient fault in generators depends on how efficiently faulty features are extracted from acquired signals from machine [5].

Time frequency domain has been proposed for analysis of acquired signals for fault detection in machines [6]. Various fault diagnosis techniques based on fuzzy and neural networks are proposed. Fuzzy expert system is having a difficulty of knowledge acquiring and maintenance of database. Neural network require training data and the data should be compatible for proper training [7,8].

Park's transformation is used to detect fault behavior in [9] by comparing signal based and model based approaches. A model based diagnosis system using wavelets is proposed for detection of various faults in [10]. The ability of different types of wavelet functions is investigated in [11]. In this paper Fault detection reliability depends on the wavelet function used for decomposition of the signal.

ANN based fault identification is proposed in [12] which is complex and handling of data for training is very difficult. Start up current monitoring procedure and for different types of faults using DWT is proposed in [13].

In this paper, wavelet packet decomposition based approach to diagnose incipient faults occurring in synchronous generators is proposed. Faults due to short circuit of stator windings are considered. In section II DQ model of synchronous generator is explained. Wavelets are explained in III section. Process of extraction and fault diagnosis is explained in IV, V sections. Simulation results using MATLAB/SIMULINK are shown in VI section.

II. SYNCHRONOUS GENERATOR d-q MODEL

The SG is described by a set of three stator circuits coupled through motion with two orthogonally placed damper windings and field winding. The stator and rotor circuits are magnetically coupled with each other.

The phase voltage equations of SG are [14]

$$i_a R_s + v_a = -\frac{d\Psi_a}{dt}$$

$$i_b R_s + v_b = -\frac{d\Psi_b}{dt}$$

$$i_c R_s + v_c = -\frac{d\Psi_c}{dt}$$

$$i_D R_D = -\frac{d\Psi_D}{dt}$$

$$i_Q R_Q = -\frac{d\Psi_Q}{dt}$$

$$i_f R_f - V_f = -\frac{d\Psi_f}{dt}$$

The d-q model of synchronous generator should express both stator and rotor equations in rotor coordinates, aligned to rotor d and q aces because, at least in the absence of magnetic saturation, there is no coupling between the two axes. Stator voltages V_a, V_b, V_c, currents Ia, Ib, Ic and flux linkages Ψ_a, Ψ_b, Ψ_c have to be transformed into rotor orthogonal coordinates.

$$T(\theta_e) = \frac{2}{3}\begin{bmatrix} \cos(-\theta_e) & \cos\left(-\theta_e + \frac{2\pi}{3}\right) & \cos\left(-\theta_e - \frac{2\pi}{3}\right) \\ \sin(-\theta_e) & \sin\left(-\theta_e + \frac{2\pi}{3}\right) & \sin\left(-\theta_e - \frac{2\pi}{3}\right) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix}$$

$$V_{dqo} = T(\theta_e)V_{abc}$$

$$I_{dqo} = T(\theta_e)I_{abc}$$

$$\Psi_{dqo} = T(\theta_e)\Psi_{abc}$$

Expressions for Ψ_d, Ψ_q, Ψ_o are as follows

$$\Psi_d = L_d I_d + M_f I_f^r + M_D I_D^r$$

$$L_d = L_{sl} + L_{dm}$$

$$\Psi_q = L_q I_q + M_Q I_Q^r$$

$$L_q = L_{sl} + L_{qm}$$

$$\Psi_o = L_{sl} I_o$$

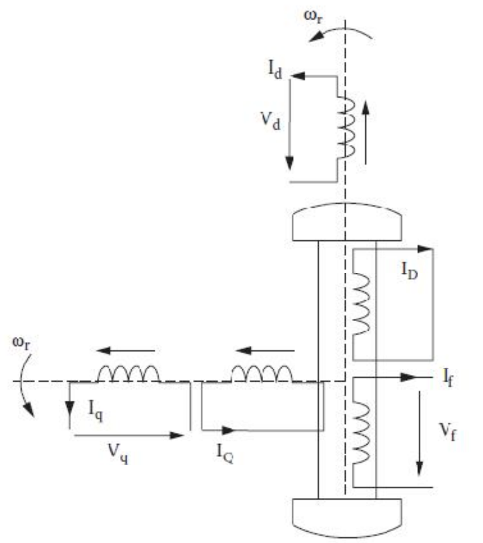

Fig.1 The d-q model of synchronous generators

For rotor

$$\Psi_f^r = \left(L_{fl}^r + L_{fm}\right)I_f^r + \frac{3}{2}M_f I_d + M_{fD} I_D^r$$

$$\Psi_D^r = \left(L_{Dl}^r + L_{Dm}\right)I_D^r + \frac{3}{2}M_D I_d + M_{fD} I_f^r$$

$$\Psi_Q^r = \left(L_{Ql}^r + L_{Qm}\right)I_Q^r + \frac{3}{2}M_Q I_q$$

The magnetic field axes of the respective stator windings are fixed to the rotor d-q axes, but their conductors are at standstill. The d-q model equations can be derived directly through the equivalent orthogonal axis machine as shown in fig.

$$I_d R_s + V_d = -\frac{d\Psi_d}{dt} + \omega_r \Psi_q$$

$$I_q R_s + V_q = -\frac{d\Psi_q}{dt} - \omega_r \Psi_d$$

The rotor equations are

$$I_f R_f - V_f = -\frac{d\Psi_f}{dt}$$

$$i_D R_D = -\frac{d\Psi_D}{dt}$$

$$i_Q R_Q = -\frac{d\Psi_Q}{dt}$$

The zero component equation is

$$I_o R_s + V_o = -\frac{d\Psi_o}{dt}$$

The motion equations are as follows

$$T_e = \frac{3}{2}p_1\left(\Psi_d I_q - \Psi_q I_d\right)$$

$$\frac{J}{p1}\frac{d\omega_r}{dt} = T_{shaft} + \frac{3}{2}p_1\left(\Psi_d I_q - \Psi_q I_d\right)$$

Consequently Per unit D-Q model equations can be written as

$$\frac{1}{\omega_b}\frac{d\Psi_d}{dt} = \omega_r \Psi_q - i_d r_s - v_d \quad ; \quad \Psi_d = l_{sl} i_d + l_{dm}\left(i_d + i_D + i_f\right)$$

$$\frac{1}{\omega_b}\frac{d\Psi_q}{dt} = -\omega_r \Psi_d - i_q r_s - v_q \quad ; \quad \Psi_q = l_{sl} i_q + l_{qm}\left(i_q + i_Q\right)$$

$$\frac{1}{\omega_b}\frac{d\Psi_o}{dt} = -i_o r_o - v_o;$$

$$\frac{1}{\omega_b}\frac{d\Psi_f}{dt} = -i_f r_f + v_f; \Psi_d = l_{fl} i_f + l_{dm}\left(i_Q + i_D + i_f\right)$$

$$\frac{1}{\omega_b}\frac{d\Psi_D}{dt} = -i_D r_D; \Psi_D = l_{Dl} i_D + l_{dm}\left(i_d + i_D + i_f\right)$$

$$\frac{1}{\omega_b}\frac{d\Psi_Q}{dt} = -i_Q r_Q; \Psi_Q = l_{Ql} i_Q + l_{qm}\left(i_q + i_Q\right)$$

$$2H\frac{d\omega_r}{dt} = t_{shaft} - t_e; t_{shaft} = \frac{T_{shaft}}{T_{eb}}; \ t_e = \frac{T_e}{T_{eb}}$$

$$t_e = -\left(\Psi_d i_q - \Psi_q i_d\right);$$

$$\frac{1}{\omega_b}\frac{d\theta_{er}}{dt} = \omega_r$$

Machine Parameters

$$l_d = l_{sl} + l_{dm}$$

$$x_d = x_{sl} + x_{dm}$$

$$l_q = l_{sl} + l_{qm}$$

$$x_q = x_{sl} + x_{qm}$$

III. WAVELET

For detection of incipient faults in synchronous generator frequency domain analysis is not reliable due to effect of other parameters. Parameters are like Voltage fluctuations effects fault frequency components, load dependency of fault characteristic amplitude and requirement of high resolution frequency with high sampling time. Time frequency analysis, which represent signal by time, amplitude and frequency, will avoid these problems while analyzing fault behavior. Wigner-Ville distribution, Short time Fourier transform and wavelet transform are type of signal analyzing processes in time frequency analysis. Analyzing components of the signal can be analyzed by Fourier transform. Short time Fourier transform (STFT) uses a window function for the information of time and frequency. Width of this window is equal to the segment of the signal. But the length of the signal limits resolution in frequency. Wavelet transform is a tool developed as solution to these problems, which is a mapping of a time signal to the time scale joint representation [15].
In wavelet transform a signal can be represented as series of oscillating functions with different frequencies at different time. Multi resolution analysis by wavelet transform is done effectively by narrow windows for high frequency analysis and wide windows for low frequency analysis. By dilating and translating, wavelet of a signal will be generated. By discretizing dilations and translations of continuous wavelets, time bandwidth product of output can be reduced. Multi resolution analysis uses scaling function based orthonormal wavelet transform. In multi resolution analysis, decomposition and reconstruction of discrete wavelet series is done by two discrete low pass and high pass filters.
In time domain and frequency domain wavelet should be a local operator. Reconstruction of the signal by wavelet transform involves wavelet admissible condition and energy conservation in time scale. Discrete wavelet transform separates data into different frequency components and resolution of each component can be studied by it. Multi scale representation of function at various levels of resolution is the main feature of DWT. It is invertible and orthogonal.

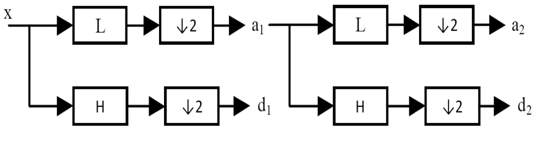

Fig 2. DWT tree

DWT is computed using cascade of filtering followed by a factor 2 subsampling as shown in fig 2. H is high pass filter and L is Low pass filter. ↓2 denotes sub sampling.

Output of the low pass filter is given by
$a_{j+1}[p] = \sum_{n=-\infty}^{+\infty} l[n-2p]a_j[n]$ (1)
Output of the high pass filter is given by
$d_{j+1}[p] = \sum_{n=-\infty}^{+\infty} h[n-2p]d_j[n]$ (2)
d_j is wavelet coefficient and $a_j$is used for next step of the transform. l and h are coefficients of low and high pass filters. Scaling function coefficients $a_j$and$d_j$are essential to be in analyzed signal to perform DWT.
Decomposition of discrete signal u(t) is given by
$u(t) = \sum_i A_{j0,k}\delta_{j0,k}[t] + \sum_{j=j0}^{j-1}\sum_k D_{j,k}\tau_{j,k}[t]$ (3)
where D and A are coefficients of detail and approximate, δ is the scaling function, τ is the wavelet function.
Scaling function is represented by
$\delta_{j0,k}[t] = 2^{j0/2}\delta(2^{j0}t-k)$ (4)
Wavelet function is represented by
$\tau_{j,k}[t] = 2^{j/2}\tau(2^j t-k)$ (5)
$\delta_{j0,k}$ is the scaling function at a scale of 2^{j0} shifted by k. $\tau_{j,k}$ is the mother wavelet at a scale of 2^j shifted by k.
By multiplying original signal with scaling function approximate coefficient can be obtained as
$A_{j0,k} = \int_{-\infty}^{\infty} u(t)\,\delta_{j0,k}(t)dt$ (6)
For a discretized signal decomposed approximate coefficient is given by
$A_{(j+1),k} = \sum_{n=0}^{N} A_{j,k}\int \delta_{j,k}(t)\delta_{j+1,k}(t)dt$ (7)
By multiplying signal with complex conjugate of the wavelet function detail coefficient can be obtained as
$D_{j,k} = \int_{-\infty}^{\infty} u(t).\tau_{j,k}^{*}(t)dt$ (8)
For a discretized signal decomposed detail coefficient is given by
$D_{(j+1),k} = \sum_{k=0}^{K} A_{j,k}\int \delta_{j,k}(t).\tau_{j+1,k}(t)dt$ (9)

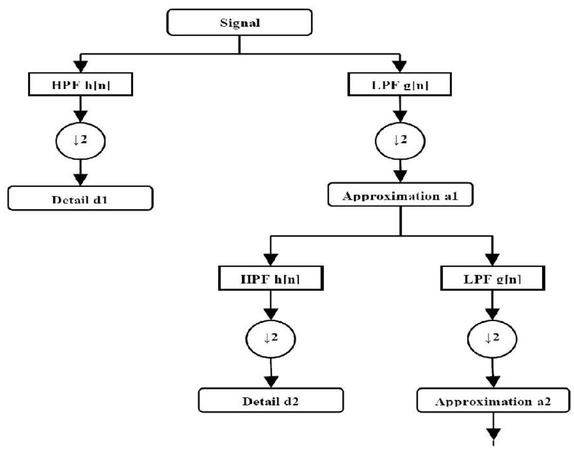

Fig 3. Wavelet Decomposition Algorithm

IV. DIAGNOSIS OF INCIPIENT FAULTS

To achieve continuous power supply to end users, prediction and diagnosis of failure in generating station is important. After effect of fault on machine, change in main parameters of the machine will lead to loss in synchronism with other machines in generating station.

Stator winding asymmetry due to fault presents uneven distribution stator currents which effects air gap flux, torque, power and speed. By better understanding behavior of electrical and mechanical characteristics of synchronous machine during healthy and faulty condition reliability of the system can be increased.

Stator current spectrum contains other frequency components also during incipient faulty condition. Motor current signature analysis (MCSA) analyses spectrum of stator current for other components presented to study the characteristics of machine. MCSA has the capability of detection different faults early with highly sensitivity. It requires less expensive equipment and can be monitored remotely.

Machine parameters can be changed depending on the effectiveness of fault. For any incipient fault occurred on stator winding creates asymmetry in generated magnetic flux which causes other frequency components in stator current spectrum. These harmonics of stator current will superimpose on stator windings. Frequency of these harmonics given by

$$\omega_{sth} = [1 \pm 2ks]\omega_s$$

ω_s is the fundamental frequency, s is the slip, k=1,2,…

V. WAVELET PACKET DECOMPOSITION

In discrete wavelet transform (DWT) details and approximation are divided. Direct expansion of this DWT is wavelet packet transform. For better representation and processing of a signal the binary tree algorithm shown in fig gives better results.

Time frequency of wavelet packet is given as

$$\tau_{j,k}^{i} = 2^{\frac{j}{2}}\tau^{i}(2^{j}t-k), i = 1,2,3 \ldots.$$

i is scale parameter, j is translation parameter, k is simulation parameter.

Scaling function $\delta(t)$ associated Scaled filter $h(n)$ and wavelet function $\tau(t)$ associated wavelet filter $g(n)$ are quadrature in nature. Fast wavelet pocket decomposition of a signal f (t) is given as

$$d_0^0(t) = f(t)$$

$$d_{j+1}^{2n}(t) = \sum_k h(k-2t)d_j^i \;\; i = 0,1,\ldots,2^j - 1$$

$$d_{j+1}^{2n+1}(t) = \sum_k g(k-2t)d_j^i$$

Wavelet packet signal is given as

$$f_j^i(t) = \sum_{i=1}^{2j} C_{j,k}^i(t)\tau_{j,k}^i(t)$$

Wavelet packet coefficients are given as

$$C_{j,k}^i(t) = \int_{-\infty}^{\infty} f(t)\tau_{j,k}^i(t)dt$$

$$\tau_{j,k}^m(t)\tau_{j,k}^n = 0 \; if \; m \neq n$$

For fault estimation energy principle applied to current signals after wavelet packet transform.

VI. SIMULATION RESULTS

Effectiveness of proposed wavelet packet decomposition fault diagnosis is tested on single machine infinite bus system using MATLAB/SIMULINK. System simulated is shown in fig 4. each phase current is recorded for various incipient faults occurred in synchronous machine. Parameters of synchronous machine are shown in table [1]. Wavelet packet decomposition is applied on each phase current during incipient fault occurrence.

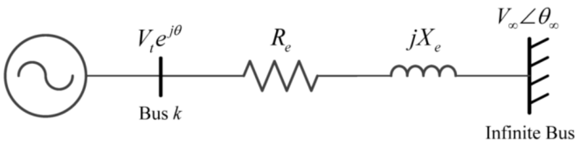

Fig 4. Single machine infinite bus system

Table 1. parameters of synchronous generator

Parameter	Value
Lad	171 mH
Laq	176.9 mH
Ra	156 mΩ
La	9.1 mH
Rfd	187 mΩ
Lfd	2.95 mH
R1d	712 mΩ
L1d	0.692 mH
R1q	1.616 Ω
L1q	132 mH
R2q	1.17 Ω
L2q	3.7 mH

System is simulated without fault initially. Three phase currents (Ia, Ib and Ic) and their reconstructed approximation and detail signals are shown in fig 5-10. Then different incipient faults are created in synchronous generator at 6 sec. for each fault three phase currents are recorded and decomposed using wavelet packet decomposition. Effect fault is more on detail coefficients because of high frequency components, hence maximum detail coefficient is considered for fault diagnosis. By defining ratio of energy change from maximum detail coefficient type of fault can be found.simulation is done for all types of faults including two phase to ground and single phase ground faults.

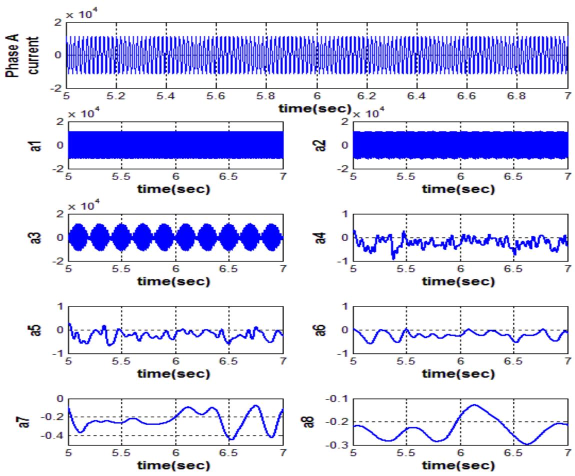

Fig 5. Phase A current and its reconstructed approximation of signal at level 1 to 8 for no fault

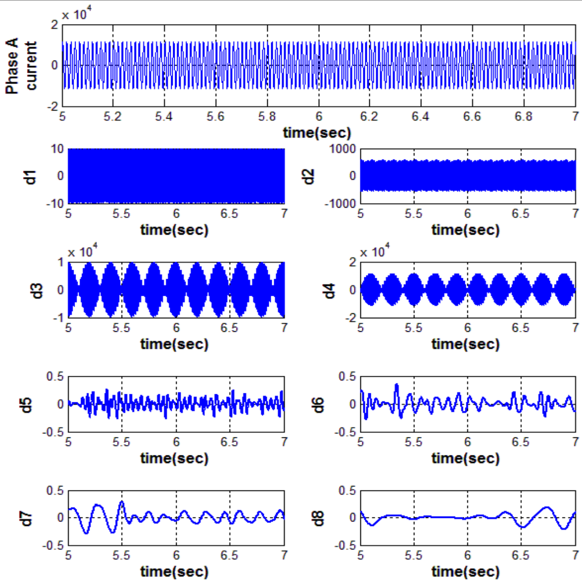

Fig 6. Phase A current and its reconstructed detail of signal at level 1 to 8 for no fault

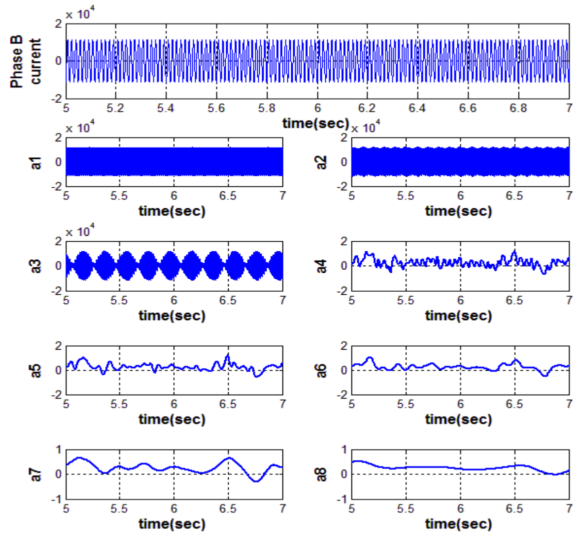

Fig 7. Phase B current and its reconstructed approximation of signal at level 1 to 8 for no fault

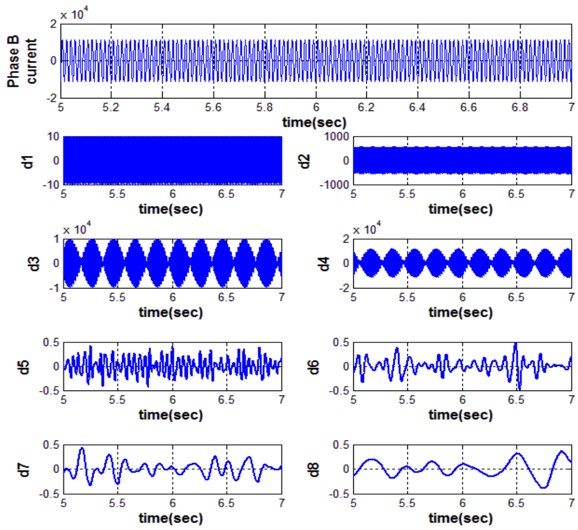

Fig 8. Phase B current and its reconstructed detail of signal at level 1 to 8 for no fault

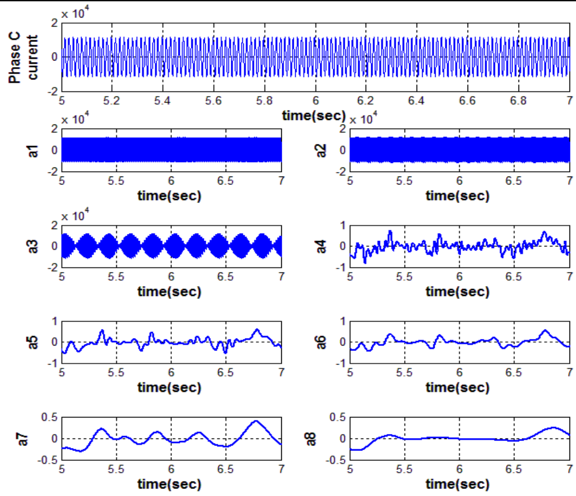

Fig 9. Phase C current and its reconstructed approximation of signal at level 1 to 8 for no fault

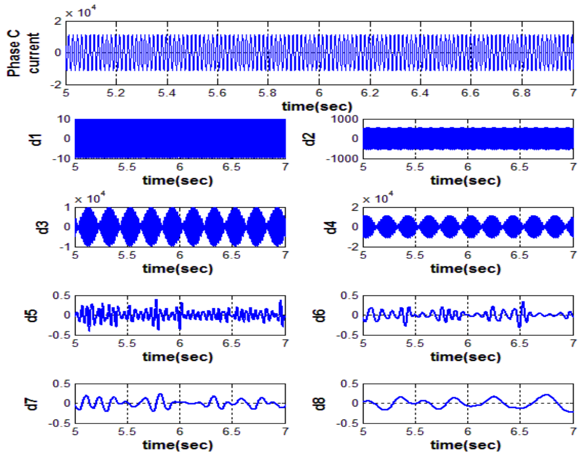

Fig 10. Phase C current and its reconstructed detail of signal at level 1 to 8 for no fault

a. Single phase to ground fault

Fault is created on each phase winding of synchronous generator and all three phase stator currents are recorded and decomposed by wavelets. Waveforms for each phase and their respective approximate and detail of signals are shown in fig 11-16.

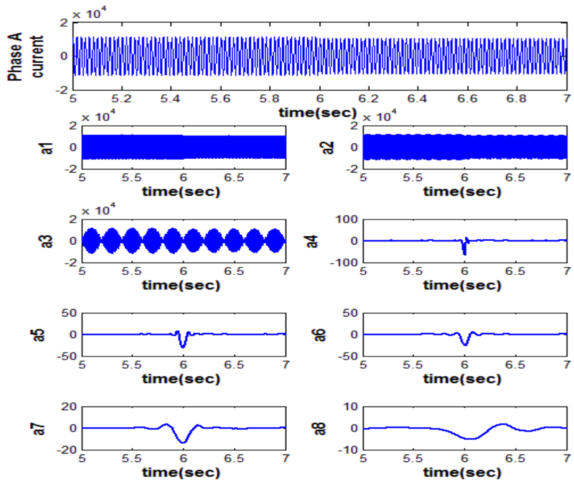

Fig 11. Phase A current and its reconstructed approximation of signal at level 1 to 8 for single phase to ground fault (AG)

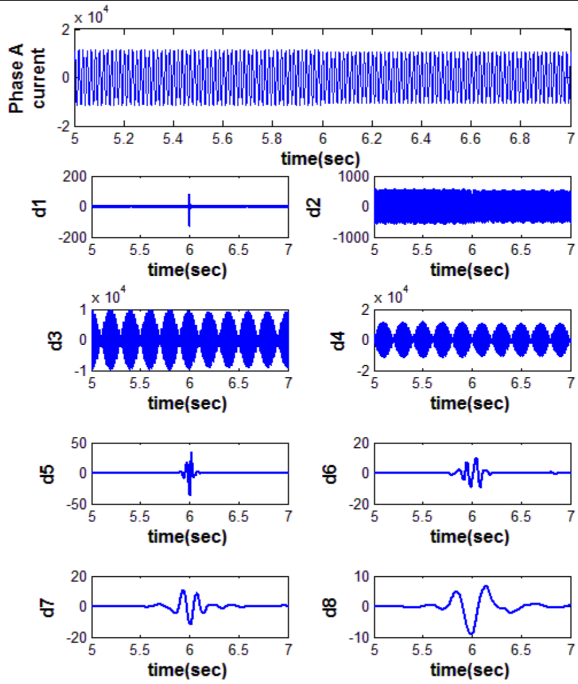

Fig 12. Phase A current and its reconstructed detail of signal at level 1 to 8 for single phase to ground fault (AG)

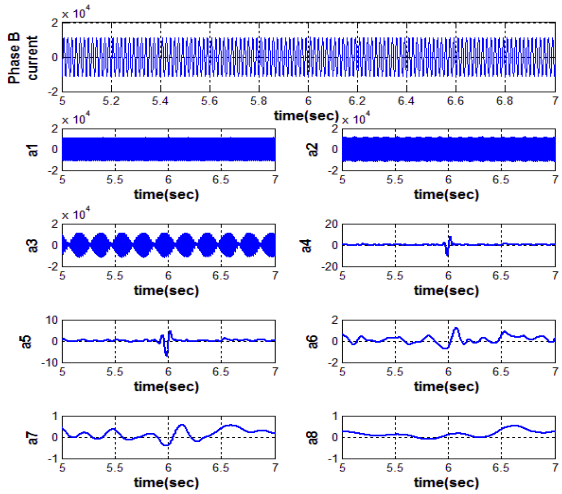

Fig 13. Phase B current and its reconstructed approximation of signal at level 1 to 8 for single phase to ground fault (AG)

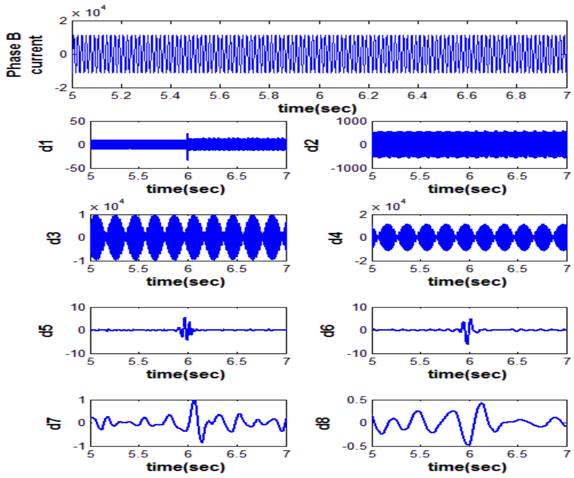

Fig 14. Phase B current and its reconstructed detail of signal at level 1 to 8 for single phase to ground fault (AG)

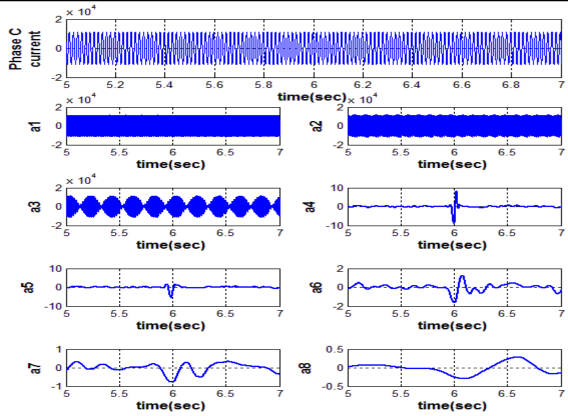

Fig 15. Phase C current and its reconstructed approximation of signal at level 1 to 8 for single phase to ground fault (AG)

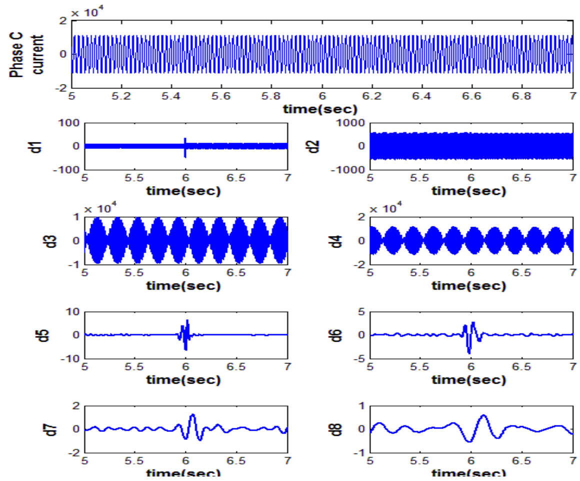

Fig 16. Phase C current and its reconstructed detail of signal at level 1 to 8 for single phase to ground fault (AG)

b. Double phase to ground fault

Fault is created between two phases of stator and currents are measured. As compared to faulty phases healthy phase is not having much difference from normal condition. Three phase currents and their detail and approximation signals are shown in fig 16-21

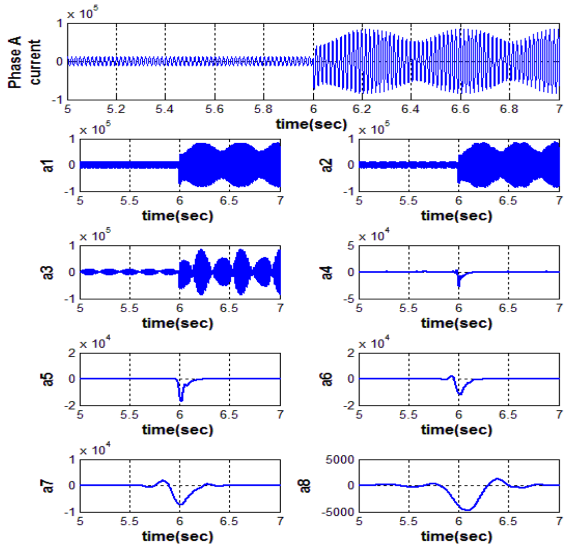

Fig 17. Phase A current and its reconstructed approximation of signal at level 1 to 8 for two phase to ground fault (ABG)

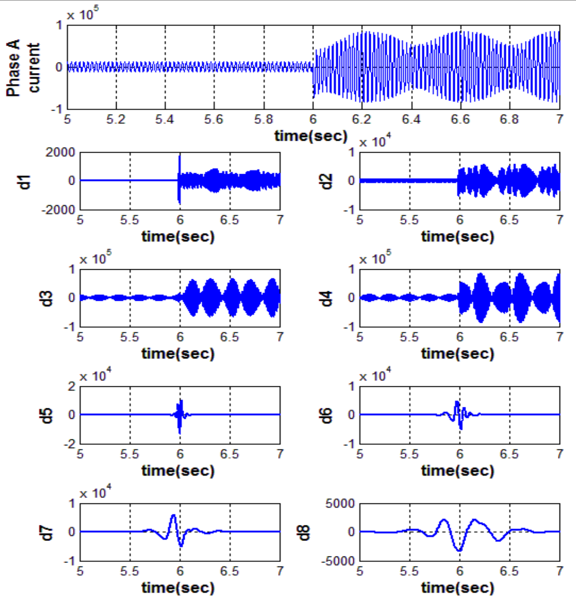

Fig 18. Phase A current and its reconstructed detail of signal at level 1 to 8 for two phase to ground fault (ABG)

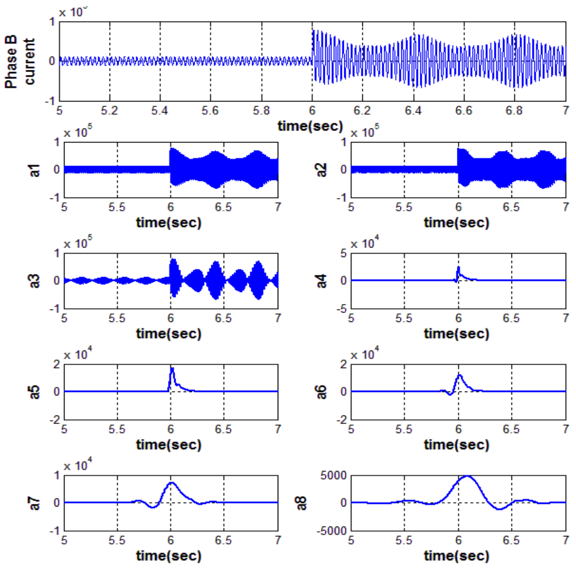

Fig 19. Phase B current and its reconstructed approximation of signal at level 1 to 8 for two phase to ground fault (ABG)

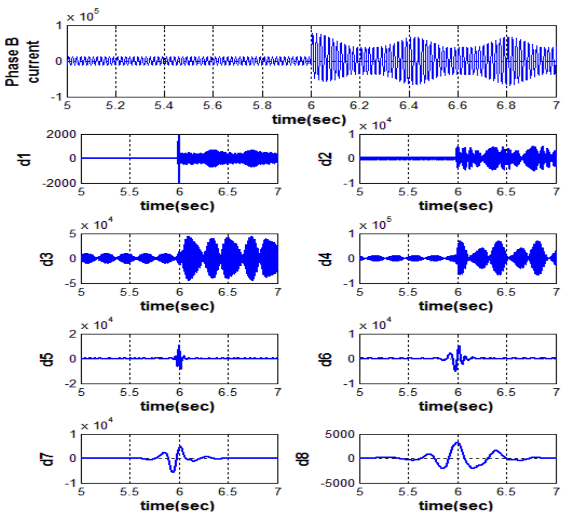

Fig 20. Phase B current and its reconstructed detail of signal at level 1 to 8 for two phase to ground fault (ABG)

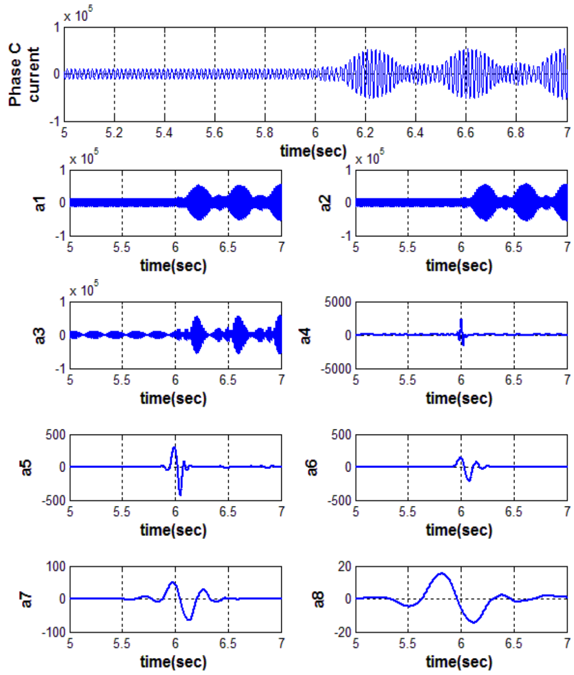

Fig 21. Phase C current and its reconstructed approximation of signal at level 1 to 8 for two phase to ground fault (ABG)

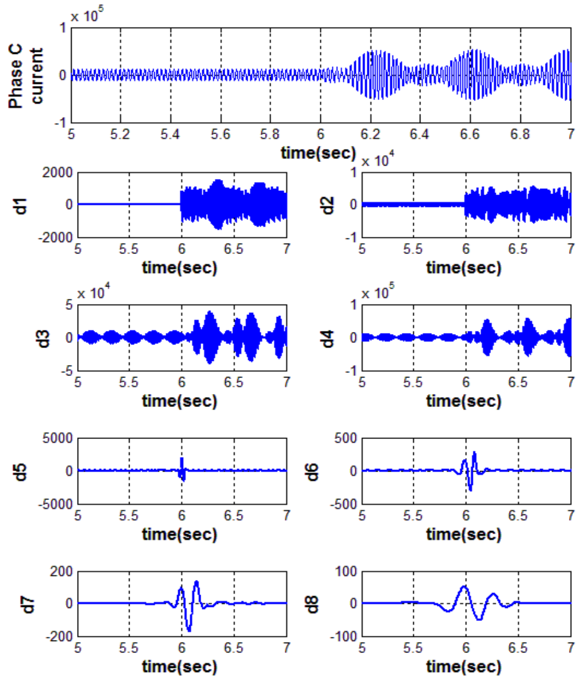

Fig 22. Phase C current and its reconstructed detail of signal at level 1 to 8 for two phase to ground fault (ABG)

Table II. Energy corresponding to the approximation values for different fault

Fault type	Ia	Ib	Ic
AG	9.9850	3.0511	10.8205
BG	9.6559	2.8416	10.8448
CG	9.5874	3.0450	11.1832
ABG	1.9048	5.9696	3.7463
BCG	1.9691	0.6560	2.5829
CAG	12.4489	2.8005	4.0456
No Fault	9.5864	3.0740	10.7879

Table III. Energy ratio and variation from normal value for different fault

Fault type	Ia		Ib		Ic	
	Energy Ratio	Variation	Energy Ratio	Variation	Energy Ratio	Variation
No fault	5.5031	0	18.3250	0	4.8080	0
AG	**5.2599**	**0.0442**	18.4430	0.0064	4.7924	0.0032
BG	5.4587	0.0081	**19.8833**	**0.085**	4.7797	0.0059
CG	5.5027	7.2686e-5	18.5062	0.0099	**4.6180**	**0.0395**
ABG	**29.3612**	**4.3354**	**9.4708**	**0.4832**	4.7684	0.0082
BCG	5.4693	0.0061	**94.3307**	**4.1477**	**20.0930**	**3.1791**
CAG	**4.2799**	**0.2223**	18.4658	0.0077	**12.7224**	**1.6461**

Energy values corresponding to approximation signals for each fault and for normal condition for each phase are shown in table II. Energy ratio for each fault is shown in table III. From both tables variation of energy ratio from normal condition defines type of fault. In any phase during fault, if the variation of energy ratio from normal condition is more than 0.01 then that phase winding is considered as faulty winding. As in table III. Healthy phases are having very less variation compared to faulty phases.

CONCLUSION

This paper presents incipient fault diagnosis of synchronous generators using wavelet packet decomposition. Three phase currents are decomposed into approximate and detail signals to find energy of approximate signal and maximum energy of detail signals to diagnose the behavior of fault. Simulation results using MATLAB/SIMULINK is presented on SMIB system. Energy ratio is recorded for each fault and for normal condition. Difference in energy ratio during fault with normal condition indicates faulty winding. Healthy phases are having very less variation compared to faulty phases.

REFERENCES

[1] Keyhani and S. M. Miri, “observers for tracking of synchronous machine parameters and detection of incipient fault,” IEEE Trans. Energy Conversion, vol. 1, no. 2, 1996.

[2] Iman Tabatabaei, Jawad Faiz, H.Lesani, M. T. Nabavi-Razavi, “ Modeling and simulation of a salient-pole synchronous generator with dynamic eccentricity using modified winding function theory,” IEEE Trans. Magnetics, vol. 40, no. 3, may 2004

[3] S. Edwards, A. W. Lees, and M. I. Friswell, “Fault diagnosis of rotating machinery,” The shock and vibration digest, vol. 30, n0. 1, pp. 4-13, 1998.

[4] Pratesh Jayaswal, A. K. Wadhwani, K. B. Mulchandani, “Machine Fault Signature analysis,” International Journal of Rotating Machinery, Volume 2008, Article ID 583982.

[5] Yao Da, Xiaodong Shi, Mahesh Krishnamurthy, “A New Approach to Fault Diagnostics for Permanent Magnet Synchronous Machines Using Elctromagnetic Signature Analysis,” IEEE Trans. On Power Electronics, vol. 28, issue 8. 2013

[6] B. Zhang *et al.*, “A new method of diagnosing turbine generator’s vibration fault based on fuzzy cluster analysis wavelet packet transform,” in *proc. 5th Int. Conf. Electrical Machines and Systems*, vol. 1, 2001, pp.339-342

[7] B. Kerezsi and I. Howard, “vibration fault detection of large turbine generators using neural networks,” in *IEEE Int. Conf. Neural Networks*, vol. 1, 1995, pp. 121-126

[8] C. Z. Wu, H. Yan, and J. F. Ma, “Method research of noise diagnosis based on fuzzy neural network,” in *Proc. ICSP*, 1998, pp. 1370-1373

[9] Combastel C, Lesecq S, Petropol S, Gentil S. “Model-based and wavelet approaches to induction motor on-line fault detection,” Control Engineering Practice. 2002; 10.5:493–509.

[10] Kim K, Parlos AG., “Induction motor fault diagnosis based on neuro predictors and wavelet signal processing,” IEEE/ASME Transactions Mechatronics. 2002; 7.2: 201-219.

[11] Yahia K, Cardoso AJM, Ghoggal A, Zouzou SE., “Induction motors airgap-eccentricity detection through the discrete wavelet transform of the apparent power signal under non-stationary operating conditions,” ISA Transactions. 2014; 53: 603-611.

[12] Zhang Z, Wang Y, Wang K., “Fault diagnosis and prognosis using wavelet packet decomposition, Fourier transform and artificial neural network,” Journal of Intelligent Manufacturing. 2013; 24:1213-1227

[13] Antonino-Daviu J, Rodriguez PJ, Riera-Guasp M, Pineda-Sanchez M, Arkkio A., “Detection of combined faults in induction machines with stator parallel branches through the DWT of the startup current,” Mechanical Systems and Signal Processing. 2009; 23.7: 2336-2351.

[14] B. Vidya Sagar and Dr. S. S. Tulasiram, “Fault Diagnosis of Synchronous Generator using Neural Network Techniques,” International of Journal of Ethics in Enginering & Management Education, Volume 2, Issue 7, July 2015

[15] Mohammad Rezazadeh Mehrjou, Norman Mariun, Mahdi Karami, Samsul Bahari Mohd. Noor, Sahar Zolfaghari, Norhisam Misron, Mohd Zainal Abidin Ab. Kadir, Mohd. Amran Mohd. Radzi and Mohammad Hamiruce Marhaban (2015). “Wavelet-Based Analysis of MCSA for Fault Detection in Electrical Machine, Wavelet Transform and Some of Its Real-World Applications,” Dr. Dumitru Baleanu (Ed.), ISBN: 978-953-51-2230-2, InTech, DOI: 10.5772/61532. Available from: http://www.intechopen.com/books/wavelet-transform-and-some-of-its-real-world-applications/wavelet-based-analysis-of-mcsa-for-fault-detection-in-electrical-machine

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