Ground fault detection of unit generator-transformer based on the statistical parameters of wavelet transform and neural networks

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Abstract—**This paper proposes an approach for the detection of a ground fault on a unit generator-transformer, based on the extraction of statistical parameters from Wavelet transform based neural network. In the simulation, the current and voltage signals were found decomposed over wavelet analysis into several approximations and details. The simulation of the unit generator-transformer was carried out using the Sim-PowerSystem Blockset of MATLAB. The statistical parameters analysis involved measurement of the dispersion and tendency factors of wavelet coefficients. Regarding of confusion matrix and receiver operating characteristic of the neural network's pattern recognition performance, the accuracy of the single line to ground fault detection of neural networks was 98.44 %. The results indicated that the tendency factor feature of wavelet transform more accurate than dispersion factor feature of wavelet transforms in distinguishing a single line to ground-fault and normal condition for a unit generator-transformer.**

Keywords—ground fault, statistical parameter, wavelet transform,

I. Introduction

Small current Ground-Fault (GF) detection has been a major concern in protective relaying for a long time. Relaying engineers and researchers often faces the challenge of developing the most suitable technique that can detect faults with reasonable reliability to secure the run through a power system [1]. In general, a step up transformer at an electric power station can be categorized either as a unit generator-transformer configuration, a unit generator-transformer configuration with generator breaker, a cross-compound generator or a generator involving a unit transformer [2, 3]. A GF on the transmission line or busbar can disturb the system configuration of the generator.

Numerous feature extraction methods based on Wavelet Transform (WT) have been used for the detection and classification of faults. Reference [4] proposes a new technique for arcing fault location by using Discrete Wavelet Transform (DWT) and wavelet networks. Fault classification procedure based on wavelet in transmission is suggested in [5]. Reference [6, 7, 8] describes the feature extraction technique based on fast WT, a fault index and wavelet power for use to detect the stator faults in the synchronous generator and transformer. Abstraction of a statistical parameter as fault detection has been used for fault detection in previous studies, but they only consisted of standard deviation, kurtosis and skewness [9]. 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 defined in reference [10].

The new approach as proposed in this paper uses tendency factor and dispersion factors of statistical parameters for single-line to ground (SLG) detection. In this research, a DWT and Artificial Neural Network (ANN) are applied to Ground-Fault detection in different locations at a unit generator-transformer. This faults waveform was decomposed through wavelet transform analysis into different approximations and details. A new Statistical Method and Neural Network Pattern Recognition approach, which includes statistical parameters of each type of ground-fault, is characteristic in nature, and was used in neural network architecture for the ground-fault diagnosis. The simulation of the unit generator-transformer was carried out using the Sim-PowerSystem Blockset of MATLAB. The statistical parameters analysis involved calculating a tendency factors including the mean, mode, median and dispersion factor including range and standard deviation values of detail wavelet coefficients. Tendency factor and dispersion factor are used as input for Neural Network Pattern Recognition.

II. Basic Theory

The WT is widely recognized as an effective technique of processing of both stationary and transient non-stationary signals simultaneously in the time and frequency domains. A WT is an instrument which functions for the extraction of the transient signals. The best select of the mother wavelet plays an important part for detecting different types of transient signals. The finest wavelet for extracting signal information is that which can produce as many coefficients as possible to characterize the individual signals.

In the proposed approach, DWT is used for feature extraction, on condition that high time and low frequency resolution for high frequency and high-frequency resolution, and with low time resolution for low frequencies are required. DWT is applied by using the subsequent equivalence [11].

$$\mathrm{DWT}(m.n) = \frac{1}{\sqrt{a_0^m}} \sum_k x(k) g(a_0^{-m} n - b_0 k) \qquad (1)$$

Where "*g(k)*" is the mother wavelet, "*x(k)*" is the signal input and *a, b* is the scaling and translation factors.

The main idea of making a feature extraction is to reduce the amount of information, whether using the original waveform or its transformation format. In this paper, for feature extraction procedure, the coefficient features of wavelet, for example, range, standard deviation, mead, mode and median of a wavelet coefficient, had to be intended.

Artificial Neural Networks is excellent in solving pattern recognition problems. In pattern recognition, a neural network can be used to categorize the input into sets of target. In this paper, a set input of tendency and dispersion factor in statistical parameters of wavelet coefficients was used for ANN input to distinguish set SLG-fault or normal target categories.

III. Research Method

The proposed of SLG-fault detection scheme is schematically drawn in Figure 1. This method is a development of reference [12]. The analysis procedure for SLG-fault detection in unit generator-transformer is explained in steps:

- Step 1: The fault signals are obtained from a simplified power system model for GF simulation using Matlab-Simulink.
- Step 2: DWT of the fault signals are obtained and analysed using MATLAB software.
- Step 3: The wavelet coefficients of the fault signals are obtained using signal decomposition.
- Step 4: The extracted tendency and dispersion factor statistical parameters of wavelet coefficients from WT in various fault simulations are fed into ANN and trained.
- Step 5: The tendency and dispersion factor of statistical parameters of WT based ANN distinguishes GF from normal condition.

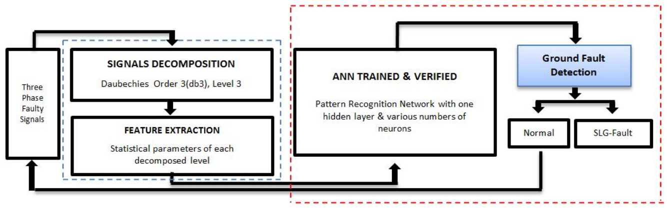


Fig.1. Ground fault detection for unit generator-transformer scheme

A suitable unit generator-transformer model is compulsory to describe the different states during SLG-fault. GF simulations are recognized using Sim-PowerSystem Blockset of MATLAB, and M-file MATLAB is used for GF detection. The power system models for GF simulation are shown in Figure 2. The data of a generator (G-1=G-2) 25 kV with several generator grounding methods included transformers (Transformer-1=Transformer-2) 25/150 kV with *Yn-Yn* transformer connections. In this paper, the simulation was carried out at different fault locations consisting of primary and secondary side of a transformer-1, and at the generator bus. Fault current and voltage used were from the generator bus (Bus-1)

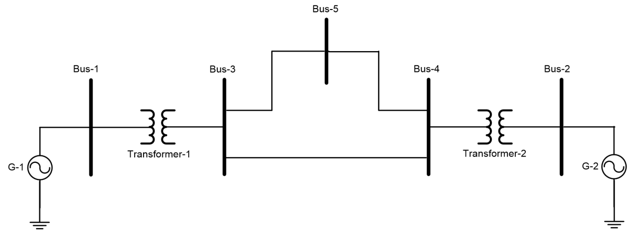


Fig.2. Simulated power system model for ground fault

IV. Analysy

A SLG-fault detection in unit generator-transformer simulations follows a number of general processes. The approach as proposed in this paper consists of three basic stages: (1) signals decomposition, (2) feature extraction and (3) ANN training and verification.

A. Signals Decomposition

In some studies, *Daubechies* mother wavelet is found efficient for the incarceration of transient occasions and frequency feature extraction during fault in the power system. In this paper, mother wavelet *db3* with the resolution level-3 was used to find the coefficient of DWT for SLG-fault detection in unit generator-transformer. Some typical original signal and parts of the coefficient for the resolution level-3 of DWT *db3* are presented in Figure 3 and Figure 4, respectively.

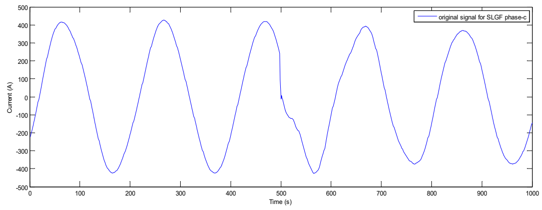
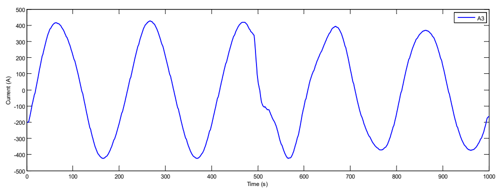
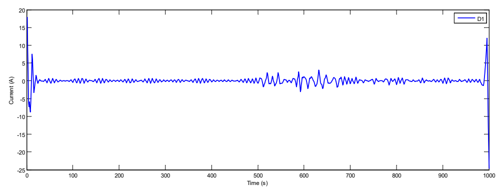


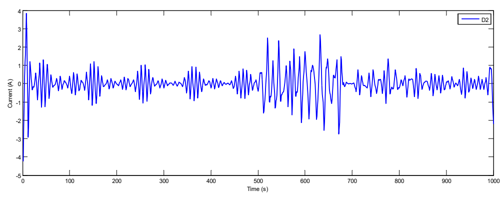
Fig.3. Original signals for SLG-fault current



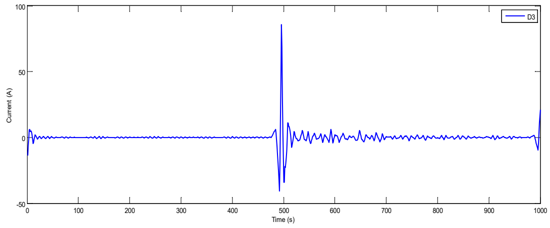
(a)



(b)



(c)



(d)

Fig. 4. Parts of DWT decomposition for current signals

b. Features Extraction

To diminish the number of ANN treating component, this paper proposes a new method for determining tendency and dispersion factor of statistical parameters of a wavelet coefficient for ANN input.

When the wavelet coefficient of the fault signals has been produced by signal decomposition, the next stage is the extraction of a dispersion factor of statistical parameters of the wavelet coefficients from WT in various fault simulations. The feature vectors of individual factors are then used as inputs for the ANN. In this paper, 24000 signals were used for tendency and dispersion factor feature extraction. The dispersion factor and the tendency of each stage of decomposition signal for the evaluation of statistical parameters for some signal can be obtained after investigation signals. For example, the value of tendency and dispersion factor of the wavelet coefficients as illustrated in Table 1 and Table 2.

Table 1. The characteristics of the tendency factor for ANN input

Stage	Phase-*a*	Phase-*b*	Phase-*c*
Value of Mean			
A_3	-249.4608	423.1126	-173.6517
d_1	0.0032	0.0135	-0.0052
d_2	-0.0007	-0.0025	0.0007
d_3	-0.0026	-0.0113	0.0046
Value of Mode			
A_3	-300.0500	421.3723	-202.4790
d_1	-3.0507	-5.7173	-29.7173
d_2	-1.0770	-3.8880	-6.1316
d_3	-1.7092	-4.0557	-13.6475
Value of Median			
A_3	-241.7799	423.5345	-181.7809
d_1	-0.0002	0.0002	0.0021
d_2	0.0002	-0.0006	-0.0047
d_3	-0.0001	-0.0007	0.0016

Table 2. The characteristics of the dispersion factor for ANN input

Stage	Phase-*a*	Phase-*b*	Phase-*c*
Value of Range			
A_3	81.156	2.4675	78.6891
d_1	6.5061	17.4744	47.6065
d_2	1.7974	5.9291	11.4281
d_3	3.1733	6.4490	39.5319
Value of Standard Deviation			
A_3	29.4445	0.8349	28.8602
d_1	0.2075	0.6716	1.9670
d_2	0.0613	0.2320	0.6874
d_3	0.1027	0.3372	1.4444

c. ANN Trained and Verified

In this paper, the pattern recognition set of rules was used for categorizing SLG-fault signals, and normal signals state in the unit generator-transformer. Pattern recognition is the procedure of training a neural network to consign the accurate target classes to a set of input patterns. After one, network has been trained, the network can be used to classify patterns it has not realized before.

The network must be able to detect of fault in several situations of a unit generator-transformer. The inputs for network are extracted from the dispersion factor of statistical parameters of current and voltage details of wavelet coefficients. WT is done to reduce the number of ANN processing element, and accordingly.

The performance of the certain ANN is subjected to several parameters, for instance, hidden layer's number, hidden neuron numbers, function of transfer, rule of training, parameters of training and initial weights and biases. The architecture of the pattern recognition of WT-ANN used in SLG-fault detection in unit generator-transformer is illustrated in Figure 5.

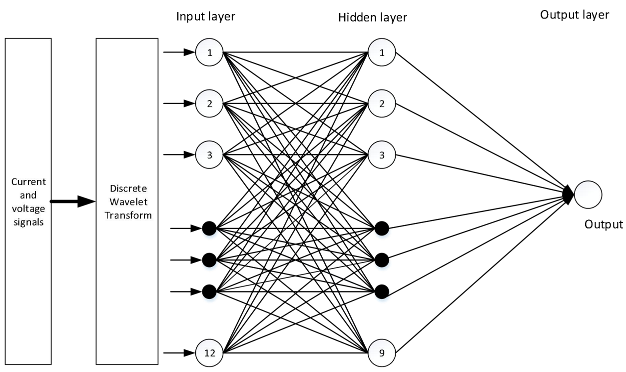


Fig.5. Architecture for WT-ANN of pattern recognition

In this paper, three layers of nodes were used in the analysis with 18 and 12 input nodes, 27 and 9 nodes of hidden layer and one output node. Models were created based on a value tendency factor (mean, median and modus) and dispersion factor (range and standard deviation) parameters of detail wavelet coefficients. 24000 sets of sample (70% set for training, 15% set for validation and 15 % set for testing) were used for each tendency and dispersion factor for ANN network.

The Receiver Operating Characteristic of tendency and dispersion factor as ANN input for this test is shown in Figure 6 and Figure 7, respectively. Area Under Curve (AUC) was 0.999 for tendency factor as ANN input and AUC were 0.923 for dispersion factor as ANN input.

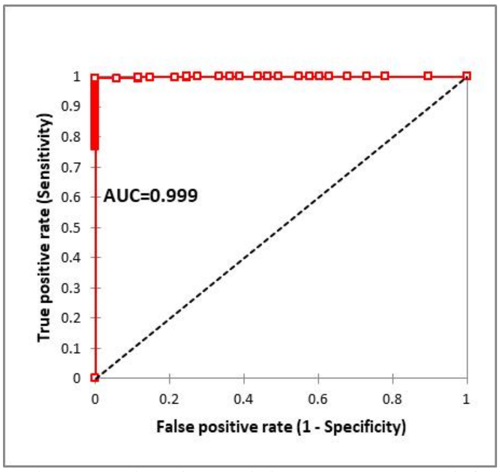


Fig .6. Receiver Operating Characteristic curve as ANN result for 18-27-1

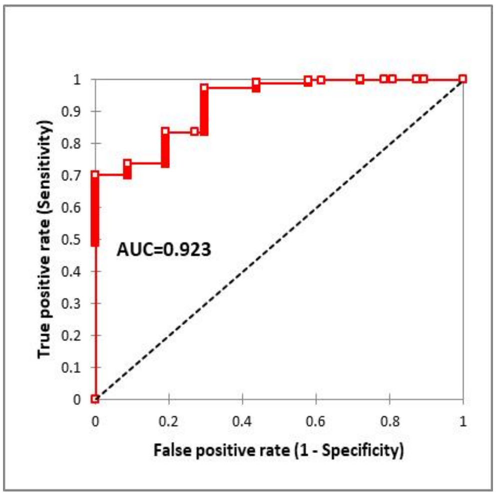


Fig.7. Receiver Operating Characteristic curve as ANN result for 12-9-1

This curve tells us how well the test. The area under the curve is a measure of the goodness of the test with accuracy 98.27 % for tendency factor and accuracy 92.65 % for dispersion factor. Table 3 shows confusion matrix for tendency factor, which reveals the number of True Positive (TP) and False Positive (FP). While the network correctly identified 21468 (89.5 %) cases as SLG-fault, it identified 279 cases normal as SLG-fault. 132 (0.5 %) cases are correctly identified as normal, while 2121 (8.5 %) SLG-fault cases are classified as normal. Table 4 also shows confusion matrix for dispersion factor, which reveals the number of True Positive (TP) and False Positive (FP). While the network correctly identified 21567 (89.9 %) cases as SLG-fault, it identified 1729 (7.2 %) case normal as SLG-fault. 33 (0.1 %) cases are correctly identified as normal, while 671 (2.8 %) SLG-fault cases are classified as normal.

Table 3. Confusion Matrix for tendency factor as ANN input

		Target Class	
		SLG-fault	Normal
Output Class	SLG-Fault	21468 **(89.5 %)**	279 **(1.2%)**
	Normal	132 **(0.5 %)**	2121 **(8.8%)**

Table 4. Confusion Matrix for dispersion factor as ANN input

		Target Class	
		SLG-fault	Normal
Output Class	SLG-Fault	21567 **(89.9 %)**	1729 **(7.2%)**
	Normal	33 **(0.1 %)**	671 **(2.8%)**

For the validation results of ANN, 3600 cases were used for this. Confusion matrix for the validation comparison for ground fault detection using JDW-ANN with ANN input of tendency and dispersion detailed in Table 5, with accuracy 98.44 % for tendency factor and accuracy 92.52 % for dispersion factor.

Table 5. Comparison of the confusion matrix for tendency and dispersion factor as ANN input for validation

		Target Class			
		Tendency Factor		**Dispersion Factor**	
		SLG-fault	**Normal**	**SLG-fault**	**Normal**
Output Class	**SLG-fault**	3220 **(89.4 %)**	44 **(1.2%)**	3255 **(90.4 %)**	266 **(7.4 %)**
	Normal	16 **(0.4 %)**	320 **(8.9%)**	3 **0.1%**	76 **(2.1%)**

V. Conclusion

Concerning the ANN performance, the results of Receiver Operating Characteristic and Confusion Matrix of Neural Pattern Recognition indicated that the proposed algorithm is enough to detect a ground-fault for a unit generator-transformer. The accuracy of the SLG-fault detection for tendency factor was 98.27 % and AUC 0.999 than 92.65 % and AUC 0.923 for dispertion factor. For validation on ANN performance, the accuracy of the SLG-fault detection for tendency factor was 98.27 % than 92.65 % for dispertion factor. In this paper, analysis of statistical parameters on wavelet coefficients as ANN input successfully detection of SLG-fault. The value of the tendency factors is more optimal than the dispersion factor on wavelet coefficients as ANN input for distinguishing an SLG-fault and normal condition for a unit generator-transformer.

References

[1] Omar A.S, Youssef, "Online Application of Wavelet Transforms to Power System Relaying", IEEE Transactions on Power Delivery, 18(2003)1158-1165.
[2] IEEE, Std C37.102™, "Guide for AC Generator Protection", 2006.
[3] J.C.Das., "Power System Relaying,: Encyclopedia of Electrical and Electronic Engineering", Wiley, 1999.
[4] H.Zhengyou, G.Shibin, C.Xiaoqin, Z.Jun, B.Zhiqian & Q.Qingquan, "Study of A New Method for Power System Transients Classification based on Wavelet Entropy and Neural Network, Electrical Power and Energy Systems", 33(2011) 402-410.
[5] Sadegh J.& Navid G., "A New Method for Arcing Fault Location using Discrete Wavelet Transform and Wavelet Networks, European Transc. on Electrical Power", 22(2012) 601–615.
[6] Pittner.S & Kamarthi.S.V., "Feature Extraction From Wavelet Coefficients for Pattern Recognition Tasks", IEEE Transactions on Pattern Analysis and Machine Intelligence, 21(1999) 83-88.

[7] Rahman, M.A, Ozgonenel O & Khan M.A., “Wavelet Transform Based Protection of Stator Faults in Synchronous Generators, Electric Power Comp. and Systems”, 36 (2007) 625-637.
[8] A.Rahmati & M. Sanaye-Pasand, “A Fast WT-Based Algorithm to Distinguish between Transformer Internal Faults and Inrush Currents, European Transaction on Electrical Power”, 22 (2012) 471–490.
[9] Baqui I, Zamora I, mazon J & Buigues G., “High Impedance Fault Detection Methodology using Wavelet Transform and Neural Network, Electrical Power System Research”, 81 (2011) 1325-1333.
[10]S.Changqin, Wang.D, Kong.F & Tse.P.W., “Fault Diagnosis of Rotating Machine based on Statistical Parameters of Wavelet Packet Paving and A Generic Support Vector Regressive Classifier, Measurement”, 46 (2013) 1551-1564.
[11]Chul-Hwan Kim, Hyun Kim, Young-Hun Ko, Sung-Hyun Byun, Raj K. Aggarwal and Allan T. Johns, “A Novel Fault-Detection Technique of High-Impedance Arcing Faults in Transmission Lines using the Wavelet Transform”, IEEE transactions on power delivery. 17(2013).
[12] Sultan, A.R., Mustafa.,M.W. & Saini,M.,”Single Ground-Fault Detection for unit generator-transformer based on wavelet transform and neural network, Applied Mechanics and Material”, Vol.818 (2016), 47-51.