Turkish Journal of Electrical Engineering & Computer Sciences

http://journals.tubitak.gov.tr/elektrik/

Research Article

Turk J Elec Eng & Comp Sci
(2016) 24: 1340 – 1350
© TÜBİTAK
doi:10.3906/elk-1312-145

Grid-connected induction generator interturn fault analysis using a PCA-ANN–based algorithm

Haydar BAYAR[1,*], **Ümit Kemalettin TERZİ**[2]

[1]Department of Electrical Education, Faculty of Technical Education, Marmara University, İstanbul, Turkey
[2]Department of Electrical and Electronics Engineering, Faculty of Technology, Marmara University, İstanbul, Turkey

Received: 20.12.2013 • **Accepted/Published Online:** 04.03.2014 • **Final Version:** 23.03.2016

Abstract: It is difficult for short circuits among the internal windings of one phase in electrical machines to be determined in a reliable and speedy manner. The failure currents that occur, especially in short circuits with a few windings, are at such low levels that they cannot be determined by relay systems. This results in growing faults and damage. In this study, we designed a model that can define winding failures successfully at very small levels by using the PCA and ANN algorithms. We tested the real-time faults and measured the system performance with the installed test rig. The developed protection model determined fault determination in very small (2.5%) winding failures with acceptable accuracy. The suggested model is a counter-speed, selective, flexible, and economical protection model that may be used for internal failures of electrical machines. It has a structure that may be used in different systems or kinds of failure with data receiving and software changes.

Key words: PCA, induction generator, faults, protection

1. Introduction

Protection systems are units that apply protection measures after defining a failure in any internal or external fault event. The purpose of an effective protection system is to make a reliable determination within the first few periods of the fault's beginning. This short definition requires a comprehensive relay coordination study, especially when the complexity and dynamic structure of the system are considered. The relay coordination must be in a structure that ensures significant properties like selectivity, speed, economy, simplicity, and reliability. Determination of an optimal structure in these parameters is difficult because of the limiting properties of relays driven by conventional sensor systems [1].

The designs of protection systems for electrical machines are the subject matter of many studies. Recent research has emphasized selective and speedy protection models for the synchronous and asynchronous generators used in renewable energy systems [2–5]. Experimental and simulation studies have focused on doubly fed induction generators (DFIGs), sudden voltage fluctuations, parallel connection systems, symmetric/asymmetric short circuits, and behavioral models in other mechanical and electrical faults [6–10]. In generator failures, various fault analysis systems have been developed for multiple machine models [11], stand-alone systems [12–14], and self-excited generators [15,16]. Effective protection models have used intelligent electronic devices, motor current signal analysis (MCSA), and artificial intelligence techniques [17–21].

*Correspondence: haydarbayar@marmara.edu.tr

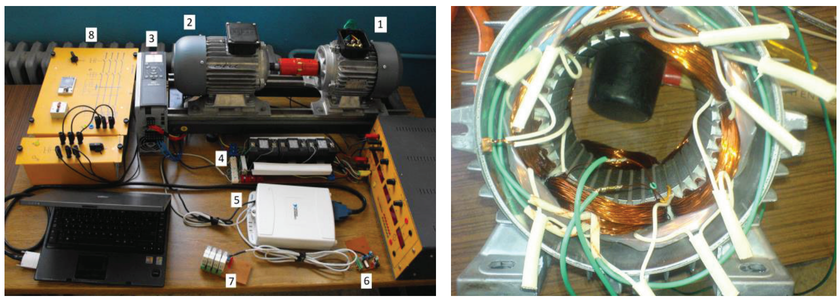
Gketsis et al. analyzed the short circuit situations of 2, 3, and 4 adjacent windings using wavelet analysis and a feedback Levenberg–Marquardt trained ANN algorithm for a 660 kW, 690 V nominal voltage asynchronous generator driven by a wind turbine to determine internal faults. The authors analyzed the maximum value and corresponding frequency variations as a basic value in the fault determination. They determined how many windings were short-circuited in a manner that required much less calculation [22]. Acosta et al. created a failure definition for a short-circuited 12% winding in a 1-phase stator winding [23]. Another study performed principal component analysis (PCA) using $\alpha - \beta$ vector particulates of a standard 4-pole asynchronous 3 HP motor fed from a PWM power inverter. For the failure and steady-state situations, the researchers obtained the eigenvalues of two different principal components and compared these values to decide whether the motor had failures [24]. Shah et al. presented a new method for determination of internal failures in DFIGs by analyzing the rotor phase currents tested with voltage dips on an additional winding wrapped on a rotor [25]. A similar purpose study was realized by Emhemed et al. in 2010 using a superconductive limiter for the failure current limitation and an analytic method that shortened the period to remain out of circuit in low-voltage induction generators (IGs) [26]. A PCA- and ANN-based approach was presented by Kılıç et al. to protection against transformer internal faults in 2011 [27]. Similarly an induction motor protection algorithm was developed to determine stator winding faults, broken rotor bars, and bearing failures using PCA and ANN by Özgönenel et al. [28]. Eftekhari et al. proposed an infrared thermal imaging method to detect stator winding short circuits in an induction motor [29]. Further work was done by Kang and Kim in 2013 for classifying faults of induction motors. In that work, singular value decomposition based feature extraction approaches are compared with the other methods and higher classification accuracies than with conventional approaches are obtained [30]. One of the latest studies about fault diagnostics in induction machines was done by Foito et al. in 2014. In their study current trajectory mass center methodology was used for diagnosing the stator winding faults in a six-phase induction motor [31].

The most dangerous damage resulting from stator faults in electrical machines is the deformation of the stator core or windings because of the heat that occurs at the point of failure. Depending on the damage resulting from the failure, long-term and costly repairs may be needed, like remanufacturing deformed core parts and rewrapping windings. In the case of stator-ground leakage failure, winding burning remains at minimum levels, because the currents complete their circuits through the ground resistance. However, determination and protection of short circuits among the windings of a phase winding is a difficult process, and in general, it does not ensure effective protection. The failure currents that occur in that case may remain below the nominal current. However, unless it is determined within a few periods, it may cause winding and core damage. In machines used as generators, the periods remaining out of the circuit and the associated costs are very important.

This study presents a new model that can provide effective, reliable, and selective protection to solve these problems. The methods used in two studies [20,21] were able to identify short circuits involving 12% of the windings. By contrast, the PCA-ANN base hybrid protection model suggested in this study shows a successful performance in a situation where 2.5% of total windings are short circuited. We performed real-time tests of the developed model on an IG and present the test results and ANN outputs in detail.

2. Materials and methods

In experimental studies, we operated a 6-pole induction machine with 0.75 kW as a generator connected to the network. This machine was driven by a 6-pole asynchronous machine with 1.1 kW. For generator operation of an asynchronous machine, the rotational speed must be above the synchronous rotational speed. We used a frequency convertor with a driver machine to control the rotational speed and the generator load across a wide interval in this study. To investigate internal electrical faults of induction generators, we extracted the tips from various points of the stator windings. A DAQ card transformed the three-phase current information from the generator to the computer via current transformers. The components of the test rig are given in Figure 1 and a wiring diagram of the experimental set is shown in Figure 2.



a b

Figure 1. a) Test rig; 1-induction generator, 2-driver motor, 3-frequency convertor of driver motor, 4-current transformers, 5-connection board of DAQ card, 6-relay driver circuit, 7-relay card, 8-network connection switch. b) Induction machine with extracted tips.

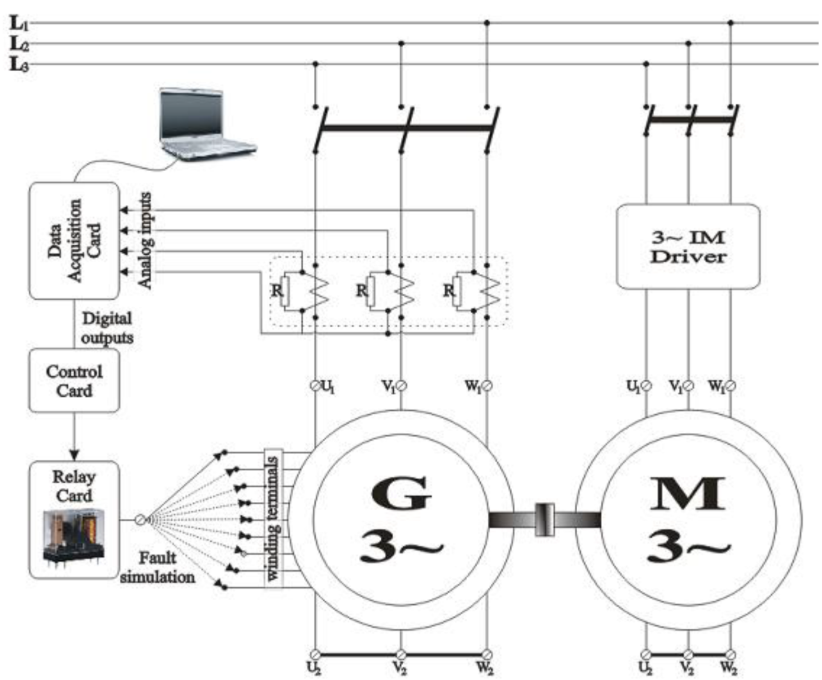


Figure 2. Wiring diagram of experimental set.

2.1. Principal component analysis

PCA is a conventional linear property determination method. It depends on the secondary statistical analysis of data, especially on the eigenvalue analysis of the covariance matrix [32].

The beginning point of PCA is the (X) data matrix, consisting of (m) observation rows and (n) variable columns. PCA can use all kinds of analytic data obtained from various resources (variables) such as various sensors, chemical treatment processes, or biological measurements for observational data [33]. Data that belong to variables in the X (data matrix) can be brought to columns having a zero mean and be scaled. The scaling process ensures the variables with different amplitudes have equal weights in the data matrix. The mean of columns of the scaled X matrix is arranged according to Eq. (2.1) to equal zero.

$$XC = X - \bar{X} \tag{1}$$

In the above equation, states mean values of the data matrix. Covariance of the arranged data matrix (XC) is calculated with Eq. (2.2).

$$R = \frac{1}{m-1} XC^T XC \tag{2}$$

The eigenvalues and eigenvectors are found from the calculated covariance matrix (R) by the singular value decomposition method.

$$R = P\lambda P^T \tag{3}$$

In (2.3), λ is a diagonal matrix that contains eigenvalues of the covariance matrix arranged from largest to smallest value $(\lambda_1 \geq \lambda_2 \geq ...\lambda_n \geq 0)$. The P matrix is a square matrix with columns consisting of eigenvectors of the covariance matrix (R). The last phase is determination of principal components, which are generally eigenvectors with high eigenvalues. Eigenvectors are lined according to the amplitudes of their eigenvalues. Eigenvectors having 80%–90% variance levels are principal components. As the number of principal components increases, the amplitudes of the eigenvalues decrease [34–37].

As shown in Figure 3, among the thirteen eigenvectors seven of them are taken as principal components. Table 1 shows that the first seven eigenvectors selected as PCs had over 84% variance levels in total.

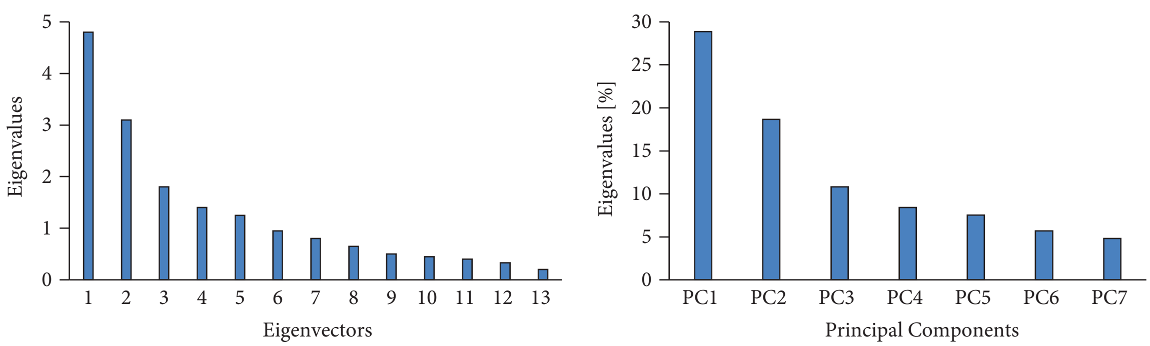


Figure 3. Eigenvectors and principal components.

2.1.1. Fault determination with PCA

Determination and definition of faults in nonlinear systems is important. To determine and control faults in industrial applications, it is obligatory to make different measurements related to each other and follow many operation processes that are nonlinear, have high noise, and change in time. By applying PCA for the purpose of failure analysis, nonlinear correlations between different processes can be eliminated, and effects of noise in the failure process can be decreased. For this reason, PCA is practical for monitoring the condition of a process or device.

Table 1. Variances of eigenvectors and selected PC's total variance.

Eigenvector	Eigenvalue	% Variance		Eigenvector	Eigenvalue	% Variance
1	4.80	28.86		8	0.65	3.91
2	3.10	18.64		9	0.50	3.01
3	1.80	10.82		10	0.45	2.71
4	1.40	8.42		11	0.40	2.41
5	1.25	7.52		12	0.33	1.98
6	0.95	5.71		13	0.20	1.20
7	0.80	4.81				
% Total variance		84.79				15.21

Hotelling T^2 and SPE (Squared Prediction Error or Q) statistical methods introduce the general characteristics of data in PCA and fault analysis. The Hotelling T^2 approach used in this study scales the internal variances of the PCA model by taking the secondary total of score vectors. With this method, monitoring the bottom space of basic compounds in real time becomes easy. Hotelling T^2 statistical variances indicate the difference between each sampling point and model in respect to the direction and amplitude of variances. The Hotelling T^2 approach for X data matrix is

$$T^2 = XP\lambda^{-1}P^TX^T \tag{4}$$

Here, P refers to the eigenvector matrix obtained from the covariance matrix and λ represents a diagonal matrix consisting of eigenvalues. Thus, T^2 is a scalar amplitude that equals the total of numerous variances. For this reason, it allows multivariant monitoring processes to be followed on a single variance. The T^2 statistic method expresses the variances in multivariant operation processes in terms of fluctuation in the basic compound vector amplitudes [34,38].

2.2. ANN structure

As shown in the Results and discussion section, PCA and T^2 statistic outputs are highly distinguishing. This why the ANN structure we use is fairly simple. It is a feed-forward system that has 3 neurons at the entrance of the network, 12 neurons in the hidden layer, and 1 neuron in the outlet layer (Figure 4).

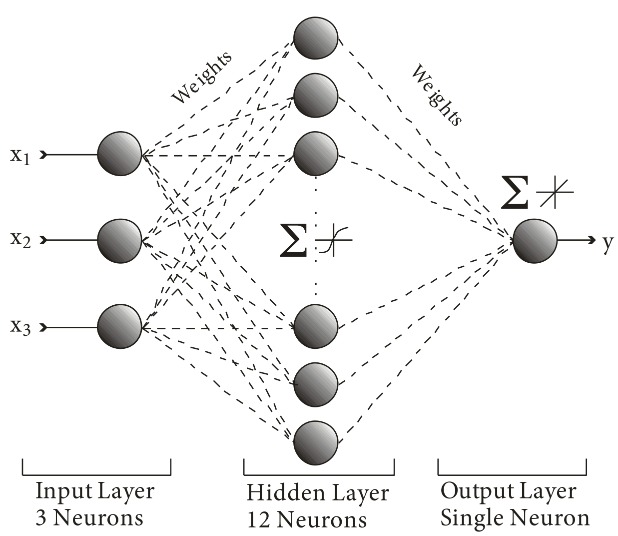


Figure 4. ANN structure.

The network is created by the Matlab Neural Network Fitting Tool. It is a two-layer feed-forward network that contains a sigmoid transfer function in the hidden layer and a linear function in the output layer. The network is trained with the Levenberg–Marquardt backpropagation algorithm. The training data set consists of T^2 outputs obtained from real-time experiments for four load levels (1/4 load, 1/2 load, 3/4 load, and full load) and four rates of in-turn winding short-circuits (2.5%, 4.3%, 9.5%, and 16.4%) and healthy working conditions. From 840 samples randomly selected 70% were for training, 15% for validation, and 15% for testing. As a result of PCA and T^2 statistical success, this relatively simple network regression is over 0.99 (R = 0.999). Network training performance is shown in Figure 5.

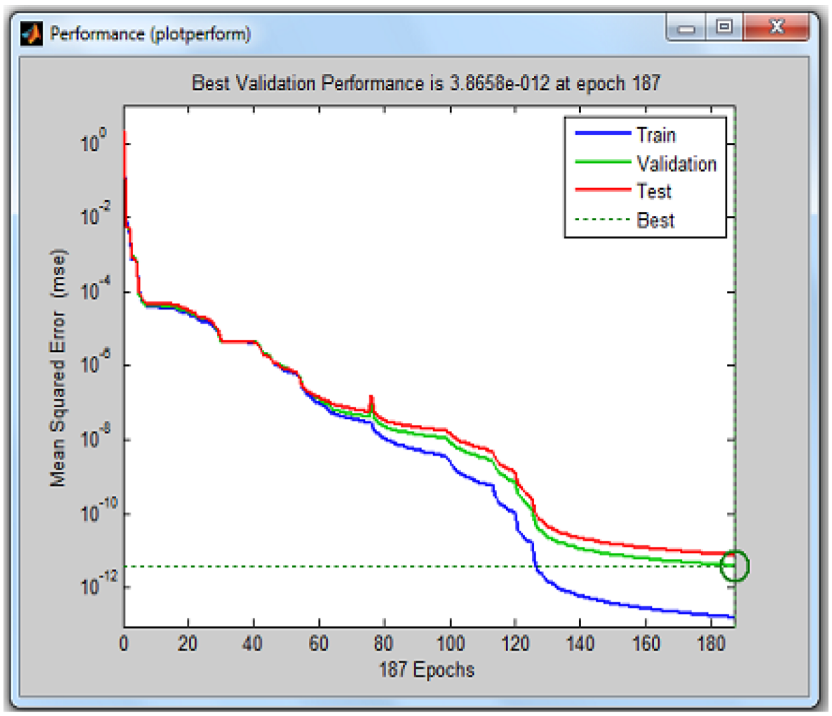


Figure 5. ANN training performance.

2.3. Other components of the experimental set

For data collecting and the establishment of the database for operating statutes with and without failure, this study used a model that operated on-line. We took data related to phase currents of an asynchronous generator that operated with the network by means of the model given in Figure 6, then processed that data with PCA, and recorded the results for use in ANN training.

In the model, the three-phase current data first taken from the generator are kept in a variable called "z," to be used later. In the next phase, incoming current data are held in buffers to transform the data inputs for PCA to matrix form. The model sample rate is 2000 and the grid frequency is 50 Hz; thus the data matrix size is 40 × 3 consisting of 40 samples of all three phases of current data along one period. Data transformed to a matrix form are processed in the PCA block and T^2 statistics are recorded for each working status.

The failure and robust T^2 data from the experiments were used to train the artificial neural network used in the fault diagnosis phase.

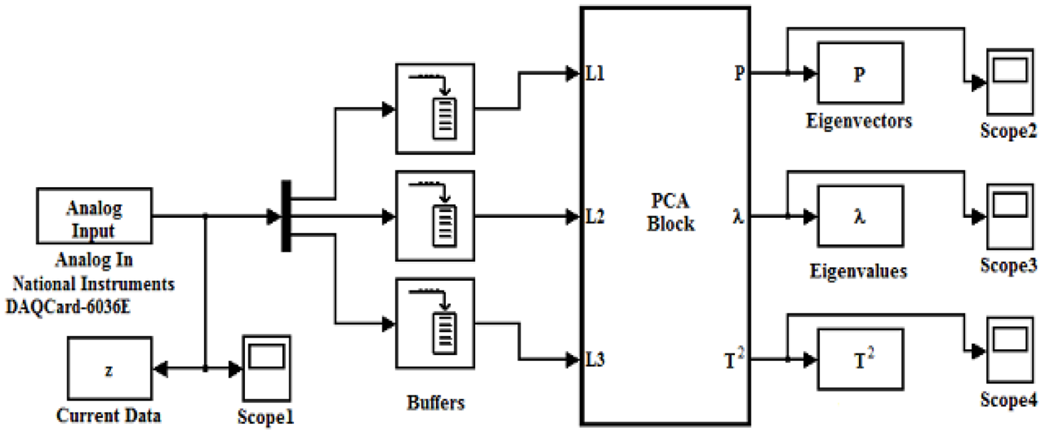


Figure 6. Real-time data acquisition model.

3. Results and discussion

The outline of the study can be summarized as follows:

- By the test rig, faulty and healthy working conditions current signals are collected and processed with PCA and Hotelling T^2 statistic.
- T^2 outputs are used in ANN training and the trained network is embedded into the real-time block.
- The system is tested against various load and short circuit situations, some of which are not included in the training data.

We created faults in a phase winding of a generator by short circuiting ends taken from the stator winding. We then used the data obtained as a result of short circuiting of a phase winding at rates of 2.5%, 4.3%, 9.5%, and 16.4% in the ANN training to determine and estimate the level of the system failures.

The current and PCA residues belonging to the smallest (2.5%) and largest (16.4%) failure modes established artificially in the phase winding are given in Figures 7 and 8. The machine operated at full load in both failure modes. The amplitude variance in phase currents, especially in 2.5% level failure, remained at very low levels, as seen in Figure 7a; 16.4% failure mode established current fluctuations that were easily recognizable.

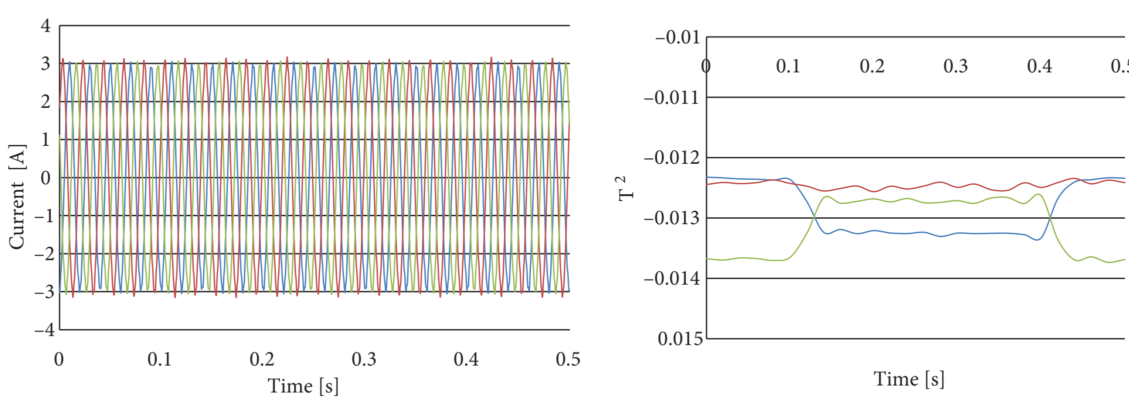


Figure 7. a) Current. b) T^2 statistical amplitude changing graphics with time at 2.5% rate of in-turn failure situation.

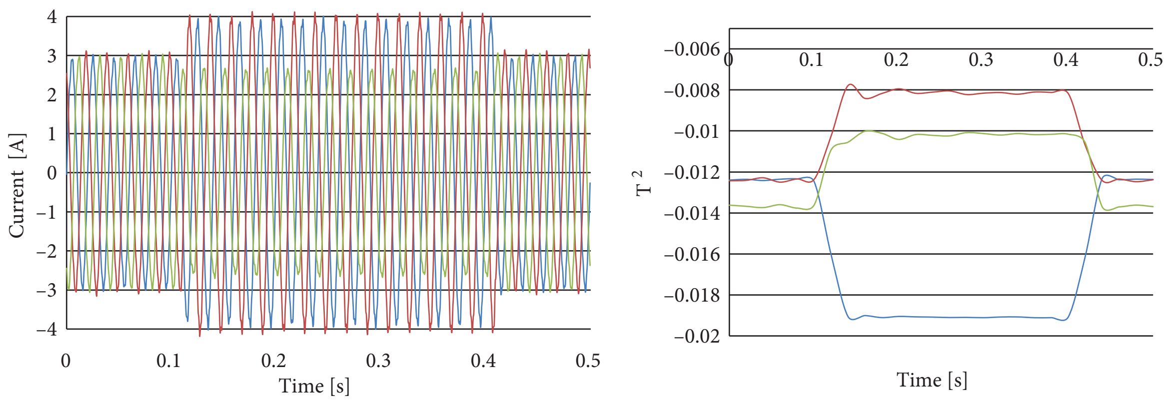


Figure 8. a) Current. b) T^2 statistical amplitude changing graphics with time at 16.4% rate of in-turn failure situation.

Three elements of the residue matrix calculated as a result of PCA were the input data for the ANN. Accuracy levels provided to obtain the target levels given in Table 2 were analyzed for four different load levels of the generator. Deviations between ANN outputs and target values obtained for 8 different winding failures in 1/4 load, half-load, 3/4 load, and full-load levels were given respectively. To measure the success of system output, 3.4%, 5.1%, 6.9%, and 12.9% faults, which are not included in the ANN training data, were included in the real-time trials.

Table 2. Real-time experimental results.

Interturn short circuit rate (%)	Target value	Generator load rate				Average deviation (%)
		1/4	1/2	3/4	4/4 (Rated)	
2.5	1.025	1.023	1.0235	1.0264	1.0258	0.033
3.4	1.034	1.0408	1.0375	1.0373	1.0326	–0.29
4.3	1.043	1.0416	1.0416	1.0452	1.0456	–0.05
5.1	1.051	1.0651	1.0555	1.0567	1.0476	–0.496
6.9	1.069	1.0675	1.0617	1.0651	1.0675	0.332
9.5	1.095	1.097	1.0926	1.0978	1.0974	–0.108
12.9	1.129	1.1439	1.137	1.1426	1.1467	–1.2
16.3	1.163	1.1644	1.164	1.1667	1.1607	–0.08

The failure mode that was the most difficult to determine in respect to amplitude and current fluctuations occurred at 1/4 workload. The machine gives current values very close to unloaded working values under this load level. In this small current, amplitude fluctuations occurring in the smallest failure mode will also remain in the smallest levels. For these conditions, failure determination was realized with ANN 0.2% fault. This failure rate reflects the difference between the estimation and the real value of short-circuited winding rates; it does not mean the failure was not recognized. For instance, in this case, 2.5% of the winding was short circuited, but ANN estimated the short-circuited winding rate as 2.3%. Determination of a very small rated failure sensitively under these conditions indicates availability of the suggested model.

The proposed system is independent of the generator's load conditions. To show that, the generator's load increased from 1/4 to full load in 10 s and ANN outputs are given in Figure 9. The generator's one phase effective current is shown on the left side and the ANN output is on the right side of the figure. As expected from a reliable protection system, load variances are recognized by the system as a normal working condition.

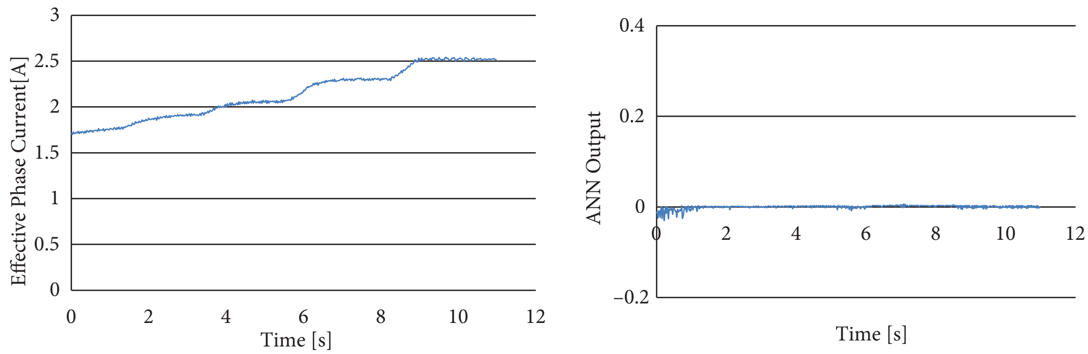


Figure 9. The ANN output corresponding with load fluctuations.

4. Conclusions

This study suggests a selective and flexible model using PCA and ANN algorithms to determine the internal winding faults of electric machines. The results obtained from experimental applications made on an IG indicate the suggested model gives reliable results also for very small amplitude winding faults that are otherwise difficult to determine. By this study, the successfully determined smallest short circuit rate in one phase windings is revealed as 2.5%, which is ahead of similar studies in the literature [12,22,23]. As the load mode and short circuit level of the machine increase, determination of winding faults becomes easier. The protection model realized in this study can be used in protection systems of small power synchronous generators, DFIGs, and other electric machines. In machines that are used as generators, if a fault is determined early, damage that requires changing of important compounds like a core can be prevented. Thus, this model can provide important technical and economic gains, mainly by reducing electrical equipment downtime.

References

[1] Rushton J, Mewes KGM. Protection of generators, transformers, generator-transformer units and transformer feeders. In: The Electricity Training Association, editor. Power System Protection 3. London, UK: Short Run Press Ltd, 1995.

[2] Sürgevil T, Akpınar E. Modelling of a 5 kW wind energy conversion system with induction generator and comparison with experimental results. Renew Energ 2005; 30: 913-929.

[3] Freitas W, Vieira JCM, Morelato A, da Silva LCP, da Costa VF, Lemos FAB. Comparative analysis between synchronous and induction machines for distributed generation applications. IEEE T Power Syst 2006; 21: 301-311.

[4] Quinonez-Varela G, Cruden A. Modelling and validation of a squirrel cage induction generator wind turbine during connection to the local grid. IET Gener Transm Dis 2008; 2: 301-309.

[5] Holdsworth L, Wu XG, Ekanayake JB, Jenkins N. Comparison of fixed speed and doubly-fed induction wind turbines during power system disturbances. IEE P-Gener Transm D 2003; 150: 343-352.

[6] Abad G, Rodriguez MA, Iwanski G, Poza J. Direct power control of doubly fed induction generator based wind turbines under unbalanced grid voltage. IEEE T Power Electr 2010; 25: 442-452.

[7] Lopez J, Gubia E, Olea E, Ruiz J, Marroyo L. Ride through of wind turbines with doubly fed induction generator under symmetrical voltage dips. IEEE T Ind Electron 2009; 56: 4246-4254.

[8] Flannery PS, Venkataramanan G. A fault tolerant doubly fed induction generator wind turbine using a parallel grid side rectifier and series grid side converter. IEEE T Power Electr 2008; 23: 1126-1135.

[9] Chen SZ, Cheung NC, Wong KC, Wu J. Grid synchronization of doubly fed induction generator using integral variable structure control. IEEE T Energy Conver 2009; 24: 875-883.

[10] Xiang D, Ran L, Tavner PJ, Yang S. Control of a doubly fed induction generator in a wind turbine during grid fault ride-through. IEEE T Energy Conver 2006; 21: 652-662.

[11] Zhang J, Dysko A, O'Reilly J, Leithead WE. Modelling and performance of fixed-speed induction generators in power system oscillation stability studies. Electr Pow Syst Res 2008; 78: 1416-1424.

[12] Wamkeue R, Kamwa I. Generalized modeling and unbalanced fault simulation of saturated self-excited induction generators. Electr Pow Syst Res 2002; 61: 11-21.

[13] Wekhande S, Agarwal V. A new variable speed constant voltage controller for self-excited induction generator. Electr Pow Syst Res 2001; 59: 157-164.

[14] Idjdarene K, Rekioua D, Rekioua T, Tounzi A. Vector control of autonomous induction generator taking saturation effect into account. Energ Convers Manage 2008; 49: 2609-2617.

[15] Joshi D, Sandhu KS, Soni, MK. Constant voltage constant frequency operation for a self-excited induction generator. IEEE T Energy Conver 2006; 21: 228-234.

[16] Jain SK, Sharma JD, Singh SP. Transient performance of three-phase self-excited induction generator during balanced and unbalanced faults. IEE Proc-C 2002; 149: 50-57.

[17] Boutsika TN, Papathanassiou SA. Short-circuit calculations in networks with distributed generation. Electr Pow Syst Res 2008; 78: 1181-1191.

[18] Widodo A, Yang B, Gu D, Cho B. Intelligent fault diagnosis system of induction motor based on transient current signal. Mechatronics 2009; 19: 680-689.

[19] Ghate VN, Dudul SV. Optimal MLP neural network classifier for fault detection of three phase induction motor. Expert Syst Appl 2010; 37: 3468-3481.

[20] Combastel, C, Lesecq S, Petropol S, Gentil S. Model-based and wavelet approaches to induction motor on-line fault detection. Control Eng Pract 2002; 10: 493-509.

[21] He Y, Tan Y, Sun Y. Wavelet neural network approach for fault diagnosis of analogue circuits. IEE Proc-G 2004; 151: 379-384.

[22] Gketsis ZE, Zervakis ME, Stavrakakis G. Detection and classification of winding faults in windmill generators using wavelet transform and ANN. Electr Pow Syst Res 2009; 79: 1483-1494.

[23] Acosta GG, Verucchi CJ, Gelso ER. A current monitoring system for diagnosing electrical failures in induction motors. Mech Syst Signal Pr 2006; 20: 953-965.

[24] Martins JF, Pires VF, Pires AJ. PCA-Based on-line diagnosis of induction motor stator fault feed by PWM inverter. In: IEEE 2006 International Symposium on Industrial Electronics; 9-12 July 2006; Montreal, Quebec, Canada: IEEE. pp. 2401-2405.

[25] Shah D, Nandi S, Neti P. Stator interturn fault detection of doubly fed induction generators using rotor-current and search-coil-voltage signature analysis. IEEE T Ind Appl 2009; 45: 1831-1842.

[26] Emhemed AS, Tumilty RM, Singh NK, Burt GM, McDonald JR. Analysis of transient stability enhancement of lv-connected induction microgenerators by using resistive-type fault current limiters. IEEE T Power Syst 2010; 25: 885-893.

[27] Kılıç E, Özgönenel O, Usta Ö, Thomas D. PCA based protection algorithm for transformer internal faults. Turk J Electr Eng & Com Sci 2009; 17: 125-142.

[28] Ozgonenel O, Yalcin T. A complete motor protection algorithm based on PCA and ANN: a real time study. Turk J Electr Eng & Comp Sci 2011; 19: 317-334.

[29] Eftekhari M, Moallem M, Sadri A, Hsieh MF. A novel indicator of stator winding inter-turn fault in induction motor using infrared thermal imaging. Infrared Phys Techn 2013; 61: 330-336.

[30] Kang M, Kim JM. Singular value decomposition based feature extraction approaches for classifying faults of induction motors. Mech Syst Signal Pr 2013; 41: 348-356.

[31] Foito D, Maia J, Fernao Pires V, Martins JF. Fault diagnosis in six-phase induction motor using a current trajectory mass center. Measurement 2014; 51: 164-173.

[32] Diamantaras KI. Neural networks and principal component analysis. In: Hu YH, Hwa JN, editors. Handbook of Neural Network Signal Processing. London, UK: CRC Press, 2001. Chapter 8.

[33] Eriksson L, Johansson E, Kettaneh-Wold N, Trygg J, Wikström C, Wold S. Multi and Megavariate Data Analysis. Part 1. Sweden: MKS Umetrics AB, 2006.

[34] Garcia-Alvarez D. Fault detection using principal component analysis (PCA) in a wastewater treatment plant (WWTP). In: International Forum 2009 Information and Communication Technologies and Higher Education – Priorities of Modern Society Development; 26-30 May 2009; St. Petersburg, Russia.

[35] Jolliffe IT. Principal Component Analysis. New York, USA: Springer-Verlag, 2002.

[36] Özgönenel O, Kılıç E. Modeling and realtime fault identification in transformers. J Frankl Inst 2008; 345: 205-225.

[37] Gemperline PJ. Practical Guide to Chemometrics. 2nd ed. Boca Raton, FL, USA: CRC Press, 2006.

[38] Li D, Zhang Z, Wang H. Fault detection and diagnosis in activated effluent disposal process based on PCA. In: IEEE 2010 International Conference on Information and Automation; 20-23 June 2010; Harbin, China: IEEE. pp. 216-221.