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Fault Diagnosis of Five-Phase Fault-Tolerant Permanent-Magnet Motor Based on Principal Component Neural Network

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Abstract—**In this paper, a new fault diagnosis method for a five-phase fault-tolerant permanent-magnet (FTPM) motor by using a compact method is proposed. The key is to create a neural network based on principle component analysis (PCA). For a current signal of a five-phase FTPM motor system, PCA theory is used to extract the main element from the fault sample data. It realizes optimum compressed of fault sample data and simplifies structure of neural network in fault diagnosis. Speed and precision of the fault classification are enhanced. The obtained results verify the effectiveness of the proposed method.**

I. Introduction

THE fault diagnosis for a five-phase motor system is the key point of rotary mechanical fault diagnosis. The five-phase motor is applied in a variety of areas including electric vehicle applications field [1], [2]. Hence, more attention is paid on the study of five-phase motor. The common faults are rotor imbalance, the loose of bearing, partial friction, oil whirl, etc. Among all the fault of a motor, the short-circuit fault is the particular one, which can cause serious damage to the motor shortly [3]. After detection, it is required to bring the machine offline to clear the fault. However, a shutdown of the running motor is not available in safety-critical applications. Hence, fault-tolerant control is pullulated [4], [5]. Based on harmonic analysis, fault-tolerant control is generally used for the multi-phase motor [6], [7]. Then the five-phase FTPM motor is proposed, which can run normally under the specific fault. By using transient co-simulation method, analysis of fault-tolerant performance of a doubly salient permanent-magnet motor drive is mentioned in [8]. Although with the new motor, the damage to the motor caused by the fault can be avoided, it is difficult to detect stator inter-turn short circuit fault. The severity of stator inter-turn short circuit fault can hardly be recognized. The most important step is to identify the location and the severity of fault quickly and accurately. Then a better fault-detection method is required.

Motor current signature analysis (MCSA) is nowadays a widely used method to detect the broken rotor system [9], [10], [11]. MCSA methods employ FFT to detect the eccentricity and stator inter-turn short circuit characteristic frequencies. Some of the frequency components are close to the stator supply frequency [12]. There are also recent studies based on wavelet technique for MCSA. However, inherent asymmetries in the machine and unbalanced supply voltages also affect the current component. In recent years, some methods have been proposed to diagnose turn fault for induction motors. Parameters estimation and intelligent modeling can be employed to several applications [13]. A noninvasive technique for diagnosing electrical faults of induction motors using a current park vector is proposed in [14]. A study of a machine fault diagnosis system by using FFT is clearly explained in [15]. These methods work correctly under steady state. They fail to detect the slowly developing turn fault under transient state due to the highly complex, non-linear nature of turn fault. Neural network has the ability to achieve nonlinear dynamic mappings with simple structure. It has rapid convergence and easy implementation [16]. Therefore, it can be used to detect stator winding turn fault in induction motors at various conditions.

In this paper, a neural network based on PCA is proposed to detect different severity of the stator inter-turn short circuit fault [17]. This work is on the basis of multi- statistics theory principle. Based on the fault characteristic method of PCA, the motor fault diagnosis recognition method has been put forward to combine PCA characteristic method and neutral network. It can be applied to accomplishing the experiment of open circuit fault diagnosis. The structure of the middle neutral network grader of fault diagnosis can be simplified by this method. The classification speed and test precision of the neutral network are improved. PCA is a dimension reduction technique used in multivariate statistical analysis, which deals with data set that consists of many variables. PCA detect the abnormal change of the process. The PCA method can efficiently be used to extract the main variable information of original data set in dependent of the process mechanism. A lower dimension input space can reduce the time necessary to train a neural network. The reduced noise may improve the mapping performance [18]. This method is also suitable for in the fault diagnosis recognition of other circuit.

II. Improved Neural Network Based on PCA

A. PCA model

PCA is a method to pre-process the input sample set, which can reflect the multi-target fault information into a few composite indicators. They are regarded as the input variables of a new network. PCA can be widely used in signal processing and neural network calculation [19]. The steps of PCA modeling are as following [20].

1) The original sample standardization is needed before data processing. In order to eliminating the effects of different dimensions and orders of magnitude, the standard deviation

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method of the mean of the standardized data is used to cope with original sample data. The matrix of evaluation data is

$$X_{m\times n} = (X_1, X_2, \cdots, X_m) \tag{1}$$

where m is the number of indexes and n is the number of evaluation objects. Compute mean vector of X

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{m} X_i \tag{2}$$

and the centralization of X :

$$Y = (Y_1, Y_2, \cdots, Y_m) \tag{3}$$

where

$$Y_i = X_i - \overline{X}\ (i=1, 2, \cdots, n)$$

2) After the establishment of the covariance matrix of standardized variables, the solution of the matrix eigenvalues and eigenvectors are calculated in order to get the principal component. Using standardized terms to get the covariance matrix of Y:

$$S = YY^T/(n-1) \tag{4}$$

Compute eigenvalues of S: $\lambda_1 \geqslant \lambda_2 \geqslant \cdots \geqslant \lambda_m$, and the corresponding eigenvectors are $U_1 \geqslant U_2 \geqslant \cdots \geqslant U_m$.

3) According to the required cumulative contribution rate, the number of principal component is gained. The contribution rate of the i-th principal components is computed on the total variance, which is the contribution rate of variance. The contribution rate of variance can be obtained:

$$\rho_i = \lambda_i / \sum_{j=1}^{m} \lambda_j \tag{5}$$

The simulated result is proposed in the paper, which judges that the cumulative sum contribution of the anterior k principal components is bigger than the 85% whether or not.

$$\sum_{i=1}^{k} \lambda_i / \sum_{i=1}^{m} \lambda_i > 85\% \tag{6}$$

4) The principal component equation and the solution of the value of all the principal components are established. The principal component value of the equation is:

$$c_i = \sum_{j=1}^{m} u_j y_j \tag{7}$$

where u_j is the component corresponding to the j-th eigenvector, y_j is the standardization value of each variable.

The value of the principal component received forms new training sample sets and testing sample sets. Normally, high variance components could contain related information, whereas small variance components are expected to contain unrelated information, which are not retained, such as measurement noise. It should be noted that the high variance components might not contain the useful information for a classification problem.

B. Improved neural network

BP neural network usually refers to the multilayer feed forward neural networks based on the error back-propagation algorithm (BP algorithm), which consists of the input layer, hidden layer and output layer [21]. The model of a 3 layers forward neural network is shown in Fig. 1.

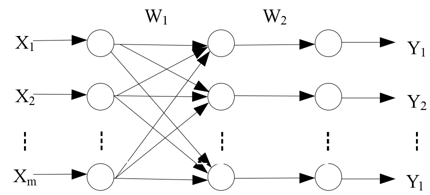

Fig.1 Three layers forward neural network model

The sigmoid neural network contains one hidden layer between the input and output variables. In the hidden layer, the transfer function is the sigmoid function defined in (8).

$$\sigma(x) = \frac{1}{1+e^{-x}} \tag{8}$$

However, the traditional BP neural network has some limitations, such as the learning process with a slow convergence speed, local minimum problems exist. While learning the new sample, BP tends to forget the old one.Therefore, focusing on the defects of traditional BP algorithm, some methods are adopted to optimize the traditional BP neural network. Additional momentum term is the most common one [22].

The additional momentum method is to modify the connection weights. The trend of modification is taken into consideration. The connection weights modification formula is thus modified as follows:

$$\Delta\omega(k+1) = (1-m_c)\mu\nabla f(\omega(k)) + m_c(\omega(k)-\omega(k-1)) \tag{9}$$

where ω is the value of the weights, $\nabla f(\omega(k))$ is the gradient of error function, m_c is the momentum factor, which is greater than zero and less than one.When the method is adopted, each change affects the next one. Additional momentum method uses a momentum factor to transfer the influence of the old change actually. Besides, the momentum is added to prevent the emergence of $\triangle\omega$ equal to zero and the emergence of local minimum.

C. Proposed new neural network method based on PCA

The block diagram of PCA-NN method is shown in Fig. 2. The fault diagnosis of five-phase FTPM motor by using a neural network has been proposed. The proposed network has many input neurons, which could consume significant time to train the network. Therefore, the PCA is used to reduce the dimension of input space [23].

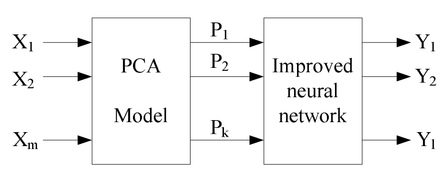

Fig.2. Block diagram of PCA-NN method

III. Application and Vericifation

A. Fault diagnosis system

The entire fault diagnosis system is shown in Fig 3. PCA is used to extract the fault characteristic value from the failure data collected. The neural network diagnoses the fault and the fault severity [24]. Network structure can be optimized. For a five-phase FTPM motor, the stator inter-turn short circuit fault is one of the most common faults [25]. Less turns short circuit fault leads to more influence on the motor running process.

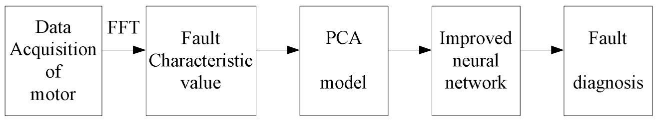

Fig.3. Block diagram of PCA-NN fault diagnosis system

B. Simulated results

The method has been tested with the three faults described in Table I. The improved neural network has 3 layers. The number of hidden neurons is set as 6 while training the neural network. Learning rate is 0.01, and training accuracy is set to 0.01.

Current signal in phase A has been collected to detect the stator inter-turn short circuit fault of the motor. The detailed current data and the corresponding harmonic current are shown in Fig. 4 and Table II. It can be obviously seen that the third harmonic of fault current increases comparing with the normal condition. Also, the more number of short circuits lead to greater harmonic.

TABLE II
HARMONIC CONTENTS OF DIFFERENT CURRENT SIGNALS

Harmonic frequency	No faults (mV)	One turn short circuit(mV)	Two turns short circuit(mV)	Three turns short circuit(mV)
2	10.774	12.945	9.3706	9.2532
3	5.9545	400.05	745.97	820.15
4	4.084	4.7372	3.6654	6.1535
5	3.2088	26.167	57.681	61.097
6	3.458	4.1877	2.5808	2.5785
7	1.7631	4.812	3.9746	2.0228
8	1.7807	2.5106	2.0965	2.3155
9	1.9445	3.2533	3.8713	4.9082
10	2.0012	2.1772	3.2253	1.7104
11	0.8791	2.8583	3.472	2.0681
12	1.4892	1.5774	2.3947	1.9746
13	1.6213	0.58821	0.87811	2.2219
14	1.3376	1.0382	1.2705	1.9565
15	1.242	0.95222	0.85032	1.1237
16	0.6939	0.95882	1.8082	1.7741
17	1.1593	2.0547	2.2732	1.6152
18	0.6748	1.3636	3.3122	2.9899
19	0.9323	1.5785	2.7727	1.057
20	0.5781	1.3887	1.2178	3.4369
21	0.5090	0.83575	3.1381	0.9631
22	1.2643	1.2003	1.1527	2.8134
23	0.5809	0.42404	1.8323	1.2327
24	0.3731	1.9965	0.36503	0.7706
25	1.0176	0.3409	1.64	3.2764
26	1.0315	2.1641	0.6443	1.4618
27	0.4601	2.005	0.0449	2.0214
28	1.4301	0.7412	1.317	2.3411
29	0.2861	2.0373	1.024	2.6583
30	0.6816	1.2354	1.4589	3.0353
31	0.3021	2.8477	152.04	3.3109

TABLE III
PRINCIPLE COMPONENT SCORES

Short circuit cumber of turns in phase A	First principal component	Second principal component	Third principal component
0	0.2199	-0.9711	1.7283
1	3.8606	0.5117	0.7188
2	-0.0922	-0.5095	0.2517
3	-0.0879	0.6359	1.1556

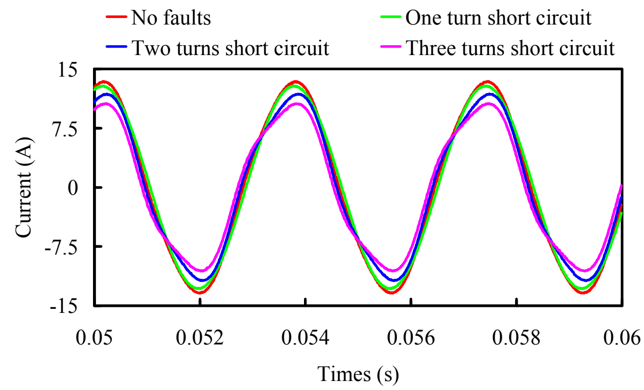

Fig. 4. Current signals of motor under different running conditions

TABLE I
DIFFERENT FAULT SIZES WITH DIFFERENT TARGET OUTPUTS OF NN

Short circuit number of turns in phase A	Target output of NN
0	0.10
1	0.35
2	0.70
3	0.90

When the single neural network method is used to detect the motor fault, the data in Table II are trained as the input of single neural network. The precision of training curve is shown in Fig. 5. By the trained NN, the fault prediction results are presented in Table IV.

However, by analyzing data in Table II using PCA, three principle components in Table III can be gained. 0.85 is chosen as energy value, and the number of indexes is reduced to 3. These principle components are also called comprehensive indexes. The principle components presented in Table III are taken as train data to train the neural network .The precision of training curve is shown in Fig. 5. Based on the given training samples, the entire fault diagnosis system is generated. The results of fault diagnosis with another set of test data are listed in Table IV. They account for that the trained NN based on PCA can predict stator inter-turn short circuit fault. Different fault severity can also be figured out by the proposed PCA-NN method. By comparing the two precise curves of training the neural network, PCA-NN consumed less time to achieve the target accuracy. From the data in Table IV, PCA-NN can predict failure accurately.

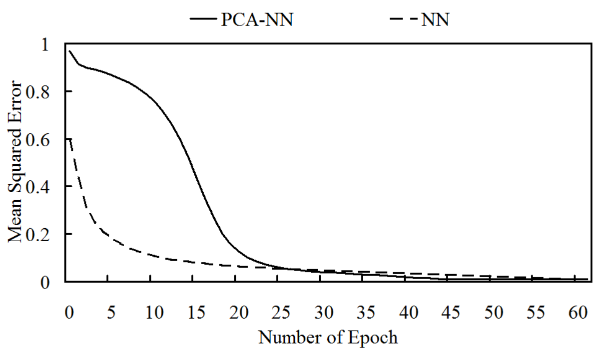

Fig. 5. Precision curve of training the neural network

TABLE IV
EXPECTED AND REAL OUTPUTS OF TRAIN AND TEST SAMPLES

Expected outputs	Real outputs by NN	Real outputs by PCA-NN
0.10	0.0738	0.0774
0.35	0.3484	0.3494
0.70	0.7032	0.7019
0.90	0.9297	0.9230

IV. CONCLUSION

A new comprehensive method based on PCA and improved neural network have been proposed to detect the inter-turn short circuit fault of the five-phase FTPM motor.The proposed algorithm, based on the PCA, allows an automatic classification of stator fault. As further scope of this paper, we can extend our research to identify the number of the shorted turns on the faulty phase. By using the proposed PCA-NN method, a comprehensive diagnosis procedure has been achieved. PCA techniques has not only contained the characteristic vector, which draws the fault sample effectively under the circumstances of the main information of data, but it also has reached the purpose of simplifying the neutral net structure. The PCA-NN method is practical to identify the fault severity. Experimental results have been presented in order to show the effectiveness of the proposed method. The proposed PCA-NN is effective and practical.

REFERENCES

[1] Q. Chen, G. Liu, W. Gong, and W. Zhao, "A new fault-tolerant permanent-magnet motor for electric vehicle applications," *IEEE Trans. Magn.*, vol. 47, no. 10, pp. 4183-4186, Oct. 2011.

[2] G. Liu, J. Yang, W. Zhao, J. Ji, Q. Chen, and W. Gong, "Design and analysisa new fault-tolerant permanent-magnet vernier machinefor electric vehicles," *IEEE Trans. Magn.*, vol. 48, no. 11, pp. 4176-4179, Nov. 2012.

[3] Q. Chen, G. Liu, W. Zhao, and M. Shao, "Nonlinear adaptive lumped parameter magnetic circuit analysis for spoke-type fault-tolerant permanent-magnet motors," *IEEE Trans. Magn.*, vol. 49, no. 9, pp. 5150-5157, Sep. 2013.

[4] J. Penman, H.G. Sedding, B.A. Lloyd, and W.T. Fink, "Detection and location of inter-turn short circuits in the stator windings of operating motors," *IEEE Trans. Energy Convers.*, vol. 9, pp. 652-658, 1994.

[5] W. Zhao, K. T. Chau, M. Cheng, J. Ji, and X. Zhu, "Remedial brushless ac operation of fault-tolerant doubly salient permanent-magnet motor drives," *IEEE Trans. Ind. Electron.*, vol. 57, no. 6, pp.2134-2141, Jun. 2010.

[6] W. Zhao, M. Cheng, X. Zhu, W. Hua, and X. Kong, "Analysis of fault-tolerant performance of a doubly salient permanent-magnet motor drive using transient cosimulation method," *IEEE Trans. Ind. Electron.*, vol. 55, no. 4, pp. 1739-1748, Apr. 2008.

[7] W. Zhao, M. Cheng, K. T. Chau, R. Cao, and J. Ji, "Remedial injected-harmonic-current operation of redundant flux-switching permanent-magnet motor drives," *IEEE Trans. Ind. Electron.*, vol. 60, no. 1, pp. 151-159, Jan. 2013.

[8] W. Zhao, M. Cheng, W. Hua, H. Jia, and R. Cao, "Back-EMF harmonic analysis and fault-tolerant control of flux-switching permanent-magnet machine with redundancy," *IEEE Trans. Ind. Electron.*, vol. 58, no. 5, pp. 1926-1935, May. 2011.

[9] W. Thomson, "On-line MCSA to diagnose shorted turns in low voltage stator windings of 3-phase induction motors prior to failure", *International Conference for IEEE IEMDC01*. Atlanta, USA, vol. 13, pp. 85-91, August 2005.

[10] Xie Ying． "Performance evaluation and thermal fields analysis of induction motor with broken rotor bars located at different relative positions", *IEEE Trans. on Magnetics*，2010，46(5)：1243-1250．

[11] Xie Ying． Characteristic performance analysis of squirrel cage induction motor with broken bars． *IEEE Trans. on Magnetics*，2009，45(2)：759-766．

[12] S.H. Chetwani, M.K. Shah, M. Ramamoorty, "Online condition monitoring motors through signal processing", *Electrical Machines and Systems, 2005. ICEMS2005*. vol. 3, pp. 2175-2179, Sept. 2005.

[13] Nandi S, Toliyat HA, "Condition monitoring and fault diagnosis of electrical machines – A review," *IEEE-IAS Annual meeting, Phoenix, AZ*, pp.197-204, 1999.

[14] S. Hayashi, T. Asakura, S. Zhang, "Study of Machine Fault Diagnosis Using Neural Networks," in *Proceedings of the 2002 Neural Networks, IJCNN '02* , Vol. 1, pp. 956 – 961 .

[15] J. Wang, "Fundamentals of erbium-doped fiber amplifiers arrays (Periodical style—Submitted for publication)," *IEEE J. Quantum Electron.*, submitted for publication.

[16] W.Y. Wang, T.T. Lee, and C.L. Liu, "Function approximation using fuzzy-neural networks with robust learning algorithm," *IEEE Trans. Syst. Man, Cyber. Part B*, vol. 27, no. 4, pp.740-747, 1997.

[17] Harkat. M.F., Mourot.G, and Ragot. J., "Non linear PCA combining principal curves and RBF-networks for process monitoring," *Proceeding of the 42nd IEEE Conference on Decision and Control*, Hawaii, USA, pp. 1956-1961, Dec. 2003

[18] S. Khomfoi, L. M. Tolbert, "Fault diagnosis system for a multilevel inverter using a principal component neural network," *Proceeding of the 37nd IEEE Conference on Power Electronics Specialists,* pp.1-7, 2006.

[19] A. Ferrer, "Multivariate statistical process control based on principal component analysis (MSPC-PCA): Some reflections and a case study in an auto-body assembly process," *Quality Engineering*, vol. 19, pp. 311-325, Oct. 2007.

[20] Zengfang, Li, Yong He, Haiyan Song. "Fault diagnosis model for engines based on principal component analysis and integrated neural network," *Journal of Agricultural Engineering*, pp. 131-134, 2006.

[21] Daqi Zhu, Hui Shi. "Principle and Application of Artificial Neural Networks," *Science Press*, Beijing, pp. 43-51, 2006.

[22] Qinglin Guo,Qi Tang. "Data mining based on improved neural network and its application in fault diagnosis of steam turbine," *Intelligent Control and Automation*, Chongqing, pp. 4051-4056, 2008.

[23] M. F. Harkat, G, Mourot, J, Ragot. "Nonlinear PCA combining principal curves and RBF networks for process monitoring," *Proceeding of the 42nd IEEE Conference on Decision and Control*, Hawaii, USA. pp. 1956-1961, 2003.

[24] M. F. Harkat, G, Mourot, J, Ragot. "Variable reconstruction using RBF-NLPCA for process monitoring," *5th IFAC Symposiumon Fault Detection, Supervision and Safety for Technical Processes*, Washington D. C., USA, 1239-1244, 2003.

[25] H. Saavedra, J. R. Riba, L. Romeral, "Inter-turn fault detection in five-phase pmsms and effects of the fault severity," *IEEE Trans. Diagnostics for Electric Machines, Power Electronics and Drives*, Valencia, pp.520-526, Aug. 2013.