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MATLAB Based Neural Network Model for Detection of Fault in Line Start Permanent Magnet Synchronous Motors

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Abstract - *The early detection of different faults will support motor operation and stop it from whole damage. Condition monitoring is extremely important to monitor the motor status and separate it under catastrophe conditions. This paper will propose a MATLAB based neural network model to find static eccentricity fault in line start permanent magnet synchronous (LSPMS) Motors. Under different combinations of fault-load conditions, the motor will be simulated to specify the characteristic of this fault. The line current will be used to extract the different major components. The efficient selected components will be used as the input of the neural network to identify the percentage of occurrence as well as the fault's harshness. The network will be trained over a definite range of static eccentricity degrees. Also, it will be tested for unseen cases to qualify the effectiveness of the trained neural network. The testing results show a detection accuracy above 96%.*

Key Words: Eccentricity faults, Line current, LSPMS Motor, Neural network, Principal Components

1. INTRODUCTION

Electrical motors are the actuators of our lives. Their application is central to many of our daily activities, especially at industrial and commercial levels. Statistics show that electrical motors consume about two-thirds of the total industrial power consumption in each society [1], with the majority of the developing countries moving toward similar industrialization. Therefore, there will soon be an increase in the demand for more efficient and robust electric motors. The major role of these motors raises the importance of investigating their behavior under different operating conditions, including healthy and faulty status. A recently developed and manufactured motor, which is commonly used in industrial applications, is the line start permanent magnet synchronous (LSPMS) motor. This motor has a self-starting capability, the ability to reach a synchronous speed, and a premium efficiency [2], [3]. LSPMS motors have been widely studied under normal operating conditions. However, under various kinds of faults, such as eccentricity, investigations are still premature [4], [5].

There are several reasons for eccentricity fault, such as overstress, rotor misalignment, bearing defection, and mistakes during the repair process. As a result, this will increases the motor's shaft vibration with higher acoustic noise and may lead to complete damaging the motor [6]. Air gap eccentricity accounts for about 5% to 15% of the total mechanical faults. However, another failure such as bearing faults leads to air gap eccentricity failure. There are three types of eccentricity fault which are static, dynamic, and mixed [7]. This paper will investigate the static type which occurs when the minimum air gap distance between the stator inner race and rotor outer race is non-uniform. In the case of static eccentricity, the rotor will rotate about a new axis rather than the stator symmetry axis while the non-uniform air gap distance will be fixed in space. This will result in unbalanced magnetic flux crossing the air gap. Therefore, a non-uniform flux will link both stator and rotor coils. The main effect of eccentricity fault will be on the motor inductances. An injection of harmonics as well as variation in the magnitude and synchronization time of the line current will occur [8].

Motor faults usually have a specific pattern to recognize the fault occurrence, such as line current symptoms, duration, and amplitude variations. Those indices or patterns can reveal the fault type and its severity, this process is called motor current signature analysis (MCSA) [9]. Artificial neural network can be trained using these symptoms for different fault-load combinations. As a result, the fault occurrence and its severity can be specified while avoiding the mathematical fault modeling or the fault index [10]. However, modeling the actual fault will save a considerable amount of time in case of simulating the motor using the finite element method (FEM).

There are some recent publications on the diagnosis of static eccentricity in LSPMS motors. The diagnosis is performed using FEM and frequency analysis. However, there is no reported work has been done on mathematical modeling of static eccentricity and fault detection using artificial neural network. The authors in [8] and [4] proposed a frequency index for static eccentricity fault detection. However, as stated by the authors, this frequency index is sensitive to any change in the motor parameters, such as the material types. Besides, Sedky [5] investigated the effects of static, dynamic, and mixed eccentricity on the motor phase current, speed, and torque characteristics. The author showed that the static eccentricity has no effect on the no-load case with a damping effect under the loaded conditions. Therefore, it can be concluded that the diagnostic of a static eccentricity in LSPMS motors is not quite investigated in the literature, and the diagnostic methods are based on frequency analysis. However, the model-based diagnostic approaches can be applied to the LSPMS motor under the static eccentricity fault as will be shown in this paper.

The objective of this paper is to develop a MATLAB based detection scheme while using the mathematical model of LSPMS motor under static eccentricity. Since there is no reported work has been done in this manner, this work is carried out. The motor will be simulated for different cases to extract different combinations of load-fault stator current. The principal components of stator line current will be extracted and prepared as an input for the ANN.

2.STATIC ECCENTRICITY

As stated before, static eccentricity occurred when the center of rotation (origin of rotor) is with constant offset from the symmetry center (origin of stator). This will lead to have a fixed maximum (and minimum) non-uniform air gap distance between stator inner and rotor outer races. Besides, this distance is time independent. Fig.1. depicts the motor geometry under static eccentricity. The degree of static eccentricity can be calculated by dividing the magnitude of static eccentricity vector over the uniform air gap distance go as follows.

$$\delta_{SE}=\frac{|OO'|}{g_0}$$

Where δ_{SE} is the degree of static eccentricity, OO' is the distance vector between the center of the stator and rotor, and g_o is the healthy uniform air gap distance of the motor.

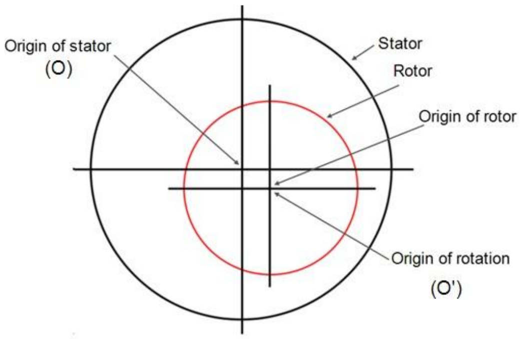

Fig -1: Motor geometry under static eccentricity.

3. MODELING OF LSPMS MOTOR AND FEATURES EXTRACTION

The mathematical model of LSPMS motor presented in [11] is utilized to simulate the motor dynamics using MATLAB® under healthy and faulty conditions. Table I shows the motor's simulated parameters. The stator line current is used as an indicator for the occurrence of static eccentricity fault. It captured at a frequency rate of 10 kHz for a total time duration of 750 ms. Various combinations of load-eccentricity degrees have been taken into account to generate the needed stator current samples.

Fig.2. depicts the stator current under 2.1 N.m load with 13%, 16%, and 19% static eccentricity degrees. The effect of static eccentricity is obvious on the time variation and magnitude of stator current. These variations will be used as distinct symptoms to differentiate between each simulated case.

Table -1: LSPMS motor specifications

Parameter	Value
Rated power (W)	750
Rated Voltage (V)	415
Stator phase resistance (Ohm)	19.15
Stator leakage inductance (mH)	0.004
Number of poles	4
Frequency (Hz)	50
Air-gap length (mm)	0.3
Outer/inner stator diameter (mm)	120/75
Number of stator/rotor slots	24/16
Axial length of stator core (mm)	75
Number of turns per slot	139
Height of stator yoke (mm)	45
Height of stator/rotor slots (mm)	13/9.5
Magnet material	Recoma-24HE
Remanent of magnet (T)	1.02

In problems deals with diagnosis using ANN, more concerns should be paid to select the most efficient feature which will be able to achieve a maximum detection range with high precision. In LSPMS motors, the frequency spectrum components aren't fully explored and specified against static eccentricity. Moreover, the frequency spectrum contains not only the faulty component, but other harmonics such as slotting, air gap space, and supply voltage are also presented in the domain. These problems can be overcome by applying the feature extraction directly to the stator current. Using principal component analysis (PCA), the dimensional reduction, as well as variable selection of the input data, can be achieved [10].

In PCA, the stator current samples are represented by new orthogonal vectors called principal components (PC). Those PC containing the most important features of the original data. In mathematics, this is defined as a linear transformation of orthogonal vectors that map the data into a new space, such that the great variance from the data is in the first dimension indicated as (F1), which is called the first PC. The second greatest variance is located in the second dimension (F2) and so on [12],[10]. First, the input row data (stator current) is divided into partitions, while each partition represents a window. As the total number of windows and points per input is known, the window size is specified. Consider the row input data $X = [X1\ X2\ \ldots\ Xj]$, where j is the number of points per input, the resulted input matrix will have the following form $W = [W1\ W2\ \ldots\ WL]T$ where L is the number of windows. The size of each window (q) is equal to the number of points per input divided by the total number of windows. Therefore, the windows matrix dimension is $L \times q$. Secondly, the covariance matrix (C) for the windows matrix (W) is calculated. The eigenvalues and eigenvectors are determined for the matrix (C). The eigenvectors are reordered according to the value of the eigenvalues in descending order. The first PC vector (Xpc) will be used as the feature vector, which has a dimension of $q \times 1$.

For example, performing PCA on the stator current with a window matrix dimension of 500 by 15, yields the following eigenvalues and variability of projection, as shown in Table II.

Table -2:. Eigenvalues variability of projection

	F1	F2	F3	F4	F5	F6
Eigenvalue	28.174	1.781	0.043	0.001	0.0	0.0
Variability %	93.914	5.938	0.143	0.004	0.0	0.0
Cumulative %	93.914	99.852	99.996	100.0	100	100

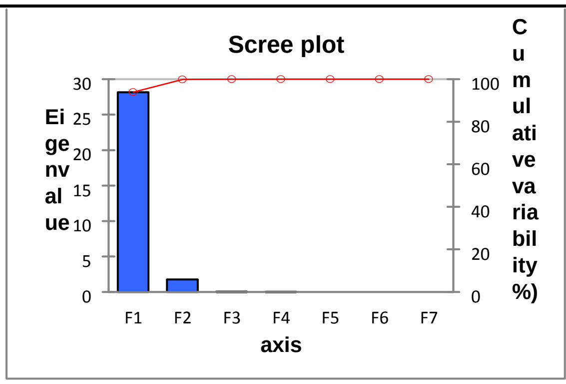

Fig -3: Eigenvalues and percent variability of different PCs.

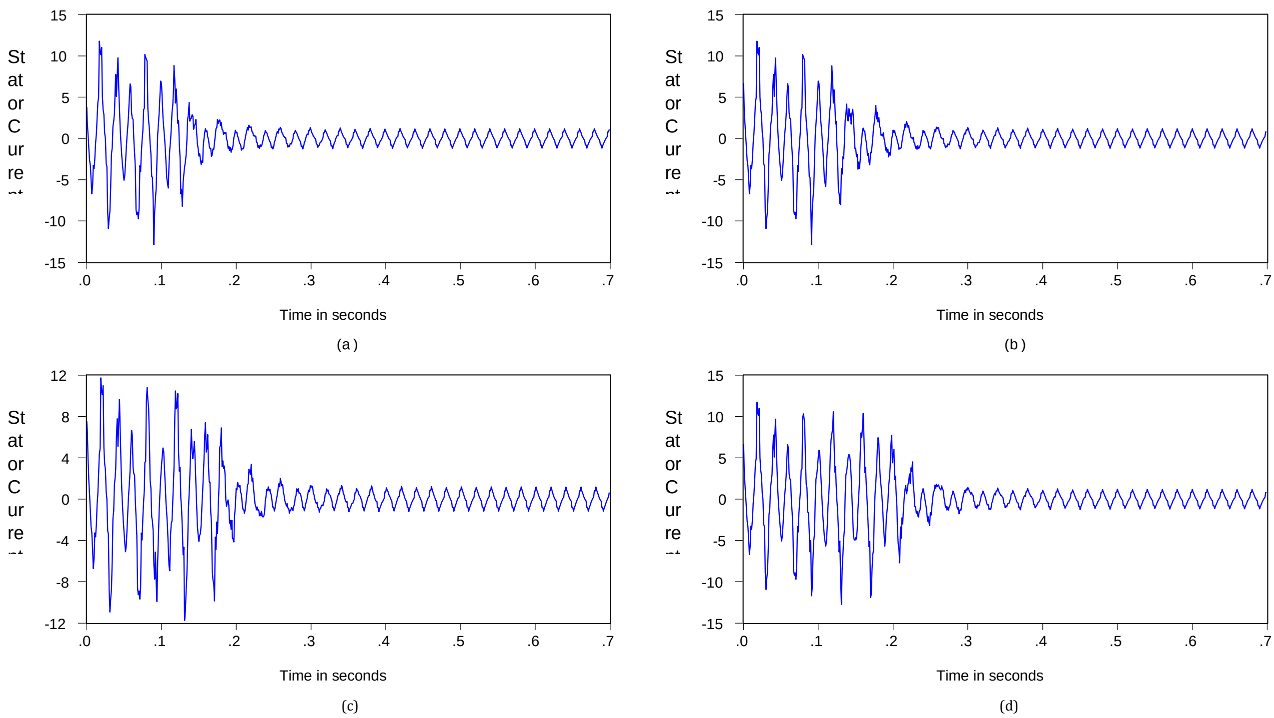

Fig -2: Simulated stator current waveforms for a load of 2.1 N.m under (a) healthy condition, (b) 13 % static eccentricity, (c) 16 % static eccentricity, (d) 19 % static eccentricity.

The variability describes how much information is carried by the first eigenvector or PC. The first component carries 93.9% of the total information in the input signal, with the largest eigenvalue of 28.1. The second axis carries only 5.9% of the total projected data. Both axes implement 99.85% of the total data as shown in Fig. 3. The variability of data projection on the second and third axis is small with 5.94% for the second axis and 0.14% for the third axis. It can be concluded that the first PC can be used with higher accuracy as the input variable to ANN with 93.9% of the variability.

4. SIMULATION RESULTS

This section will present the training and testing results of trained ANN. The stator line current data is obtained after simulating the mathematical model. The feature extraction process is applied to utilize PCA, which indicates that the first principal component (F1) carrying 93.91% of the total information curried by the original row data. Therefore, the first principal component will be used as input to the ANN for training purposes. The performance characteristic will be determined based on the percentage error, accuracy, and mean square error. This paper will assume a predefined error value between the tested and output value of static eccentricity degree by the designed ANN. The error values are considered to be 10%, 15%, and 20%. The accuracy is determined by dividing the total amount of correct predicted output over the total tested samples. After multiple experimentations to find the suitable neural network parameters, the best results are obtained with a network with 2 hidden layers, 10 neurons in the hidden layers, Levenberg-Marquardt learning method, stopping conditions for epochs, and MSE of 1000 and $1\times10-8$, respectively. The neural network has been trained under different operating conditions include various eccentricity degrees and input load values. Table III and Table IV show the trained eccentricity degrees and loads, respectively.

Table -3: Degrees of SE used in the training process

Percentage of static eccentricity degrees for training process (δs)							
6%	8%	10%	11%	13%	15%	17%	19%
21%	23%	25%	27%	29%	30.5%	32%	33%

Table -4: Input load values used in training process

Input load values for training process (N.m)									
0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	1	1.1
1.3	1.6	1.8	1.9	2	2.1	2.2	2.3	2.4	2.5

Considering the first principal component as an input for the designed ANN, Table V presents the simulation results. As it can be noticed, the number of inputs decreased gradually while observing the accuracy and network performance. It is obvious that case 5 results in higher accuracy compared to other cases with 98.75% accuracy under 20% difference error, 97.5% with 15% difference error, and 95.6% under 10% difference error.

Table -1: Results summary considering 1st PC as input to ANN

Case	Number of Inputs	Accuracy %			
		Error 20%	Error 15%	Error 10%	MSE
1	75	93.75	89.375	79.375	5.65E-07
2	50	97.5	95.625	94.375	4.46E-07
3	30	95.625	94.375	90.625	5.11E-07
4	25	93.75	92.5	89.375	1.71E-08
5	15	98.75	97.5	95.6	1.05E-05
6	10	90	86.25	81.875	6.21E-08
7	6	97.5	96.25	94.375	7.93E-07

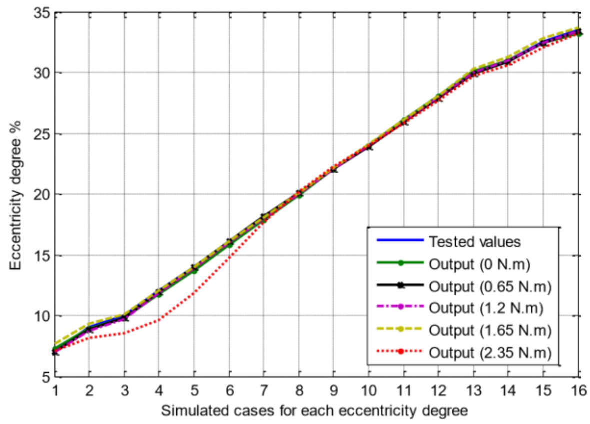

Fig -4: Testing results under different operating conditions.

The testing results of the proposed artificial neural network is shown in Fig. 4. The testing process has been made over a responsible range, for completely unseen values, of load and eccentricity degrees. It can be noticed that at higher load values and lower eccentricity degrees, the difference error slightly increases.

5. CONCLUSION

In this paper, a mathematical-based neural network model for detecting static eccentricity in LSPMS motors has been presented. The motor dynamic model has been simulated to collect the stator current data under different operating conditions, which include healthy and faulty cases. A neural network is trained for a specific range of eccentricity degrees and a set of input loads. Besides, it has been tested for unseen values to qualify the effectiveness of the proposed model. Results show a maximum and minimum detection accuracy of 98.75% and 95.6% under 20% and 10% difference error between the tested and predicted eccentricity degree values, respectively.

REFERENCES

[1] R. Saidur, "A review on electrical motors energy use and energy savings," ELSEVIER, Renewable and Sustainable Energy Reviews, vol. 14, no. 3, pp. 877–898, 2010.

[2] A. Hassanpour Isfahani and S. Vaez-Zadeh, "Line start permanent magnet synchronous motors: Challenges and opportunities," ELSEVIER, Energy, vol. 34, no. 11, pp. 1755–1763, 2009.

[3] M. H. Soreshjani and A. Sadoughi, "Conceptual comparison of line start permanent magnet synchronous," JWEET, vol. 3, no. 1, pp. 26– 36, 2014.

[4] M. Karami, N. Mariun, M. R. Mehrjou, M. Z. A. Ab Kadir, N. Misron, and M. A. Mohd Radzi, "Diagnosis of static eccentricity fault in line start permanent magnet synchronous motor," in IEEE International Conference on Power and Energy, PECon, 2014, pp. 83–86.

[5] M. Moustafa and M. Sedky, "Diagnosis of static , dynamic and mixed eccentricity in line start permanent magnet synchronous motor by using FEM," International Journal of Electrical, Robotics, Electronics and Communications Engineering, vol. 8, no. 1, pp. 29– 34, 2014.

[6] H. Hooshmandi, M. Ebrahimi, A. Davoudi, and A. Pouramin, "Analytical derivation of induction motors inductances under eccentricity conditions," Progress In Electromagnetics Research B, vol. 60, no. May, pp. 95–110, 2014.

[7] H. A. Toliyat, M. S. Arefeen, and A. G. Parlos, "A method for dynamic simulation of air-gap eccentricity in induction machines," IEEE Transactions on Industry Applications, vol. 32, no. 4, pp. 910– 918, 1996.

[8] M. Karami, N. Mariun, M. Rezazadeh Mehrjou, M. Z. A. Ab Kadir, N. Misron, and M. A. Mohd Radzi, "Static eccentricity fault recognition in three-phase line start permanent magnet synchronous motor using finite element method," Mathematical Problems in Engineering, vol. 2014, 2014.

[9] A. Siddique, G. S. Yadava, and B. Singh, "A Review of stator fault monitoring techniques of induction motors," IEEE Transactions on Energy Conversion, vol. 20, no. 1, pp. 106–114, Mar. 2005.

[10] V. N. Ghate and S. V. Dudul, "Cascade neural-network-based fault classifier for three-phase induction motor," IEEE Transactions on Industrial Electronics, vol. 58, no. 5, pp. 1555–1563, 2011.

[11] I. Hussein, Z. Al-Hamouz, M. A. Abido, and A. Milhem, "On the Mathematical Modeling of Line-Start Permanent Magnet Synchronous Motors under Static Eccentricity," Energies 2018, vol. 11, no. 197, 2018.

[12] G. P. Zhang, "Neural networks for classification: a survey," IEEE Transactions on Systems, Man and Cybernetics, vol. 30, no. 4, pp. 451–462, 2000.

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