Diagnosis of Stator Winding Inter-Turn Shorts in Induction Motors Fed by PWM-Inverter Drive Systems Using a Time-Series Data Mining Technique

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***Abstract*---An effective technique for diagnosis of stator winding inter-turn shorts in induction motors fed by PWM-inverter drive systems is proposed. This is done through the use of a Time-Series Data Mining technique which identifies and extracts hidden and inherent patterns (characteristics) in the machine phase currents, that can be used for fault identification. This technique can effectively detect and determine the severity of stator inter-turn faults in motors by analyzing the extracted fault signatures of these faults in comparison with the healthy performance signatures. In addition, it will be seen from the experimental results that the proposed technique is immune to motor "non-idealities" such as inherent manufacture-based motor asymmetry due to motor structural imperfections, performance measurement imperfections, and supply voltage unbalances, which result in departure of performance results from those of an ideally balanced 3-phase machine. In this paper, the case-study under investigation is a 230-volt, 60-Hz, 2-pole, 2-hp, squirrel-cage three-phase induction motor-drive system. The experimental results will demonstrate the soundness and robustness of this technique for reliable fault diagnostics.**

***Index Terms*---Data mining, fault diagnostics, on-line condition monitoring, stator winding inter-turn shorts, time series, space vector, induction motor, PWM inverter.**

I. INTRODUCTION

IN RECENT YEARS, diagnosis of stator winding inter-turn shorts has received considerable interest from industry and academia. Such faults may start as incipient turn-to-turn defects and undergo a longer period of time before they evolve into a total insulation breakdown condition [1], [2]. The situation becomes worse when motors are fed from inverter drives, which is due to the voltage stresses imposed by the fast switching of the power semiconductors of such inverters. Consequently, such incipient winding faults will rapidly progress to more severe faults, such as turn-to-ground, turn-to-turn, or phase-to-phase faults, which will cause irreversible damage to these stator windings and cores.

The most direct consequence of stator winding inter-turn shorts is the asymmetry such faults introduce in the motor-drive circuitry and consequent asymmetry in the machine currents, flux linkages, and voltages [3], [4]. These current, flux linkage, and voltage asymmetries lead to poor efficiency and adverse conditions in the machine windings and magnetic cores, and consequently cause ultimate breakdowns and consequent damages in such machines of various forms. Therefore, thorough and comprehensive characterizations of the machine performance under stator winding incipient inter-turn faulty conditions are important in order to detect and determine the severity of such incipient faults and their progression with time versus the healthy condition.

A substantial amount of research has been conducted in the past to diagnose stator winding inter-turn faults in electric motor-drive systems [2], [5]-[13]. One such method for stator inter-turn fault detection is based on analyzing the spectrum of the axial leakage flux component of the machine [5]. However, this method requires the installation of sensors which are costly, and sometimes inappropriate when the motor is operating in an adverse environment. Other methods are based on detecting unbalances (asymmetries) of the machine such as detecting the negative-sequence current component [2], [6], [7] or negative-sequence impedances [6]. Also, inter-turn fault detection has been addressed in [8] through monitoring the presence of certain rotor-slot-related harmonics at the terminal voltage of the machine immediately after switch-off of the stator winding. Furthermore, neural network and artificial intelligence methods have also been applied to detect stator winding inter-turn faults [9]-[11].

Recently, a new and unique method for fault monitoring and diagnostics in induction motors (IM) based on Time-Series Data Mining (TSDM) has evolved [12], [13]. This technique, which is based on a time-delay embedding process, can reveal and extract hidden and inherent patterns (characteristics) in the voltages and currents that can be used for fault identification. This technique can effectively detect and distinguish the types of faults in motor-drive systems by analyzing the extracted fault signatures of these faults in comparison with the healthy performance signatures. The types of faults studied in [12], [13] are static and dynamic eccentricities, broken bars, and broken end-ring connectors in induction motors. Upon distinguishing the fault types, this TSDM approach can also reveal the severity of the faults from the fault signatures. As revealed in [12], [13], the TSDM was applied only for direct line-start operating condition, that is without the presence of any electronic drive for torque-speed control.

In this work, the TSDM technique is employed to diagnose stator winding inter-turn shorts in a case of an induction motor

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energized from a PWM-inverter drive system. The TSDM technique presented here is based on a similar concept given in [12], [13], but in a different approach for fault identification, the details of which will be clearly explained in this paper. It is of importance to mention that the TSDM technique presented here is immune to motor "non-idealities" such as inherent motor asymmetry due to motor structural and manufacturing imperfections, performance measurement imperfections, and supply voltage unbalances, which result in asymmetry of the machine as a 3-phase electrical device. Hence, diagnostic schemes which are based on measuring negative-sequence current or impedance have to be carefully implemented to take into account the inherent motor "non-idealities". However, this is not the case here as these motor "non-idealities" have been incorporated into the TSDM diagnostic scheme through the initial acquisition of the healthy motor's performance data. Again, this will be detailed later on in this paper. The machine under investigation here is a 230-volt, 60-Hz, 2-pole, 2-hp, squirrel-cage three-phase induction motor-drive system, in which one of its phases was manufactured with phase winding taps for "experimental mimicking" of incipient inter-turn shorts. The experimental results will demonstrate the soundness and robustness of this technique for reliable fault diagnostics.

II. Time-Series Data Mining Technique

In this section, the algorithm of the TSDM technique is clearly explained. The TSDM technique, which is based on a time-delay embedding process [12], [13], transforms the time series data (time-domain waveform) into a different processing state space called a reconstructed phase space (RPS) [14], [15]. Given the time series data:

$$I = \left\{ i_n,\ n = 1 \ldots, N \right\} \tag{1}$$

where, n is the time index, the RPS matrix, $\mathbf{I}$, is defined by its row vectors whose elements are time-lagged versions of the original time series data, as follows:

$$\mathbf{I} = \begin{bmatrix} i_{1+(d-1)\tau} & \cdots & i_{1+\tau} & i_1 \\ i_{2+(d-1)\tau} & \cdots & i_{2+\tau} & i_2 \\ \vdots & & \ddots & \\ i_N & \cdots & i_{N-(d-2)\tau} & i_{N-(d-1)\tau} \end{bmatrix} \tag{2}$$

where, i_n is the original time series data, N is the number of observations (number of data samples in a waveform), d is the embedding dimension, and τ is the time lag. It is important to point out that each row vector of $\mathbf{I}$ is a single point in the RPS. Here, the time lag, τ, is determined using the first minimum of the automutual information function, from which the embedding dimension, d, can be estimated using the false nearest neighbor method [16].

It had been proven by Takens [17] that the RPS is topologically equivalent to the original state space of the system, and therefore the full dynamics of the original system are accessible in this RPS. Based on this characteristic, the hidden pattern that is captured from the RPS has to be residing in the original system, which cannot be easily detected from a frequency spectral analysis, or other methods of examination of the time domain profile of the physical phenomenon's waveform under consideration.

As mentioned earlier, stator winding inter-turn shorts introduce asymmetry (unbalance) in the machine phase windings. Hence, it is insignificant to use any of the machine phase currents as the time series data in the RPS if the location of the stator inter-turn short is unidentified. Also, the use of the developed torque profile for TSDM is not recommended here. This is because, in order to obtain the torque data, one way has to measure such torque using a torque transducer, which is relatively costly and thereby adds an extra sensor with consequent additional encumbrance to the diagnostic system. Another way is to measure the phase currents, the terminal voltages, and the speed of the motor, from which the torque can be obtained by computing the input motor power minus the ohmic losses, and divided by the rotor speed. However, to obtain the stator ohmic losses, one would need to know the stator resistances of all phases at any time because of the changes in values introduced when stator winding inter-turn shorts occur. However, this is not a feasible approach. Therefore, a method which is based on stator current space vector is introduced here, which will include the asymmetry effects of the windings into a single set of time series data. The space vector of the stator currents is defined as the sum of space vectors of individual phases, as follows [18]:

$$\vec{i}_s(t) = \frac{2}{3}\left\{ i_{sa}(t) + \alpha i_{sb}(t) + \alpha^2 i_{sc}(t) \right\} \tag{3}$$

where, i_{sa}, i_{sb}, and i_{sc} are machine stator phase currents, and $\alpha = e^{j2\pi/3}$ is a complex space operator. The current space vector in (3), which is a function of time, is a complex number. Therefore, the absolute value of the current space vector will be used here as the time series data for the TSDM.

Upon generating the RPS using the time series of current space vector, the next step is to categorize the current space vector signals into different classes (healthy and faulty, where the faulty classes can be further divided into the number of shorted turns) using Gaussian Mixture Models (GMMs) [15]. This is done by learning the GMM probability distribution for each class in the RPS, which is defined as follows:

$$p(\mathbf{x}) = \sum_{m=1}^{M} w_m p_m(\mathbf{x}) = \sum_{m=1}^{M} w_m N\left(\mathbf{x}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m\right) \tag{4}$$

where, M is the number of mixtures, $N\left(\mathbf{x}; \boldsymbol{\mu}_m, \boldsymbol{\Sigma}_m\right)$ is a normal distribution with mean, $\boldsymbol{\mu}_m$, and covariance matrix, $\boldsymbol{\Sigma}_m$, and w_m is the mixture weight having the constraint of $\sum w_m = 1$ [15]. The number of mixtures, M, can be determined based on the classification accuracy which tends to increase with the increased number of mixtures, provided there is sufficient data to train on the GMM. The remaining parameters of (4) can be estimated using the well-known

Expectation Maximization (EM) method [19]. After developing a GMM for each signal class, the next step is to classify the test current space vector signal based on the trained (learned) models. This is done using a Bayesian maximum likelihood classifier, which computes the conditional likelihoods of the test signal under each trained model and selects the model with the highest likelihood. The likelihoods are computed on a point-by-point basis from the trained models, as follows [15]:

$$p(\mathbf{X} \mid c_i) = \prod_{n=1+(d-1)\tau}^{N} p(\mathbf{x}_n \mid c_i) \tag{5}$$

where, $\mathbf{X}$ is an RPS matrix of dimension, d, and time lag, τ, of the test signal, $\mathbf{x}_n$ is a point in the RPS, and $p(\mathbf{x}_n \mid c_i)$ is the probability of $\mathbf{x}_n$ given the *i*th class, which is calculated using (4). The classification is:

$$\hat{c} = \arg \max_i p(\mathbf{X} \mid c_i) \tag{6}$$

where, $\hat{c}$ is the maximum likelihood class.

In summary, there are two stages in the TSDM process, a block diagram of which is depicted in Fig. 1. The first stage is the training (learning) stage in which only the trained data (signals) of the different classes (healthy and faulty) under investigation, as well as the number of mixtures, M are required. From this information, a GMM for each class is developed. The second stage is the monitoring (classifying) stage in which the machine phase currents are monitored, measured, and classified based on all the trained models using the Bayesian maximum likelihood classifier. The machine phase currents that are used in the training and monitoring stages of the TSDM have to be first transformed into current space vectors before being used as the subject time series data in the TSDM process.

As mentioned earlier, this technique presented here is somewhat different from the method used in [12], [13] where the radius of gyration around the center of mass of the points in the RPS was used as a fault identification parameter. For more information, [12], [13] should be consulted. Also, another advantage of this technique over the one given in [12], [13] is that only machine phase currents are required here for measurement, whereas the less accessible torque profile was used as the time series data in [12], [13]. Again, as mentioned earlier, one way to obtain the torque data is to use a torque transducer, which will add to the cost of the diagnostic system, and perhaps introduce extra diagnostic system reliability questions that one can do without. Another way is to measure the phase currents, the terminal voltages, and the motor speed, from which the torque can be calculated. In earlier work of [12], [13], the values of stator resistances were known since the faults that were being investigated did not have any effect on the stator resistances, and therefore they were ascertained beforehand. In other words, resorting to diagnostics based on torque calculation from monitored speed, currents, and voltages or direct torque measurements, the reliability of the diagnostic system will degrade since more parameters measurement will likely introduce more measurement errors to the system, and consequently more errors to the diagnostic algorithm. Experimental results are presented next to demonstrate the validity of the proposed TSDM technique.

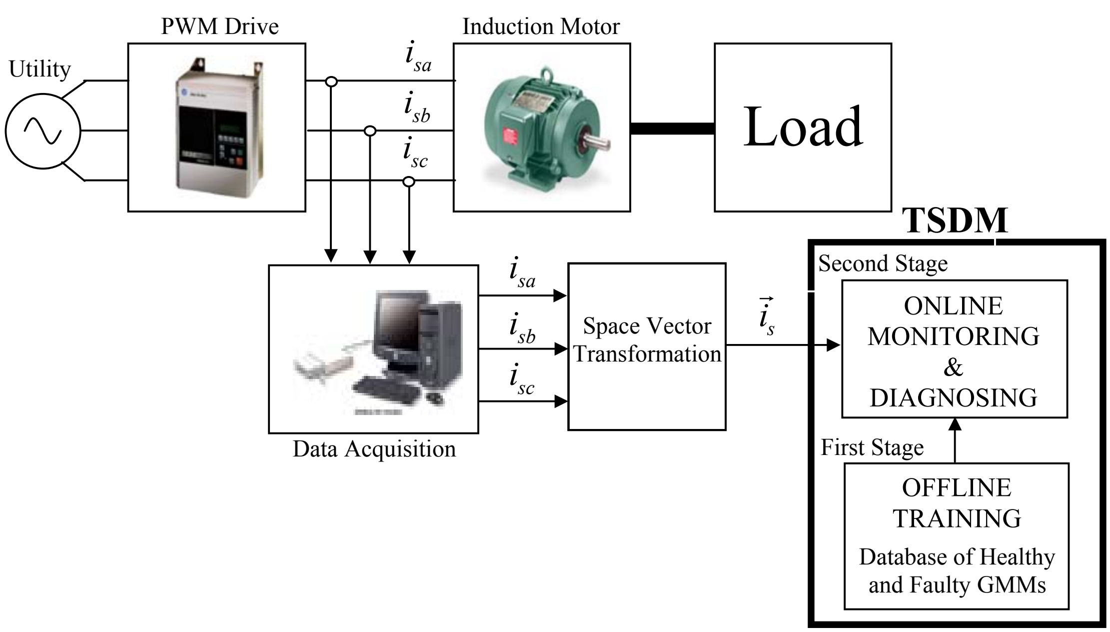

Fig. 1. Block diagram of TSDM diagnostic process.

III. Experimental Setup

Experimental data were obtained on a specially rewound 230-volt, 2-pole, 2-hp squirrel-cage induction motor fed from a commercially available PWM-inverter drive. The motor has a phase winding that was prepared with taps to enable "experimental mimicking" of incipient inter-turn faults by externally short-circuiting segments of the winding using external resistors of relatively small value, see the schematic winding diagram of Fig. 2 and the actual motor with tapped winding in Fig. 3. There are a total of six taps on the winding, as shown in Fig. 2, which allows one to simulate one through five shorted turns out of 108 turns per phase. The stator phase currents data were obtained at a data acquisition sampling frequency of 50 KiloSample/sec. A complete laboratory setup of the motor-drive system is illustrated in Fig. 4.

The stator phase currents of the motor under healthy and one shorted turn condition (through an external shorting resistance of 0.1Ω) are shown in Figs. 5 and 6, respectively. As may be observed in Fig. 5, the three phase stator currents are unbalanced, which is due to the inherent motor structure imperfections. These inherent motor manufacturing imperfections and performance measurement imperfections

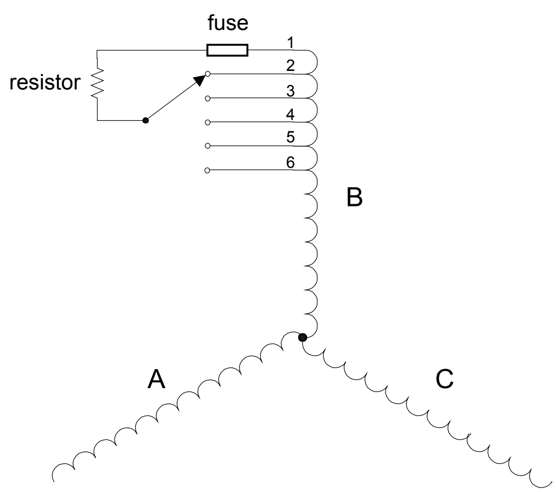

Fig. 2. Schematic diagram of stator windings with taps.

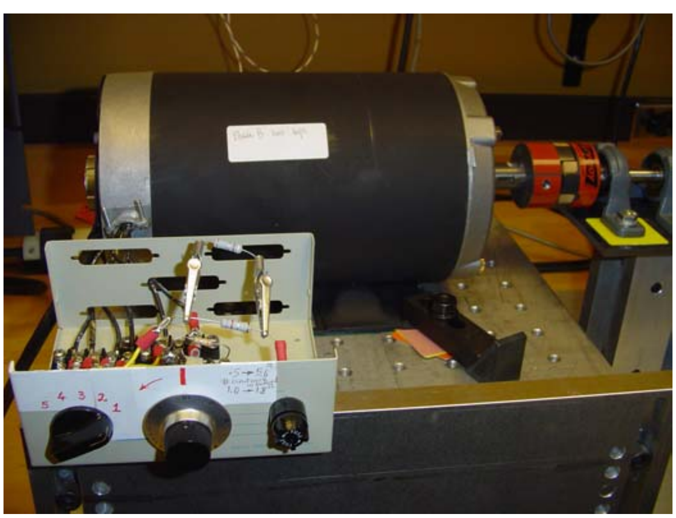

Fig. 3. Actual motor with tapped winding.

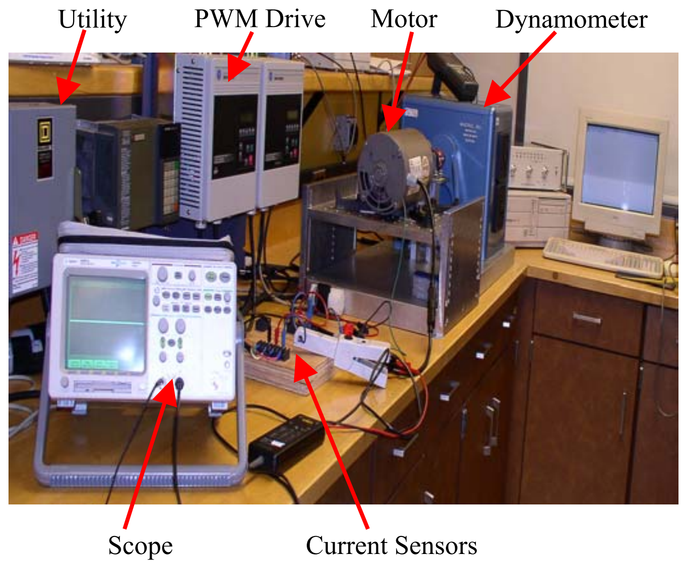

Fig. 4. Laboratory setup of motor-drive system.

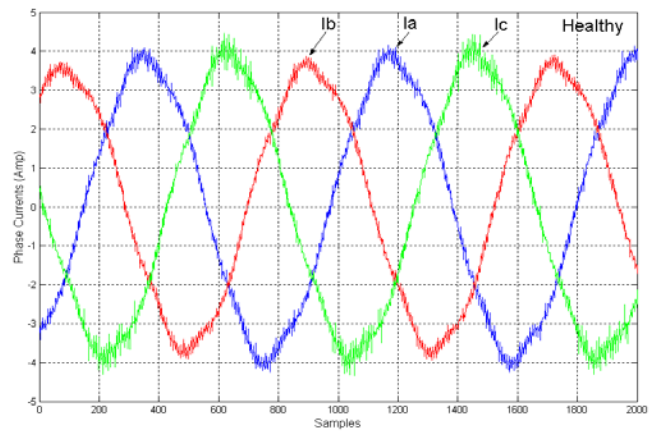

Fig. 5. Stator phase currents under healthy condition.

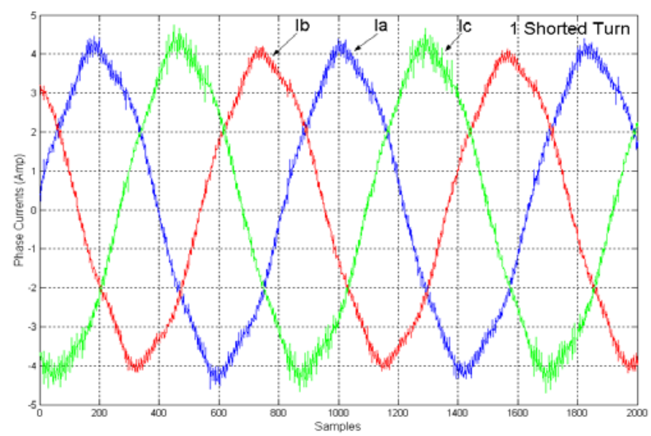

Fig. 6. Stator phase currents under one shorted turn condition.

are naturally incorporated into the TSDM during the training stage, and hence produces a more reliable database for purposes of fault diagnostics through the comparisons with the data of the fault cases which follow. By examining Figs. 5 and 6, it is indeed difficult to conclude whether a stator fault has occurred because of the above mentioned motor imperfections which cause phase current and flux linkage asymmetries under the healthy condition. Therefore, diagnostic methods such as measuring the negative-sequence current or impedance will be inadequate and leave much to be desired if the motor imperfections are not taken into account. The following section will describe the TSDM application to the machine phase currents, through its current space vector concept, to accurately detect and distinguish the type of fault at hand.

IV. Time Series Data Mining Application and Results

The time-delay embedding process, which was briefly described above, was applied to the current space vector of (3) for the cases of healthy and one through five shorted turns. In addition to the training set of data, two sets of test data were obtained using the same induction machine for the healthy and one through five shorted turns cases at the same sampling frequency of 50 KiloSample/sec. These two sets of time series test data were obtained from two separate groupings of samples for each fault over the three second period for which data was recorded. The training set and the two test sets were sequentially staggered in time as shown in Fig. 7. These test data were then processed and analyzed using the TSDM technique. The probability distributions of these test data with respect to the training data are shown in Tables I and II, respectively. It can be seen from Tables I and II that the classification accuracy of the two sets of test data is 100%. Therefore, it can be concluded that the TSDM technique can accurately detect and classify the type of fault.

This present study, which established the "proof of principle" of this method, will be extended in near future work to include factors such as manufacturing quality variability within the same class of motors of identical design and ratings. Future work will also include using the TSDM technique for power conditioner fault diagnosis, which will be very useful from the standpoint of improved drive design, reliability, protection, and fault tolerant control.

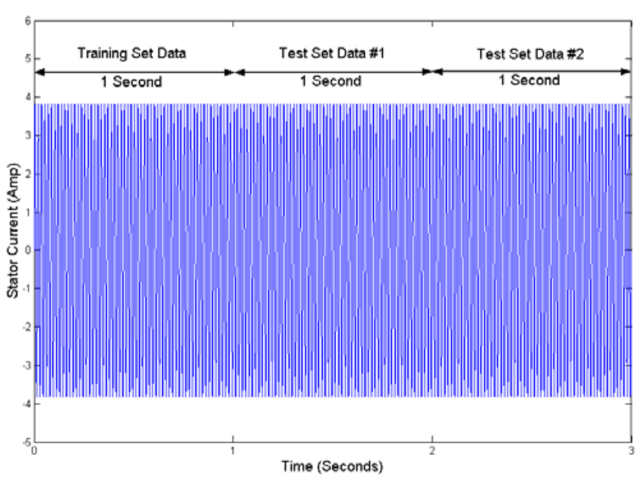

Fig. 7. Time series training and test sets data.

TABLE I
PROBABILITY DISTRIBUTIONS OF TEST DATA #1

		Test Data #1					
		Healthy	1 Turn	2 Turns	3 Turns	4 Turns	5 Turns
Training Data	Healthy	**1.000**	0.994	0.990	0.958	0.996	0.998
	1 Turn	0.977	**1.000**	0.945	0.987	0.953	0.996
	2 Turns	0.994	0.967	**1.000**	0.915	0.995	0.981
	3 Turns	0.950	0.984	0.910	**1.000**	0.932	0.976
	4 Turns	0.993	0.980	0.991	0.940	**1.000**	0.990
	5 Turns	0.983	0.992	0.959	0.977	0.983	**1.000**

TABLE II
PROBABILITY DISTRIBUTIONS OF TEST DATA #2

		Test Data #2					
		Healthy	1 Turn	2 Turns	3 Turns	4 Turns	5 Turns
Training Data	Healthy	**1.000**	0.989	0.986	0.965	0.993	0.997
	1 Turn	0.970	**1.000**	0.935	0.992	0.955	0.985
	2 Turns	0.997	0.981	**1.000**	0.926	0.997	0.987
	3 Turns	0.946	0.974	0.902	**1.000**	0.925	0.969
	4 Turns	0.994	0.982	0.988	0.945	**1.000**	0.993
	5 Turns	0.985	0.997	0.961	0.989	0.965	**1.000**

V. Conclusion

In this work, a proposed fault diagnostics method, based on TSDM concepts applied to the stator current space vector, for identification of winding inter-turn shorts of induction motors energized from PWM-inverter drive systems was presented. The TSDM technique, which is based on the time-delay embedding process, transforms the machine phase current space vector into a reconstructed phase space, where hidden patterns or information in the machine phase currents under healthy and stator inter-turn short-circuit conditions can be extracted and classified. It was shown from the experimental results that the TSDM technique possess a very high degree of classification accuracy under healthy and stator fault conditions, and hence can be considered as a promising tool for stator and rotor fault diagnostics of various kinds.

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