RELIABLE INTELLIGENT FAULT DIAGNOSIS SYSTEM FOR ELECTRICAL MACHINES

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Abstract -- Theory of everything (ToE) Einstein dream: coherent theoretical framework of physics that fully explains and links together all physical aspects of the universe; Finding a ToE is one of the major unsolved problems in physics.

During the past fifteen years and thanks to computation capacity there has been a substantial amount of research into the creation of new diagnosis failures techniques and intelligent fault diagnostics methods for electrical machine drives because of the need to increase reliability and to decrease the possibility of production loss due to machine breakdown. This paper presents an innovative diagnosis strategy merges several techniques together into a common framework to achieve these goals and overcome the deficiencies of diagnosis.

A multi-class classifier method based on the statistical Hidden Markov Mode (HMM) and Neural Networks (NN) related stator fault diagnosis of electrical machines. Current strategy therefore consists of a mix of two levels. The HMM-NN Reliable Intelligent Fault Diagnosis System is composed of two steps: the Feature Extraction step and the Diagnosis step. The algorithm of each step is well developed. The model parameters are computed by using the training out puts of the diagnosis phase. The algorithm estimates the failure state probability for each sampled observation. Time-frequency features extracted from the machines current is used as the health indicator. The experimental results prove that the efficiency of the good strategies lies in the integration even different types of machines and equipment parts, and provide for a consistent diagnostics capability.

Index Terms—Automatic, Electrical Machine, Fault Diagnostics, Induction Motor, Hmm, Multi-Class Classification, Nn, Time-Frequency, Switched Reluctance Motor

NOMENCLATURE

Symbol	Quantity
N	Number of states in the model
S	Individual states
qt	State at time t
M	Number of distinct observation symbols per state
V	Individual symbols
$A = aij$	State transition probability distribution
$B=\{bj(k)\}$	Observation symbol probability distribution
$\pi = \{\pi i\}$,	Initial state distribution
O	Observation sequence
A	Ambiguity function
$mi[\eta,\tau]$	Mean of location (η,τ)
$Vi[\eta,\tau]$	Variance of location (η,τ)
α,β	Forward and Backward
μ	Mean of each state
Σ	Variance of each state
P	Probability observation

I. INTRODUCTION

Rotating electrical machines are widely used in the world's industrial life, and there is a strong demand for their reliable and safe operation. Faults and failures of critical electro-mechanical parts can lead to excessive downtimes and generate costs of millions of euros in reduced output, emergency maintenance and lost revenues. Thus, finding efficient and reliable fault diagnostics methods especially for electrical machines is extremely important. In the industry, model-based methods are still most common choice for condition monitoring of electrical machinery, but during last decade also different kinds of AI based methods have established a firm position.

The fast growth of computation capacity has brought new possibilities to develop fault diagnostics and condition monitoring methods for modern industrial plants. Firstly, it has given possibilities to build sophisticated numerical models of diagnosed systems in healthy operation and in different fault situations, and simulation times to provide the important virtual measurement data have drastically decreased. Secondly, enhanced Artificial Intelligence (AI) based methods have become common alongside with statistical model-based methods. For example Neural Networks (NN) and Hidden Markov Model (HMM) have attracted a wide following in the area of fault diagnostics.

Stator winding is one of the weakest components of electric machine. This part is contributes around 40% of machine failure. Combination several stresses that categorized into electrical, thermal, mechanical and environmental during operating condition are involved the ageing process. Investigation on combination of several stresses show that temperature and voltage have higher decreasing effect on insulation lifespan than frequency [1]. Stator winding failures are dangerous damages.

Based on this fact, the automatic fault diagnosis and early fault detection system is needed to increase reliability and reduce maintenance cost. Since past few decades, development of diagnostic techniques has receives intense interest of researcher.

HMM-NN is a relatively new machine learning method based on statistical learning theory and flexible tool for learning and recognizing system

faults. HMM-NN based classifier is claimed to have better generalisation properties than NN based classifiers or HMM based classifiers per separat. In addition to this, *HMM-NN* based classification is interesting, because its efficiency does not depend on the number of features of classified entities. This property is very useful in fault diagnostics, because the number of features to be chosen to be the base of fault classification is thus not limited. The aim of this thesis is to build a multi-class classifier based fault classification scheme for electrical machines.

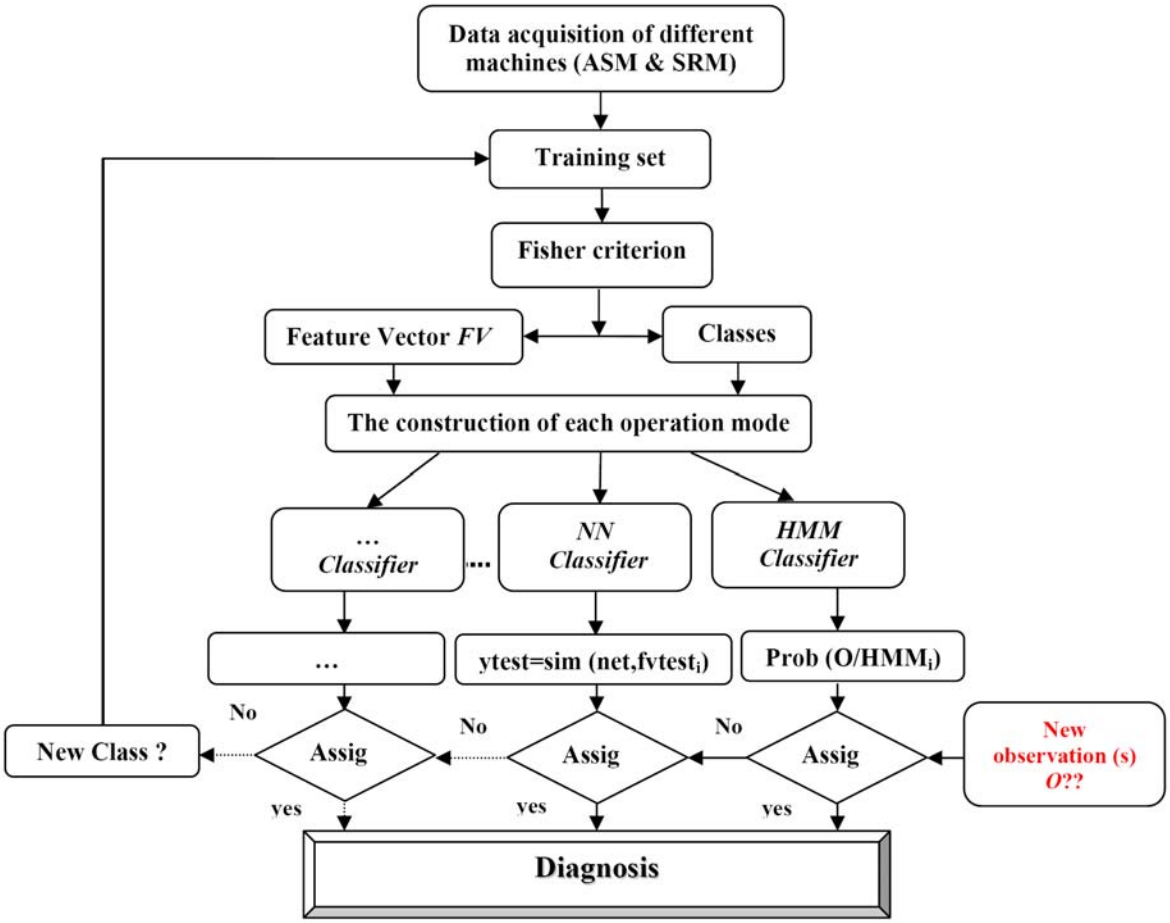


Fig. 1. General diagram of the reliable intelligent fault diagnosis system based multi-class classifier system by HMM-NN.

HMM-NN: The proposed algorithm consists of the following main steps, required to build automatic fault diagnosis system, including (*i*) the data acquisition, (*ii*)
construction of training set, (*iii*) data analysis for feature extraction and collection of large set of features to construct each operating mode, (*iv*) and (*v*) the selection of classification method to identify the state of the machines during test time. The block diagram of the system has been shown in Fig. 1 the fault diagnosis classifier techniques has been used as multi-class classifier, where we have a single classier which classifies the test data instance into one of the possible four classes. Our multi-class classifier is a probabilistic approach in which, we learn a probability distribution for each class using the training data corresponding to this class. The test data is classified by finding the maximimizing the Likelihood values overall classes.

The paper is divided to consideration of traditional statistical-based methods and Artificial Intelligence (AI) based methods. In Section 3, we described the details of the fault diagnostic methodology based classifier the base of HMM-NN is explained. In Section 4, Simulation and experiment validation is presented. Finally, in Section 5, some conclusions are made from the results.

II. INNOVATIVE DIAGNOSIS STRATEGY

A. Structure of intelligent Fault Diagnostic System

The structure for the automatic fault diagnosis system is illustrated in Fig. 1. The system is composed of the following two major phases: *1)* feature vectors extraction based on the smoothed ambiguity plane designed for maximizing the separability between classes using Fisher's discriminant ratio; and *2)* HMM and NN classification;

After the features are extracted from the set of training data, we built a model which is capable of classifying unknown test data instances. There are large numbers of classification techniques which can be used. In this work, we have explored and experimented with some of those techniques

combined e.g. NN and Probabilistic Classifier HMM etc.

B. Feature Vectors Extraction System

First, an acquisition current signals data of switched reluctance machine (SRM) and induction machine (IM) has been obtained by experimental.

Second, the narrow-band ambiguity function of current signal is computed. The ambiguity plane $A(\eta,\tau)$ function for a given signal $\chi(t)$ is defined as

$$A_{\chi}(\eta,\tau) = \int_{-\infty}^{\infty} x(t)\, x^{*}(t+\tau) e^{j2\Pi\eta t}\, dt \qquad (1)$$

where $\chi(t+\tau)$ =represents the signal at a future time $(t+t)$ and $\chi^{*}(t+\tau)$ =is the complex conjugate of $\chi(t+t)$.

Third, Fisher's Discriminant Ratio (*FDR*) is designed to get *N* locations from the ambiguity plane, in such a way that the values in these locations are very similar for signals from the same class, while they vary significantly for signals from different classes. The discrimination between different classes is made by separating the class *i* from all remaining classes {*i+1... n*} [2]. Consequently, three kernels are designed to separate between classes of machine using FDR. For further details, please refer to our previous work [2] and Wang equations [3]. By multiplying kernel with a given signal ambiguity plane, we will find κ feature points for this signal. We put them into a vector in order to create the training feature vector *FV* train (κ) of class *C*.

Fourth, in order to optimize the size of the feature vectors we have simply used the Particle Swarm Optimizer (PSO). This method possess a multi-objective version and has been shown a successfully optimize a wide range of continuous functions. This selection enables to reduce computing times. Features those are not selected are removed from the final considering them as redundant or superfluous. It is worth to mention that in some cases the recognition rate increases with the decrease in the feature vector dimension. The algorithm in pseudo-code follows

C. HMM-NN Classifier

After designing the kernels, using examples from each of the *C* classes, actual classification is performed. Given a particular unknown test signal vector (the classifier is not trained on this example); the classifier estimates the class membership of this example. The classification of the new observation *O* in one of *C* classes realized by combined classification techniques.

I. HMM Classier:

The Hidden Markov Model (HMM) was introduced by Rabiner [4], as a powerful statistical modeling tool. HMM method proved tremendously useful in a variety of applications, including speech recognition [5], artificial intelligence [6], prognosis and detection of electrical faults [7], [8]. As compared to the other commonly used prediction techniques, HMM is easier in terms of model interpretation and unlike model based technique does not require modeling of the system.

HMM Based Classifier algorithm is composed of three parts: initialization of HMM parameters, reestimation of HMM parameters and classification of unknown observation. The algorithm of each part is well explained in the [9], [10]. After obtaining a HMM model for each observation we can classify any unknown observation. The probability of the new observation is calculated for all the HMM constructed previously, for which the probability is maximum; determine the type of the fault as expressed by the following equation.

$$P(\overline{O}|\overline{\lambda}) > P(O|\lambda) \qquad (2)$$

The calculation of the HMM probabilities for the tested signals which do not belong to the training set of the faults is done along these feature vectors.

Three left-right HMMs were used to model the fault features.

II. NN Classier:

Considerable interest has been shown in the literature in the application of neural networks for the problem of fault diagnosis.

The combination of different neuron functions in different neuron layers provides a wide capability of weights adjustments in order to relate the inputs to the proper output classes. A feed-forward Neural Network with an input, two hidden and an output layers, offers enough mathematical capabilities to design complex nonlinear classifiers, which will be able to cover a wide range of nonlinear systems [11].

A simple feed-forward ANN with an input, a hidden (with 5 neurons) and an output layer are proposed. The transfer function of tangent sigmoid type was applied for the hidden layer and a linear function for output layer. From this perspective, the training problem can be considered as a general function optimization problem, with the adjustable parameters being the weights and biases of the network, and the Levenberg-Marquardt can be straightforward applied in this case.

The networks are trained with normal data, all fault feature data, and corresponding output assigned as binary code; thus, the output of this network is nearly 0 and 1 as binary code. The binary code is sent to the fault diagnosis to decode the fault type and its location.

IV. SIMULATION AND EXPERIMENT VALIDATION

The experimental data are collected in laboratory Electrical Machines Department of T.U. –Cluj. The test machines used in this work is a four-phase modular SRM having on its axis a *Siemens 1XP8001-1* (1024) encoder; a particularly designed four-phase power converter; a *dSPACE 1104* system used to control the system; a PC with Matlab-Simulink and System Desk software, that compiled the dSPACE program; a system of 4 current sensors connected to dSPACE used for data acquisition; a dc source feeding the encoder (*Hameg HM7044*); a torque

meter with a digital display (*Leroy Somer ModMeca 3*); a stroboscope; an induction machine for loading purposes fed through an autotransformer (Fig. 2 shows the SRM motor's bench), and a three-phase asynchronous motor squirrel cage MV 1046-385 with fault simulator. The rated data of the tested three-phase squirrel cage induction machine were: 0.55 hp, 220V, 2.9A and 1450(FL) r/min as illustrated in Fig. 3.

Signals recorded by the acquisition system (see Fig. 4) are the three supply currents of the machine.



Fig. 2. The experimental setup of the SR motor.

In the described system, data acquisition card was used to acquire the current samples from the motor operating under different load conditions. The data acquisitions are made under steady state condition over a period of 5 s, with a sampling frequency of 20 kHz. Let 100 000 points for each of the measured signals.

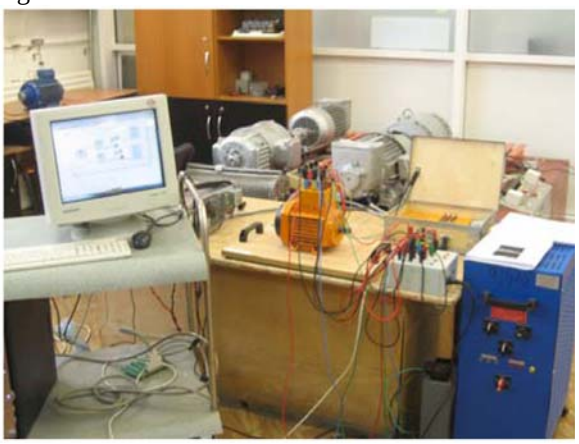


Fig. 3. The experimental setup of the AS motor.

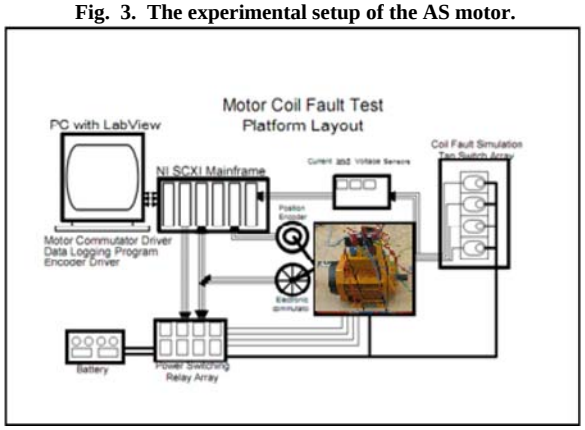


Fig. 4. Signals acquisition system.

TABLE I
SUMMARY OF DIAGNOSIS LEVELS & EXPERIMENTAL CONDITIONS ANALYZED

Operating mode		Numbers of samples		Load level	Diagnosis test
		training set	test set		
asynchronous motor	healthy class	10	5	0%	1. Diagnosis between healthy and one single fault
	open-circuit class	10	5	100%	
	Short-circuit class	10	5		2. Diagnosis between healthy and two single fault
switched reluctance motor	healthy class	10	5	0%	
	one coil opened class	10	5	50%	
	four coil opened class	10	5		3. Diagnosis between healthy and combined faults
	one phase opened class	10	5		

A list of features vectors is extracted from the current signal analysis i_a. Finally, 140 features are determined. The data acquisition set on the machines consists of 10 examples of stator current. A summary of the different diagnosis requirement levels is summarized in Table I. Different operating conditions from the machines were considered; healthy, short-circuit and open circuit faults. The open circuit faults were imposed by disconnecting different coils.

The training set is carried out on 10 current examples. The last five current examples are used to test the system classification. The training set for the stator winding faults and for the healthy machine was made, each one, from 10 examples of no-load current. Stator fault kernel is designed for obtaining the points location of maximum separation between stator fault class and the healthy motor class. Ambiguity plane of two kernels is computed from N=500*500 points. The classification consists on the separation of faults classes.

The classification algorithm is applied to detection of three kinds of SR and ID machine faults. Thus, the following classes are considered:

1) SR class of one coil opened;
2) SR class of one phase opened.
3) ID class of open circuit;
4) ID class of short circuit.

Classification by HMM-NN of the test vectors is shown in Fig. 5. and Fig. 6.

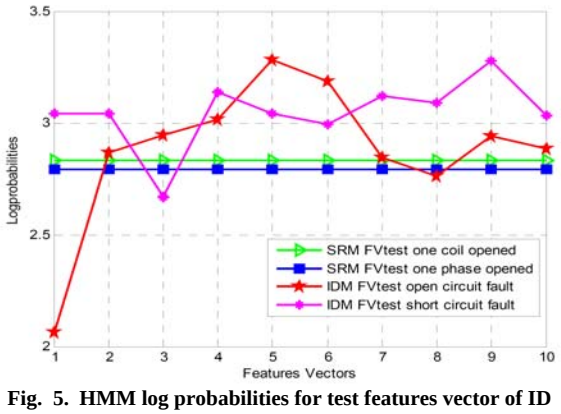


Fig. 5. HMM log probabilities for test features vector of ID and SRM.

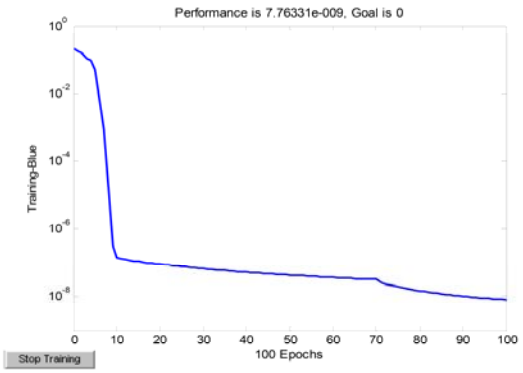


Fig. 6. Training curve for the NN using the Levenberg–Marquardt algorithm.

Fig. 5. shows Probabilities logarithm for the first 10 points of the test feature vectors concerning the windings fault of SRM and ID. The probabilities of the test feature vector of switched machine are clearly separable from the probabilities of the test feature vectors of induction machine for the first 5 points. Consequently, the signals tested are clearly separable and identified accurately.

An extensive classification experiments were conducted to determine the optimized neural network structures in which the size of the network should be kept as small as possible. This is imposed by the generalization capabilities that the network must possess. It was noticed that the best performance was obtained for the training set with those models whose hidden layer (with 5 neurons) had five neurons and an output layer Fig. 6.

CONCLUSION

Through previous research, it has seen that the single diagnosis system may encounter a number of difficulties associated with misclassification if did not diagnosed correctly the observations (the new or rejected observations).

In this paper, an intelligent fault diagnosis system based classification of machines windings faults has been proposed. The HMM combined with the NN have been used as a multi-classifier tool in order to assign the class of the new observation(s).

The success of the classification systems depend very much on the effectiveness of the extracted features. Therefore, smoothing quadratic TFRs is considered as the best way to extract the essential information for classification.

The concept of the idea expanded to include alongside a set of diagnosis tools different types of machines "multi-class" for a robust diagnosis (despite the cost of diagnosis!).

The architecture of this methodology has been described as well its implementation in a real case of windings fault.

The obtained results show the efficiency of the proposed methodology for the detection, diagnosis, and the prognosis of windings faults in electrical machines.

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