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Three Phase Induction Motor Faults Detection by Using Radial Basis Function Neural Network

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Abstract: In the present study the Artificial Neural Network (ANN) technique for the detection of (bearing and stator inter turn faults) incipient faults in an induction motor bas been explored. Radial basis function approach has been used for ANN Training and test. Three phase instantaneous currents and angular velocity depending on rotor speed are utilized in proposed approach. An experimental setup is used to implement an online fault defector

Key words: Three-phase induction motor, neural network, incipient faults, radial basis function

INTRODUCTION

Modeling and simulation are indispensable when dealing with complex engineering systems. It makes it possible to do essential assessment before systems are built, it can alleviate the need for expensive experiments and it can provide support in all stages of a project from conceptual design, through commissioning and operations. Induction motors are the most important electric machinery in all the fields of industry. Their role in industry increased after the development of adjustable speed drives. Their low prices, ruggedness and efficiency make them attractive in a variety of applications. These motors are exposed to many loading and environmental conditions. This, acting together with the natural aging of the motor may lead to many failures (Bonnnett and Soukup, 1992).

Hence, monitoring the motor condition is crucial to detect any fault in an early stage eliminating the hazards of severe motor faults. Faults can be treated before totally damaging the machine and consequently that will reduce the maintenance cost and shutdown time. Thus, there is a growing need for a simple, reliable technique to detect incipient faults in an online mode.

Several schemes for detecting inter turn faults and bearing faults were proposed. According to Stavrou *et al.* (2001) a fault detection scheme is based on measuring the negative sequence impedance. Monitoring the high order spectra of the radial machine vibration is proposed (Chow, 1997). Detection based on measuring the line to neutral voltage was proposed in (Joksimovic and Penman, 2000), but it is limited to star connected machines with an accessible neutral. Monitoring current harmonics is proposed in several schemes (Kolla and Varatharasa, 2000; Cash *et al.*, 1998; Benbouzid, 2000). A lot of work has been reported in literature for ANN based techniques for induction motor fault identification. Researchers have extensively used multilayer ANN structure and back propagation algorithms for online fault detection of induction motors. For the inputs to the ANN most of the researchers have gone for RMS values of three phase voltages and current quantities (Farag *et al.*, 1996; Schoen *et al.*, 1995; Siddique *et al.*, 2003; Penman and Yin, 1994)

In the present study focuses on three different motor conditions: healthy motor, bearing faulty motor and stator faulty motor condition. The instantaneous values of three phase currents and angular velocity depending on rotor speed have been utilized for the inputs to the ANN. Further the radial basis function approach has been used for ANN Training and test. The motor studied here is a 15 hp asynchronous machine with a squirrel cage rotor. The data is provided by a experimental tests of a real induction motor load conditions.

FAULTS IN INDUCTION MOTOR

Of all the electrical machines, induction motors are the most common in industry due to their simplicity, rugged structure, cheapness and easy maintainability. A three phase induction motor is the most popular poly phase induction motor.

There are several different types of faults that can manifest themselves in an induction motor. Faults are often classified according to where they occur in the motor. The most common faults are stator faults, rotor faults, bearing faults and eccentricity faults. These faults are mechanical in nature, but they have varying effect on the electrical signatures of the motor. The most common faults can be further classified according to Benbouzid (2000) as follows:

- Stator inter turn faults
- Rotor faults due to broken rotor bars
- Static or dynamic air-gap irregularities
- Bent shaft (dynamic eccentricity)
- Bearing and gear box failures.

Faults can occur due to external effects, mistakes in production or assembly, or due to bad operating habits. Frequently faults occur due to several factors. For example, motor faults are frequently internal, such as bearing or winding faults, but the reason can be external, such as overheating caused by excessive dirt.

ANN FOR INDUCTION MOTOR FAULT IDENTIFICATION

From the examples ANN captures the domain knowledge. ANN can handle continuous as well as discrete data and have good generalization capability as with fuzzy expert systems. An ANN is a computational model of the brain. They assume that computation is distributed over several simple units called neurons, which are interconnected and operate in parallel thus known as parallel distributed processing systems or connectionist systems. Implicit knowledge is built into a neural network by training it. Several types of ANN structures and training algorithms have been proposed in literature (Stavrou *et al.*, 2001; Joksimovic and Penman, 2000).

The basic form of RBF architecture involves entirely three different layers. The input layers is made n_p of source nodes while the second layer is hidden layer of high enough dimension which serves a different purpose from that in a multilayer perception. The output layer supplies the response of the network to the activation patterns applied to the input layer. The transformation from the input layer to hidden is nonlinear whereas the transformation from the hidden from unit to the output layer is linear.

The transfer function for a radial basis neuron is:

$$\text{radbas}(n) = e^{-n^2}$$

This function calculates a layer's output from its net input.

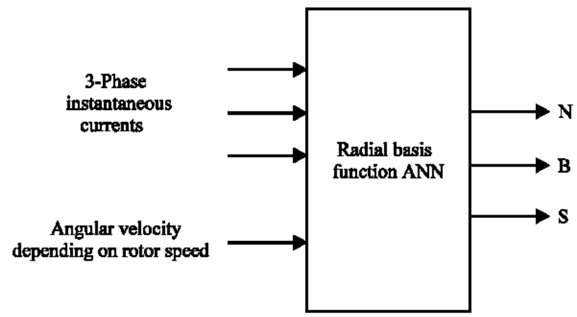

Fig. 1: RBFANN for induction motor faults detection

For effective detection of induction motor incipient fault, the selection of proper inputs and outputs of ANN, structure of the network and training of it using appropriate data should be done with utmost care. In the present study, inputs are selected as instantaneous values of three-phase currents and angular velocity depending on rotor speed, totaling 4 in all. The NN outputs have been termed as N, B and S, which represent the No faults, bearing faults and Stator faults as shown in Fig. 1. Any one of the outputs B, S approaching 1 indicates faults in induction motor. If N approaches 1, it indicates there are no faults, e.g., output 100 indicates No faults. Similarly, output 010 indicates Bearing faults and so on.

EXPERIMENTAL SETUP

In order to verify the proposed fault signature, it was checked experimentally. As shown in Fig. 2, the experimental setup included an induction motor of a 15 hp, 380 V, 1500 rpm three phase induction motor, driving an 11-KVA alternator via a flexible coupling, a data acquisition system and two linked computer.

Results: In Fig. 2, it was used a fault detector to check bearing and stator faults of the squirrel cage induction motor. At the same time, it has got a strong structure for parasites and noises from the motor mile. The network is trained using the radial basis function ANN under MATLAB Neural Network tool box (GUI). The trained network is tested with data sets consisting of trained data of 15 data sets (5 data sets each for individual conditions). These tested results are shown in Table 1. These test data sets shows the output results, for each fault situation. It is clear from the Table 1 that the ANN has successfully detected the faults. The output of the ANN for a particular fault is nearly the same as expected.

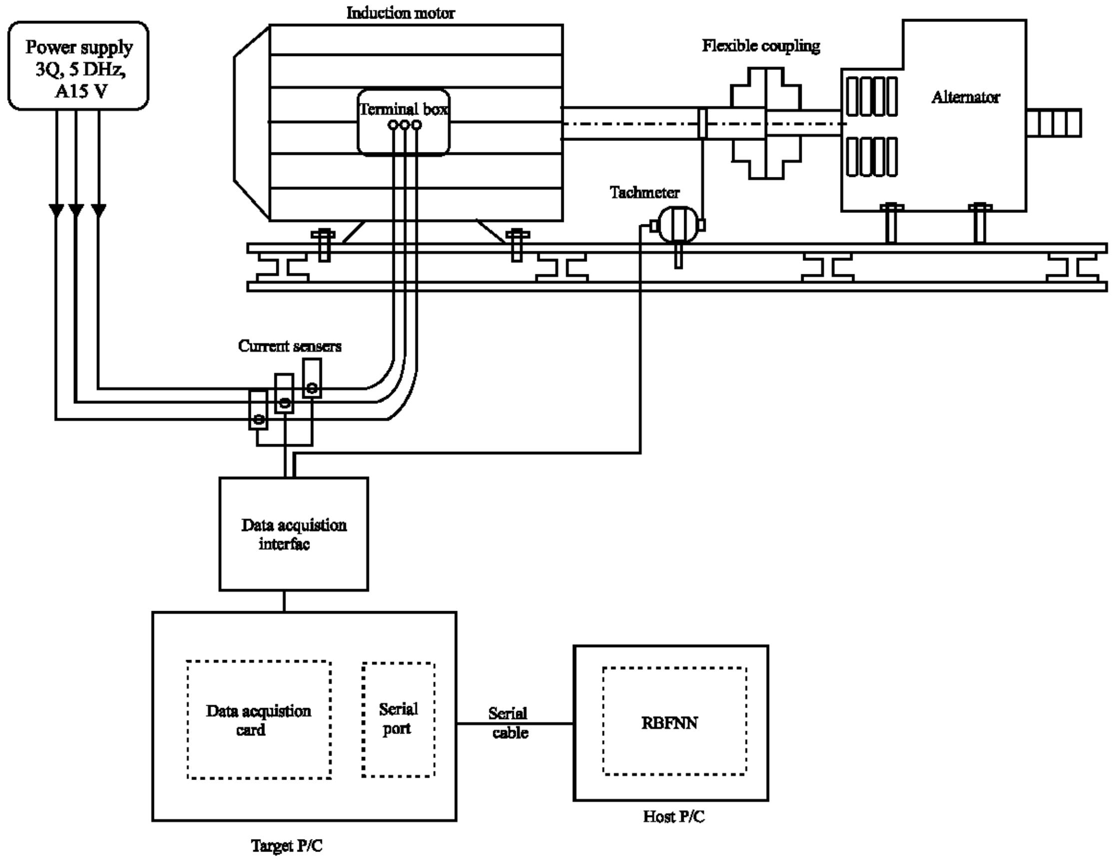

Fig. 2: The experiment set for fault detection of induction motor

Table 1: Testing results of the RBF neural network

Test inputs to trained ANN				Output results		
i_a	i_b	i_c	w	N	B	S
-8.9575	24.268	-5.047	314.15	1.0207	0.0188	0.0270
30.929	19.985	-11.594	309.29	0.9646	-0.0026	0.0131
-43.829	5.471	4.953	311.80	1.0281	-0.0103	0.0318
-14.396	20.286	-9.484	304.58	0.9988	0.0825	-0.0202
25.258	20.935	-17.525	307.09	1.0141	0.0072	0.0032
43.889	-12.884	0.154	314.18	-0.0323	0.9845	-0.0585
-30.125	15.854	14.273	311.32	-0.0118	0.9793	-0.0329
4.8439	22.849	-27.693	307.26	-0.0098	0.9986	0.0690
24.929	0.89235	-25.822	304.43	-0.0202	1.0554	0.0166
27.815	-21.241	-6.564	309.29	0.0032	1.1097	0.0039
15.831	-28.523	12.693	314.27	-0.0082	0.0135	1.0343
-7.122	-20.411	27.532	312.45	0.0105	0.0078	1.1821
-25.366	1.277	24.089	308.67	0.0095	0.0174	0.9470
-26.666	22.239	4.428	306.96	0.0051	0.0048	1.1087
-10.323	28.985	-17.919	304.89	-0.0161	-0.0058	1.1475

CONCLUSIONS

In the present study the Radial Basis Function (RBF) based ANN has been explored for detection of bearing and stator faults on a three-phase induction motor. The experiment fault data has been used for training and testing. The experimental results show that RBF can be very successively used for the incipient fault detection of induction motor. The results also show that the instantaneous values of three phase currents and angular velocity depending on rotor speed are good enough to be used for inputs to ANN. This shows that it can solve many problems that have mathematical and time difficulties.

ACKNOWLEDGMENT

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