Status Review On Neural / Fuzzy Logic Techniques For Induction Motor Condition Monitoring

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ABSTRACT

Condition monitoring of induction motors is an established maintenance strategy for the detection of incipient faults as to avoid the unexpected failure. Now a days artificial intelligence techniques are being preferred over traditional protective relays for the condition monitoring of induction motors. In this paper an attempt has been made to review the applications of neural/fuzzy artificial intelligence techniques for induction motor condition monitoring. Expert system, fuzzy logic system, artificial neural networks, genetic algorithm have been extensively reported in literature. These systems and techniques are integrated into each other and also with more traditional techniques. A brief description of various AI techniques highlighting the merits and demerits of each has been discussed. The futuristic trends on condition monitoring of induction motors are also indicated.

INTRODUCTION

The induction motors are known as main work horse of industries because of various techno-economic reasons. These motors face different types of stresses during operation. These stresses might lead to some modes of failures. Hence the condition monitoring becomes necessary in order to avoid catastrophic failures [1-3,7].

The Artificial Intelligence (AI) techniques have certain distinct advantages over traditional condition monitoring approaches [4-5,13,18,28,30,35,44]. In the present paper an effort has been made to present a review of the application of AI techniques especially neural network and fuzzy logic for induction motor condition monitoring. These systems can be integrated together and also with other traditional techniques [4,11,15,39].

This paper aims at presenting a review on the subject of applications of neural/fuzzy techniques for induction motor condition monitoring. A number of publications [1-50] have been reviewed. This paper is presented in seven sections. Starting with an introduction, the subsequent sections cover the classification of induction motor faults, the various AI techniques, Neural/Fuzzy techniques for induction motor condition monitoring, comparison of various AI techniques, futuristic trends and the conclusion.

CLASSIFICATION OF INDUCTION MOTOR FAULTS

The main faults of induction motors can be broadly classified as follows[10,31]:

- Stator faults resulting in opening or shorting of one or more of a stator phase winding
- Abnormal connection of the stator windings
- Broken rotor bar or cracked rotor end-rings
- Static and/or dynamic air-gap irregularities
- Bent shaft
- Shorted rotor field windings
- Bearing and gearbox failures

VARIOUS ARTIFICIAL INTELLIGENCE (AI) TECHNIQUES

AI is basically the study of mental facilities through the use of computational models [32]. AI tools are of great practical significance in engineering to solve various complex problems normally requiring human intelligence [1,5-6,30]. The powerful tools among these are expert system(ES)[8,9], fuzzy logic system(FLS)[32], artificial neural network(ANN) [1,45], Neural-Fuzzy [43], genetic algorithm(GA) [46], GA assisted ANN [35] and Support Vector Machines (SVM)[47].

Expert System

The expert system (ES) is an AI tool embodying knowledge about a narrow domain for the solution of problems related to that domain. It consists of a knowledge base containing domain knowledge (expressed as any combinations of 'IF-THEN' rules, factual statements, frames, objects, procedures and cases) and an inference mechanism (which manipulates the stored knowledge to produce solutions).

Fuzzy Logic System

These are based on a set of rules. These rules allow the input to be fuzzy, i.e. more like the natural way that human express knowledge. ES becomes more practical with the use of fuzzy logic. The knowledge in an ES employing fuzzy logic can be expressed as fuzzy rules (or qualitative statements). A reasoning procedure enables conclusions to be drawn by extrapolation or interpolation from the qualitative information stored in the knowledge base.

Artificial Neural Network

ANN captures domain knowledge from the examples. They 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. ANNs 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.

Genetic Algorithm

A genetic or Evolutionary algorithm operates on a group or population of chromosomes at a time, iteratively applying genetically based operators such as crossover and mutation to produce fitter populations containing better solution chromosomes. It is basically a stochastic optimization procedure inspired by natural evolution.

Support Vector Machine

SVMs are the methodologies for creating functions from a set of labeled training data. These function can be a classification function (the output is binary: is the input in a category) or the function can be a general regression function. For classification, SVMs operate by finding a hyper surface in the space of possible inputs, which attempts to split the positive examples from the negative examples

NEURAL/FUZZY LOGIC TECHNIQUES FOR INDUCTION MOTOR CONDITION MONITORING

Recently AI techniques are being extensively used for induction motor condition monitoring [4,28-30,35-36,43]. The main steps of an AI based diagnostic procedure can be classified as signature extraction, fault identification, and fault severity evaluation.

The various AI techniques, reported in literature, for the induction motor condition monitoring are ESs, ANNs, FLSs, and Neuro-Fuzzy systems.

Artificial Neural Network for Induction Motor Condition Monitoring

The fault severity evaluation can be done by the supervised neural network, which can synthesize the relationship between the different variables constituting input vectors and the output diagnostic indexes, which indicate the fault severity, starting from examples utilized in the learning procedure [11-14,16-21,23-27,29,33,37].

ANN architecture to quantify a stator short-circuit has been shown in Fig.1 [35]. Here I_n, I_p, s, s_r are respectively the negative and positive sequence stator currents, the slip and rated slip. I_n is independent of the operating conditions and it constitutes a reference variable for inter-turn failure diagnostics. While $_{Ip}$ is dependent both on the short circuit percentage and slip value.

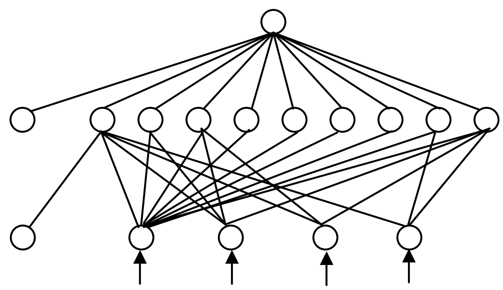

Fig. 1. ANN architecture for short circuit fault diagnosis

Fuzzy Logic System for Induction Motor Condition Monitoring

The induction motor condition is described by linguistic variables [13,18,21,34]. Fuzzy subsets and the corresponding membership functions describe parameter amplitude. A knowledge base consisting of rule and databases is built to support the fuzzy inference. The block diagram of FLS for induction motor condition monitoring is shown in Fig.2 [38]. Fuzzy rules and membership functions are constructed by observing the data set.

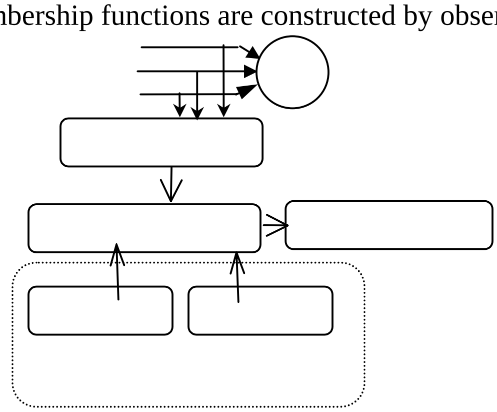

Fig. 2. Fuzzy logic based induction motor condition monitoring

Neural-Fuzzy System for Induction Motor Condition Monitoring

By merging fuzzy logic and ANN techniques, a neural-fuzzy fault detector is obtained which learns the stator faults and the condition under which they occur through an inexperienced and noninvasive procedure [15,39-40,43]. The neural-fuzzy system is an ANN structured upon fuzzy logic principles, which enables this system to provide qualitative description about the machine condition and the fault detection process.

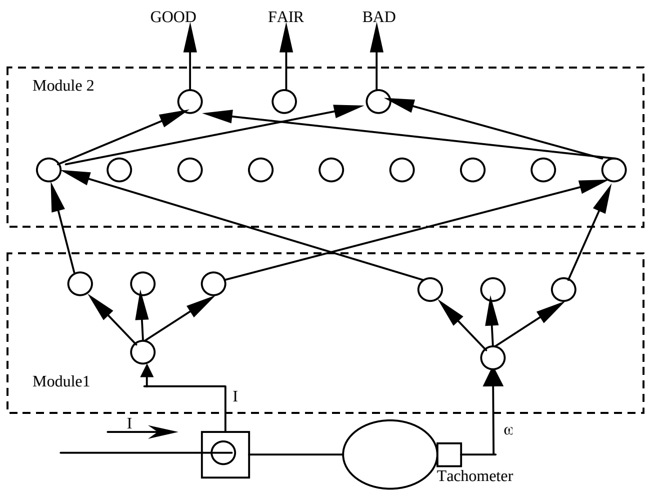

Fig. 3. Neural-Fuzzy architecture for short circuit fault diagnosis

The knowledge is provided by the fuzzy parameters of membership functions and fuzzy rules This neural-fuzzy fault detector is constructed, as shown in Fig.3, using two modules: The fuzzy membership function module (Module 1) and the fuzzy rule module (Module 2). The guideline for the training of neural-fuzzy machine fault detector is given as flowchart in reference [4]. Multiple adaptive neuro-fuzzy system (ANFIS) units have been suggested for multiple fault detection [15].

COMPARISON OF VARIOUS AI TECHNIQUES

ANN techniques for condition monitoring sometimes do not give efficient results because of the noise present in the signals and usage of feature set that do not describe the signals accurately and local convergence of gradient based learning. A GA used to select best set of feature set from the available set of features. A multi layer feed forward ANN can be trained with GA as a global search technique to overcome the local convergence problem. ANNs and SVMs both learn from experimental data, and are universal approximators which can approximate any function to a desired level of accuracy. After learning ANNs and SVMs both are given with the same mathematical model and they can be presented graphically with the same so-called ANN's graph. They differ by the learning methods. SVMs and ANNs are the 'black box' modeling with no previous knowledge required but there are measurements, observations, records and data while FLSs the 'white box' modeling using structured knowledge of experience, expertise or heuristics. The ANN stands to the idea of learning from the data while FLS stands to the idea of embedding the human knowledge into workable algorithms.

FUTURISTIC TRENDS

AI techniques are slowly replacing the human interface for the induction motor condition monitoring giving rise to the concepts of automated diagnosis.

- The research, till date, has been concerned with the use of neural and fuzzy logic in conjunction with various statistical preprocessing techniques, including higher order statistics, bispectrum, trispectrum, cyclostationary statistics and wavelets[41-42]. GAs ha also been utilized for the feature selection for neural techniques, choosing the optimal set of input features for the neural network for better performance [43,49].
- SVM techniques have great scope for the development of induction machine intelligent diagnostic systems.
- GA assisted fuzzy-neural systems based self-repairing electric drives will have tremendous scope in future [50].
- Neural-Fuzzy systems to be used for simultaneous multiple faults detection [48].

CONCLUSION

The neural/fuzzy techniques have been extensively used for the induction motor condition monitoring recently. This paper reviews the applications of these techniques for induction motor condition monitoring. Other new AI techniques GA and SVMs are now being explored to be combined with neural/fuzzy techniques for efficient and faster condition monitoring purposes. The relative comparison of these techniques has also been discussed. These techniques promise to have greater role in induction motor condition monitoring systems in future.

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