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Applications of Artificial Intelligence Techniques for Induction Machine Stator Fault Diagnostics: Review

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Abssrran: **The on-line fault diagnostics technology for induction machines is fast emerging for the detection of incipient faults as to avoid the unexpected failure. Approximately 3040% faults of induction machines are stator fa ults. This paper presents a review of recent developments in applications of artificial intelligence techniques for induction machine stator fault diagnostics. Now a days artificial intelligence (AI) techniques are being preferred over traditional protective relays for fault diagnostics of induction machines. The spplieation of expert system, fuzzy logic system, artificial neural networks, genetic algorithm have been considered for fault diagnostics. These systems and techniques can be integrated into each other with more traditional techniques. A brief description of various AI techniques highlighting the merits and demerits of each other have been discussed. Fault diagnosis of electric motor drive systems using AI techniques has been considered. The futuristic trends are also indicated,**

I. INTRODUCTION

The induction machines are known as work horse of modem industries because of various technical and economical reasons., These machines face various stresses during operating conditions. These stresses might lead to some modes of failures. Hence the condition monitoring becomes necessary in order to avoid catastrophic failures. A lot of work has been reported in the literature regarding the concept of induction machine condition monitoring [I-371.

Approximately 30-40% of induction machine faults are stator faults. Hence implementing the predictive maintenance on induction machines requires diagnostic tests or monitors sensitive to stator condition [I,4,17].

The Artificial Intelligence (AI) techniques have numerous advantages over conventional fault diagnostic approaches [5]. Besides giving improved performance these techniques are easy to extend and modify. These can be made adaptive by the incolporation of new data or information.

In the present paper an effort has been made to present a review of the recent developments in the area of stator fault diagnostics of induction machines based on Al. The application of expert systems (ES), artificial neural networks (ANN), fuzzy logic systems (FLS) and genetic algorithm (CA) techniques has been covered. These systems can be integrated into each other and also with other traditional techniques.

This paper aims at pre'senting a comprehensive survey on the subjeci of applications of AI techniques for induction machine stator fault diagnostics. A number of publications [I-1001 are reviewed and classified in six categories. The first category of publications [I-371 is on general texts, review papers, standards, and patents, while second category [38-401 are on classification of stator faults. Third category [41-521 includes brief introduction of various AI techniques. Next category [53-901 is on AI based induction machine fault diagnostics. The fifth categoty [91-971 includes A1 based fault diagnostics of electric drives. The last and sixth category [98-IOO] of reviewed publications is on futuristic trends of stator fault diagnostics using AI techniques. However, some publications belong to more than one category and have been classified based on their dominant contribution.

This paper is presented into following eight parts. Starting with an introduction, the subsequent sections cover the classification of stator faults, the various AI techniques, AI based stator fault diagnostics, comparison of various AI techniques, AI Based fault diagnostics of electric drives, futuristic trends and the concluding remarks.

II. CLASSIFICATION OF STATOR FAULTS

The stator is subjected to various stresses such as thermal, electrical, mechanical and environmental [3840], which severely affect the stator condition leading to faults [17]. The stator defectdfaults can be broadly classified into following two categories.

A. Stator Core Defects/Faults

The most common defectsifaults of core are related to either laminations or frame as enumerated below:
Laminations (core hot spot, core slackening), frame (vibration, circulating currents, loss of coolants, earth faults).

B. Stator Windings Defects/Faults

The most common defects/faults of stator windings are related to either 'end winding portion' or 'slot portion' as given below:

End winding portion (local damage to insulation, fretting of insulation, contamination of insulation by moisture, oil or dirt, damage to connectors, cracking of insulation, discharge erosion of insulation, displacement of conductors, tum-to-turn faults), slot portion (fretting of insulation, displacement of conductors).

111. VARIOUS AI TECHNIQUES

Basically AI is the study of mental facilities through the use of computational models [16]. It has produced a number of tools since its emergence as a discipline in mid 1950s. The tools are of great practical significance in engineering to solve various complex problems normally requiring human intelligence [73]. The powerful tools among these are expert system (knowledge- based system) [46,51], FLS [41,46,51], ANN [42,44-47,51-521, Neural-Fuzzy [43], GA [46,49], GA assisted ANN [45] and Support Vector Machines (SVM)[59].

A. Expert System

The expert system (ES), also known as knowledge-based systems (KBS), is basically computer programs embodying knowledge about a narrow domain for the solution of prsblems related to that domain. An ES mainly consists of a knowledge base and an inference mechanism. The knowledge base contains domain knowledge, which may be expressed as any combinations of'IF-THEN' rules, factual'statements, frames, objects, procedures and cases. While the inference mechanism manipulates the stored knowledge to produce solutions.

B. Fuzzy Logic System

A demerit of ordinary, rule-based ES is that they cannot handle new situations not covered explicitly in their knowledge bases. These ESs cannot give any conclusions in these situations. The FLSs 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 [XS]. The use of fuzzy logic can enable ESs to be more practical. The knowledge in an ES employing fuzzy logic can be expressed as fuzzy rules (or qualitative statements). A reasoning procedure, the compositional rule of inference, enable' conclusions to be drawn by extrapolation or interpolation from. the qualitative information stored in the knowledge base.

C. Arti/icial Neural Nehvork

ANN can capture domain knowledge from examples [46]. They can readily handle both continuous and 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. Some ANNs can be trained by typical input patterns and the corresponding expected output patterns. The error between the actual and expected outputs is used to strengthen the weights of the connections between the neurons. This type of training is knowti as supervised training. Some of ANNs are trained in an unsupervised mode, where only the input pattems. are provided during training and the network leams automatically to cluster them in groups with similar features.

D. Geietic Algorithm

GA is a stochastic optimization procedure inspired by natural evolution. It can yield the global optimum solution in a complex multi-model search space without requiring specific knowledge about the problem to be solved. 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 [46].

E. Support Vector Machine

SVMs are the methods for creating functions from a set of labeled training data. The 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 will attempt to split the positive examples from the negative examples.

IV. AI BASED STATOR FAULT DIAGNOSTICS

Recently AI techniques are being preferred over traditional protective relays for fault diagnostics to manage data acquisition and processing in order to increase the diagnostic effectiveness [SO]. The main steps of an AI based diagnostic procedure are 'signature extraction', 'fault identification' and 'fault severity evaluation'

The faults of an induction machine supplied by sinusoidal voltages are linked with the harmonic content of the stator current, i.e. each fault is associated with the presence of specific harmonic components.

The various AI techniques for the fault diagnostics of stator faults, which have been reported in literature, are ESs, ANNs, FLSs, and Neural-Fuzzy systems.

A. Expert Systems for Stator Fault Diagnostics

A computer program for performing a suitable data acquisition and a Fast Fourier transform (FFT) is to be activated for stating the stationary condition of the machine. Some of the current spectrum components depend on the machine speed or slip. In such cases the task architecture of the machine diagnostic expert system should be like Fig.1.

The expert system inference engine filters the harmonic components and to perform the reduction of the large amount of spectral information to a suitable level. The knowledge of a component trend makes the ES a robust threshold handler, which decides to consider or ignore a particular failure component [54-55]. The system can determine a fault situation by doing the signature extraction and fault identification from the combined derived information from the trends of the various harmonic components and the machine operating conditions.

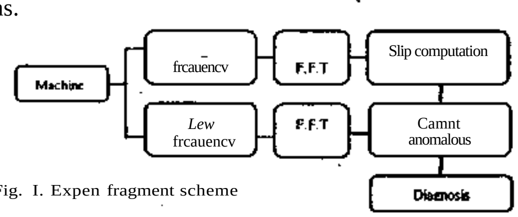

Fig. I. Expen fragment scheme

B. A ilif&al Neural Network for Stator Fault Diagnostics

The fault seventy 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 leaming procedure. [56-58, 60-61, 63-64, 67-72, 74-75, 77, 80, 84, 1001.

ANN architecture to quantify a stator short-circuit has been shown in Fig. 2 [801. Here I_n, I,, s, s_r are respectively the negative and positive sequence stator currents, the slip and rated slip. 1. is independent of the operating conditions and it constitutes a refeience variable for inter-tum failure diagnostics. While ^ is dependent both on the short circuit percentage and slip value.

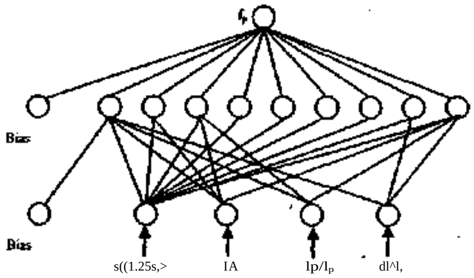

Fig. 2. ANN architecrure for rhon circuit diagnosis

A continual on-line training (COT) algorithm with low data memory and computational requirements has been developed given for ANN based stator winding tum fault detection which does not require training prior to commissioning [84].

C. Fuzzy Logic Sysfem for Stnfor Fault Dingnoslies

For induction machine fault diagnostics, the machine condition is described by linguistic variables [58,62,66,79,85]. Fuzzy subsets and the corresponding membership functions describe stator current amplitude. A knowledge base consisting of rule and databases is built to support the fuzzy inference.

The block diagram of FLS for fault diagnostics of induction machines is shown in Fig. 3 [85]. Fuzzy rules and membership functions are constructed by observing the data set.

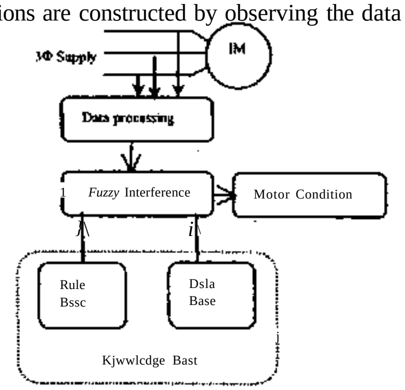

Fig. 3. Fuuy logic based induction machine hull diagnosis

D. Neural-Fuzzy System for Sfutor Fouk Dingnostics

By merging hzzy logic and ANN techniques, a neural-fuzq fault detected is obtained which leams the stator faults and the condition under which they occur through an inexperienced and noninvasive procedure [59,65,80,86-871. 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. 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.4, using two modules:

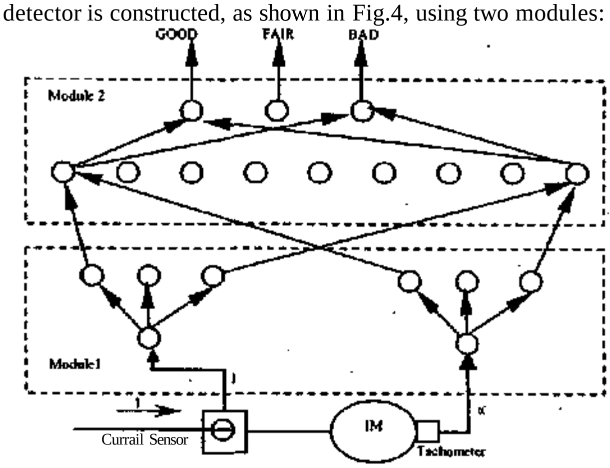

Fig. 4. Neura-Fuzzy architecture for shon circuit diagnosis

(a) The fuzzy membership function module (Module 1)

(b) The fuzzy rule module (Module 2).

The guideline for the training of neural-fuzzy machine fault detector is given as flowchaFt in Fig.5. Multiple Adaptive Neuro-Fuzzy System (ANFIS) units have been suggested for multiple fault detection [84].

V. COMPARISON OF VARIOUS AI TECHNIQUES

ANN modeling techniques for fault diagnosis sometimes does not give satisfying results. 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 are some of the most probable reasons for the 'not so good' results. The concept of feature selection and genetic training are used to improve the classification accuracy and to reduce the computational time. A simple GA is 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.

A drawback of CA is that it has no concept of an "optimal solution," or any way to test whether a solution is optimal. Both the ANNs and SVMs leam from experimental data, and are universal approximators in the sense that they can approximate any function to any desired degree of accuracy.

After leaming ANNs and SVMs, these 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 leaminy- 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.

VI. AI BASED FAULT DIAGNOSTICS OF ELECTRIC DRIVES

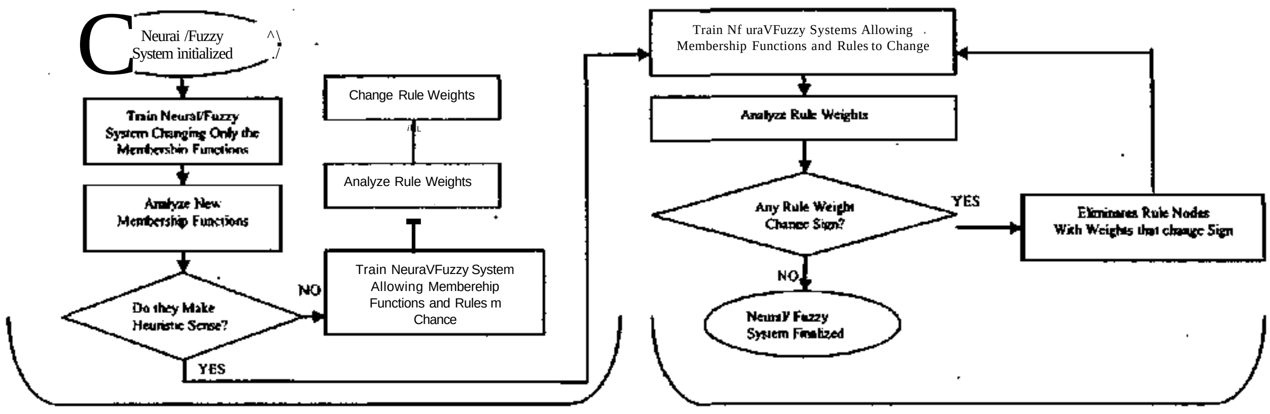

Fig. 5 Flowchan for training of neumllfuzzy machine fault detector

The machine diagnostic systems of the induction machines supplied by a frequency convener have to be combined with the fault possibilities of the convener [SO]. The literature is rich regarding the classification and analysis of true fault operations of single components of electric systems. The predictive diagnostic approach has been developed by researchers regarding subsystem<.

In the case of closed loop drives the impact of control loops on the machine fault effects has been reported in literature recently [96-971. A sophisticated procedure is to be adopted for the machine condition because of the fact that the control itself modifies the behaviour of supply variables. The typical spectrum lines due to faults in the machine input currents are present in the voltage spectrum also. The manipulated variables can be sensed beyond the motor terminal. Because the regulators in presence of faults will force the controlled variables to the reference values, the controller outputs change, reflecting fault entity and type. New indices can be retrieved for manipulated variables also.

AI techniques are being applied for designing and realization of the control of fault-tolerant systems. The concept of CA-based self-repairing drives was first discussed in publication [24]. AI based self-repairing and self-constructive controllers and estimators have been implemented. The automated diagnostics is also, possible using the automated self-repairing feature.

VII. FUTURISTIC TRENDS

AI techniques are slowing replacing the human interface for the monitoring of stator faults giving rise to the concepts of automated diagnosis.

- There is a significant opportunity to add intelligence to motors, providing a level of communications and diagnostic capability. The intelligence can be built into the motor's terminal box so that the overall package requires no more space [98].
- Till date the research has been concerned with the use of ANNs and fuzzy logic in conjunction with various different statistical preprocessing techniques; including higher order statistics, bispectrum, trispectrum, cyclostationary statistics and wavelets GAS have also been utilized to carry out feature selection for the ANN, choosing the optimal set of input features for the ANN to give an accurate performance [99].
- SVM techniques can be explored for the development of induction machine intelligent diagnostic systems.
- A assisted neural and fuzzy-neural systems based self-repairing electric drives will have tremendous scope in future [80,9O].
- The new developments in AI e.g. data mining, or the extraction of information and knowledge from large databases, and multi-agent systems, or distributed self organizing systems will have a great impact in stator fault diagnostics of induction machines 1461.
- Neural-Fuzzy systems to be extensively used for the detection of multiple faults at the same moment.
- The design of controllers and estimators for different types of drive systems to be greatly influenced by self-repaiting and self-constructing systems.

VIII. CONCLUSION

AI has produced a number of powerful tools over the years, which are being used extensively for various engineering applications including fault diagnostics. This paper has reviewed the applications of four of these tools, namely, knowledge based systems, fuzzy logic, artificial neural network and genetic algorithm for stator fault diagnostics of induction machines. The relative comparison of these tools has also been discussed. These techniques promise to have greater role in electric drive diagnostic systems in future.

REFERENCES

- General Tcilrmeview ArticledStsndardsf Patents

[I] Motor Reliability working Group, "Report of Large Motor Reliability Survey of Industrial and Commercial lnstallatians Pan I, and 11," *IEEE Trom lnd Applicant.* "01. IA, 1985.

(21 G.B.Kliman and J.Stein."lnduction motor fault detection via pasrive current monitoring- A brief survey," in *Proc. 44th Meeting of the Mechanicof Fo!lures Prevemion Group,* pp. 49-65. Apd 1990.

[3] W.T.l%omson, "Research and development of on-line diapxtic monitoing systems for electrical machines," fEE *Col/. Insrrumenmtion 01 Rotaring El&trieol MochinPs,* pp.S11 -517,199I.

[4] O.V.Thmsen and M.Dalva. "A survey of faults on induction motors in offshore oil industry, petrochemical industry, gas lerminals, and oil refineries," *IEEE Trans. lad.* Applicant, vol. 31, pp. 1186-1196, sept.lOct.lOct. 1995.
151 F. Pilippetti. G. Fraanceschini. and C. Tassoni, "A SUN~Y of AI techniques approach for induction machines on-line diagnowicr," in *Proc.PEMC'Y6,* vol. 2, Budapest, Hunghary, 1996, pp. 314-318.
161 M.E.H.Benbourid, " Bibliography on lnduclion Molors Faults Detection and Diagnosis," IEEE *Trans. Energv Conversion,* ~01.14, pp.1065-1073, Dec. 1999.
[7] S. Nandi and H. A. Toliyat, -Condition monitoring and fault diagnosis of elelrid machines - -a review," IAS 1999,vol.l, pp.197-204,1999.
181 W. 7. Thompson, "A review of on-line condition manitoting techniques fw three phase squirrel induction motors - Pasf, present and future," in *Pmc. SDEMPED'PP,* pp. 3-18,1999.
[9] M.EI H.Benbouzid, "A review of induction motors signature analysis as a medium for faults detection," lEEE *Tmns. hdusrriol Electronics,* "01.47, pp.984-993,Oct.ZWO.
[IO] R.Belmans and K.Hameyer, "Different approaches to the prevenlive Maintenance of induction motors." in *ploc.lCEM'96,* pp. 423428, 1996..
[Il1 V.Warren and G.Stone, "Recent developments in diagnostic lesting of stator windings, *IEEE Mog.Electrical Inrulotion.* vd.14, pp. 16-24, SeptJOct.1998.
[I21 C.M.Riley. B.K.Lin,T.G.Habetler and R.R.Schoen, "A method for ~engorless on-line vibration monitoring of induclion machines,"lEEE *Tmn,nd. AppliO"* vol. 34,pp.l240-1245, Nov.lDec.1998.
[I31 C.M.Riley, B..K.Lin. T.G.Habetler and G.B.Kliman, "Sfalor current harmonícs and their causal vibratíons: A preliminary investigation of sensor less vibration monitoring applications," *IEEE Trons.lnd. Applicanr,* vol. 35,pp 94-99,Jan.lFeb. 1999.
[I41 S.Moreau, J.C.Trigeassou, G.Champenois and J.P. Gauben, "Diagnosis of induction machines: A procedure for electrical faull Delection and laalization, in Prw. *IEEE SDEMPED'99,* pp. 225-229, 1999.
[IS] A.Stavrw, H.G.Sedding and J.Penman, Turrent monitoring for detecting inter-tum shon circuits in induction motars,"lEEE *Trans. Energy Conversion,* va1.16, pp.32-37, Mar.2001.
1161 E.Chamitak and D.McDermt1, *An$cid Inrelligence.* Addison-Wesley, New York, 1985
[171 P.J.Tanver and J.Penman, *Condition Monimmg qf Electricol Machine$,* Research Studies Press **Ltd.,** 1987.
[181 P. E. Goldberg, *Generic Algorilhni in Search Oprimiiorion ond Mochine Lporni&.* New York Addisan-Wesley, 1989.
[191 G. Winstanley, *Aniliciol Intelligence in Enginewing,* John Wiley & Sons, New York, I99I
1201 L.Davir, *Hondbook qf Genetic Algorithms,* Van Nntrand. New York, NY, 1991.
[Zl] P. Vas, *Parameter Estimation, Condirion Monironngr. and Diogmsi$ qf Elecrricol Machines.* Oxford, and U.K.: Clarendon Press, 1993.
[22] M.Y.Chow, *Methodologies Gf Using Neural Network and Fuzz). Logic Technologies ,for Mom Incipient Fault Detection,* World Scientific Publication Co. Pte. Lfd., 1997.
[23] C.M.Ong, *Dynamic Simulation ~/ EIecrric Mochinev,* Prenrice Hall PTR, 1998.
[24] P. Vas, *Arri~~iol-l~telligenrB~~~d Elecrricol Mochiner and Drives. Applicorion qf Fuzzy, Nard FuzzyNeurol and Generic-Algorithm-BmedTechniquPr.* Oxford, U.K.: Oxford Univ. Press, 1999
[25] N. Cristianini and 1. Shawe-Taylor, *An Introdecrion 10 Support Vector Moehinrs,* Cambridge Universiry Press, 2000.
[26] V.Kecman, *Leoming ond Sqli Compuring,* MIT Press, Cambridge, 2001.
(271 S.Rusrell and P.Norvig, *Art@cid Inrelligence-A Modern Approach,* Pearson Educalion (Singapore)Re.Ltd, Delhi, 2002.
(281 *IEEE riondord ,err procedure /or polyphase induction moiorr and generorors,* IEEE Standard 112-1996, 8 May 1997.
(291 *IEEE Srandord Terr Procsdure for Sinzle-Phose Induction Molors,* IEEE Standard 114-2001.
[30] *Rotating ekclrical machines - Port 17: Coge induction molm when ,/ed tom cowerrerr - Applicorion ..mide,* EC 60034.17 26-Mar-2002
[31] *'Rotating electric01 machines : Po, 12: Srorring perlbrmance qf single-ped rhreephore cuge induction motors,* IEC 60034-12 09-Apr-2002.
1321 Rolaring elecirical machines - Pan 26: Effects of unbalanccd voltages on the performance of three-phase induction motors, IEC 60034-26 I 7-Muy-2002.
1331 Code of practice for installation and maintenance of induction motors, Bureau of lndian Standards IS: 900-1992,1992.
[34] Md. A.Ma~mr, X.Xu and F.Liang, "Fault isolation in an induction motor conlrol syslem", U.S.Patent 5 469 35I, Nov. 21, 1995.
[35] G.B.Kliman,'"fum Fault Detection," U.S.Pamt 5 477 163, Dec. 1995.
[36] T.Petsche and S.J.Hanson, "Neural network auto-aSSOeiator and method for induction motor manitoring,"U.S.Patent 5 576 632, Nov.19, 1996.
[37] T.Petsche and C.Garren, Radial basis function neural network auto-asswiator and method for induction mofor moniloring,"U.S.Palent 5 574 387, Nov. 12, 1996.

- **Classification or stator faulls**

1381 A.H. Bonnet1 and G.C. Soukpup, Rotor failures in squirrel cage induction motors, *IEEE Trans. Ind. Applicant.* vol. IA-22, pp.1165-1173, Nov.IDec. 1986.
[39]A.H. Bonnet, Cause and analysis of stator and rotor failures in three-phase squirrel-cage induction motors," *IEEE Tmnr. Ind. Appliconr,* ~01.28, pp 921-437, JulylAug.1992.
[40] Induction Motors (LVMV) Failures and its hevention, Guidelines for motor installations, www.indiaelectricmarket.com lcgi-hinliemhomell recent advanceJinductionmotor.

- Various AI Techniques

[41]L.Zadeh, "Furry **sels,"** Inform. Cam., no. 8, pp. 338-353, 1965.
[42] Y.Fukuyama and Y.Ueki, Hybnd fault analysis system using neural networks and artificial intelligence," in *ploc. IEEE Ind. Sym. on Circuils and* Sysrems. ~01 .4, pp.1709-I712, I992
[43] 1. R. lang, "ANFIS: Adaplive network baaed fuuy inference syslem, *"lEEE Trans. Swr.. Mon. Cybern,* vol. 23, pp. 665-685, MaylJune 1993.
[44] M.Kerunovic, I.Rikalo and D.J.Sohalic,"High-speed fadl detection and classification with neural nets," *Electric Power* Systems Research, ~01.34, pp.109-116, 1995.
(451 X.Wang and M.Elbuluk, "'Neural Network control of induction machmr using genetic algorithm training," in *Proc.lEEE Industr). Applicotionr Conf.* "01.3, pp1733-1740, 1996.
[46] D.T.Pham and P.T.N.Pham, "Artificial Intelligence in Engineering," htl. 1. of Machine Twls & Manufacture. ~01.39, pp. 937-949.1999.
[47] D.Bonas. M.CasIills and J.C.Monlano,"Wavelet and neural stn+Nre: A new twI for diagnostic of power syslem disturbances,"lEEE *Tmm Ind. Applzconl.* ~01.37, pp.184-190, Jan. 2001.
14x1 T.Phumiphak and C. Chat-ulhai, "Estimation of induction molor parameters based on Field Test coupled with Genetic Algorithms," in *Proc. PO WERCON 2lJlJ2,* VoI 2,pp. l199-1203, 20O2
[49] What is a Genetic w Evolutionary Algorithm?," wu?v.soI~cr som I gahanics.htm.
[SO] J.Plat1, "Suppon Vector Machines," w.research. microsoR. comlusersl **jplaili** svm. html.
[51] W.HU and Z.Zhou, "Condition monitoring and fault diagnosis of modem manufacturing systems," www.sot.city.ac.uk/~ce702/manuf.htmlftcon.
[52] "Introducing neural netwarks,"wu?v.neusi~"c~~.comiTechnologicslnn intmhrm.

* AI Based fault Dhgnoslier of induction machines

1531 S.Williamson and K.Mirzoian," Analysis of cage induction motors with s18tor winding faults," lEEE *TransPower App. ond Syrr..* vol. PAS-104, pp.1838-1842, July 1985.
[54] D. Leith, N. D. Deans, and L. 1. D. Stewart, Tondition mbnitoring of electrical machine using real time expen systems," in *Proc. ICEM'BX,* vol. 3, Pisa, Ihaly. Sept. 1988, pp. 297-302.
[SS] F F.Fhppeui, G. Franceschini, M. Manelli, and C. Tasioni, "An approach lo knowledge rrprr~entafion about induction machine diagnostics in expcn systems," in *Proc. ICEMW,* vol. 3, Pisa, Italy, Sept. 1988, pp.289-296.
[S6] J.Luo and Quan-Fa Yang, " A New Scheme of Fault Detection based on Neural Nets," in *ProdEEE lntl. Sym. on Industrial Elecrronics. ~01.2.* pp.580-583. 1992.
I571 F.Filippem. "Neural networks approach lo elmfric machine on-line diagnositcs," in *Proc Fifih Erropean Coil: Power Elecnonrcs and App1ic"iion.I.* pp.213-218. 1993.

[ss] M.Y.Chaw and P.V.Goade, "The advantages and challenges of machine fault detection using anificial neural network and h a y logic technologies," in *Proc. 7hirw Sixth Midwerl Symp. On Circuit$ and Systems,* v d l , pp708-711, Aug.1993.

1591 P.V.Gwde and M.Y.Chow, "A Hybrid FuayMeural System used to extract heuristic knowledge from a fault detection problem," in *Proe. 7hird Conl Fuiry Systems,* "01.3, pp.1731 -1736, 1 994.

[W] R.Di Stefana, S.Meo and MScarano, "Induction motor faults diagnostic via anificial neural network (ANN)" in *Proc. ISIE'94,* pp.220-225, May 1994.

[61] J.Penman and C.M.Yin, "Feasibility of using unsupervised learning, artificial neural networks far the condition monitoring of electrical maehines,"lEE *Proc.Elecw.Power Appl.,* vol.14I, no. 6,pp317.322,Nov. 1994.

1621 M.Y.Chow, 'me advantages of machine fault detection using artificial neural network and h a y logic technologies," in *Proc. IEEE lntl. Cool Indurrrial Technology,* pp83-87, Dec. 1994.

1631 Z.Chaohai, M.Zongpan and Z.Qijie, '%-line incipient fault detection of induction motors using artificial neural networks," in *ploc. IEE Intl. CO"(Indurlrial Technology,* pp.458462, Dee.1994.

[64]S.L.Ho and K.M.Lau, "Dctection of Faults in Induction Motors using Anificial Neural Networks," in *Proc. Seventh Inll. CO"~ On Electrid Mochines ond D~ives,* pp.ll -I J, 1995.

[65] P. V. Gwde and M. Y. Chow, "Using a neuralJhzy system to extract knowledge of incipient fault in induction motors (Pan I and Pan U)," *IEEE Trons. Ind. Eleclron,* vol. 42, pp. 131-146, Apr. 1995.

1661 F. Filippetti, G. Franceschini, C. Tasronì, and P. Vas, "A fuzzy logic approach 10 on-line induction motor diagnosis based on stator current monitoring," in *Proc. Inl. Symp. Stockholm Power Technoloa-— EleclridMachines and Drives,* Stockholm, Sweden, June 1995, pp. 2 70-274.

1671 F.Filippetti, G.Franceschini and C.Tassoni, "Neural networks aided on-line diagnostics of induction motor rotor fad&," *IEEE Trans. Ind. Awiicont,* ..~01.31. m.892-899. JulvlAua.. 1995.

[6X]R.R.Schoen, B.K.Lin, T.G.Habetler, J.H.Schlag and %Farag, "An unsupervised. on-line system for induction motor fault detection using stator Current monito~ng,˜,lEEE *Tronr. Ind Applicant.,* I, pp. I280-1286,Nov.lD~. 1995.

[69] F.Filippetti, A.Uncini, C.Piam, P.Campolueci, C.Taassani and G.Franceschini, "Neural network architectures for fault diagnosis and parameter recognition in induction machines," in Proc. MELECON'96, v0I. I. pp289-293, May 1996.

[70]K.Gulez, B.Karlik and S.V.Ulun, "Designing artificial neural networks for fault detection in induction motors with the TMS320CJODSP," ESEE, Patis, Texas Instruments, Sept. 1996.

(711 B.Huo and A.M. Trrynadlowski, " Stator Fault Detector for AC Motors BasedonIheTMS320F243DSPConrroller," w.6 comlscl docsigeneral ldrplfestproceedingsi fest2000lunr001 ..@f

1721 A.C.McCwmick and A.K.Nandi, " Classification of the rotating machine condition monitoring using anificial neural networks," in *Proe. Inan. Mech.Engrs,* ~01.211, pp.439450, 1997.

(731 F.Filippeni, G.Franceschini, C.Tassoni and P.Vas, "AI techniques in induction machines diapartics including the speed ripple effect," *IEEE Trans. Ind. Applicml,* vol. 34,pp.98-108. Jan.lFeb.1998.

[74] G.Bctta, C.Ligu.3" and A.Pietrosanto, "An advanced neural-network-based insttllment fault detection and isolation scheme,"lEEE *Trans. Instrumenlolion and Measurement.* ~01.47, pp.507-512, Apr. 1998.

[75] L.Kruger. D.Naunin and C.Garbrecht, "Stochastic and neural models of an induction motor," *Molhemarics ond Compurerr in Simuiolion,* "01.46. pp.313-324. 1998.

1761 M.E.H. Benbowid et al.. "Induction motors faults detection and localization using stator current advanced signal processing techniques," *IEEE Tran. Power Electron,* vol. 14, pp. 14-22, Jan 1999.

[77] S.Kolla and L.Varatharasa, "Identifying three-phase induction motor faults using artificial neural networks,"/5v4 *Trans.,* voL39.pp.433^139, 2000.

[78] N.Arthur and J.Penman, "Induction machine condition monitoring with higher order spectra,'7£££ *Trans. Industrial Electronics,* vol. 47,pp.l031-1041,Oct.2000.

[79] I.Lasurt, A.F.Stmnach and J.Peman, "A funy logic approach to the interpretation of higher order spectra applied to fault diaposis in electrical machines," in *Proc. NAFIPS. IV* Inrl. Coil Of the Fuzq Iqfonnolion Processing Sociery,* pp. 158-162, 2000.

[SO] F.Filippetti, G.Franceschini C.Tassoni and P.Var,"Reeent developments of induction motor drives fault diagnosis using AI techniques. *IEEE Trans. Indurlriol Electronics,* vol. 47,pp.994-1003, 0~1.2000.

1811 U-M.Yang and J.Penman, "Intelligent detection of induction motor bearing faults using current and vibration mcmito"ng," in *Pmc COMADEM,* pp.461 *470.* Dec.2000.

[82] A.V.Barkav and N.A.Ba*ova, "The anificial intelligence systems for machine condition monitoring and diagnostics by vibration," www.vibrotek.eomlarticles/intelectcngi"d~~.htm.

1831 M.Arkan, D.K.Perovic and P.Unswonh, "Online s~tor fault diagnosis in induction motors," *IEE ploe.Eleelr.Power Appl.,* ~01.148, pp.537-546.Nov.2001.

1841 R.M.Tallam, T.G.Habetler and R.G.Harley, "Continual on-line training of neural networks with applications in electric machines fault diagnosis," in Prw. EEE 32'6 Power Electronics Specialists Conf., pp.2224-2228,2OOl.

[85] M.E.H.Benbouzid, "A simple fuzzy logic approach for induction motors stator condition monitoring," in *Proc. IEMDC,* pp. 634-639,2001.

[86] Z.Ye, B.Wu and A.R.Sadeghian, "Eleatical machine fault detection using adaptive neurc&zy inference," in *Proc. Join1 gk IFSA World Congress and 2ff* NAFlPS lnll. CO&vol.* l,pp.390-394, 2WI.

[87] Y.Zhongming, W.Bin and A.R.Sadeghian, "Electrical Machine Fault Detection using Adaptive New-Fuzy Inference," in *PrmJoinl ninlh IFSA World Congress and lnvenlielh NAFIPS lvorld Congress,* 2001, pp.390-394.

[88] C.Combastel, S.Lesecq, S.Petropol and S.Gentil, "Model-based and wavelet approaches IO induction motor on-line fault detection,*"Conrrol Engineering* Practice, voI.10,pp.493-509,2002.

[89] K.Kim and A.G.Parlos, "Induction motor fault diagnosis based on neuropredictorr and wavelet signal *pmcessing.lEEE/ASME Tmnr. Mechorronies,* ~01.7, pp.201-219, JunZ002.

[9°i J.Zhang. " "hming Diagnostic Knowledge Through Neural Networks and Genetic Algorithms." hnp:llwww.ici.ralicil~~~~~l~i~23l~~4.html

• AI Bared Fault Diagnostics of Electric Drives

[SI] R. Spec and A. K.Wallace, "Remedial strategies for brushless DC drives failures," *IEEE Tronr. Ind. Applicot,* vol. 27, pp. 259-266. MadApr.1990.

1921 A. C. ~enfrew and J. x. Tian, "me use of knowledge-based system ~n mwer electronic circuit fault diaenosis." In *Proc. EPE93.* vol. 7,Brfghton, U.K., Sept. 1993, pp. 5742.

[93] G. Franceschini, G. Gentile, N. Rotondale, C. Tassoni, and M. Tursini,"An approach Io knowledge-base repracnrvtion in elecwic drive fault diagnosis," in *Proc. ICEM'94,* vol. 2, Paris, France. Sept. 1994, pp.358-362.

1941 D. Kastha and B. K. Bose, "Fault mode ringle~phare operation of a variable frequency induction motor drive and improvement of pulsating torque characteristics." *IEEE Trans. Ind. Electron,* vol. 41, pp. 426-433,Aug. 1994.

[951 R. S. Wiser, M. Shagginger, C. Kral, and F. Pirker, "The integration of machine fault detection into an indirect field oriented induction machine drive control scheme," in *Cool Rec. IEEE-IAS Annu. Meeling,* SI. Louis, MO, Oct. 1998, pp. 278-285.

I961 A. Bellini, F. Filippetti, G. Franceschini, and C. Tassoni. "Closed loop confr~l impact on the diagnosis of induciion motor faults," in *ConJ RedEEE-IAS Annu. Meeting,* Phoenix, AZ, Oct. 1999, pp. 1913-1921

1971 A.Bellini, F.Filippeni, G.Franccwhini and C.Tassoni, 'Clased~-loop control impact on the diagnosis of induction motors faults," *IEEE Trmr. Ind. Appliconr.* "01.36, pp. 1318.1329, Sept.lOct.lOd.2000.

* Futuristic Trends

[98] "The future for electric motors?," www.industrialtechnology .co.uk / 2001/oct/abb.html, Oct.2001.

[99] A K. Nandi and L B Jack, "Condition Monitoring Using Intelligent Systems," www.liv.ac.uk/EEE/research/spc/projectl 3.htm

[100]NJulun and S.Swamamani, "Genetic Optimization of Multi Layer Feed forward Neural Network,'1 www.stle.org/aririual_meeting _2OO3 /am _ 2OO3_AbstractsItem.cfm?seq=39O.