Fault Diagnosis Methods for AC Induction Motors

Rodrigo López Cárdenas[1] and Luis Pastor Sánchez Fernández[2]

[1] Center for Computing Research
National Polytechnic Institute, México
rodrigo@correo.cic.ipn.mx
[2] lsanchez@cic.ipn.mx

Abstract. This paper presents a review and evaluation of developments in the field of diagnosis of electrical machines. It covers model-based techniques, knowledge-based techniques and signal techniques, organized in quantitative approach and qualitative approach. Exposes briefly drawbacks and benefits of principal methods and their combination. Then compares the principal methods and finally, suggests an hybrid method that can overcome their individual limitations and take advantage of particular merits.

1 Introduction

Motors are the workhorses or our industry. Safety, reliability, efficiency, and performance are some of the major concerns and needs for motor systems applications. They are essential components in most of today's manufacturing and production industries. The key for a successful motor operation are a quality motor, understanding of the application, choice of the proper maintenance of the motor [1] [2].

A fault is to be understood as a non permitted deviation of a characteristics property which leads to the inability to fulfill the intended purpose. This can be done by checking if particular measurable or unmeasurable estimated variable are within certain tolerance of the normal value. If this check is not passed, this leads to a fault message.The functions up to this point are usually called monitoring or fault detection, this is followed by a fault diagnosis: the fault is located and the cause of it is established [3].

2 Quantitative approach

Previous supervision of technical process was restricted to checking directly measurable variables for upward or downward transgression of fixed limits or trends. This could be automated by using simple limit-value monitors. Various faults in the process could be then detected, but only after the measurable output values had been effected considerably. The problem is orientate process faults with the aid of the measurable input and output variables $U(t)$ and $Y(t)$ and mathematical models with nonmeasurable disturbance signals, nonmeasurable process parameters and partially measurable and partially nonmeasurable internal state variables [3].

2.1 Measurable signals

Measurable input signals $U(t)$ and output signals $Y(t)$ can be directly used to monitor changes in the process.

Limit and trend checking is a method well know and commonly used to check signal's limits $Y(t)$, is this excess a maximum value Y_{max} or fallen below of a minimum value Y_{min}. The normal state is:

$$Y_{min} < Y(t) < Y_{max} \tag{1}$$

This is referred to as an absolute value check. The limit check can also be applied on the trend $\dot{Y}(t)$ of the signal $Y(t)$. The normal state is:

$$\dot{Y}_{min} < \dot{Y}(t) < \dot{Y}_{max} \tag{2}$$

also a combination of absolute value and trend checking is possible.

If only limit checking is applied, the limits usually are set on safe side to allow sufficient time for counteractions. However, this can lead to false alarms if the variable return to the normal state without external actions. This disadvantage can be avoided, if the affected signals $Y(t)$ can be predicted. This also allows to predict the time of exceeding a threshold. In order to this, mathematical models have to be used [3].

2.2 Mathematical models

The task consist of the diagnosis of faults in a dynamical system by measuring the available input and output variables $U(t)$ and $Y(t)$. Process with parameters that can be linearized around one operating point are usually described by an ordinary differential equation

$$\begin{aligned} y(t) + a_1\dot{y}(t) + a_2\ddot{y}(t) + \ldots + a_n y^{(n)}(t) &= b_0 u(t) \\ +b_1\dot{u}(t) + b_2\ddot{u}(t) + \ldots + b_m u^{(m)}(t) & \end{aligned} \tag{3}$$

Additive faults at the input or output can be modeled by [4]

$$\begin{aligned} y(t) + a_1\dot{y}(t) + a_2\ddot{y}(t) + \ldots + a_n y^{(n)}(t) = b_0 u(t) \\ +b_1\dot{u}(t) + b_2\ddot{u}(t) + \ldots + b_m u^{(m)}(t) + f_y + b_0 f_u \end{aligned} \tag{4}$$

The process model parameters $\theta^T = [a_1 \ldots a_n \mid b_1 \ldots b_m]$ are more o less intricate relationships of several physical process coefficients, e.g. mass, speed, drag coefficient, viscosity, resistances. If a fault within the process changes one or several parameters by $\Delta\theta_j$ the output signal changes and the parameter estimation indicates a change $\Delta\theta(t)$. Generally, the process parameters θ, depend on the physical process coefficients **p**. $\theta = f(p)$ via nonlinear algebraic equations. If the inverse of this relationship exists

$$p = f^{-1}(\theta) \tag{5}$$

then changes Δp_i of the process coefficients can be calculated. These changes in process coefficients are in many cases directly related to faults [3]. A necessary requirement of this procedure is, however, the existence of the inverse relationship Eq. 5.

The linear process can be described in state-space form as

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{6}$$
$$y(t) = Cx(t) \tag{7}$$

To reconstruct the states from measurable input and output signals a state observer can be used, the feedback matrix H must be selected properly to assure that the observer is stable, where $e(t)$ is the output error.

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + He(t) \tag{8}$$
$$e(t) = y(t) - C\hat{x}(t) \tag{9}$$

The process is now influenced by disturbances and faults as fallows [4]

$$\dot{x} = Ax(t) + Bu(t) + Fv(t) + Lf_L(t) \tag{10}$$
$$y(t) = Cx(t) + Nn(t) + Mf_M(t) \tag{11}$$

$v(t)$ and $n(t)$ represent the unmeasurable disturbances at the input and output, respectively, $f_L(t)$ denotes the input fault, acting through L on $x(t)$. $f_M(t)$ denotes the output fault acting through M as an output change $\Delta y(t)$.

For the state estimation error the following equations hold if the disturbances $v(t)$ and $n(t)$ are both zero

$$\dot{\tilde{x}} = [A - HC]\tilde{x}(t) + Lf_L(t) - HMf_M(t) \tag{12}$$
$$e(t) = C\tilde{x}(t) + Mf_M(t) \tag{13}$$

$F_L(t)$ and $f_M(t)$ are additive faults, because they influence $x(t)$ and $e(t)$ by a summation. Essentially, the residual $e(t)$ is the basis for different faults detection methods based on state estimation.

If faults appears as changes ΔA, ΔB or ΔC of the parameters the process behavior becomes

$$\dot{x} = [A + \Delta A]x(t) + [B + \Delta B]u(t) \tag{14}$$
$$y(t) = [C + \Delta C]x(t) \tag{15}$$

and the state estimation error

$$\dot{\tilde{x}} = [A - HC]\tilde{x}(t) + [\Delta A - H\Delta C] + \Delta Bu(t) \tag{16}$$
$$e(t) = C\tilde{x}(t) + \Delta Cx(t) \tag{17}$$

The faults ΔA, ΔB and ΔC are multiplicative faults, because they influence $x(t)$ and $e(t)$ by a product with the variable $x(t)$ and $u(t)$. In this case the residual changes depends on parameter change as well as input and state variable change. By analyzing the information of faults included in the residuals series, faults can be detected and diagnoses. For more information see chapter two of [4].

The process parameter techniques try to monitor the process directly, based on physical laws whereas the state variable techniques must assume the process parameters as known and try to monitor the signals. Of course, both techniques complement one another. Its disadvantage is that it requires an accurate motor model, one advantage of using a parameter estimation method is that a motor can be modeled accurately. According to the magnitude of coefficient changes, the degree of seriousness of the fault can be estimated. However, it may be difficult to get the relationship between the model parameters θ_j and the physical process coefficients p_i, moreover, when the state estimation method is used, the influence of large modeling error cannot be ignored.

2.3 Signal model

Methods based on signal analysis include, principally, vibration analysis and current analysis. Vibrations analysis is used to detect for example unbalance and bearings faults, whilst current analysis is used to sense rotor faults associated with broken rotor bars and mechanical unbalance [5]. These methods make use of signal models, such a spectrum, correlation function, Fourier transform, etc, to analyze the measured signal. A signal analysis is another source of information if changes of these signals are related to faults, then, features of motor operating conditions can be extracted and used for motor faults detection and diagnosis.

The main advantage of this kind of method is that accurate model is avoided. However, this kind of method only uses the output signals of motor, but no input signals, therefore, the relationship between input and output is not considered. Because of high cost of accurate sensing devices, this method is usually considered useful for large motor only [6].

3 Qualitative approach

Methods based on knowledge include expert system method, fuzzy logic and neural networks. An expert system can be built to detect and diagnose motor faults according to the experience accumulated by an engineer. An experienced engineer can usually detect and diagnose motor faults by observing the motor's operation performance, without knowing or understanding the exact system dynamic, unfortunately, engineer's experience is difficult to describe and be transmitted or automated [7].

Soft computing is considered as an emerging approach to intelligent computing, which parallels the human mind ability to reason and learn in circumstances with uncertainty and imprecision. In contrast with hard computing methods that only deal with precision, certainty and rigor, it is effective in acquiring imprecise or sub-optimal, but economical and competitive solutions to real world problems. In general, soft computing methods consist of three essential paradigms: neural networks, fuzzy logic and genetic algorithms [8].

3.1 Neural networks-based methods

With artificial neural networks, human expertise can be partially imitated and that neural network can be trained to detect faults based solely on input-output examples without the need of mathematical models. The motivation of employing neural networks for motor fault diagnosis is due to their self-adaptation and nonlinear approximation abilities which can be used to extract the relationships between different input and output variables to diagnose and indicate possible faults. We emphasize that the learning procedure is usually guided by human experts.

The neural network performance depends on the chosen input variables which must be optimal fault indicators moreover, the diagnosis performance can be affected by problems like selection of neural network structure, over training or under training, and slow convergence speed. However, the critical shortcoming of neural network-based motor fault diagnosis is that qualitative and linguistic information from motor operator cannot be directly utilized or embedded in the neural network structure. Additionally, is difficult to interpret the input and output mapping of the training neural network into meaningful fault diagnosis rules [8] [9].

3.2 Fuzzy logic-based method

A system based on fuzzy logic allows the translation of heuristic and linguistic terms into numerical values via fuzzy rules and membership functions to approach the performance of the diagnostic system to the real world.

The major drawback of fuzzy logic is that not provide an exact solution to the problems (the solution are fuzzy in nature) moreover, the design of such system heavily depend on the intuitive experienced acquired from expert operators. The fuzzy membership functions and fuzzy rules cannot be guaranteed to be optimal in any sense. Furthermore, fuzzy logic systems lack the ability of self-learning which is compulsory in some highly demanding real-time fault diagnosis cases. The above drawbacks can be partly overcome by the fusion of neural networks and fuzzy logic techniques [7] [8] [9].

3.3 Diagnosis using neural-fuzzy techniques

To overcome the mentioned problems about neural network system and fuzzy logic system, we can build a hybrid neural/fuzzy system that take advantage of the feature of both technologies while minimizing their drawbacks. The idea behind the fusion of this two technologies is to use the learning ability of neural networks to implement and automate fuzzy systems. A possibility is to use inference systems like Adaptive Network based Fuzzy Inference System (ANFIS) or Fuzzy Adaptive Learning Control/decision Network (FALCON) [1] [10].

3.4 Genetic algorithms-based diagnosis

A Genetic Algorithm is a derivate-free and stochastic global optimization method inspired by the laws of natural selection and genetics, they use the concept of Darwin's theory of evolution, which is based on the rule of the survival of the fittest. These algorithms do not need functional derivate information to search for a set of parameters that minimize (or maximize) a given objective function [11]. Hence, it is attractive to employ genetic algorithms to optimize the parameters and structures of neural networks and fuzzy logic system instead of using back-propagation learning algorithm alone. Since genetic algorithm is only an auxiliary optimization method, it cannot be applied independently in practice. The combination of genetic algorithms with other motor fault diagnosis schemes has demonstrated enhanced performance in global and near-global minimum search. However, optimization with genetic algorithms often involves heavy computing, and is therefore quite time-consuming [8].

4 Comparison and evaluation of methods

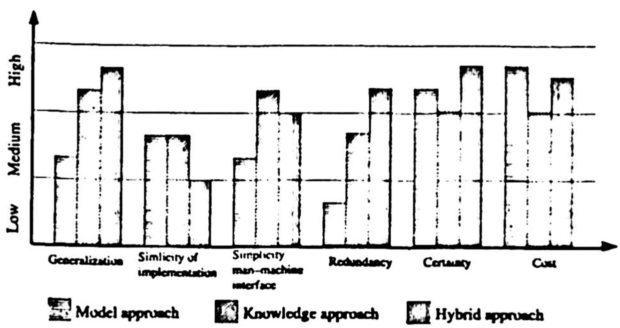

Fig. 1. Comparison of three principal methods

The Fig. 1 shows a comparative graphic of three principal methods: model-based approach, knowledge-based approach and hybrid-based approach with six topics: generalization, simplicity of implementation, simplicity of man-machine interface, redundancy, certainty and cost. Each topic evaluates each method in three ways with adjectives like low, medium and high.

Since self-adaptation, nonlinear capabilities and linguistic rules is common to knowledge-based method, this kind of methods are able to generalize deeper that mathematical model, because the operation of the mathematical model is just for the model for which it was created. Therefore, a mix of both techniques can improve the performance. To implement model-based approach and knowledge-based approach an engineering designer or experienced personnel with high specialization is required, this can be a drawback in hybrid technique due to the mix of methods. Since is difficult to express or to analyzes raw data of many processes, the model technique is shorter that both others, at the other hand, express knowledge in crisp value is easiest, hybrid technique has intermediate point. Redundancy is the capacity of disposing repeated information, since the mix of methods is logic that hybrid method has the greatest redundancy. Obviously, if exists redundancy in diagnostic the certainty will grow supported by intrinsics certainty of mathematical model, because of that, the hybrid certainty is highest. Cost, according to the experts, is always below in knowledge techniques and, therefore in hybrid techniques than mathematical techniques.

5 Suggested method

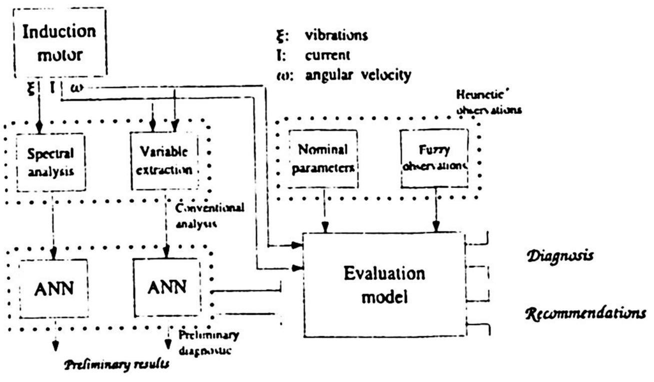

Fig. 2. Suggested scheme of induction machine diagnostic

Our schema, Fig. 2, consist of typical and more commonly used variables, like vibrations, angular velocity and current consumption, moreover, it makes use of nominal parameters, that is, manufacturer specifications and operator observations. This model is divided in two principal parts. the first one takes measurable signals and process them to extract unmeasurable and characteristics parameters by means of classical analysis and simulation models.

Firstly, analysis spectral of vibrations is introduced into an artificial neural network previously trained to detect anomalies in vibration signature. At parallel path, motor's angular velocity and current consumption are utilized by another artificial neural network previously trained with computer simulation data of well state motor and faults state motor, to detect possible faults conditions.

This double path, named preliminary diagnostic, provides diagnostic redundancy that can be used by evaluation model. The evaluation model can make use of preliminary results, direct measurements or both analysis. Moreover, to better inference and decision capability makes use of nominal parameters and fuzzy observations. This last block, could use knowledge base techniques, decision trees or neural/fuzzy inference systems.

At this moment, we are working on motor simulation model and searching the best inference architecture to recreate our model. Results will be published next.

6 Conclusion

In this paper we gave an overview of principal developments in the field of diagnosis of electrical machines. We reviewed model-based techniques, knowledge-based techniques and signal techniques as well as their combinations, advantages and disadvantages were discussed too. Finally we expose briefly an hybrid method that makes use of quantitative and qualitative techniques to overcome their individual limitations and take advantage of particular merits.

References

1. Altug, S., Chow, M.-Y., Trussell, H.J.: Fuzzy inference system implemented on neural architectures for motor fault detection and diagnosis. IEEE Transactions on Industrial Electronics **46** (1999) 1069-1078.
2. Chow, M.-Y.: Guest editorial special section on motor fault detection and diagnosis. IEEE Transactions on Industrial Electronics **47** (2000) 982-983.
3. Isermann, R.: Process fault detection based on modeling and estimation methods. - A Survey. Automatica. **20** (1984) 387-404.
4. Patton, R.J., Frank, P.M., Clark, R.N. (Eds.): Issues of fault diagnosis for dynamic systems. Springer, Great Britain 2000.
5. Benbouzid, M.H.: A review of induction motors signature analysis as a medium for faults detection. IEEE Transactions on Industrial Electronics **47** (2000) 984-993.
6. Liu, X.-Q., Zhang, H.-Y., Liu, J., Yang, J.: Fault detection and diagnosis of permanent-magnet DC motor based on parameter estimation and neural network. IEEE Transactions on Industrial Electronics **47** (2000) 1021-1030.
7. Chow, M.-Y.: Methodologies of using neural networks and fuzzy logic technologies for motor incipient faults detection. World Scientific, Singapore 1997.
8. Quiang, S., Gao, X.Z., Zhuang, X.: State-of-the-art in soft computing-based motor fault diagnosis. Control Applications, 2003. CCA2003. Proceedings of 2003 IEEE Conference on Control Applications. **1** (2003) 1381-1386 vol. 2.
9. Filippeti, F., Franceschini, G., Tassoni, C., Vas, P.: Recent developments of induction motor drives fault diagnosis using AI techniques. IEEE Transactions on Industrial Electronics **47** (2000) 994-1004.
10. Jang, J.-S. R.: ANFIS: adaptive-network-based fuzzy inference system. IEEE Transactions on Systems, Man and Cybernetics **23** (1993) 665-684.
11. Jamshidi, M., Coelho, L.S., Krohling, R.A., Fleming, J.F.: Robust control system with genetic algorithms. CRC Press, USA 2003.