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A Bayesian Information System for Predicting Stator Faults in Induction Machines

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Abstract: The approach adopted in this paper focuses on the faults prediction in asynchronous machines. The main goal is to explore interesting information regarding the diagnosis and prediction of electrical machines failures by the use of a Bayesian graphical model. The Bayesian forecasting model developed in this paper provides a posteriori probability for faults in each hierarchical level related to the breakdowns process. It has the advantage that it can give needed information's for maintenance planning. A real industrial case study is presented in which the maintenance staff expertise has been used to identify the structure of the Bayesian network and completed by the parameters definition of the Bayesian network using historical file data of an induction motor. The robustness of the proposed methodology has also been tested. The results showed that the Bayesian network can be used for safety, reliability and planning applications.

Keywords: Induction machine, faults, Bayesian network, Stator, Maintenance

1. Introduction

In a concept evolution, corrective maintenance has become a disadvantage with regard to preventive maintenance. This preventive maintenance must make it possible to avoid faults of equipment in use. The cost analysis must highlight a gain in relation to the faults that it avoids. To implement this type of maintenance on vital electric motors, monitoring systems have been put in place [1]. Through these systems, preventive visits make it possible to accumulate information relating to the behaviour of the motor. The majority of vital electric motors are monitored in real time. Conditional based maintenance of large electric motors is therefore maintenance depending on experience and involving information collected in real time. Conditional based maintenance is characterized by the highlighting of the weak points of the induction motor. Depending on the case, it is desirable to put them under surveillance and, from there, to decide on an intervention when a certain threshold is reached.

Indicators are initially defined for monitoring the induction machine. These indicators depend mainly on the type of constraint. Besides electrical constraints, thermal stresses, mechanical stresses and environmental conditions, improper operation can affect the life of the induction motor. The most important parts of the motor to be inspected are: the stator windings, the rotor winding, and the mechanical part of the rotor. The vibration analysis, the analysis of the signature of the electric current, and the acoustic analysis are mainly the techniques used for the monitoring and the diagnosis of induction motors. In recent decades these techniques have been improved by the use of artificial intelligence methods. This hybridization of techniques has shown promising results and made the conditional maintenance of induction motors more efficient.

Adaptive Neuro-Fuzzy Inference System (ANFIS) have been used to analyse vibration signals of a faulty induction motor [2]. In this study, the correlation between the motor fault types and their corresponding characteristic frequency spectra using the Adaptive Neuro-Fuzzy Inference System show that the developed system is very performing and robust for fault diagnosis. In another research work [3], the technical orbits Park was implementing, strengthened by the application of the Fourier transforms to the Park vector of the stator current allowed the identification of the unbalance defect at low frequency. Other researchers have used both vibration and current signature for fault prediction in the induction motor. In [4] it was presented a contribution in which multiclass support vector machine (MSVM) algorithms have been trained at various operating conditions using the radial basis function kernel and tested for the same operating conditions. The obtained results are in the form of percentage fault prediction. Other works have been based on the acoustic signature for the isolation, diagnosis and early detection of electrical and mechanical faults [5, 6, 7].

Recent contributions have been developed in the last years based on probabilistic and statistical analysis. Fuzzy algorithm-based induction motor fault diagnosis systems have been designed in [8]. The main objective of this algorithm is to evaluate the probability of various types of motor faults. In a similar contribution [9], the authors tried to show how to construct the hierarchical fuzzy inference nets with the propagation of probabilities concerning the uncertainty of faults. A probabilistic model for induction machines was developed by [10]. Based on measuring the current of a healthy induction motor a recursive probability density estimation algorithm was proposed for real-time fault detection. All the models developed and the techniques used are specific to certain specific situations. It also does not allow the detection and diagnosis of all faults at the same time and give information on isolated faults. The diagnosis is a complex procedure especially in the case of simultaneous faults. However, the only way to better diagnose the induction motor is to exploit feedback and information's about fault occurrence in the equipment.

This paper deals with the fault analysis of a vital induction motor. The main objective of the work was to investigate stator element problems in the high power motor. The proposed method relies on two main phases: The first phase is the definition of causal links between causes and consequences. This will allow defining the probabilities of each fault in the induction machines. The second phase of the study concerns the definition and the implementation of an appropriate corrective maintenance program to combat the issue.

The paper is organized as follows. Section 2 is dedicated to present the Bayesian approach. In section 3 we describe steps to build a Bayesian graphical model. Before ending by giving some conclusions in section 5, section 4 is devoted to the application of the developed Bayesian network in a real case study.

2. The Bayesian approach

Probabilistic inference has been widely used in recent years to solve a variety of problems. One of the best-known techniques is Bayesian inference. It is used in diagnosis and prediction initially in the field of medicine and is currently widely used in the industrial field. Bayesian reasoning is the basis for solving reasoning problems under uncertainty and in the presence of incomplete information. These tools have also shown a great interest in the field of maintenance, reliability and safety.

Bayesian networks are graphical models, called also causal networks or probabilistic networks. They combine graph theory and probability theory [11]. To solve problems related to diagnosis we will give preference to the Bayesian networks since they are simple and easily readable and understandable by a non-specialist. The second advantage is the use of new information. In the presence of new information, the Bayesian network takes over the calculation of the branch concerned by this new information only. This is something that makes Bayesian network easy to calculate and therefore minimizes errors. Another advantage of Bayesian networks is the ability to make inference for diagnosis and prediction from the same model. A Bayesian network is a compact tool that allows conducting at a time, quantitative and qualitative fault analysis.

Bayesian network consists mainly of nodes and a set of edges. Discrete or continuous random variables are modelled by the nodes. The edges define the causal relationships between the variables. Inference in a Bayesian network represents the calculation of probabilities. Two types of nodes exist in Bayesian graphical models: parent nodes and children. For child nodes without parents the a priori probabilities are defined by the modeller, while for the parent nodes the probabilities are conditional and they are calculated by the Bayes theorem given by the formula (1).

$$P(\mathrm{A/B}) = \frac{\mathrm{P(A).P(B/A)}}{\mathrm{P(B)}} \tag{1}$$

Example:

The measurement of vibration and electric current are two means of controlling the state of induction motors widely used in conditional based maintenance. In this example, and in a maintenance workshop, the expert made the following observations in case of similar induction motors, which work in the same conditions:

- If an induction motor has a current consumption higher than the rated current (electrical fault), then for 2 motors out of 5 there are reported abnormal vibrations;
- If a motor does not show electrical fault, then 4 motors out of 5 do not show any vibration.
- Half of the motors from the park present electrical fault.

Calculate the probability that, if a motor has a vibration, then it also presents electrical fault?

By applying formula (1):

$$P(B) = P(A) \times P(B/A) + P(\bar{A}) \times P(B/\bar{A}) = \frac{1}{2} \times \frac{2}{5} + \frac{1}{2} \times \frac{1}{5} = \frac{3}{10}$$

$$P(A/B) = \frac{P(A) \times P(B/A)}{P(B)} = \frac{\frac{1}{2} \times \frac{2}{5}}{\frac{3}{10}} = \frac{2}{3}$$

A posteriori probabilities of the causes: The 2/3 of the motors presenting vibration, presents also electrical fault. This result denotes a clear impact of the electrical fault on the evolution of the vibration in the engine. From uncertain to certain environment the expert can make decision that the vibration in the motor is the consequence of an electrical fault.

Bayesian network is an acyclic oriented graph. It prohibits dependencies children nodes towards parent nodes. According to the conditional independence and the chain rule, BNs represent the joint probability distribution P(V1,

$V2, \ldots, V_n$) where C(Vi) are the parents of Vi or causes of Vi in the Bayesian network. In a general context, a network is called Bayesian if it realizes Markov factorization condition. So a Bayesian network is defined by:

$$P(\mathrm{V1}, \mathrm{V2}, \cdots, V_n) = \prod_{i=1}^{n} P(V_i \ / CV_i)) \quad (2)$$

3. Bayesian graphical model design

For a long time, researchers started using real-time maintenance monitoring data, collected from sensors, for predictive maintenance and health monitoring of rotating machines. However, there is a lack of prior studies that investigated the forecasting of faults probability. In this paper, we studied three phase induction machines which are widely used in industry. Some issues have not explicitly been addressed in prior studies such as: the possibility of fault predicting in induction machine using the historical file of the machine and data collected from trend curves given by the automatic monitoring system. Another issue is the opinion of the maintenance expert regarding the faults which can occur, and their relationships. The objective of the Bayesian approach is to optimize the availability and avoid accidental breakdowns. We aim to minimize the probability of fault or any incident that affects the reliability of the machine.

As discussed in the previous section, a Bayesian network consists of a structure and parameters. To construct the structure of the Bayesian network it is often necessary to call on an expert. For our case, a bibliographic investigation allowed us to construct the structure of the network given in *Fig. 1*. The logic is to look for the causal links between the basic events representing in general the causes and the intermediate events representing the consequences. It should be noted here that the hierarchical level of the network structure reflects the degree of fault analysis and fault correction means. The consequence of a cause can itself be a cause for another consequence. Increasing the hierarchy of the scenarios of the breakdown gives more precision to the diagnosis. The top event represents in general the fault of the element concerned by the study, for our case study, the stator.

Bayesian network parameters represent a priori probabilities and conditional probabilities. The exploitation of the experience feedback by the use of the information recorded in the historical files of the motor are at the base of the definition of the parameters of the Bayesian network. For conditional probabilities the causality is strict which means that the presence of a cause inevitably leads to the fault appearance. Also, it means that each conditional probability is equal to 1.

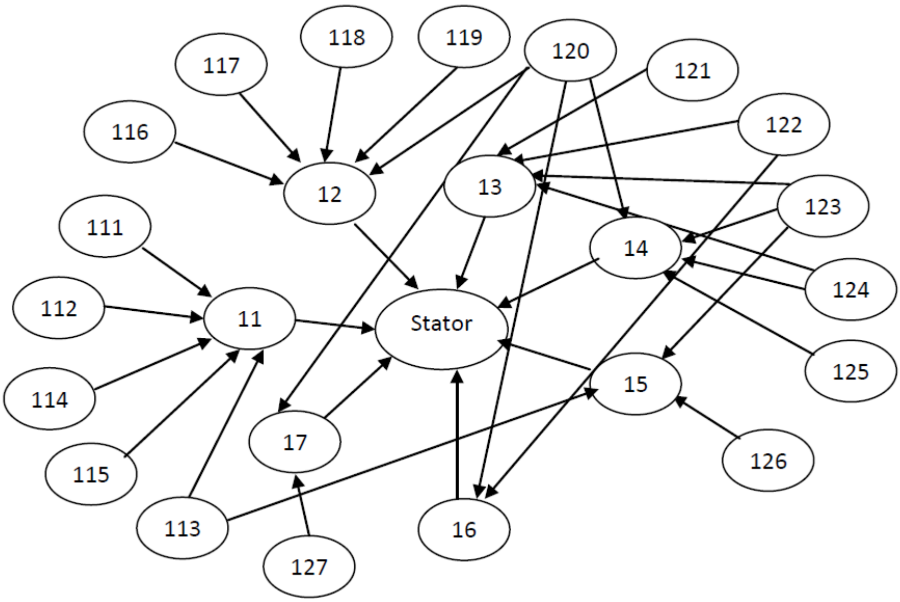

Figure 1: The Bayesian network modelling the fault prediction of stator element.

For causes which represent the child variables in the Bayesian network of *Fig. 1*, a priori probabilities are given. For the consequences which represent the parent variables the probabilities are conditional and they are calculated by inference in the Bayesian network. For the stator fault analysis of the induction motor, it is possible to define 17 probable causes, and 7 intermediate consequences that can cause faults in the stator of the induction motor. The causes are: unbalanced magnetic pull, winding motion, unbalanced power supply, overloading, rotor strike, crushing of the turn by the carcass, thermal cycling, an abrasion of the insulation, laminations slack slot wedges, shock or vibration, damage to insulation during insertion of windings, frequent starting, extreme temperature, extreme humidity, overvoltage, slacking of coils, and slack joints. The consequences are: vibration, stator carcass fault, insulation fault, stator turn-turn faults, stator phase-phase faults, displacement of conductors, and connectors failure.

4. Model application

The induction motor studied in this article is three-phase. The technical characteristics of this device are given by the nameplate of *Table 1*. The role of the induction machine is very important and its availability is essential. It is a motor used by a company involved in the field of petroleum engineering.

Table 1: The nameplate of the motor.

380 volts three-phase induction motor	
Type	M3KP280SMB4B3
Power	90 kW
Rated load current	166 A
Speed	1491 rot/min
Frequency	50Hz
COS Φ	0.87
Insulation Class	F
Tmax	40°C
3 PHASE	Delta connecte
The diameter of the end of the motor shaft	75mm.
Motor shaft length	140mm

In order to exploit the experience feedback and to obtain a permanent update of the predictive maintenance plan of the induction motor, the priorities will be defined according to the determination of the most likely faults on the stator of the machine. For reliable prediction of faults, the starting information (model inputs) must be accurate. A priori probabilities given in *Table 2*. are defined on the basis of the factual information, on the one hand, and the more or less complex measurement results recorded in the historical files, on the other hand.

Table 2: The inputs of the model or a priori probabilities.

Causes	Code	A priori probabilities
Unbalanced magnetic pull	111	0.088
Winding motion	112	0.028
Unbalanced power supply	113	0.1
Over loading	114	0.001
Rotor strike	115	0.001
Crushing of the turn by the carcass	116	0.023
Thermal cycling	117	0.001
An abrasion of the insulation	118	0.079
Laminations slack slot wedges	119	0.001
Shock or vibration	120	0.045
Damage to insulation during insertion of windings	121	0.001
Frequent starting	122	0.075
Extreme temperature	123	0.001
Extreme Humidity	124	0.045
Overvoltage	125	0.001
Slacking of coils	126	0.001
Slack joints	127	0.001

In the Bayesian approach used in this work, the relation between causes and effects is given by a conditional probability table. Example of the conditional probability table of the consequence 17 which represents Connectors Failure is given by *Table 3*.

Table 3: Conditional probability table for variable "Connectors Failure".

	120	True		False	
	127	True	False	True	False
17	True	1	1	1	0
	False	0	0	0	1

It is possible to update information by inference in the Bayesian network of *Fig. 1*. The a posteriori probabilities computed from the Bayesian network are given in *Table 4*.

An example of calculation is given for the variable "Connectors Failure" as follows:

P (17= True) =
P (17= True/120= True, 127= True) × P (120= True) × P (127= True) +
P (17= True/120= True, 127= False) × P (120= True) × P (127= False) +
P (17= True/120= False, 127= True) × P (120= False) × P (127= True) +
P (17= True/120= False, 127= False) × P (120= False) × P (127= False)

P (17= True) = (1 × 0.045 × 0.001) + (1 × 0.045 × 0.999) + (1 × 0.955× 0.001) + (0 × 0.955 × 0.999)

P (17= True) = 0.000045 + 0.044955 + 0.000955 + 0 = **0.045955**

Table 4: The outputs of the model or a posteriori probabilities.

Element	Fault	Code	A posteriori probabilities
Stator		1	0,39925971
	Vibration	11	0,20377724
	Stator carcass fault	12	0,14239256
	Insulation fault	13	0,11759662
	Stator turn-turn faults	14	0,089798138
	Stator phase-phase faults	15	0,1017991
	Displacement of conductors	16	0,116625
	Connectors Failure	17	0,045955

From these a posteriori probabilities, it is possible to make decisions on the corrective actions to be taken in a certain environment. These diagnostic results also provide the ability to organize actions in order of priority. It should be noted that the probability of having a defect in the stator is 0.39%, which is significant and the main fault in descending order are respectively: Vibration, Stator carcass fault, Insulation fault, Displacement of conductors, Stator phase-phase faults, Stator turn-turn faults, and finally Connectors Failure.

5. Conclusion

In this work a Bayesian network model has been introduced as a mean to enable maintenance staff to assess the probability of faults and the priorities of corrective actions. By this, the company can consider a first step to incorporate an Information System into their supervision system and thus actively contribute to a reliable monitoring system. The integration of the developed Bayesian information system might have a significant impact on the existing supervision system and might thus lead to increase the availability of vital machines. Also, the integration of the Bayesian information system minimizes the costs related to accidental damages and other inconveniences caused by these damages. This paper also shows a concept evolution for predictive maintenance. In addition to decision making support, it is possible to predict and anticipate faults rather than real-time detection. It is found that faults could be identified correctly and decisions could be made with certainty.

The model structure is standard for all induction motors. The parameters are specific for each machine. However, a weighting coefficient is necessary for the definition of intervention priorities and in order to make the presented approach more reliable. This coefficient must take into consideration the criticality of the machine. A FMECA (Failure Mode Effects and Criticality Analysis) study can be used to define this coefficient.

We are going to address this approach in a future paper which will demonstrate the usefulness of the Bayesian methodology in rotor fault prediction of vital induction motors. Such an extension of this research is important for ensuring adequate assessment of the probability of each fault, whilst taking into account the influence of other monitoring parameter on the a posteriori probability evaluation.

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