Experiences concerning the application of electric machines steady state models for diagnostic purposes

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Abstract. In this paper, the application of steady state models of electric machines for detecting and tracking incipient faults is reported. After highlighting the simplicity and feasibility of these methods, two examples are explained: detecting inter-turn stator windings short circuits in induction motors and detecting this kind of fault, but at synchronous generators excitation windings. In the last case, the practical difficulties for fulfilling the necessary tests, advise to employ Artificial Neural Networks. The successful application of this emergent technology is demonstrated by means of a case study.

1 Introduction

Electric machines are one of the most important components of all kinds of industrial plants. Currently, all the electricity that feeds these plants is produced in electric generators and more than 60% of the electric power consumed by them is by means of electric motors.

It is evident then, the importance of keeping these machines operating in a reliable and efficient way and the necessity of reducing to a minimum its outages that are very harmful from the economical point of view.

In order to achieve these goals, it is essential to count on a predictive maintenance system based upon a continuous tracking of any incipient fault. This system makes it possible to take out the machine when a maintenance period is scheduled or, in the worse case, without any surprise [1].

The main faults that occur in an electric machines are, firstly, the mechanical ones such that rotor eccentricities or misalignment and bearings problems, as follows, the insulation

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failures that causes inter-turn short-circuits and finally the presence of broken rotor bars in squirrel cage induction motors or in synchronous generators damper winding [2] [3].

One of the most important types of method for detecting motor faults is the *Frequency Domain* that relies on a spectral frequency analysis of the stator current, the rotor vibration amplitudes, the axial flux or the machine electromagnetic torque [1-5]. Another type of method is the *Model Based*, which compares the actual behaviour of the machine with its healthy performance based on its models [1] [2] [6-14].

This paper addresses the principal aspects of this kind of method applied to electrical machines, and explains some author's experiences on its applications.

2 Electric machines models for diagnostic

The rotating electrical machines are electromechanical energy conversion devices that convert electric energy to mechanical energy or vice versa. This process is characterized for the existence of two well defined and different states or modes of operation: the *Steady State* and the *Dynamic or Transient State* [15] [16] [17].

At the steady state, the principal variables of the machine remain constant. The most important performance variables of the machine in this state are the current (rotor, stator or both), the speed, the active and reactive power consumption and the power factor. These variables are greatly influenced by the existence of any fault at the mechanical or at the electric system. For example, a damage bearing increases the current and the active power consumption, the presence of inter-turn short circuit in the rotor of a synchronous generator increases its excitation current for delivering the same active and reactive power to the mains and so on.

On the other hand, the transient or dynamic state occurs when the machine is transitioning between two steady states or is submitted to a mechanical or electric disturbance. The more important variables to be analyzed in this case are the currents, the speed and the electromagnetic torque as a function of time. The dynamic performance is also affected by a fault, generally, the transient phenomena are delayed and the oscillatory behaviour is different.

This permit to state a *Normal Operation Model,* this is the model of a "healthy machine", and comparing it with the actual machine performance (steady or transient) is possible to detect the presence of a failure and its level or depth.

As it is well known, the first stage in establishing a model is to identify adequately its parameters. Because of that, another kind of motor method for diagnostic purposes is the so called *Parameters Detection Method* since a failure situation always changes some machine parameter [2] [18-21].

Generally, it is more difficult to identify and obtain a dynamic model than a steady state model, because of that, this paper concentrates in this kind of models reporting some author's experiences. First, a method to detect incipient faults at stator winding induction motor is treated and finally a method to detect excitation winding failures in a synchronous generator applying Artificial Neural Networks (ANN) is reported.

3 Steady state models for failure diagnostic in induction motor stator

This method is based upon the well known induction motor equivalent circuit shown in Fig. 1. With this model, after the parameter identification, it is possible to carry out the characteristics of the motor. This characteristic expresses that, in a healthy motor, for any load torque, there will be a specific speed of rotation, current and power factor.

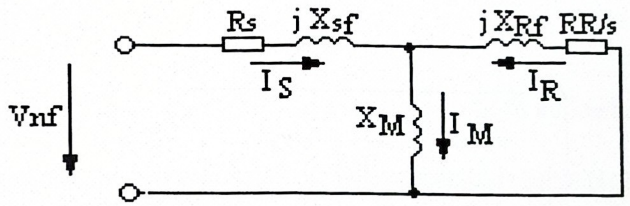


Fig 1. Induction motor equivalent circuit for a healthy motor

The parameters of this model are:

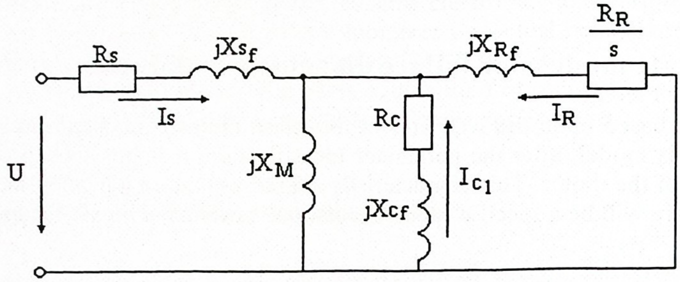
- R_S, the stator winding resistance per phase
- X_{Sf} and X_{Rf}, the leakage reactance of stator winding and rotor winding per phase.
- RR, the rotor winding resistance per phase and
- X_M, the magnetizing reactance

These parameters are identified with the no load test, the blocking rotor test at variable frequency and the measurement of the stator resistance and its temperature correction [22]. Due to the skin effect, the rotor resistance and leakage reactance are function of the slip, the corresponding equations are:

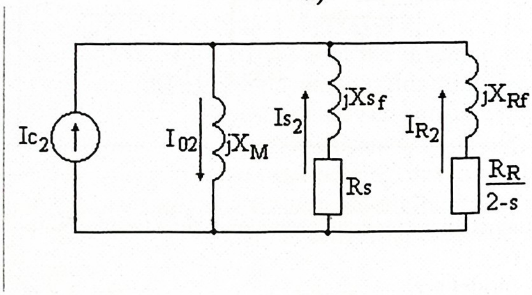
$$RR = K_1 + K_2.\sqrt{s}$$
$$X_{Rf} = K_3 + \frac{K_4}{\sqrt{s}} \qquad (1)$$

The parameters of these equations are identified utilizing the blocking rotor test at variable frequency. On the other hand, if inter-turn short-circuits are present, these short circuited turns can be considered as a new closed winding similar to the single phase induction motor. The current that circulates through this winding creates a pulsating flux that can be decomposed into two components: a positive sequence and a negative sequence, that are equal in value and speed of rotation but one rotates in same direction of motor rotation and another in opposite direction

This situation translated to the equivalent circuit model looks as depicted in Fig. 2.



a)



b)

Fig 2. Induction motor equivalent circuit for a motor with short circuited turns. a) Positive sequence b) Negative sequence.

I_{C1} and I_{C2} are the positive and negative current components, and the parameters of the new branch in parallel with the magnetizing reactance are:

$$R_c = \frac{R_s}{\alpha}$$
$$X_{cf} = \frac{X_{sf}}{\alpha} \qquad (2)$$

In this equation, α is the percent of turns in short circuit. A MATLAB program was elaborated, such that, varying the slip from 1 to 0, calculates the current, the speed, the power factor and the torque with and without short circuited turns and finally, plots the characteristics for both cases. The results of current and power factor, applied to a 6 kV, 1

MW, 8 poles, 60 Hz motor (belonging to a feed water pump of a thermal power plant), are shown in Fig. 3 and Fig. 4.

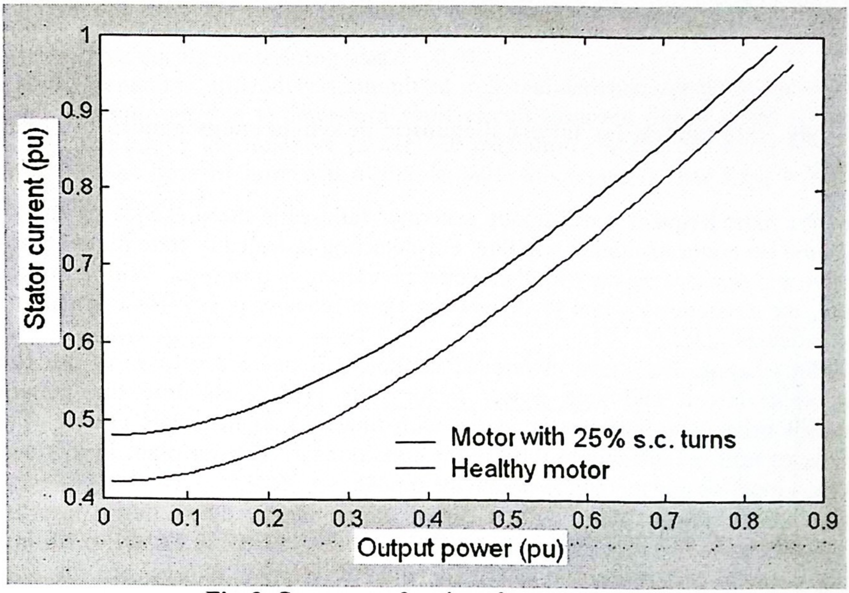


Fig. 3. Current as a function of an output power

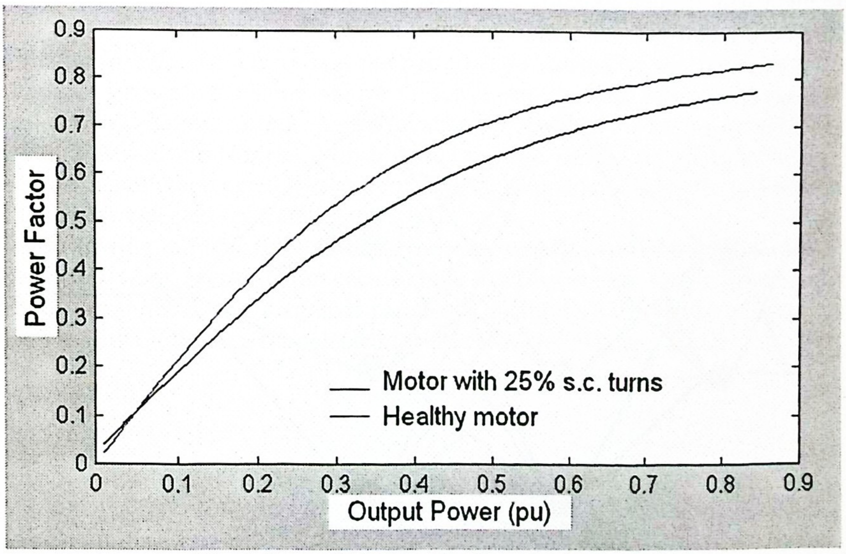


Fig. 4. Power factor as a function of output power

Since is easy to realize analyzing the figures, by measuring the differences between the motor and the model current and power factor, it is possible to detect and incipient fault and track its development because these differences increases with the depth of the failure.

4 Steady state models for failure diagnostic in synchronous generators excitation winding

One of the most frequent synchronous generator failures is the presence of short circuit turns in the generator excitation winding. For detecting it, a steady state model that relates the active and reactive power with the excitation current is proposed. With a faulted rotor winding, the excitation current to deliver the same reactive power for a constant active power increases [23].

In order to apply the above mentioned method it is necessary to carry out the open circuit, short circuit and zero power factor tests [17], each time the generator is maintained because its parameters varies with time due to materials ageing. The zero power factor tests are difficult to fulfil in the conditions of a power plant so it is advisable to devise a more simple method to obtain the model.

The solution of this problem could be carried out employing a Function Approximation. As it is well known, the best choice is an Artificial Neural Network (ANN) profiting by its learning capacity and robustness [24]. The training patterns chosen are the values of active power P and reactive power Q corresponding to a specific excitation current I_{exc}. This method was applied to a 13, 2 kV, 60 MW, turbo generator using the information collected during two years in Antonio Maceo Power Plant located at Havana, Cuba [25] [26].

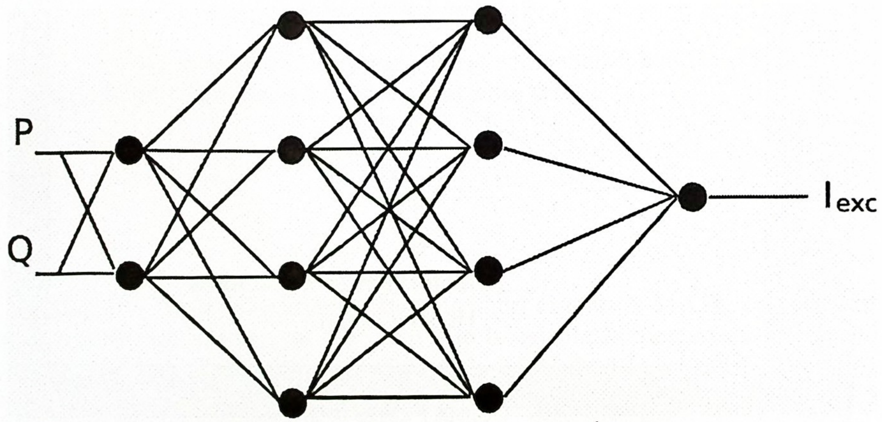


Fig. 5. Artificial neural network topology

The Levenberg Marquadt backpropagation algorithm was utilized. By means of the trail and error method the network topology and the values of the training coefficient η and momentum M were determined. In this case, a network with two hidden layers of five neuron (see Fig 5) and a value of $\eta = 0.2$ and $M = 0.9$ was the best choice. The maximum permissible error during the training was $\varepsilon = 0.01$.

The turbo generator utilized was submitted to a maintenance outage at the middle of 1996 and a shutdown due to inter-turn short circuit occurred during 1998 summer. A report with the active and reactive power, the excitation current, the stator current and excitation voltage hour by hour was available. With this report, a Data Base at Microsoft Access was prepared.

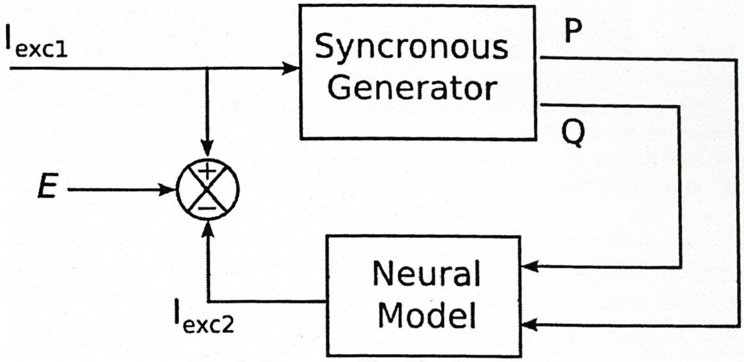


Fig. 6. Generator Identification Scheme

Due to the instruments errors and the perturbation caused by the variation of voltage and frequency, not all the same values of active and reactive power correspond to the same value of excitation current. A statistical and probabilistic analysis demonstrated that the values followed the Normal Probabilistic Law was carried out in order to justify the utilization of an average excitation current. The data appertaining to the first months after the outage were selected for training the ANN.

At the following months, the trained ANN was compared with the data taken each hour and the errors were averaged for each month. This value was called *Monthly Average Error* and was utilized as a diagnosis parameter. In figure 7 the values of this parameter for the 14 months following the selected for the ANN training, are shown.

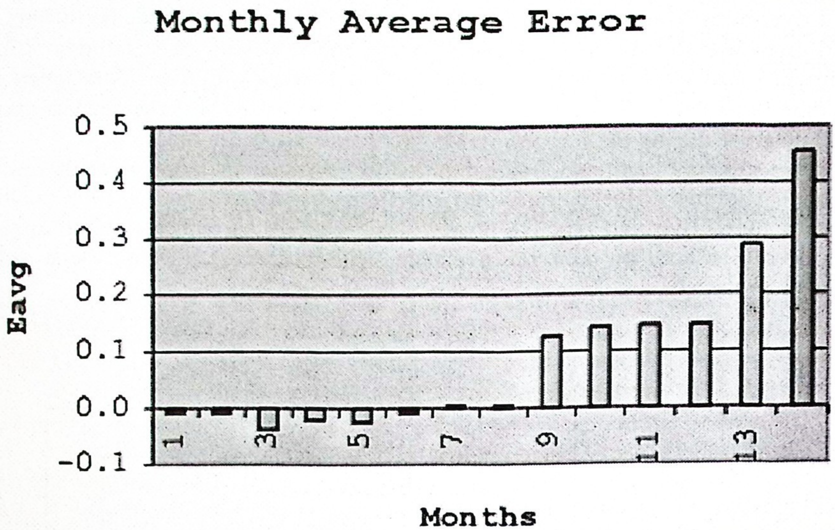


Fig. 7. Monthly average error.

Since is easy to see, before the 9th month, the errors were very small and oscillating around zero. This means that there was no appreciable inter-turn short-circuits. At the following four months, the errors are positive, their values greater than 0.1 and almost constant. At the 13th month, the error is more than doubled and at the 14th month reached a value equals to 0.45. At this time, the generator was stopped, the rotor was extracted and a great deal of the excitation winding was with inter-turn short circuit.

6 Conclusions

By means of these two examples, it is easy to realize the advantages of applying steady state models of electric machines to the diagnostic of incipient faults in order to adopt a predictive maintenance policy.

In both cases, well-known machines characteristics were utilized and, to determine them, only are necessary to fulfil conventional tests and when it is difficult or impossible to identify the needed parameters, some Artificial Intelligence (AI) Technique could be applied successfully.

These methods could be applied to the detection of another electric machine failure situation such as induction motor broken rotor bars, machine mechanical damage and other related faults.

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