ANN Approach for the Detection of Winding Insulation Condition in the Single Phase Induction Motor

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Abstract – This paper presents an ANN approach for the detection of winding insulation condition in the single-phase induction motor. The dynamics of the induction motor is described and it is shown that the winding insulation condition is a nonlinear function of motor current, speed and winding temperature. There are different methods of detection of winding insulation level with their own merits and demerits. A neural network is trained with real time data generated in laboratory. Detailed simulation results using MATLAB are presented. The testing results of the network are also given. The training and testing results are compared and it is found that the two results have consistency.

Keywords: Induction motor, artificial neural network (ANN), Insulation condition, Stator winding, nonlinear mapping.

I. INTRODUCTION

The use of small and medium size induction motors in industry is extensive and continuous. These machines are exposed to wide variety of environments and conditions. The various causes for weakening of insulation of these electrical machines are: (i) Aging, (ii) Switching surge, (iii) Heat, (iv) Contamination by oil, (v) Incipient faults, (vi) Damage during installation, etc. A turn-to-turn short circuit of winding would cause decrease in equivalent turns of the winding of the machine. It results in to rise in input current to winding. This causes the increased heating in the core due to additional I^2R losses and drop in speed. The increased heating will cause a corresponding temperature rise around the winding, there by decreasing the life expectancy of the winding insulation. This winding insulation failure will cause additional shorted turns, further rise in temperature, and a further increase in the rate of deterioration of winding insulation. If left unchecked, this process will cause eventual destruction of the relative winding and render the machine in operate [1].

The paper proposes a neural network based insulation level detector for small and medium size electrical machines. This Artificial Neural Network (ANN) based detector avoids the problem associated with traditional schemes such as continuous online monitoring by experts, parameter estimation approach, etc. In the present technique more readily available information such as input current, speed of motor, and temperature of winding are used for decision making, [2]-[3].

Neural network toolbox in MATLAB environment is used to optimize the network. The data required to train the neural network is generated real time in the laboratory on specially designed single phase, squirrel cage 1.25 kW induction motor. The stator winding turns are brought out for the shortening in steps, which gives the effect of shortening of motor winding turns. This result of evaluation indicates that the neural network based insulation level detector predicts the winding condition of the motor to a satisfactory level of accuracy.

This ANN insulation level detection of winding methodology is not only limited to single phase, squirrel cage induction motor but can also be applied to many other types of machines with the appropriate modifications.

II. DYNAMICS OF INDUCTION MOTOR AND FORMULATION OF PROBLEM

The stator winding, the most vulnerable component of the squirrel cage type ac induction motor is subject to shorted turns caused by deterioration and failure of stator winding insulation due to excessive temperature, age or vibration. In this paper, the motor is assumed to be operating at steady state with a known load torque condition. One common motor fault i.e. turn to turn short circuit is studied. Therefore, the main or running winding of the machine is only considered for the steady state performance [4].

The flux linkage in the stator winding of the motor is given as, \[ \lambda_s = [\lambda_{ms} \lambda_{ar}]^T \] and in the rotor is given as, \[ \lambda_r = [\lambda_{ar} \lambda_{sr}]^T \] Where the subscripts m and a represents the main and auxiliary winding of the machine while the subscripts s and r represents the stator and rotor of the machine shown in Fig. 1. The derivative of the flux linkages in the stator is \( \dot{\lambda}_s = i_s R_s - v_s \) and in the rotor is \( \dot{\lambda}_r = i_r R_r - v_r \).

Where, \( R_s = \begin{bmatrix} r_{ms} & 0 \\ 0 & r_{ar} \end{bmatrix} \) and \( R_r = \begin{bmatrix} r_{mr} & 0 \\ 0 & r_{wr} \end{bmatrix} \)

The vector \( i_s = [i_{ms} \ i_{ar}]^T \) represents the stator winding currents, \( i_r = [i_{mr} \ i_{wr}]^T \) is the rotor winding currents, \( v_s = [v_{ms} \ v_{ar}]^T \) the stator winding voltages, and, \( v_r = [v_{mr} \ v_{wr}]^T \) is the rotor winding voltages which are zero for the squirrel cage rotor motor. At steady state and/or small perturbation conditions, the flux linkages can be approximated by a linear relationship with respect to currents, expressed as,

\[
\begin{bmatrix}
\lambda_s \\
\lambda_r
\end{bmatrix} =
\begin{bmatrix}
L_s & M \\
M & L_r
\end{bmatrix}
\begin{bmatrix}
i_s \\
i_r
\end{bmatrix}
\]
where \( L_s \) is the stator inductance, \( L_r \) is the rotor inductance and \( M \) is the mutual inductance between stator and rotor with respect to the corresponding rotor position. From the fundamental electromagnetic theory, the flux linkage of winding is a function of number of equivalent turns of the winding. The equivalent turns for both main and auxiliary winding are expressed by a vector \( N_e = [N_{sN}, N_{aN}]^T \) for the stator winding and \( N_e = [N_{rN}, N_{aN}]^T \) for the rotor winding. The motor parameters, such as winding resistance and inductance, will change due to changing values of equivalent turns. The same motor structure with different values of equivalent turns will yield a different performance. For a squirrel cage induction motor, the rotor is robust, and \( N_r \) is generally assumed to be constant, while \( N_s \) will change value due to deterioration in the stator winding. When \( N_s \) is variable, \( i_s, L_s, M \) become function of \( N_s \). This can be expressed as,

\[
i_s = f_i(N_s) \tag{1}
\]

The electrical torque of the motor, \( T_e \), is a function of motor parameters and given as,

\[
T_e = i^* \frac{\partial}{\partial \theta} M i,
\]

Thus, \( T_e \) is a function of \( N_s \). The equation of motion for the motor can be written as,

\[
T_e(N_s) = J \dot{\omega} + B \omega + T_l
\]

where \( \dot{\omega} \) is the time derivative of rotor speed, \( \omega \), \( J \) is the inertia of the rotor and connected load, \( B \) is the damping coefficient of the motor, and \( T_l \) is the load torque, which is assumed to be known. From this equation, it is clear that the rotor speed is also a function of \( N_s \) and can be mentioned as,

\[
\omega = f_\omega(N_s) \tag{2}
\]

A decrease in winding equivalent turns will increase stator-winding current; thus causing increased heating due to additional I^2R losses. The increased heating will cause a corresponding temperature rise in the stator, there by decreasing the life expectancy of the stator winding insulation. Stator winding insulation failure will cause additional shorted turns, further increase in temperature, and a further increase in the rate of deterioration of the stator winding insulation. From this, the relation exists between the stator equivalent number of turns, stator current and temperature of winding. Thus, the stator equivalent turns \( N_s \) become the function of temperature, \( \tau \). This can be expressed as,

\[
\tau = f_\tau(N_s) \tag{3}
\]

Under steady-state condition, the auxiliary winding is disconnected and the main winding of the stator is remaining in the operation. Therefore, the stator main winding equivalent turns \( N_s \) is used to replace \( N_{sN} \). Thus, for simplicity of notation, \( N \) is used to replace \( N_s \), where as \( N_{aN} \) will be ignored.

Let, \( I \) be the rms values of \( i_{ms} \), \( \omega \) be the average speed of rotor and \( r \) be temperature of motor winding. By combining and manipulating, equations (1), (2) and (3) with stator main equivalent winding equivalent turns, \( N \) as variable, the steady-state current, \( I \), rotor speed, \( \omega \) and temperature of winding, \( \tau \) can be represented by a set of nonlinear algebraic equations, \( f = [f_1, f_2, f_3] \), which are functions of main winding equivalent turns, \( N \). Therefore, the nonlinear equation can be given as,

\[
f(I, \omega, \tau, N) = 0 \tag{4}
\]

This equation suggest that indications of the condition of the winding can be obtained from the measurements of the stator current \( I \), rotor speed \( \omega \) and the stator winding temperature \( \tau \). These parameters \( I, \omega, \tau \) are found to be very sensitive to the changing conditions of the stator winding. More over, all these parameters are easily accessible and can be measured accurately. From the induction motor dynamics analysis given in equation (4), there exist a relationship,

\[
\mu_1: (I, \omega, \tau) \rightarrow (N)
\]

which is highly nonlinear due to the non linearities present in the induction motor. An accurate mathematical model of \( \mu_1 \) is difficult to obtain. As stated before, the condition of the main winding is reflected in the numerical values of the main winding equivalent turns, \( N \). For our application, the values of \( N \) which quantitatively describes the motor are quantized into three conditions (good, fair and bad) to yield \( N_c \) which qualitatively describes the motor condition. This qualitative description of the motor’s condition is more suitable for the detection of winding insulation condition [5]. A second relationship \( \mu_2 \) is used to denote the relationship from quantitative description \( N \) to qualitative description \( N_c \) is given below.

\[
\mu_2: (N) \rightarrow (N_c)
\]

As a result, the relationship \( \mu \) from \( (I, \omega, \tau) \) to \( N_c \) can be written as composition of \( \mu_1 \) and \( \mu_2 \). Therefore, the relationship \( \mu \) is expressed as,

\[
\mu: \mu_1 \circ \mu_2 : (I, \omega, \tau) \rightarrow (N_c)
\]

Mapping \( \mu \) is very complex due to high degree of nonlinearity of induction motor dynamics and of descriztization involved; thus obtaining an accurate analytical expression for \( \mu \) for a given induction motor is rather difficult. However this complexity can be avoided by training a neural network to learn the desired mapping of \( \mu \) based solely on input-output examples that can be obtain accurately.
Therefore, for the detection of winding insulation condition (inter turn insulation failure), the inputs to the neural network detector are stator main winding input current, $I$; rotor speed, $\omega$; and stator winding temperature, $r$, and the desired network’s output is $N_c$, i.e. the qualitative conditions of stator inter-turn winding insulation. Although, the activation of the output node is a continuous function, the training data sets present discrete target values of $1$, $0.67$ and $0.33$ to the neural network, which correspond to relative conditions of good, fair and bad respectively [6]-[7].

III. LABORATORY SETUP FOR DATA GENERATION

Forty training and testing data patterns have been generated according to uniform distribution over the operating conditions under consideration on the laboratory test stand shown in Fig. 2. The laboratory test stand was configured so that possible stator winding condition was represented in the training data. The laboratory test stand configured with 1.25 kW single-phase squirrel cage induction motor and it is coupled with 1.5 kW dc machine. There is two purpose of this dc machine. First, it acts as a generator and supplies a constant current load and there by provides a constant torque load to the shaft of the ac single-phase squirrel cage induction motor, which is under performance. Second, by increasing the load on generator up to its full capacity, the generator also provides a variable torque load corresponding to additional loading. This cause excess loading on motor shaft and the motor draws more current. Moreover, to create the effect of inter-turn insulation failure, the stator main winding is shorted by taking out 10% of its turns.

The input current to the motor is sensed by current transducer, the speed of rotor is sensed by tacho-generator and the temperature of the main winding of motor is sensed by temperature sensor. Initially, the motor is run at its full capacity with the appropriate generator loading. All the normal parameters are recorded. Further the stator winding turns have been shorted in steps. This is performed to create the effect like inter-turn insulation failure or short circuit. As the stator main winding turns were shorted in steps, the input current increases, thus the winding temperature rises and correspondingly the speed of rotor will alter. All these parameters were recorded with motor running on full load. The same procedure is followed for different load condition. With all these measurable parameters, i.e. stator main winding input current, $I$; rotor speed, $\omega$; and stator winding temperature, $r$, the relative insulation level or condition of stator main winding, $N_c$ was evaluated using thermal and efficiency criteria.

IV. ANN STRUCTURE FOR THE DETECTION OF WINDING INSULATION CONDITION

An ANN is composed of interconnected units (neurons) with a deterministic nonlinear activation function as shown in Fig. 3. The neural network is trained by adjusting the numerical values of the weights or network interconnections between each unit. Once the neural network is appropriately trained the network weights will contain the non-linearity of the desired mapping, so that the difficulties of mathematical modeling can be avoided [8].

The neural network structure has three layers of neurons. The first layer is known as input layer and consists of three neurons (inputs) i.e. current, temperature and speed. The second layer is the hidden layer and in our case, this layer has ten neurons. The output layer contains one neuron and it represents the insulation condition the motor winding. Sigmoid activation function is used for input and hidden layer. The momentum and biases of number are considered to design the network respectively.

For training of network back propagation algorithm is used. The values of training data are taken in p.u. system so that it is applicable for wide range of small motors. The activation function used for the neurons is sigmoid function.

After the network training, it can be used for decision making for the detection of motor winding insulation condition. In simple words, we can say that a trained network is like an expert, which can take decision for the motor winding insulation or inter-turn short circuit fault condition. The network parameters have been selected by trial and error. The ANN was found to provide good performance in the detection of stator winding hidden layer and one output.

V. SIMULATION AND RESULTS

The performance of this trained neural network is shown in Fig. 4-6. In Fig. 4, the error versus epochs is shown. The network is trained within 54 epochs and met the goal of error of 0.0001. The network performance error is 0.9796 $10^{-5}$. The accuracy of the network is as high as 99.28% is achieved.
The ANN is trained with the 34 patterns. The Fig. 5 shows the comparison between target and trained output. In Fig. 5, the curve with solid line shows the target, while the dotted line indicates the trained output after the network training. It is seen from the figure that target and the trained output are approximately same.

The testing of the network is performed with 6 patterns, which is different from the input data. The trained output is indicated by dotted line and the tested output is indicated by the circle points as shown in Fig. 6. It is found that the trained and tested output results are closely matching.

VI. CONCLUSIONS

The objective of this paper is to develop a methodology for the detection of winding insulation condition of single phase, squirrel cage induction motor. The main advantage of this technique is that it avoids the complicated mathematical modeling. The performance of the network is judged with the real time data. It is seen from the result that this methodology used to detect winding insulation condition works excellently.

VII. REFERENCES