

# Diagnostic of three-phase induction machine based on neural networks

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**Abstract.** Motors are essential components in most of today's manufacturing and production industries. Condition monitoring of electrical machines is a very important factor in achieving efficient operation of industrial processes. The rigorous requirements of modern electrical machines also necessitate condition monitoring systems, which enable the continuous monitoring of the system under all operations conditions. In this paper, characteristic patterns of well-operation three-phase squirrel cage induction machine are extracted from simulation, then varying some parameters, we can observe the behavior of induction machine to detect malfunctions.

## 1 Introduction

The induction machine is used in a wide of applications as means of converting electric power to mechanical work. It is without doubt the workhorse of the electric power industry. Pump and steel mill are applications of large multiphase induction motors, on a smaller scale, single-phase induction motors are widely used in household appliances as well as in hand and bench tools.

Three-phase squirrel cage induction motors are essential components in most of today's manufacturing and production industries. Safety, reliability, efficiency, and performance are some of the major concerns and needs for motor systems applications [1] [8].

Section two presents the three-phase induction machine mathematical model and justifies the mathematical transformation from *abc* variables to *dq* variables. Section three shows simulations of different ratings induction machine, section four deals with well-operation patters conformation and artificial network structure finally, section five is the conclusion.

## 2 Induction motor model

The idealized circuit model of a three-phase induction machine is described by six first-order differential equations, one for each winding, three of stator and

three of rotor. Although the rotor is a squirrel cage rotor, for simulation effects, is considered as winding rotor. These differential equations are coupled to one another through the mutual inductances between windings. In particular, the stator-to-rotor coupling terms are a function of rotor position, thus, when rotor rotates, these coupling terms vary with time [2].

Changes of variables are used in the analysis of ac machines to eliminate time-varying inductances, mathematical transformations as  $dq$  can facilitate the computation of transient solution of the induction model machine by transforming the differential equations with time-varying inductances to differential equations with constant inductances, moreover, this transformation reduces to four the number of electrical energy storage state variables, that is, only four first-order differential equations are needed instead six.

The transformation equation from  $abc$  variables to  $dq$  variables is given by

$$\begin{bmatrix} f_q \\ f_d \\ f_0 \end{bmatrix} = [\mathbf{T}_{qd0}(\theta)] \begin{bmatrix} f_a \\ f_b \\ f_c \end{bmatrix} \quad (1)$$

where the variable  $f$  can be phase voltages, currents, or flux linkages of the machine. The  $dq0$  transformation matrix,  $[\mathbf{T}_{qd0}(\theta)]$  is

$$[\mathbf{T}_{qd0}(\theta)] = \frac{2}{3} \begin{bmatrix} \cos \theta & \cos \left( \theta - \frac{2\pi}{3} \right) & \cos \left( \theta + \frac{2\pi}{3} \right) \\ \sin \theta & \sin \left( \theta - \frac{2\pi}{3} \right) & \sin \left( \theta + \frac{2\pi}{3} \right) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad (2)$$

and its inverse is

$$[\mathbf{T}_{qd0}(\theta)]^{-1} = \begin{bmatrix} \cos \theta & \sin \theta & 1 \\ \cos \left( \theta - \frac{2\pi}{3} \right) & \sin \left( \theta - \frac{2\pi}{3} \right) & 1 \\ \cos \left( \theta + \frac{2\pi}{3} \right) & \sin \left( \theta + \frac{2\pi}{3} \right) & 1 \end{bmatrix} \quad (3)$$

One of the most popular induction motor model is Krause's model detailed in [3], the equations in flux linkage are as follows:

$$\dot{\psi}_{qs} = \omega_b \left[ v_{qs} - \frac{\omega}{\omega_b} \psi_{ds} + \frac{r_s}{x_{ls}} (\psi_{mq} - \psi_{qs}) \right] \quad (4)$$

$$\dot{\psi}_{ds} = \omega_b \left[ v_{ds} - \frac{\omega}{\omega_b} \psi_{qs} + \frac{r_s}{x_{ls}} (\psi_{md} - \psi_{ds}) \right] \quad (5)$$

$$\dot{\psi}_{qr} = \omega_b \left[ v_{qr} - \frac{\omega - \omega_r}{\omega_b} \psi_{dr} + \frac{r_r}{x_{lr}} (\psi_{mq} - \psi_{qr}) \right] \quad (6)$$

$$\dot{\psi}_{dr} = \omega_b \left[ v_{dr} - \frac{\omega - \omega_r}{\omega_b} \psi_{qr} + \frac{r_r}{x_{lr}} (\psi_{md} - \psi_{dr}) \right] \quad (7)$$



$$\dot{\omega}_r = \left( \frac{P}{2J} \right) (T_e - T_L) \quad (8)$$

$$\psi_{mq} = x_M \left( \frac{\psi_{qs}}{x_{ls}} + \frac{\psi_{qr}}{x_{lr}} \right) \quad (9)$$

$$\psi_{md} = x_M \left( \frac{\psi_{ds}}{x_{ls}} + \frac{\psi_{dr}}{x_{lr}} \right) \quad (10)$$

$$\frac{1}{x_M} = \frac{1}{x_m} + \frac{1}{x_{ls}} + \frac{1}{x_{lr}} \quad (11)$$

where:

- $d$  : direct axis
- $q$  : quadrature axis
- $s$  : stator variable
- $r$  : rotor variable
- $\psi_{ij}$  : flux linkage
- $v_{qs}, v_{ds}$  :  $q$  and  $d$ -axis stator voltages
- $v_{qr}, v_{dr}$  :  $q$  and  $d$ -axis rotor voltages
- $\psi_{mq}, \psi_{md}$  :  $q$  and  $d$  magnetizing flux linkage
- $r_s, r_r$  : stator and rotor resistance
- $x_{ls}, x_{lr}$  : stator and rotor leakage reactance
- $P$  : number of poles
- $J$  : moment of inertia
- $T_e$  : electrical output torque
- $T_L$  : load torque
- $\omega_e$  : stator angular electrical frequency
- $\omega_b$  : motor angular electrical base frequency
- $\omega_r$  : rotor angular electrical speed

For a squirrel cage induction motor as in the case of this paper,  $v_{qr}$  and  $v_{dr}$  are set to zero.

The induction machine dynamic equivalent circuit is shown in Fig 1, note that  $E_{qx}$  and  $E_{dx}$  are the unique electrical energy storage elements. The figure shows too the current direction and voltage bias of the transformed variables.

### 3 Model simulation

We start from the premise that we have only a mathematical model that supposes of well-operation induction motor. From this point, the simulations are done to various rating machine with free acceleration, that is, no-load. Then, varying some parameters, for example, resistance, we can observe the behavior of induction machine and extract particular conclusions.

The Table 1 shows various types of induction motor parameters, each machine is a 4-pole, 60Hz, 1800 rpm (synchronous speed) and three phase induction motor. The parameters are expressed in ohms using the 60Hz value of the reactances, the voltage is rated rms line-to-line voltage, and  $J$  includes inertia of the

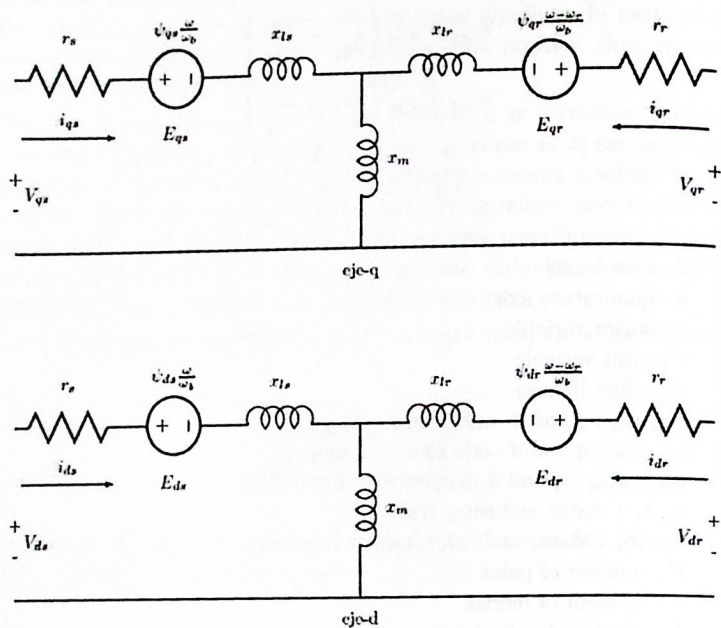


Fig. 1. Dynamic equivalent circuit of an induction machine

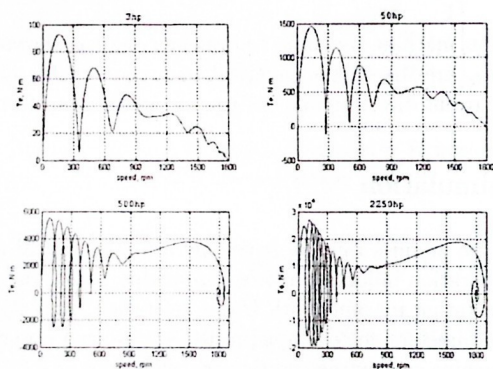


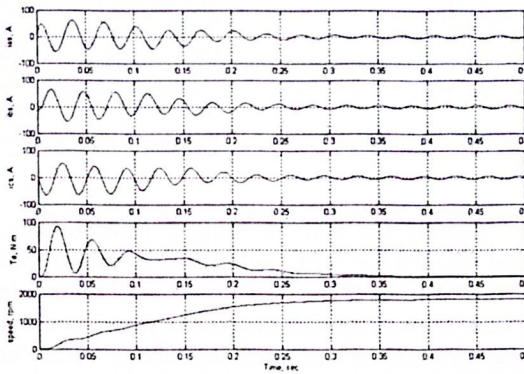
Fig. 2. Torque versus speed characteristics during free acceleration

load which is assumed to be equal to the inertia of the rotor. Rotor resistance and rotor leakage induction are referred to stator side [3] [4].

**Table 1.** Induction machine parameters

| Motor Rating<br>HP | Rating<br>V | $r_s$<br>$\Omega$ | $r_r$<br>$\Omega$ | $x_m$<br>$\Omega$ | $x_{ls}$<br>$\Omega$ | $x_{lr}$<br>$\Omega$ | $J$<br>$kg - m^2$ |
|--------------------|-------------|-------------------|-------------------|-------------------|----------------------|----------------------|-------------------|
| 3                  | 220         | 0.435             | 0.816             | 26.13             | 0.754                | 0.754                | 0.089             |
| 50                 | 460         | 0.087             | 0.228             | 13.08             | 0.302                | 0.302                | 1.662             |
| 500                | 2300        | 0.262             | 0.187             | 54.02             | 1.206                | 1.206                | 11.06             |
| 2250               | 2300        | 0.029             | 0.022             | 13.04             | 0.226                | 0.226                | 63.87             |

The differential equations that describes the induction machine were simulated on a computer using Matlab (like presented in [5]) with parameters of Table 1. The Fig. 2 shows the simulation reliability and depicts speed versus time characteristics during free acceleration (no load), Fig. 3 shows all machine variables of 3hp induction motor.



**Fig. 3.** Machine variables with no-load of 3hp induction machine

Because friction and windage losses are not taken into account, the machine accelerates to synchronous speed.

## 4 Characteristic patterns of operations

The characteristic patterns are conformed by nominal and dynamic variables. The nominal variables are manufacturer values, that is, horse power, line-to-line voltage, nominal current, revolutions per minute and number of poles; the dynamic variables can be extracted from simulation analysis or through physical measurements. Since non-invasively scheme proposed, we have suggested the



following signals and variables: peak current per phase ( $i_p$ ), steady current per phase ( $i_n$ ), time that each current reaches its steady value ( $t_n$ ) and, time that rotor speed reaches its steady value ( $t_s$ ).

Some malfunctions can be simulated varying machine parameters, for example, stator resistance affects motor efficiency, rotor resistance also affects motor efficiency but, had a profound effect on the shape torque-speed curve; increase the phase resistance of all coils simulates an increased temperature; inter-turn short circuit have a cumulative effect in decreasing the magneto motive force (MMF), as consequence the self-inductance and resistance of this phase winding changes, as does the mutual inductance between that phase and all others circuits in the machine; losses resulting from friction can be split up into Coulomb and Viscose friction, it can be simulated varying inertia parameter [7] [4] [6].

From above information, we can derive three kinds of situations: 1) motor efficiency, 2) winding performance and 3) friction problems. To simulate each of this situations we have modified certain parameters, the Table 2 show the condition types and the way of implementing.

Table 2. Condition types and its implementation

| Condition | Condition Type       | Simulation method                                        |
|-----------|----------------------|----------------------------------------------------------|
| 0         | Normal               | None                                                     |
| 1         | Motor efficiency     | Increase rotor and stator resistance                     |
| 2         | Windings performance | Decrease stator resistance and stator leakage inductance |
| 3         | Friction problems    | Increase value of inertia                                |

The Fig. 4 - 6 confront the well-operating simulation (solid line) with malfunction simulation (dashed line). The patterns to recognize malfunction or well-operating are extracted from these results and are grouped in sets to train a neural network. The Table 4 show some results from simulation data without and with parameters variations such indicated above. From these data, we can observe that the principal alterations have effect on speed curve with a displacement from well-operating original curve and, with transient current, that is, increase o decrease of its peak value.

## 5 Malfunction identification using neural networks

For identification, an artificial neural network (ANN) with three layers is adequate due to their powerful nonlinear function approximation [8] [9] [10]. The input neurons are determined by number of nominal and dynamic variables, while number of output neurons are determined by the number of situations, that is, only three neurons. Since all motors are 60Hz, 4-pole and 1800rpm, the neuron inputs are: 1) horse power, 2) line-to-line voltage, 3-5) peak current for each phase, 6) steady state current and 7) rotor establishment time. The behavior of output neurons for each condition is shown in Table 3.

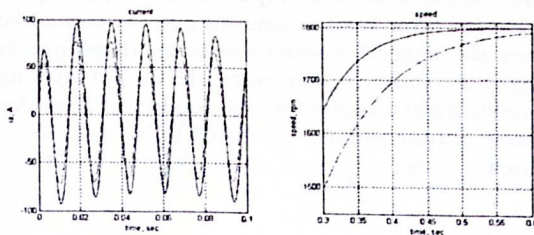


Fig. 4. Motor efficiency simulation for patterns extraction

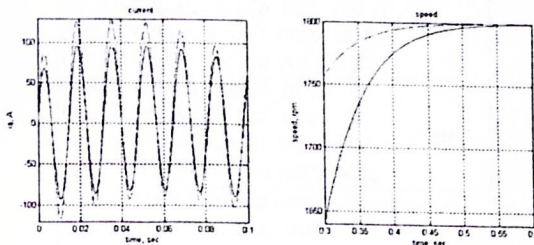


Fig. 5. Winding performance simulation for patterns extraction

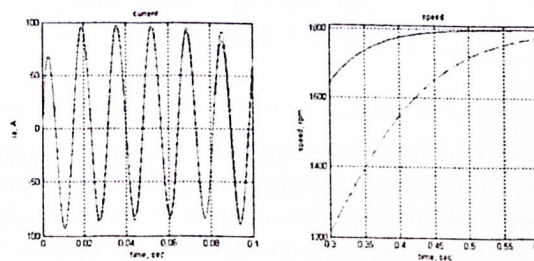


Fig. 6. Friction problems simulation for patterns extraction

Table 3. Training output samples

| Condition | Neuron output |          |          |
|-----------|---------------|----------|----------|
|           | Neuron 1      | Neuron 2 | Neuron 3 |
| Normal    | 0             | 0        | 0        |
| One       | 1             | 0        | 0        |
| Two       | 0             | 1        | 0        |
| Three     | 0             | 0        | 1        |



The neural network consist of an input layer, output layer and two hidden layers. The first hidden layer has ten neurons and the second layer six neurons. Both hidden layers use sigmoid transfer functions, these functions compress an infinite input range into a finite output range, the output layer use linear transfer function. The training input samples for each condition are conformed as in Table 4, while the training output samples are listed in Table 3. The Fig. 7 show the neural network architecture.

Table 4. Patterns extracted from simulating data

| Condition | hp   | volt | $i_{pb}$ | $i_n$  | $t_s$  |
|-----------|------|------|----------|--------|--------|
| Normal    | 3    | 220  | 102.83   | 6.6943 | 0.3915 |
|           | 50   | 220  | 674.20   | 28.097 | 0.5751 |
|           | 500  | 2300 | 1160.6   | 34.023 | 1.4945 |
|           | 2250 | 2300 | 6735.9   | 141.56 | 2.5369 |
| One       | 3    | 220  | 80.037   | 6.6935 | 0.3415 |
|           | 50   | 220  | 552.79   | 28.101 | 0.5312 |
|           | 500  | 2300 | 1049.4   | 34.004 | 1.005  |
|           | 2250 | 2300 | 6297.6   | 141.56 | 1.7035 |
| Two       | 3    | 220  | 130.07   | 6.7904 | 0.3205 |
|           | 50   | 220  | 552.79   | 28.101 | 0.5312 |
|           | 500  | 2300 | 1572.4   | 34.381 | 0.9897 |
|           | 2250 | 2300 | 9066.7   | 142.78 | 1.8453 |
| Three     | 3    | 220  | 102.98   | 6.6946 | 0.585  |
|           | 50   | 220  | 674.78   | 28.737 | 0.8531 |
|           | 500  | 2300 | 1160.7   | 34.005 | 2.059  |
|           | 2250 | 2300 | 6736.2   | 151.56 | 3.6299 |

The backpropagation algorithm used during training was resilient backpropagation. This algorithm is used to calculate derivatives of performance with respect to the weight and bias variables, consist of taking the derivative sign to determine the direction of weight update, the size of weights change is determined by a separately update value [11].

The Table 5 list the neural network output results. Of these data, several conclusions can be extracted: although all data are within a permissible rank, there are some deviation that neural network is difficult to identify. This drawback can be overcome increasing training patterns in number and description quality, in addition, increase the number of hidden layer can improve the results. Finally, the artificial neural network by itself can not provide heuristic knowledge of the motor because of its blackbox approach, therefore, a fuzzy logic system is a easily implement tool that utilizes heuristic reasoning and could provide extra solutions. Clearly, all patterns are not under noise because we take a snapshot of certain values, opposite case if we make an analysis of shape curve, where measurements can be affected by noise.



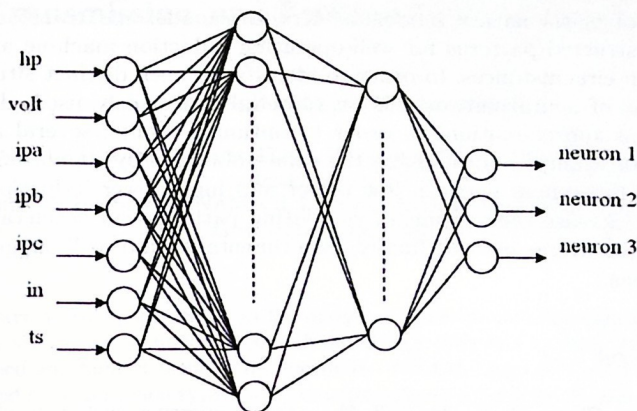


Fig. 7. Neural network architecture

Table 5. Neural network results with some patterns test versus expected values

| Condition | 3hp         | 50hp        | 500hp       | 2250        |
|-----------|-------------|-------------|-------------|-------------|
| Normal    | 0.2539 — 0  | 0.3463 — 0  | 0.1133 — 0  | 0.1192 — 0  |
|           | 0.2314 — 0  | 0.3401 — 0  | 0.1268 — 0  | 0.1258 — 0  |
|           | 0.1773 — 0  | 0.0845 — 0  | 0.1159 — 0  | 0.1027 — 0  |
| One       | 0.8252 — 1  | 0.9790 — 1  | 0.8802 — 1  | 0.9430 — 1  |
|           | -0.1540 — 0 | -0.0539 — 0 | -0.1070 — 0 | -0.0539 — 0 |
|           | 0.0529 — 0  | -0.0257 — 0 | -0.0719 — 0 | -0.1099 — 0 |
| Two       | -0.1098 — 0 | -0.0931 — 0 | -0.0410 — 0 | -0.0602 — 0 |
|           | 0.8760 — 1  | 0.8681 — 1  | 0.9258 — 1  | 0.9431 — 1  |
|           | 0.0233 — 0  | 0.162 — 0   | -0.1034 — 0 | -0.1029 — 0 |
| Three     | -0.1599 — 0 | 0.0740 — 0  | -0.0462 — 0 | -0.0230 — 0 |
|           | -0.1711 — 0 | 0.0827 — 0  | -0.0530 — 0 | -0.0274 — 0 |
|           | 0.7969 — 1  | 1.1033 — 1  | 0.9683 — 1  | 0.9724 — 1  |

## 6 Conclusions

This paper described the construction of patterns to recognize different condition to which an induction machine can present. Through simulation analysis by means of mathematical models as Krause's model and transformations as  $dq$ , we constructed patterns for well-operating induction machine and possible malfunction circumstances. In order to identify between distinct situations, the applications of neural networks is an essential tool widely used, due to their capacities of approximation. In order to optimize results, several actions can be taken, for example, normalizing the values obtained by simulation can avoid the values' differences between low power and high power induction machine. Obviously, increase the amount of simulating patterns can accelerate the neural network convergence and finally, experimental results will suggest possible modifications.

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