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Artificial Neural Networks Applied to Obtain Saturation Curves of a Three Phase Induction Motor

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Abstract- **This article presents the analysis of the saturation curves of a three phase induction motor, obtained analytically and experimentally. To determine the approximate curves a comparison between the use of Artificial Neural Networks and Polynomial Approximations are proposed.**

1. INTRODUCTION

The design of an optimized induction machine requires knowledge of the magnetization curve, occasionally resulting density distribution of the magnetic field occurs in the nonlinear region of its equivalent magnetic circuit. Due to this fact the magnetic saturation in induction machines is the subject of several studies. When the induction machine is used in studies involving its operation as induction motor, fed by electronic voltage or current power converters or operating as a self-excites induction generator with the aid of capacitors, the analysis of saturation is of great importance.

One way of dealing with this problem is to obtain a mathematical model of the induction machine, using only data from their external terminals, without the introduction of probes or devices inside the electrical machine.

Data from several studies attest to the quality of the mathematical model used being employed for this purpose, however there is still need to obtain the magnetization curve. These curves can be obtained experimentally, but their representation in the form of a suitable mathematical equation is a more complex challenge. The use of old techniques such as French curves, Splines, Bezier curves can be considered obsolete when compared with the polynomial approximation.

The possibility of developing a mathematical equation for the magnetization curve of the induction machine enables its use in the development of projects of electric machines faster and more efficiently, as well as determining their behaviour at different points extrapolated in the obtained equations .

This paper discusses the approximation of the experimental curves of magnetic saturation of an induction machine using two different techniques: the classical polynomial approximation and the use of Artificial Neural Networks. It analyzes the fundamental component and the third harmonic of the magnetic harmonic functions of the induction machine. It alsot discusses the possibility to predict the magnetization curve using fewer points.

2. OBTAINING EXPERIMENTAL HARMONICAL MAGNETIZATION CURVES

To obtain the magnetization curve points the induction machine is driven by a synchronous motor, with a balanced three-phase sinusoidal voltage system in the stator, it is possible to vary the effective voltage value. The instantaneous values of the voltages and currents, for each rms voltage, are experimentally obtained.

The values obtained include the iron losses of the no load induction machine. For this study the machine representation of the iron losses are removed from the circuit. After eliminating the current component of the loss the circuit has become the instantaneous values of the voltages and currents without the iron losses.

Using these values, knowing the resistance and leakage inductance per phase by means of (1) and (2) we obtain the instantaneous values of the linkage magnetic flux for phases a, b and no load machine. [1]

$$v_x = r_x . i_x + \frac{d\lambda_x}{dt} \tag{1}$$

Where v_x, r_x, i_x, λ_x - voltage, resistance, current, and linkage magnetic flux relating to the phase x, respectively.

$$\lambda_x = L_{d(x)}.i_x + \lambda.m_x \quad (2)$$

where: $L_{d(x)}$, $\lambda.m_x$ - leakage inductance and magnetizing flux, from x phase, respectively. It's assumed only the fundamental harmonic, from the spatial distribution of magnetic force, for different values of the rms voltage source.

The magnetizing flux is provided by (3).

$$\lambda.m_i = \sum_h F_h(\overline{FM})\cos[h(\alpha - \theta_i)] \quad (3)$$

Where $F_h(\overline{FM})$ - magnetic harmonic function.

It's possible to obtain the values of Harmonic Functions Magnetization from (4) .

$$fmm(\theta) = FM.\cos(\theta - \alpha) \quad (4)$$

where : FM ,θ ,α - maximum value of the fundamental component (fmm) from the machine, angle which defines any position along the machine air gap from a fixed reference axis in the stator , angle which defines the instantaneous angle position FM , respectively. We have (5):

$$\overline{FM} = \frac{FM}{2K} \quad (5)$$

Decomposing the magnetizing flux using the Fourier series, we obtain $F1(\overline{FM})$ and $F3(\overline{FM})$, which are the maximum values of their fundamental and third harmonic, respectively.

Bringing the results for all effective values of the tested strain, has the points of Figures 1 and 2.

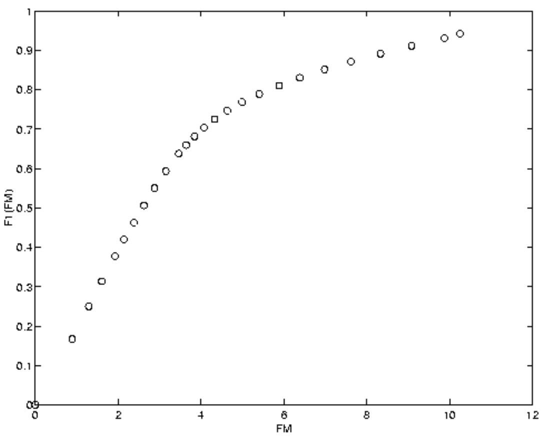
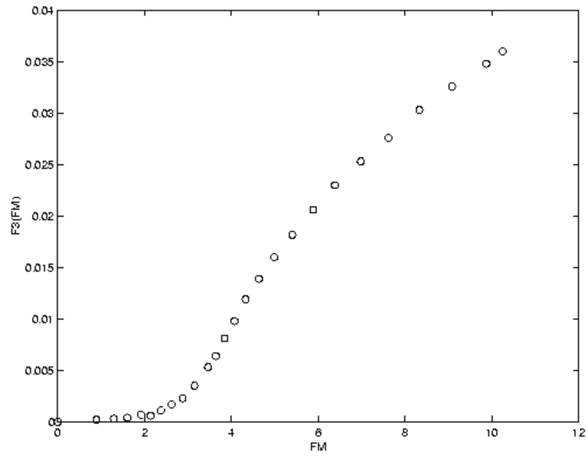


Fig 1. Points of fundamental harmonic of $F_h(\overline{FM})$.

Figure 2 . Points of the third harmonic of $F_h(\overline{FM})$



An important test to be done is to check the variation as a function of time. This variation should be almost linear, thus demonstrating that $F_h(\overline{FM})$ functions are time invariant for a given rms value of the supply voltage. This was observed in the analyzed induction machine. [1] [2]

3. POLYNOMIAL APPROXIMATION OF MAGNETIZATION CURVES

There are several methods of making suitable adjustment curves for a number of known points such as the use of series of sines [3] , Fourier analysis [4] rational functions [5] or by polynomial fitting. The polynomial fit was performed according to the package Matlab® with the "polyfit" command to determines the best coefficients of a polynomial, whose degree is provided. The data are interpolated by minimizing the sum of error distances of the given points to the points of the calculated polynomial. The choice of the degree of the polynomial will depend on an analysis of the results using different degrees of polynomials.

For the work presented in this paper was investigated the error between the curve points and the actual points used, the standard deviation and the shape of the trend curve. For the fundamental component F_h the polynomial of degree 7 proved the most suitable among the other analyzed, while the analysis of the third harmonic of F_h the polynomial of degree 8 showed better results. Both harmonic components were used for comparison by using the approximation RNAs. It should be emphasized that the results obtained with the fundamental component were better than those obtained with the third harmonic in both approximation methods used.

Figure 3 shows the results obtained with the fundamental polynomial approximation, and the actual points marked.

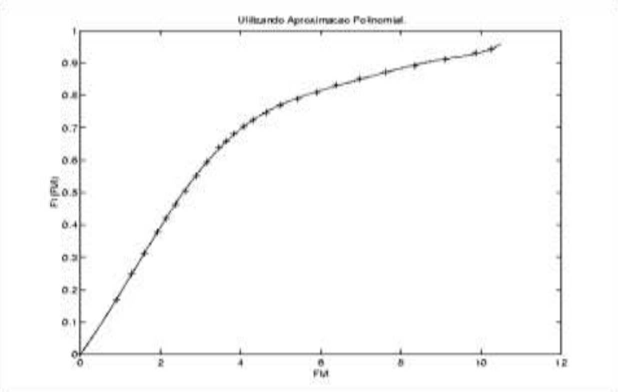


Figure 3- Polynomial approximation of the fundamental, best fit with 7 degree.

Figure 4 shows the result obtained with the polynomial approximation of the third harmonic, with the actual points marked thereon.

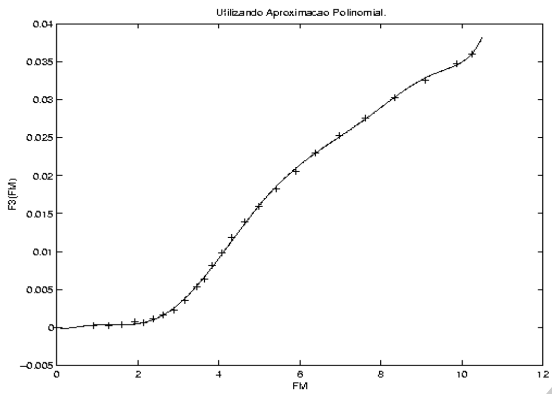


Figure 4 - Polynomial approximation of the third harmonic, best fit with 8 degree.

4. ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial Neural Networks (ANN) was inspired by biological models of human neurons. Currently due to its high level of development as well as the excellent results obtained with its application in several fields with pattern recognition problems, they have wide application in engineering problems, including the hysteresis loop [6]. Ownership of ANNs related to pattern recognition and interpolation has been a major attraction for its use particularly in electrical engineering.

The known data are entered in the ANN input and through connections to the following propagated artificial neuron, until they reach the outlet which shows a numerical value. The ANNs using known inputs and outputs are defined as supervised.

The determination of “weights” associated connections of this order to minimize the known relationship between input and obtained by the network is the goal of the call history of technical training the ANN.

One way is to use ANNs as a problem of curve fitting (approximation). The best fit is measured in statistical form. Networks of Radial Basis Function (RBF) are widely used for interpolation , in its most basic format involves three layers: The first layer consists of source nodes (sensory units) that connect to the network environment, the second layer , single hidden network , applies a nonlinear transformation of the input space to the hidden space, and this high dimensionality in most cases , the output layer is linear , providing the network response to standard signal applied to activation input layer . Cover 's theorem talks about the reason for this sequence. [7] Figure 5 shows the format of RBF used in this study.

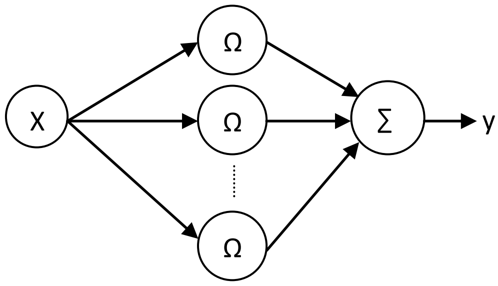


Figure 5 – RBF model used

The computational simplicity of application makes it attractive for applications involving the RBFs approximation of functions, which are chosen for the development of the work presented in this article.

The Gaussian function, shown in (6), is one of the most used for the RBF. [7]

$$\Omega_{ij}(x) = e^{-\frac{(x-w_{i,j})(x-w_{i,j})}{2\sigma_j^2}} \qquad (6)$$

Where the indices i and j refer to the connection between the signals input x in the path i to j in the RBF layer, the term σ refers to a normalization parameter.

5. RESULTS OBTAINED USING RBF

Was used the same data for training polynomial approximation using RBF networks. After training with the fundamental and third harmonic components the results are presented in Figures 6 and 7, where the points used to train the RBF are marked with "+".

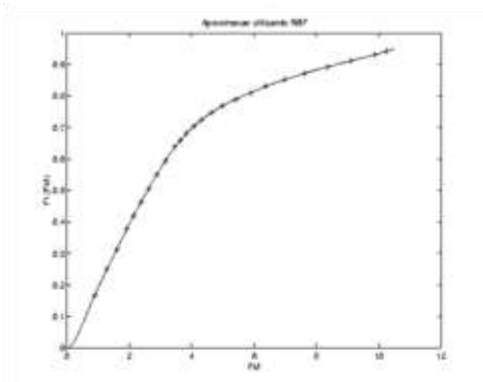


Figure 6- Approximation of the fundamental using RBF

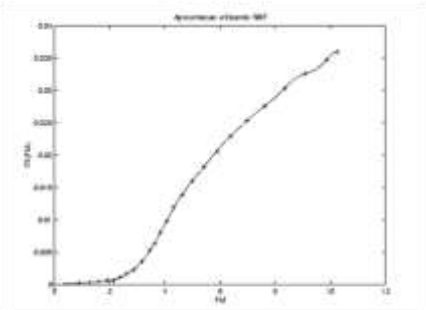


Figure 7- Approximation of the third harmonic using RBF

6. COMPARISONS OF THE APPLIED METHODS

The results obtained with the fundamental were visually similar when compared visually. But the performance of RBF is superior when it comes to the third harmonic.

Table I shows the values of the mean absolute error and standard deviation determined by both methods, when compared with the values estimated by functions generated with the approximations and the data points. It's possible to see in the table top precision of the method using the RBF, compared with the polynomial approximation.

It is noteworthy that the degree of polynomial that achieved the best mean absolute error and standard deviation was used for comparison with the RBF.

Table I Comparisons – Polynomial x RBF

RBF	Mean	Standard Deviation
Fundamental (F1(FM))	$3{,}94.10^{-5}$	$4{,}23.10^{-5}$
3rd Harmonic (F3(FM))	$4{,}19.10^{-5}$	$4{,}08.10^{-5}$
Polynomial Approximation	Mean	Standard Deviation
Fundamental (F1(FM))	$1{,}30.10^{-3}$	$7{,}61.10^{-4}$
3rd Harmonic (F3(FM))	$1{,}64.10^{-4}$	$1{,}16.10^{-4}$

7. CONCLUSIONS

The use of ANNs for determining a characteristic equation of the magnetization curves of an induction machine proved to be feasible, and results more efficient as compared to the polynomial approximation.

The feasibility of a rapid determination of the parameters of RNA, when using the RBF networks, make possible adoption of this method for approaching magnetization curves. This application is not limited to induction machines, and may be extended to other devices or elements dependent on the magnetization curve data for their calculations.

The research presented here is still in progress now being made new comparisons with other models addressing future actual estimate the characteristic curve using a lower amount of points.

There are also studies on the feasibility of estimating the magnetization curve using a smaller amount of input data.

10. REFERENCES

1. J.T. Resende, Modelagem de Indução Trifásica Incluindo a Saturação Magnética – Análise Dinâmica do Gerador de Indução Auto-Excitado, Uberlândia – MG, UFU – Universidade Federal de Uberlândia - Brazil, 1999, 172 p.
2. D. Bispo, L. M. Neto, J.T. Resende, "A new Strategy for Induction Machine Modeling Taking Into Account Magnetic Saturation", IEEE Transactions on Industry Applications, Vol. 37, N.6, 2001.
3. M. T. Abuelma'atti, "Modeling of Magnetization Curves for Computer-Aided Design", IEEE Transactions on Magnetics, Vol. 29, N.2, 1993.
4. G. Goev, V. Masheva, M. Mikhov, "Fourier Analysis of AC Hysteresis Loops", IEEE Transactions on Magnetics, Vol. 39, N.4, 2003.
5. J. Rivas, J.M. Zamarro, et. Al, "Simple Approximation for Magnetization Curves and Hysteresis Loops", IEEE Transactions on Magnetics, Vol. 17, N.4, 1981.
6. C. Serpico, C. Visone, "Magnetic hysteresis modeling via feed-forward neural networks" IEEE Transactions on Magnetics, Vol. 34, N.3, 1998.
7. S. V. Kartalopoulos, Understanding Neural Networks and Fuzzy Logic – Basic Concepts and Applications, IEEE Press, EUA, 1996