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# A Strategy for Induction Motor Stator Flux Estimation Using Neural Networks

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**Abstract — Given the importance of the stator magnetic flux in the control of speed and torque of induction machines, this paper aims at presenting an Artificial Neural Network technique for stator flux estimation. A special network configuration is proposed and simulation results are presented. The estimator results are promising in view of the new training strategy presented. An analysis is carried out which shows excellent performance within a spectral frequency range used in several applications.**

## I. Introduction

Industry is main economic activity either in advanced or less developed countries and three-phase induction motors are often used in industrial applications [1] [2]. These motors are studied in some aspects like: theoretical principles, motor design and construction, energy balance and operation [3].

The most important characteristics of operation are variable speed and torque control [4] [5]. The control of induction motors torque and speed can be complicated in certain applications. The control strategy can be implemented either in open-loop or closed-loop mode. Closed-loop control requires the feedback of machine variables, which can be implemented either using sensors or state estimation techniques [5] [6] [7].

In open-loop control, the great challenge is the correct induction machine stator flux estimation. The right induction machine stator flux estimation implies the right developed electromagnetic torque estimation [4] [5].

It's possible to get a strategy for stator flux that satisfies speed and torque control for specific applications. Amongst the known estimators, there are Artificial Neural Networks (ANNs), which are efficient ones [8]. The ANNs have simple architecture without complex numerical processing after network training [9].

This paper proposes to estimate the stator flux behavior (steady-state) using an Artificial Neural Network (ANN) through the approximation of stator flux temporal values that describe the induction motor stator flux dynamics. A specially built architecture, based on default Multi-Layer Perceptron (MLP), was developed. This architecture is easily implemented in microcontrollers.

## II. Technique of Stator Flux Estimation

The technique of stator flux estimation is described and illustrated in Fig. 1. Looking estimation in open-loop control is necessary to get currents and voltages in stator for stator flux estimation.

Based on symmetrical and balanced three-phase induction motor modeling [10], reference frames theory [10] and Indirect Self Control [11] [4], (1) and (2) are enough to estimate stator flux. From (3) to (6) is possible to estimate rotor flux then rotor position.

$$\lambda_{ds}^{s} = \int \left( v_{ds}^{s} - r_s \cdot i_{ds}^{s} \right) dt \tag{1}$$

$$\lambda_{qs}^{s} = \int \left( v_{qs}^{s} - r_s \cdot i_{qs}^{s} \right) dt \tag{2}$$

$$\lambda_{qm}^{s} = \lambda_{qs}^{s} - L_{ls} \cdot i_{qs}^{s} \tag{3}$$

$$\lambda_{dm}^{s} = \lambda_{ds}^{s} - L_{ls} \cdot i_{ds}^{s} \tag{4}$$

$$\lambda_{qr}^{s} = \frac{L_r}{L_m} \cdot \lambda_{qm}^{s} - L_{lr}^{'} \cdot i_{qs}^{s} \tag{5}$$

$$\lambda_{dr}^{s} = \frac{L_r}{L_m} \cdot \lambda_{dm}^{s} - L_{lr}^{'} \cdot i_{qs}^{s} \tag{6}$$

The superior index 's' means in the stationary reference frame variable, being:

$v_{ds}^{s}\left(v_{qs}^{s}\right)$ Stator voltages d frame (q frame)

$i_{ds}^{s}\left(i_{qs}^{s}\right)$ Stator currents d frame (q frame)

$\lambda_{ds}^{s}\left(\lambda_{qs}^{s}\right)$ Stator flux d frame (q frame))

$\lambda_{dr}^{s}\left(\lambda_{qr}^{s}\right)$ Rotor flux d frame (q frame)

$r_s\left(r_r\right)$ Stator Resistance (Rotor)

$L_{ls}\left(L_{lr}^{'}\right)$ Stator leakage Inductance (Rotor)

$\lambda_{dm}^{s}\left(\lambda_{qm}^{s}\right)$ Air-gap flux d frame (q frame)

$L_m$ Magnetization Inductance

$L_r$ Rotor Inductance

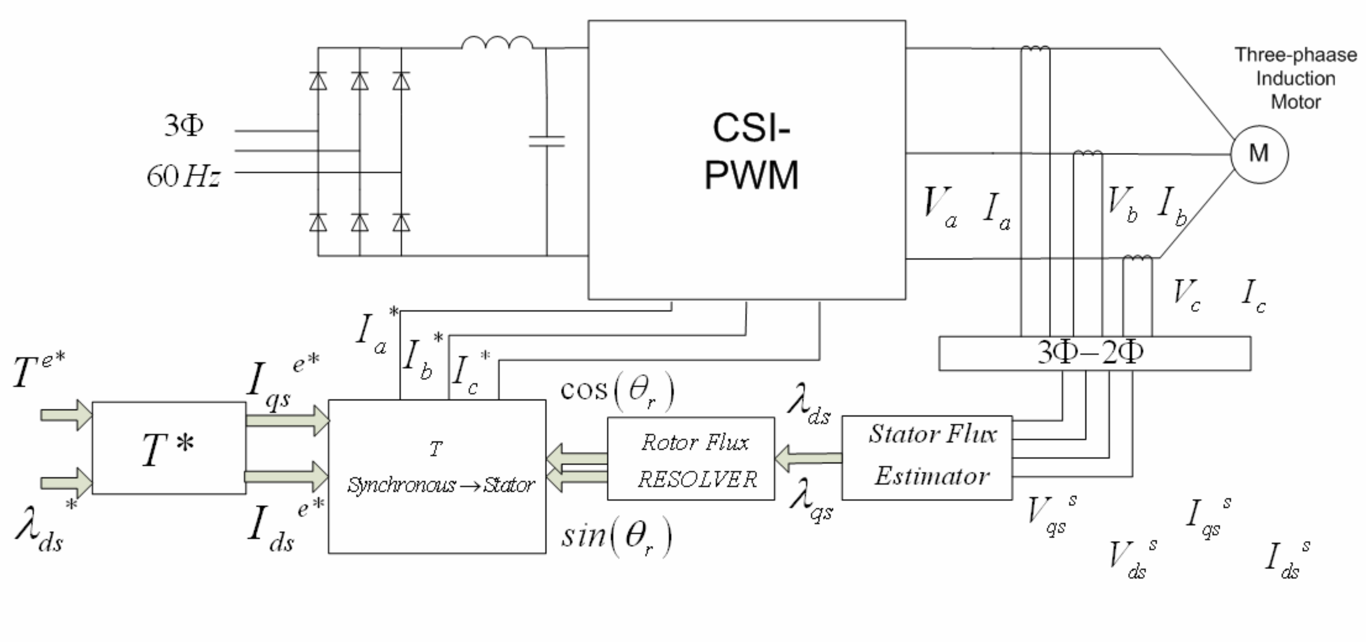


Fig. 1. Blocks diagram of induction motor vector control with stator flux estimator

Equation (7) describes electromagnetic torque ( $C_e$ ) in relation to stator flux, stator currents and poles number ( $P$ )

$$Ce = \frac{3P}{4} \cdot \left( \lambda_{ds}^{s} \cdot i_{qs}^{s} - \lambda_{qs}^{s} \cdot i_{ds}^{s} \right) \tag{7}$$

Based on equations from (1) to (6) stator flux (hard measurement) is directly influenced for stator current and stator voltage (easily measurement). From this, a new way to estimate is considered. The next section describes used ANN.

## III. Artificial Neural Network

The ANN used was MLP network, whose mathematical model and training network is explained in next sections. The network and training network was implemented in environment MATLAB® using functions of Neural Network Toolbox.

### A. MLP Network

Each neuron is described by (8) and (9).

$$net_i\left(w_i, x\right) = \sum_{j=1}^{n} w_{ij} \cdot x_j + \theta_i \tag{8}$$

$$y_i = f\left(net_i\right) \tag{9}$$

Where, $net_i\left(w_i, x\right)$ is the linear function basis, $w_{ij}$ is i-neuron weight in respect j-input, $x$ is j-input array, $\theta_i$ is the bias for i-neuron, $y_i$ is output for i-neuron and $f(\cdot)$ is the activation function.

The hyperbolical tangent function is used as activation function to hidden layer and the linear function is used to output layer.

### B. MLP Training and Learning

Was used for network training "Backpropagation", Batch gradient descent with "momentum" (m) and variable learning rate. The mean square error (MSE), described in (10), is considered the error between estimated stator flux and simulated one.

$$E = \sum_{p=1}^{P} E_p = \frac{1}{2} \cdot \sum_{p=1}^{P} \sum_{j=1}^{S} \left( d_j^p - y_j^p \right)^2 \tag{10}$$

Variable learning rate ($\eta$) is described by (11) and (12), where the learning rate is modified by incremental learning rate ($\eta_{inc}$) or decreasing learning rate ($\eta_{dec}$) depending on the actual error.

$$\begin{aligned} \eta &= \eta \cdot \eta_{inc} \\ &\quad or \\ \eta &= \eta \cdot \eta_{dec} \end{aligned} \tag{11}$$

$$w_{ij}(t+1) - w_{ij}(t) = \Delta w_{ij}(t+1) = \eta \left( \frac{\partial Ep}{\partial w_{ij}(t)} \right) + m \cdot \Delta w_{ij}(t) \tag{12}$$

Where, $w_{ij}(t+1)$ are the new weights after learning and $w_{ij}(t)$ are the earlier weights.

## IV. MLP LAYOUT

The MLP is based on 4 inputs ( $v_{ds}$ , $v_{qs}$ , $i_{ds}$ and $i_{qs}$ ) and 2 outputs ( $\lambda_{ds}$ and $\lambda_{qs}$ ).

The network with only hidden layer setting (8 neurons) approximated satisfactorily the estimation function as [9] but, without processing input data (memory). Important characteristic for future applications.

Another aspect to be highlighted is the computational effort, which is decreased in the stator flux estimator, unlike Shi [6].

The network presented slow learning for stator flux q frame. Therefore were proposed two networks with only hidden layer for each network, whose input are the same, but the output from one hidden layer network did not affect the other network output. This approach assures the same errors (MSE) for both outputs.

The first MLP layout was like 4-8-2. To preserve the same number of neurons in the hidden layer, was proposed 4-5-1 layout to q frame and 4-3-1 layout to d frame (in spite of distinct networks). This approach aims to compare the first layout with the second. The Fig. 2 shows the adopted layout.

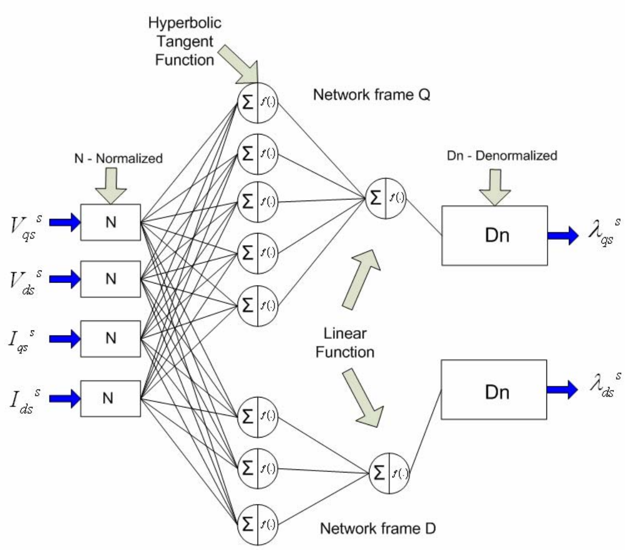


Fig. 2. MLP Layout utilized as stator flux estimator

## V. DESCRIPTION OF INDUCTION MOTORS USED

The database used for simulation was gotten of the motor model by Krause [10]. Two motors were used: 2.2 kW (3 HP) rated power and 7.5 kW (10 HP) one. Nominal frequency of both motors is 60 Hz. Mechanical torque in motor shaft used for simulation was 12.6 N.m and the simulation time was 8 seconds. The motors have 4 poles and squirrel-cage rotor.

They are in LAMOTRIZ/UFC (Laboratory of Energy Efficiency in Motor Systems), partnership between ELETROBRÁS and UFC. The motors parameters are in Tab. 1.

Where, $J$ is moment of inertia and $B$ is viscous friction. The simulation was implemented in environment MATLAB®/Simulink using block sets of Power Systems Toolbox.

TABLE I
INDUCTION MOTORS PARAMETERS

| PARAMETER | 2.2 kW | 7.5 kW |
|---|---|---|
| $r_s\,(\Omega)$ | 4.34 | 1.89 |
| $r_r\,(\Omega)$ | 4.34 | 1.07 |
| $L_m\,(mH)$ | 219.4 | 158.4 |
| $L_{ls}\,(mH)$ | 11.5 | 9.2 |
| $L'_{lr}\,(mH)$ | 11.5 | 9.2 |
| $B\,(N.m.s)$ | 0.0008 | 0.0465 |
| $J\,(kg.m^2)$ | 0.0013 | 0.0104 |

## VI. STRATEGY OF NETWORK'S TRAINING FOR STATOR FLUX ESTIMATION

The strategy must be compatible with induction motor indirect self control. For this, the range of frequencies is not below of 20 Hz.

### A. *First Strategy of Network's Training*

The network training is carried out in only one frequency and the testing in a range of other frequencies. Therefore, the performance of the estimation in the approximation of stator flux temporal values and the percentage error of the calculated torque can be assessed. As an example, the first training was carried out using 60Hz and the frequencies of 50 Hz, 40 Hz, 30 Hz and 20 Hz was used by testing. Then, 50 Hz was used in the training and 60, 40, 30 e 20 Hz were used in the testing. Similarly, the training and testing process was repeated for 40, 30 e 20 Hz.

### B. *Second Strategy of Network's Training*

In this strategy, the network training is carried out in all frequencies and testing in all range of frequencies. The same errors of first strategy can be assessed. The range of the first and second test goes from 20 Hz to 60 Hz (20 Hz – 30 Hz – 40 Hz – 50 Hz – 60 Hz).

## VII. NETWORK PERFORMANCE

Table 2 presents performance of the estimation in the approximation of stator flux temporal values (MSE-F) and the percentage error of the calculated torque (%-T) in first strategy to 2.2 kW motor. The error of the torque calculated from the estimated flux was smaller than 10% when the network was trained in 40Hz.

For all other training frequencies, there were errors greater than 10% at some testing frequencies.

TABLE II
PERFORMANCE OF THE ESTIMATION – 2,2 kW MOTOR – FIRST STRATEGY

| TRAININGS | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FREQUENCIES | | 60 Hz | | 50 Hz | | 40 Hz | | 30 Hz | | 20 Hz | |
| ERRORS | | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T |
| TESTS | 60 Hz | 0.128 | 1.41% | 0.001 | 2.75% | 0.005 | 7.96% | 0.024 | 15.98% | 0.067 | 25.77% |
| | 50 Hz | 0.001 | 2.51% | 0.048 | 1.55% | 0.004 | 5.96% | 0.013 | 11.51% | 0.064 | 26.25% |
| | 40 Hz | 0.003 | 5.90% | 0.005 | 7.82% | 0.080 | 0.84% | 0.005 | 8.26% | 0.036 | 20.24% |
| | 30 Hz | 0.005 | 8.42% | 0.006 | 9.19% | 0.002 | 5.98% | 0.060 | 1.32% | 0.029 | 20.37% |
| | 20 Hz | 0.008 | 11.14% | 0.012 | 16.53% | 0.007 | 9.76% | 0.007 | 6.71% | 0.055 | 2.19% |

TABLE III
PERFORMANCE OF THE ESTIMATION – 7,5 kW MOTOR – FIRST STRATEGY

| TRAININGS | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| FREQUENCIES | | 60 Hz | | 50 Hz | | 40 Hz | | 30 Hz | | 20 Hz | |
| ERRORS | | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T | MSE-F | %-T |
| TESTS | 60 Hz | 0.062 | 1.82% | 0.002 | 4.01% | 0.004 | 5.20% | 0.009 | 10.82% | 0.071 | 30.52% |
| | 50 Hz | 0.001 | 3.10% | 0.125 | 2.11% | 0.004 | 4.92% | 0.006 | 9.05% | 0.062 | 28.15% |
| | 40 Hz | 0.005 | 9.52% | 0.003 | 6.25% | 0.062 | 1.04% | 0.002 | 6.11% | 0.029 | 19.82% |
| | 30 Hz | 0.058 | 10.53% | 0.004 | 7.56% | 0.002 | 5.26% | 0.069 | 1.90% | 0.022 | 17.54% |
| | 20 Hz | 0.024 | 21.52% | 0.015 | 16.60% | 0.005 | 5.11% | 0.009 | 13.62% | 0.038 | 1.25% |

Table 3 presents the same performance in first strategy to 7.5 kW motor. The network presented a similar behavior. For the 40 Hz frequency, the calculated torque errors were no higher than 5%. For all other training frequencies, there were errors greater than 10% at some testing frequencies.

Using the second strategy, the results for this network were not satisfactory for both motors. The errors in the calculated torque were greater than 10% in the frequencies below 40 Hz, however the errors stayed around 5% for the frequencies above 40 Hz. Table 4 presents MSE-F and %-T for 2.2 kW motor and Tab. 5 presents MSE-F and %-T for 7,5 kW motor both trained in second strategy.

## VIII. CONCLUSION

The frequency range from 20 Hz to 60 Hz can be estimated by MLP layout proposal and it must be trained only one frequency: 40 Hz. The %-T are smaller than 10% ,confirming the estimator performance in steady-state. For greater power motors, this characteristic is accented. The %-T were no higher than 5%.

In others training frequencies, the result is not satisfactory with errors %-T greater than 10%. The second strategy is only satisfactory in the frequency of 60 Hz and 50 Hz for 7.5 kW rated power motor. This strategy is satisfactory from 30 Hz to 60 Hz for motor of 7.5 kW rated power also. Therefore, the range of operation for smaller motors is greater.

Another point to be considered are the MLP layout 4-5-1 and 4-3-1, with the same inputs. This layout not disturb MSE-F of the each output. The influence of one input in another is clear and this layout filtering this noise in each output.

As new analysis, the comparison between this estimator and another, like Kalman Filter or Fuzzy estimator, must be considered for optimum steady-state operation in vector control of induction motors.

## IX. ACKNOWLEDGMENT

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TABLE IV
PERFORMANCE OF THE ESTIMATION – 2,2 kW MOTOR – SECOND STRATEGY

| TRAININGS | | | |
|---|---|---|---|
| ERRORS | | MSE-F | %-T |
| TESTS | 60 Hz | 0.001 | 1.70% |
| | 50 Hz | 0.003 | 6.45% |
| | 40 Hz | 0.002 | 6.08% |
| | 30 Hz | 0.003 | 6.37% |
| | 20 Hz | 0.017 | 23.16% |

TABLE V
PERFORMANCE OF THE ESTIMATION – 7,5 kW MOTOR – SECOND STRATEGY

| TRAININGS | | | |
|---|---|---|---|
| ERRORS | | MSE-F | %-T |
| TESTS | 60 Hz | 0.002 | 6.55% |
| | 50 Hz | 0.002 | 8.97% |
| | 40 Hz | 0.003 | 12.30% |
| | 30 Hz | 0.004 | 15.43% |
| | 20 Hz | 0.007 | 20.83% |

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