Speed Estimation of Induction Motors using Neural Networks in the Rotating Coordinate

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Abstract: In this paper speed estimation of induction motors is prescribed by a neural network. The neural network carries out it's computing in the rotating coordinate of vector control analysis for constant rotor flux. It is shown that in the rotating coordinate because of the lack of signals oscillations, speed estimation can be done with a smaller and more implementable neural network and learning will be easier and faster. The resulting estimation will be more satisfactory. For analogy speed estimation of induction motors in the statorfixed coordinate is presented.

Key-Words: Speed Estimation, Neural Network, Vector Control, Induction Motor

1 Introduction

In sensorless speed control of induction motors via vector control analysis, one can use inputs (stator currents and voltages) and output (speed) equations to find an appropriate relation between inputs and output. But these equations are achieved via some simplifying assumptions. Then it is wise to use a neural network and let it find more satisfactory relationship between inputs and output from real data values. Two sets of data values are available:

1. Set of signals in the statorfixed coordinate.

2. Set of signals in the rotating coordinate.

ANN's learning can take place with both of these sets. The first set will lead to a general purpose but complex speed estimator. The second set will lead to a small and easily implementable ANN, but it can be used only in vector controlled drives. These drives have become quite popular in recent years.

In vector control method we can find control strategies to achieve the same control behaviour as a DC machine, that is separated control for the excitation and the torque [1],[2],[6].

The main object of this work is to present a simple ANN speed estimator in the rotating coordinate and

compare it with other methods. In this analogy Mehrotra's et al. paper [3] is taken into consideration for speed estimation in the statorfixed coordinate and Ben-Brahim's [4] and Wishart's et al [7] papers are considered for the rotating coordinate This paper consists of the following parts. In section 2 the block diagram of the control system is described. This control system uses vector control method with constant rotor flux. In section 3 the problem of speed estimation in the statorfixed coordinate is described. Section 4 deals with the problem of speed estimation in the rotating coordinate. Finaly the paper is concluded in section 5.

2 Control system

Figure 1 shows control system block diagram. Parameters of the motor which is used in the simulation is in the appendix.

The asynchronous machine is fed from a voltage source inverter (VSI). The control system uses current feedback. For motor dynamics simulation a simple model is used which is presented in [2].





Figure 1:Block Diagram of the Control System.

In this control system constant rotor flux is considered and all of the analysis are in the rotating coordinate.

In figure 1 the block No.1 simulates induction motor dynamics, block No.2 uses stator currents and voltages to constructing magnetization current, torque and estimated speed. In this block, speed estimation is done by neural network. Current reference signals (i_{sq} and i_{sd}) are constructed in block No.3 and finally block No.4 delivers requested voltages to the motor. Simulations are done by MATLAB/Simulink software.

3 Speed estimation in the statorfixed coordinate

In [3] speed estimation is done by neural network in the statorfixed coordinate.In that paper two methods are presented. In the first method the following equations are considered:

$$w_{r} = \frac{-\sigma^{2} di_{sd}/dt + R_{r}L_{s} i_{sd} - R_{r} \int V_{xd} dt - L_{r} V_{xd}}{\sigma^{2} i_{sd} + L_{r} \int V_{xd} dt}$$
(1)

Figure 2: Real and Estimated Speed in the First Method.

$$w_{r} = \frac{\sigma^{2} di_{sq}/dt - R_{r}L_{s} i_{sq} + R_{r} \int V_{xq} dt + L_{r} V_{xq}}{\sigma^{2} i_{sd} + L_{r} \int V_{xd} dt}$$
(2)

$$V_{xd} = u_{sd} - R_s i_{sd}$$
$$V_{xq} = u_{sq} - R_s i_{sq}$$
$$\sigma^2 = L_m^2 - L_r L_s$$

In which,

 w_r is mechanical angular frequency of the rotor. u_{sd} , u_{sq} are d and q components of the stator voltages respectively.

 R_s is stator ohmic resistance .

 L_s , L_r , L_m are stator inductance rotor inductance and magnetizing inductance respectively .

One of the necessary condition for an ANN to approximate a function is that the function be square integrable in the n-dimentional unit hypercube[5]. This condition is obviously not satisfied by either (1) or (2) because both equations have singularities. thus numerators and denominators are learned separately and then the output of these ANNs are passed through a zero crossing filter.



Figure 3: Real and Estimated Speed in the Second Method.

The actual and estimated speeds are shown in Fig.2 This result is achieved after giving 6 million vectors of inputs.

This method must face two problems [2]:

1. This technique would require very high performance A/D converter and dedicated ANN hardware to implement it in real time.

2. It requires some form of zero- crossing filter. This would pose a problem if this scheme has to be implemented on an ANN chip.

In the second method the following equation is considered:

$$w_{r} = \frac{(\sigma^{2}p - R_{r}L_{s} - R_{s}L_{r} - R_{s}R_{r}/p)I_{s} + (L_{r} + R_{r}/p)V_{s}}{j[(\sigma^{2} - R_{s}L_{r}/p)I_{s} + (L_{r}/p)V_{s}]}$$
(3)

In which,

 $\begin{array}{l} I_{s}=i_{sd} + ji_{sq} \\ V_{s}\!=\!u_{sd} + ju_{sq} \end{array}$

This method uses a 2-hidden layer, 10 -input, single output ANN to estimate speed of the motor. We must take into consideration, that in equation (3) there exist a non-singular function between the induction motor speed and the stator quantities. The learning is done via 7.5 million iterations. The actual and ANN recovered speeds are shown in Fig.3. Obviously this is not a satisfactory estimation.



Figure 4: Speed Estimation in the Second Method with Modification.

This estimation can be improved if the magnitudes and phase angles of all the quantities are given instead of their d-q components. The respone of the ANN in this case is shown in Fig.4.

If the speed estimation passes through a low pass filter a better estimation will be achieved(Fig.5)

As in previous method, this method must face those two problems too.

4 Speed estimation in the rotating coordinate

In the previous methods the ANN's inputs (stator currents and voltages) change much more faster than ANN's output (estimated speed). The use of the rotating coordinate in which ANN's inputs change much more slower than the previous state, (Fig .10) is, therefor preferable.

In [4] speed estimation is done via an on-line neural network in the rotating coordinate. In this method the following equations are considered:

$$\Phi_{\rm r} = L_{\rm r} (V_{\rm s} - R_{\rm s} i_{\rm s} - \sigma L_{\rm s} i_{\rm s}) / L_{\rm m}$$
(4)
$$\lambda_{\rm r} = (-I / T_{\rm r} + w_{\rm r} J) \lambda_{\rm r} + L_{\rm m} i_{\rm s} / T_{\rm r}$$
(5)
$$I=[1 0; 0 1]$$

$$J=[0 -1; 1 0]$$

In equation (4) w_r (rotor speed) has not appeared, but in equation (5) w_r has appeared directly. Φ_r in equation (4) is assumed to be actual rotor flux and equation (5) is implemented by a 3-input, single output on-line neural network .

In this neural network one of the weights corresponds to the speed magnitude.

The learning procedure uses the error between rotor flux in equation (4) and ANN's output to change the weights. A good flux estimation will leads to a good speed estimation.

This method loses one of the must important benefits of ANNs, in this method motor parameter variation aren't considered. For instance if L_m (magnetizing inductance) varies because of the motor saturation or R_r (rotor ohmic resistance) varies because of the temperature variation, the estimated speed of ANN doesn't vary.

Another work is [7] in which speed estimation is done in the rotating coordinate. There is a risk of saturation since there is no control over the flux.

In the following method a 1- hidden layer, 3-input, single output ANN in the rotating coordinate is used to estimate the rotor speed.

Consider the following equation:

$$w_r = (u_{sq} - R_r)(1 - \sigma)L_s i_{mr} / i_{sq}$$
 (6)

in which, i_{mr} is magnetization current.

Comparing equation (6) with equations (1) and (2), it can be seen from this analogy that equation (6) is simpler. In section 3, first and second methods need Integrators, Differentiators and T.D.L.s, but in this method they are not appeared.

This neural network (Fig.9) uses i_{sd} , i_{sq} , u_{sq} as inputs and estimates the rotor speed. ANN's output can be used without any filtering (compare with second method in section 3). This neural network is so small which can be a part of the control system.(compare with two methods in section 3 in which dedicated

ANN hardware is required.) Thus this method reduces implementation problems. Actual and ANN recovered speed are shown in Fig.6. Error between actual and recovered speeds is shown in Fig.7. Training Results are ploted in Fig.8.



Figure 5: Real and Estimated Speed in the Second Method with Filter.



Figure 6: Real and Estimated Speed in the Last Method



Figure 7: Error Between Real and Estimated Speed in the last Method.

In section 3 to circumvent the problems of large data files and substantial training times, the whole drive system with the ANN was simulated in C++ on a SUN SPARC-10 workstation. But in this method MATLAB/ Simulink software has proven sufficient.

5 Conclusion

In this paper speed estimation in the rotating coordinate is compared with speed estimation in the statorfixed coordinate. Speed estimation in the rotating coordinate has the following benefits:

1.Smaller neural network.

- 2.Better speed estimation.
- 3.Fewer implementation problems.

4.Faster learning .

Also our suggested neural network achieves a good robustness to motor parameter variation if learning is sufficient.

Appendix

Asynchronous Machine Parameters:

$f_a = 50$	Hz
$Z_p = 3$	
$M_{\rm N} = 149$	Nm
$U_{\rm N}\ = 380$	V
$P_N = 15$	kw
L _s =34.3	mH
L _r =34.1	mH
$L_{m} = 34.2$	mH



Figure 8: Training Results in the Last Method



Figure 9: Neural Network Block Diagram in the Last Method.



Figure 10: Stator Volages and Currents in the Rotating Coordinate.

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