Speed estimation of the three-phase induction motor with Volts/Hertz control using artificial intelligence techniques

J E Salamanca¹, J L Diaz Rodriguez¹, and A Pardo Garcia¹
¹ Facultad de Ingenierías y Arquitectura, Universidad de Pamplona, Pamplona, Colombia

E-mail: jexuz27@gmail.com, jdiazcu@gmail.com

Abstract. This paper deals with the design and development of a prototype for speed estimation of a three-phase squirrel cage induction motor using Volts/Hertz control. The speed estimation was using an embedded electronic device with an adaptive neuro-fuzzy inference system. In this way, it is expected to increase the reliability of the rotor speed measurement. For the estimation, the currents and voltages that feed the induction motor were taken as input data to training an adaptive neuro-fuzzy inference system. Additionally, a Volts/Hertz control technique was used to test the operation of the estimator at different operating speeds, comparing the estimation with a speed sensor coupled to the machine shaft. The estimation was supported on a Raspberry Pi 3B hardware. The algorithms were developed using Simulink, which allows a graphical block interface that facilitates the understanding of the system. For the power stage, a multilevel converter was developed, thus, ensures a low total harmonic distortion.

1. Introduction

Power electronics have led and extended the extensive use of three-phase induction motors. Further ratifying its preponderant role in current industrial processes where speed control is required, such as conveyor belts, overhead cranes, pumps, elevators, compressors, among others. The squirrel cage electric motor has the most advantages such as its low weight-to-power ratio, lower maintenance, and reduced-price compared to other electric motors. Generating a greater demand for this type of electric motor in industrial applications. With the advent of modern control techniques, using power electronics and the latest advances in digital electronics such as microprocessors and digital signal processors (DSP). These devices allow precise and agile control of the speed of the three-phase induction motor. To achieve the best dynamic indicators of motor control, control methods based on the variation of the frequency of the electrical network should be used. This is achieved using inverter-type static converters.

Power inverters allow the magnitude, frequency, and phase of the voltage applied to the motor to be controlled at the same time. Thus, facilitating the introduction of various modern speed control strategies, among which we can mention intelligent control techniques such as neural networks [1], sliding mode control [2], Volts/Hertz control [3], vector control [4], etc. Regardless of the nature of the speed control used, it is necessary to implement induction motor speed feedback. It can be done with the use of encoders, resolvers, tach generators, optical sensors, among others. These devices must be installed directly on the rotor shaft and require certain maintenance routines. Besides, they depend on a precise location to generate the appropriate measurement. Therefore, within the objectives of this work is to propose a method that allows obtaining the measurement of the induction motor speed without an installed sensor, allowing the development of sensor less control techniques.
Several speed estimation strategies have been developed and applied to the induction machine control, among which are neural networks (ANN) [5], adaptive reference model systems (MRAC) [6], extended Kalman filter (EKF) [7], fuzzy logic [8], etc. Therefore, the voltages and electrical currents that feed the machine would be taken as input data of an adaptive neuro-fuzzy inference system, and in this way obtains an estimated output of the rotor speed.

2. Induction motor modeling

To model the behavior of the induction motor, the mathematical equations that govern the operation of the electrical machine are used. In such a way that the estimated value can be obtained first by digital simulation. Considering that the motor parameters are measured respecting the stator winding, all the rotor variables must refer to this winding. In this way Orille [9] propose, the Equation (1) to Equation (4) show the voltages of the three-phase induction motor. Where $\omega$ is the angular speed in an arbitrary reference frame and $\omega_r$ is the angular speed of the rotor. Equation (5) to Equation (8) show the electrical currents, where $X_{ls}$ and $X_{lr}$ are the stator and rotor leakage reactance in the stator reference frame.

\begin{align}
v_{qs} &= p\lambda_{qs} + \lambda_{ds}\omega + r_s i_{qs}, \quad (1) \\
v_{qs} &= p\lambda_{ds} - \lambda_{qs}\omega + r_s i_{ds}, \quad (2) \\
v_{qr} &= p\lambda_{qr} + \lambda_{dt}(\omega - \omega_r) + r_r i_{qr}, \quad (3) \\
v_{qr} &= p\lambda_{qr} - \lambda_{qr}(\omega - \omega_r) + r_r i_{qr}, \quad (4) \\
i_{qs} &= \frac{1}{X_{ls}}(\Psi_{qs} - \Psi_{mq}), \quad (5) \\
i_{ds} &= \frac{1}{X_{ls}}(\Psi_{ds} - \Psi_{md}), \quad (6) \\
i_{qr} &= \frac{1}{X_{lr}}(\Psi_{qr} - \Psi_{mq}), \quad (7) \\
i_{dr} &= \frac{1}{X_{lr}}(\Psi_{dr} - \Psi_{md}). \quad (8)
\end{align}

The variable $\omega$ is the electrical angular speed according to the applied voltage. The $i_{qr}$ and $i_{dr}$ are the electrical currents of the q and d frame of the rotor, with the stator as a reference, while the $i_{qs}$ and $i_{ds}$ are the currents of the q and d frames of the stator. Where $\lambda$ is the flux linkage and $\Psi_{qs}$, $\Psi_{ds}$, $\Psi_{qr}$ and $\Psi_{dr}$ are the resulting fluxes. The equations of the resulting voltages were solved regarding $\Psi_{qs}$, $\Psi_{ds}$, $\Psi_{qr}$ and $\Psi_{dr}$, which can be observed in Equation (9) and Equation (10).

\begin{align}
\Psi_{mq} &= X_m(i_{qs} + i_{qr}') = X_{md}\left(\frac{\Psi_{qs}}{X_{ls}} + \frac{\Psi_{qr}'}{X_{lr}}\right), \quad (9) \\
\Psi_{md} &= X_m(i_{ds} + i_{dr}') = X_{md}\left(\frac{\Psi_{ds}}{X_{ls}} + \frac{\Psi_{dr}'}{X_{lr}}\right), \quad (10)
\end{align}

where $X_{mq}$ is expressed by Equation (11).

\begin{equation}
X_{mq} = X_{md} = \frac{1}{\frac{1}{X_m} + \frac{1}{X_{ls}} + \frac{1}{X_{lr}}}. \quad (11)
\end{equation}
Equation (5) to Equation (8) are substituted into Equation (1), Equation (2), Equation (3), Equation (4), Equation (9) and Equation (10). Later obtaining the stator and rotor voltages in the direct and quadrature q frames, shown in Equation (12) to Equation (15). Finally, the electromagnetic torque Equation was obtained the Equation (16), together with the mechanical rotor speed Equation (17), and the mechanical rotor position Equation (18) [9] can be seen in:

\[
\Psi_{qs} = \frac{\omega_e}{p} \left[ v_{qs} + \frac{\omega_e}{\omega_e} \Psi_{ds} + \frac{r_s}{x_{ls}} (\Psi_{mq} - \Psi_{qs}) \right],
\]

\[
\Psi_{ds} = \frac{\omega_e}{p} \left[ v_{ds} + \frac{\omega_e}{\omega_e} \Psi_{qs} + \frac{r_s}{x_{ls}} (\Psi_{md} - \Psi_{ds}) \right],
\]

\[
\Psi^{'}_{qr} = \frac{\omega_e}{p} \left[ v_{qr} - \left( \frac{\omega - \omega_e}{\omega_e} \right) \Psi^{'}_{dr} + \frac{r_r}{x_{lr}} (\Psi_{mq} - \Psi^{'}_{qr}) \right],
\]

\[
\Psi^{'}_{dr} = \frac{\omega_e}{p} \left[ v_{dr} - \left( \frac{\omega - \omega_e}{\omega_e} \right) \Psi^{'}_{qr} + \frac{r_r}{x_{lr}} (\Psi_{md} - \Psi^{'}_{dr}) \right],
\]

\[
T_e = \left( \frac{n_p}{4 \omega_e} \right) \left( \Psi^{'}_{qr} i_{dr} - \Psi^{'}_{dr} i_{qr} \right),
\]

\[
\omega_r = \frac{1}{p} \omega_e - \frac{1}{p} (T_e - T_l),
\]

\[
\theta_r = \frac{1}{p} \omega_r.
\]

2.1. Induction motor modeling for simulation

Once the equations that describe the behavior of the electric motor have been obtained. They are programmed in Simulink as a set of 5 subsystems: abc / dq frames, flux, currents, dq / abc frames, and EM block. The induction motor block model is shown in Figure 1. This model has a three-phase voltage set as inputs. Through the model, 42 variables of the machine are obtained, including voltages, currents, magnetic flux, and mechanical variables.

![Figure 1. Block diagram for the induction motor model.](image)

Figure 2 shows some of the variables that the simulated model delivers in the no-load state, such as the electric currents \(i_{qs}, i_{ds}, i_{qs}, i_{dr}\), torque, and rotor speed.
3. Volts/Hertz control

The development of the V/Hz control strategy is based on the developed induction motor model. From the behavior of the machine using the respective control, its performance is validated. Bearing in mind that with this control strategy the aim is to keep the voltage/frequency relationship at the motor input constantly and thereby maintain the magnetic flux at the maximum value in the air gap without saturating the electrical machine. Thus, keeping this relationship constant is the primary objective of control. This ensures that the machine will not operate in the saturated region or even cause the weakening of the magnetic flux. In both cases affecting the mechanical torque delivered by the motor shaft [10]. The control law that governs this strategy is expressed in Equation (19) [10]. Where \( K_v \) is the proportionality constant between the peak value of the applied voltage waveform (\( V_p \)) and the frequency (\( f \)) of the power supply.

\[
K_v \equiv \frac{V_p}{f}.
\]  

(19)

The Figure 3 shows the block diagram for the simulation of this control strategy. To validate the behavior of the motor, we used 7 reference speeds, at 1800 rpm, 1700 rpm, 1500 rpm, 1300 rpm, 1400 rpm, and 1600 rpm. Figure 4 shows the Volts/Hertz control simulation (red color) and the setpoint speed (blue color).

4. Rotor speed estimator based on neuro fuzzy adaptive inference system

The adaptive neuro-fuzzy inference system (ANFIS) can create an input and output map from emulating human knowledge, using hybrid learning techniques for this purpose. The proposed ANFIS generated an input and output map for a given input and output data set [11]. Trigger function parameters are set like artificial neural network weights, allowing membership rules and functions to be adjusted automatically. Figure 5 represents a generalized ANFIS system [12].
Fuzzy mapping can be represented by a fuzzy association matrix and then translated to the activation regions. Figure 6 shows the ANFIS topology as a tunable network. Fixed nodes are circles and adaptive nodes are shown as rectangles, which are adjusted in the respective training.

![Figure 5. Basic inference system diagram.](image)

![Figure 6. ANFIS network for the emulation of the inference system.](image)

In the first layer of the neural network, the parameters of the input membership function are adjusted. The second and third layers perform fuzzy operations. The fourth and fifth layers are where weighting is performed to obtain the system output \( f \) [12]. If the training data set has \( P \) entries, the measurement error (or energy function) is the sum of the squared errors [11], as shows Equation (20).

\[
E_p = \sum_{m=1}^{L} (T_{m,p} - O_{m,p}^L)^2 ,
\]

(20)

where \( T \) is the desired output vector, \( L \) the number of layers, and \( O \) is the output vector, so the measure error can be expressed as the Equation (21) [11].

\[
E = \sum_{p=1}^{P} E_p .
\]

(21)

The error rate of the output node can be obtained from Equation (20) using the descending gradient method, as the Equation (22).

\[
\frac{\partial E_p}{\partial O_{L,p}^L} = -2(T_{i,p} - O_{L,p}^L).
\]

(22)

For internal nodes \( k \), the error rate can be derived by the chain rule [11], by this way we obtain Equation (23).

\[
\frac{\partial E_p}{\partial O_{L,p}^k} = \sum_{m=1}^{k+1} \frac{\partial E_p}{\partial O_{m,p}^k} \frac{\partial O_{m,p}^{k+1}}{\partial O_{L,p}^k}.
\]

(23)
In this case, the error rate of an internal node can be expressed as a linear combination of the error rates of the nodes in the next layer. Using $\alpha$ parameter as the network adjustment parameter, we obtain the Equation (24) [11].

$$\frac{\partial E_P}{\partial \alpha} = \sum_{\alpha \in S} \frac{\partial E_P}{\partial \alpha^*} \frac{\partial \alpha^*}{\partial \alpha}.$$  

(24)

where $S$ is the set of nodes whose outputs depend on $\alpha$. The derivative of the global error measure $E$ respecting $\alpha$ shown in Equation (25) [11].

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{P} \frac{\partial E_p}{\partial \alpha},$$  

(25)

where $\alpha$ is expressed according to Equation (26).

$$\Delta \alpha = \eta \frac{\partial E}{\partial \alpha},$$  

(26)

where $\eta$ is the learning rate that can be expressed according to Equation (27) [11].

$$\eta = \frac{q}{\sqrt{\sum \alpha \left(\frac{\partial E}{\partial \alpha}\right)^2}},$$  

(27)

where $q$ is the size of the step or the length of each gradient transition in the parameter space; which can be varied to change the convergence rate [11].

4.1. Simulation of the adaptive neuro fuzzy inference system

The application of the inference system for the induction motor speed estimation was carried out using MATLAB. Where the system was implemented using as input data the three-phase voltages and currents that feed the machine. The output data of the speed measured with a Hall effect sensor on the machine shaft. Figure 7 shows the training system interface. In the application of the velocity estimator, 6 membership functions of the Gaussian type were used for each layer. The system is evaluated by applying the root mean square of the RMSE error obtaining a speed value of 109 rpm. The response of the estimator is observed in Figure 8 where the blue line represents the response of the Volts/Hertz control measured with the physical speed sensor. The red line represents the speed estimate for the speeds mentioned above. A slight delay at motor starting is verified for the estimated signal. Then, the machine accurately follows the speed sensor response with a very small steady-state error of 1.5%. Being somewhat higher in speed transitions where it reaches 10.1%.

Figure 7. Membership functions setting in the ANFIS graphical user interface. Figure 8. Estimated speed (red color) and measured speed (blue color).
5. Conclusions
Adaptive neuro-fuzzy reference systems present a viable alternative in the implementation of induction motor speed estimation. With which only small steady-state errors are achieved with a high degree of precision, suitable for application in sensor less control. ANFIS systems training can take significant time. Therefore, it is of great importance to correctly parameterize the membership functions and in this way affect a significant decrease in the error in the desired output. The proposed estimator works well at speeds of ± 10 rpm deviation concerning training speeds. This range can be broader if the characteristics of the ANFIS network are improved.

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