POSITION SENSOR ELIMINATION USING A NEURO-FUZZY TECHINIQUE IN A SRM: DESIGN AND IMPLEMENTATION

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Abstract— A new technique of position sensor elimination for SR Drives is proposed. It uses only phase voltages and the reference current signals to obtain the rotor speed/position estimation automatically since the estimator is based on a neuro-fuzzy learning structure. Experimental and simulation results are presented and discussed, analyzing its performance in online and offline operation.

Keywords— **Switched reluctance machine, Intelligent control, Neuro-fuzzy systems, Sensorless operation**

1 Introduction

The correct excitation of the phases in a switched reluctance motor in synchronism with the rotor position is necessary to a good performance of the operation of the SRM (Oliveira, 2000). A resolver or encoder can solve totally this requirement. (Oliveira, 2002). In some applications, these sensors are not desirable for different reasons: cost, size, weight, inertia and reliability. This article makes a review of some strategies of elimination of position sensor in switched reluctance drives and proposes a new strategy using a neuro-fuzzy learning methodology.

The operation of the SRM is based on the variation of the magnetic flux as a function of the rotor angular position. The basic equation of phase voltage is given by:

$$v_j = Ri_j + \frac{d}{dt}\sum_{k=1}^{n}\lambda_{kj} \quad (1)$$

Where: n is the total phase numbers, v_j is the voltage applied in phase j, R is the winding resistance per phase, λ represents the magnetic flux and t is the time.

The dependence of the flux with the position is the key point for the SRM operation without position sensor. Inevitably, the great majority of the existing techniques of sensor elimination are based on this basic principle to obtain the rotor position information.

There are five speed regions that classify the strategies types of position sensor elimination (Figure 1), regions 1, 2 and 3 are below the base speed (smallest speed where you can extract the maximum power) and where torque remains constant. These regions offer flexibility for the current control and there is always a moment, during the commutation sequence, when a determined phase is not energized. At this moment, one voltage pulse signal is injected in this phase with the objective to measure the inductance. Depending on the current time fall and its value, the position can be estimated. Some limitations to this estimation strategy are the eddy current effects in the iron and mutual magnetic linkage between phases (Harris, 1990), (Eshani, 1994), (Hussain, 1994).

In region 3, techniques based on diagnosis signals start to have some limitations about accuracy and precision in this speed level (Suresh, 1998), (Al-Bahadly, 2000) and (Kosaka, 2001).

In region 4, the EMF raises and become greater than the DC bus voltage. Consequently, the motor must operate in single pulse. In this situation, the EMF limits the current and the speed does not reach the desired value (constant power region). Operation in region 5 (very high speeds) requires high efficiency time algorithms due to physical limitation control in operate it in so high speeds. In this situation definitely the motor is operating in single-pulse (Lumsdaime, 1990).

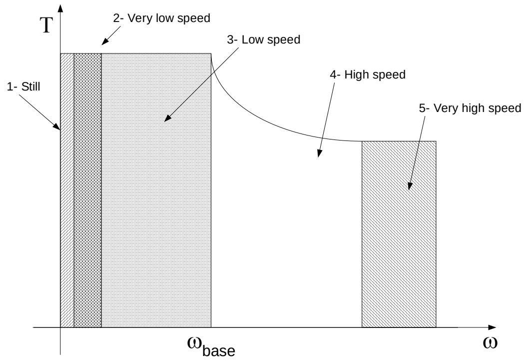


Figure 1 - Operating modes in sensorless control.

2 Training and Operation

Nowadays, the use of identification techniques using neural nets (Hang, 1998), (Ben-Brahim, 1999), (Cincotti, 1996) and fuzzy logic (Ertugrul, 2000) is growing up. They have the ability to estimate values from a set of inputs, mapping in a satisfactory way an output signal. From the ideas presented in these articles and also from the work of (Mese, 2000), we have developed a new strategy to estimate the SR rotor position. It is based on a neuro-fuzzy system (Costa Branco, 1998), with four inputs: the voltage signals in all three phases and the reference current. As output, the estimator gives the motor speed that, after integrated, produces the rotor position.

The neuro-fuzzy estimation is presented in this item as a rule learning method through examples. It uses a representative mathematical model of a neural net whose neurons represent membership functions of fuzzy logic system. The system has five gaussian membership functions for each one of the four inputs. The choice of the gaussian shapes is made in a way to allow that for any value of input all the rules of the function would be activated.

The first stage activity of the training is to fuzzify the inputs. After the input fuzzification using the gaussian membership functions, we calculate the matrix that will keep the antecedents for each rule. The next step is the system defuzzification using the center of gravity method.

The use of phase voltage and current signals to estimate the rotor position is sufficiently common. However this methodology always have some restrictions. To understand how to develop an estimator, we must remember the equation (2) describing the system dynamically.

$$v = R.i + \frac{d\lambda}{dt} \tag{2}$$

We know that flux is a function of θ and i

$$\lambda = f(\theta, i) \rightarrow \frac{d\lambda}{dt} = \frac{\partial\lambda}{\partial\theta}.\frac{d\theta}{dt} + \frac{\partial\lambda}{\partial i}.\frac{di}{dt} \tag{3}$$

If we replace (3) into (2), the result is indicated by (4) and (5)

$$v = R.i + \frac{\partial\lambda}{\partial\theta}.\frac{d\theta}{dt} + \frac{\partial\lambda}{\partial i}.\frac{di}{dt} \tag{4}$$

$$\frac{d\theta}{dt} = \frac{1}{\frac{\partial\lambda}{\partial\theta}}.\left(v - R.i - \frac{\partial\lambda}{\partial i}.\frac{di}{dt}\right) \tag{5}$$

As seen in the equation (5), we can create a relation between the position variation, current, voltage and stator resistance of the machine. There are works that use this technique, as shown in Figure 2. The inputs are phase voltage and phase current signals. Flux values λ are obtained by voltage and current integration , as shown in the Figure 2.

With the estimation proposed in this work, we include the non-linearity of the flux inside the estimator. The inputs shown in Figure 3 are: voltage variation at each phase and respective reference current. The reason of using voltage variation is based on the need to include the non-linearity, related to the flux, inside the estimator. This need is due to the time dependence prevailing between voltage and flux and, consequently, the relation between position and flux.

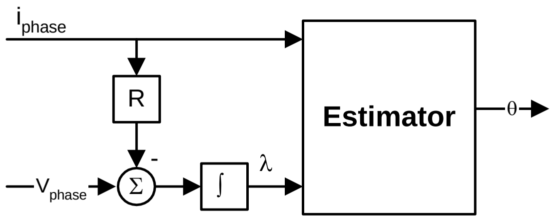


Figure 2 – Conventional SR rotor position estimator

A neuro-fuzzy system training is operated using three phase voltage inputs V(k), and three V(k-1), and the current reference $i_{ref}(k)$ (Figure 3).

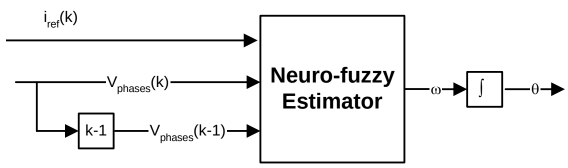


Figure 3 – Proposed SR rotor position estimator.

It is important to remember that voltage have discrete values of -150V, 0V and +150 V, as shown in Figure 4. Therefore, to obtain adequate voltage values for training, it is necessary to use a low pass filter of second order because for the same voltage values one would get different position values. Using this filter we get continuous voltage values allowing an adequate training. Figure 4 presents the voltage signal in one phase before and after the filtering process.

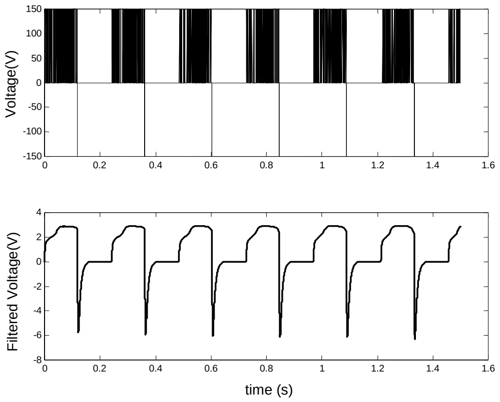


Figure 4 – Voltage in phase 1, before (up) and after (down) the filter

Figure 3 is better represented by Figure 5 when one includes the low pass filter (Butterworth second order filter, equation (6)).

$$\frac{1}{\frac{s^2}{(100\pi)^2}+\frac{\sqrt{2}s}{50\pi}+1} \qquad (6)$$

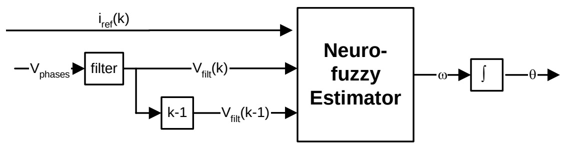
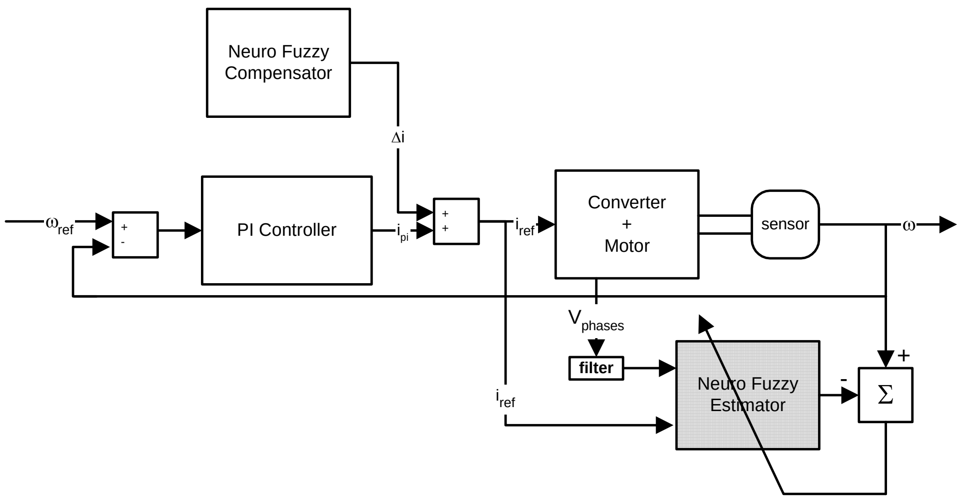


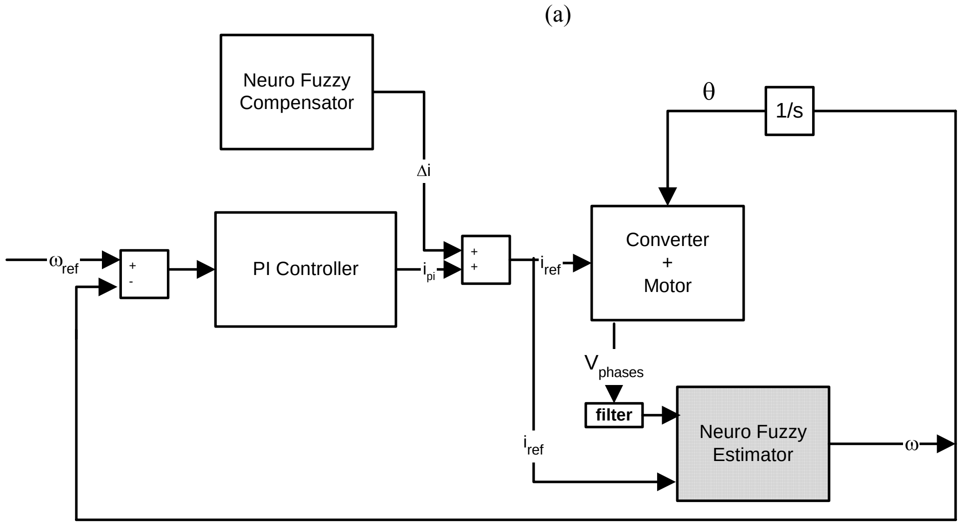
Figure 5 – Neuro-fuzzy estimator with filter

Figure 5 shows the capability of the neuro-fuzzy net in estimating the motor speed, thus facilitating the elimination of the position sensor.

With a representative amount of motor data for training, the system can generate a function approximating the correlation between V, I and ω. Figure 6 (a) shows how the neuro-fuzzy estimator is trained offline and later used as an estimator of speed and position (Figure 6(b)).



(a)



(b)

Figure 6 – (a) Training phase and (b) Operation phase

3 Simulated and Experimental Results

3.1 Offline Training

The first step to assure the neuro fuzzy operation is to generate a training data set, initially obtained with a constant value in reference current (in our case 1,5A). For this current value, the motor speed is 62 rpm (Figure 8).

The estimator is first trained for only one operating point (1,5A; 62 rpm). However, when the system was operated in closed loop speed control, with the reference speed fixed in 62 rpm, imperfections are found in the estimation. These are shown in the position curve of Figure 7 but with no significant magnitude.

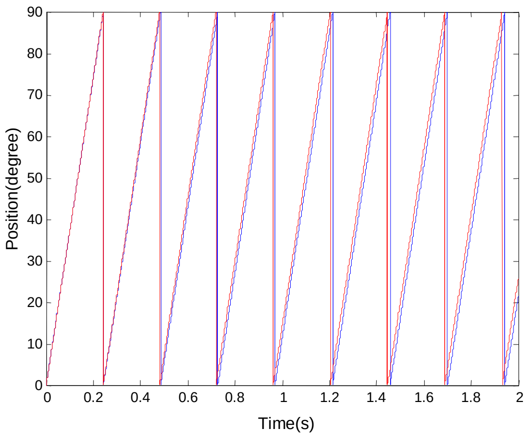


Figure 7 – Estimated (blue) and measured (red) rotor position signals: offline training simulation

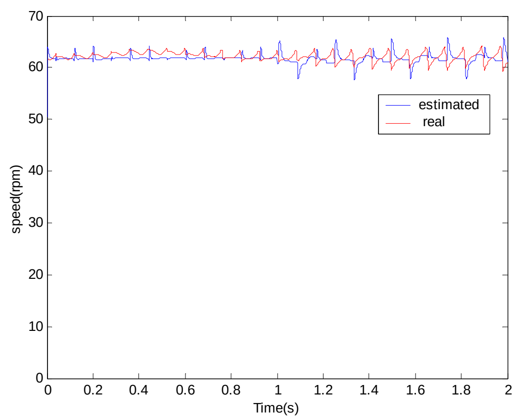


Figure 8 - Estimated and measured speed: offline training simulation

For our experimental tests, a signal conditioner based on a voltage sensor (LEM) was developed, being the voltage filter designed using operational amplifiers.

The estimated and measured speed in a closed loop control is shown in Figure 9. A small variation in the signal is due to numeric error in offline operation, but this noise does not disturbs the system, because it is a high frequency spike.

Training data is obtained with 1000 points and the test data are composed of 500 distinct points, with a different data set. For A reference speed of 100 rpm, the acquisition of the voltage signals, current and speed was made. Voltage and current signals acquired are plotted in Figure 10 and Figure 11, respectively.

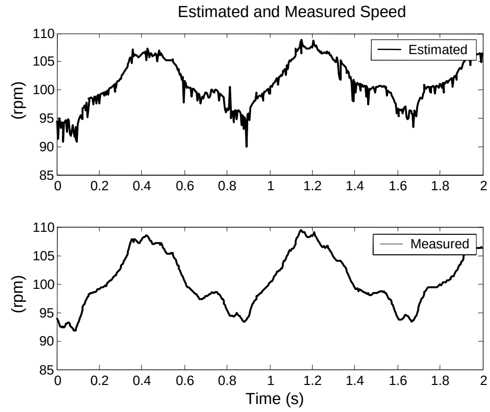


Figure 9 – Estimated and measured speed : offline training: experimental

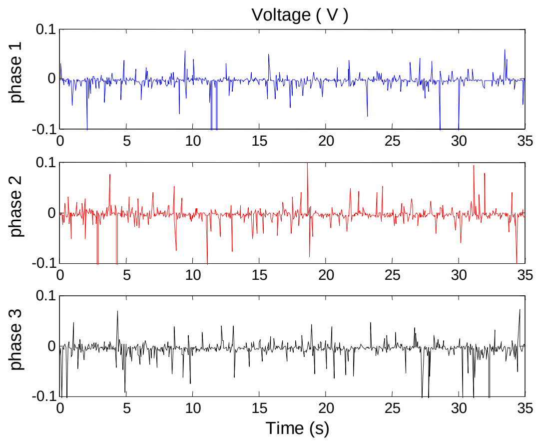


Figure 10 – Filtered voltage (all phases): experimental

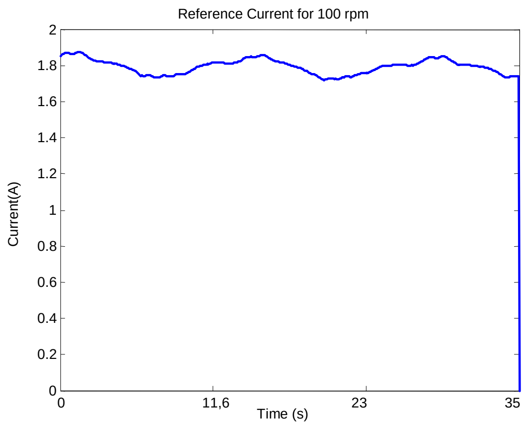


Figure 11 – Reference current: experimental

3.2 Online Training

After a correct sensorless operation in offline training, the next step is the online training and

operation based on the neuro-fuzzy learning structure. For a long-term operation, we obtain a training data set each second. The system is trained while the acquisition is made. This online acquisition is produced in the same way as the offline acquisition.
Figure 12 shows the result for 35 seconds. Until 12 seconds, the neuro fuzzy system is trained with 100 rpm speed reference. At. 13 seconds, the speed reference changes to 150 rpm, and the training goes until 25 seconds. At this moment, the reference change again to 100 rpm but the neuro fuzzy training stops to operate and only the estimator is present. This shows that the neuro-fuzzy estimator has learned the previous structure used for 100 rpm. The least mean square speed error of this operation is shown in Figure 13.

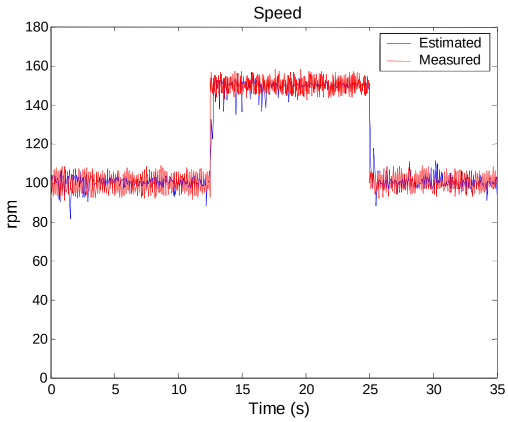


Figure 12 – Real and estimated speed: experimental results, online operation

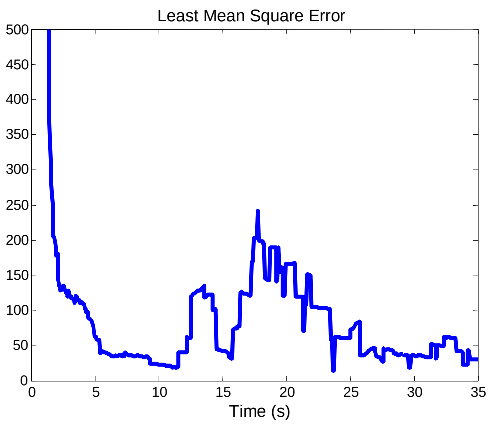


Figure 13 – Least mean square speed error

To conclude the presentation of the experimental results, we present the motor operation without the position sensor in closed-loop speed control using the Neuro-fuzzy estimator learning in online. The experimental system operates with training until t=20 seconds. After the neuro-fuzzy systems stops its online training and only the estimator operates without position encoder. The speed signal in Figure 14 has shown the moment when the estimator began to operate alone without the sensor. We can observe that in this moment the motor oscillates but only a few cycles until de learning process stabilizes

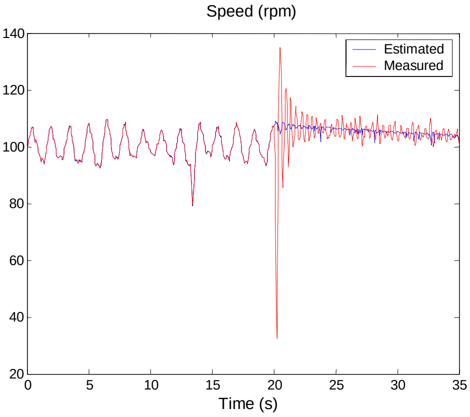


Figure 14 – Estimated and Measured Speed: experimental, online operation until 20 s.

Figure 15 shows the current shape in one phase when the motor is operating without sensor but with our estimator. The imperfection in current signal is due to the small estimation error, but the performance of the machine does not decrease.

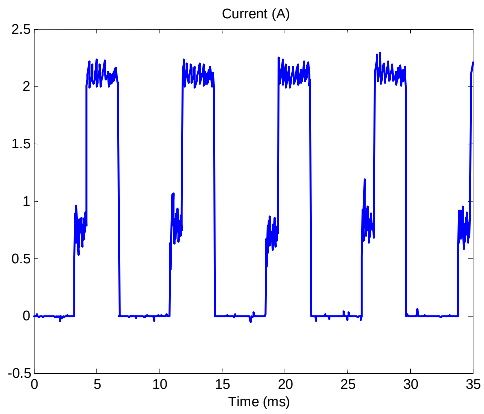


Figure 15 – Phase current waveform when the SR drives operates only based on the estimated position.

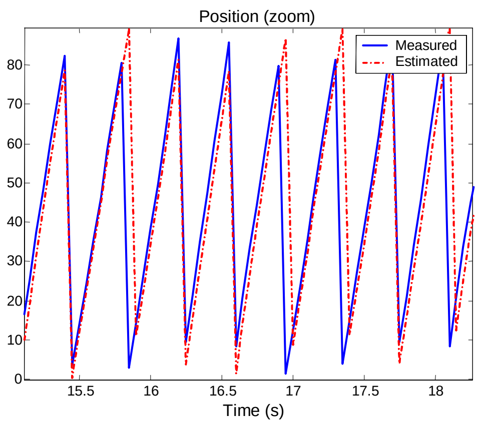


Figure 16 – Estimated/measured rotor position: experimental, online learning

Figure 16 shows a zoom of the estimated/measured rotor position signal when the switched reluctance motor operates without sensor. The estimation signal tracks the real position with a good accuracy. The difference between Figure 16 and Figure 7 is that this latter shows an open loop speed control with offline training and the Figure 16 shows a closed loop speed control with online operation.

4 Conclusion

A review about types of elimination position sensors in switched reluctance motors was presented.
A new technique using artificial intelligence was used to obtain a speed/position of the SRM.
Simulated and experimental results have demonstrated the feasibility to use this technique to eliminate the encoder of the SRM.
Online and offline training/operation was developed, and good results have been achieved.

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