DEVELOPMENT OF A NEURO FUZZY TECHNIQUE FOR POSITION SENSOR ELIMINATION IN A SRM

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Abstract – **This article has the objective to present a brief revision of the techniques more generally used in the position sensor elimination in a Switched Reluctance Motor. For each speed level, different techniques are indicated for a good system operation. A new technique of position sensor elimination is presented, based in intelligent techniques with neural nets and fuzzy logic. It uses only phase voltages and the reference current signals to obtain the position estimation. Experimental and simulation results are presented showing its good performance but also some points that are currently being improved.**

KEYWORDS

Switched Reluctance Motor, Neuro-fuzzy Technique, Sensorless Operation

I. INTRODUCTION

The perfect operation of a switched reluctance machine depends essentially on the correct excitation of the phases in synchronism with the position of the rotor. A resolver or encoder can solve totally this necessity. They are capable of giving the necessary information of the position for the correct application of the pulses.

In some applications, these sensors are not desirable for different reasons: cost, size, weight, inertia and reliability. This article presents some strategies of elimination of sensors in switched reluctance motors and proposes a new strategy using neuro-fuzzy learning.

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

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

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 flux in the stator and t is the time.

The dependence of the flux with the position is the key point for the operation without sensors. Inevitably, the great majority of the existing techniques of sensors elimination are based on this basic principle to obtain the position information. The typically measured variables are: voltage, current, current rising time or current falling time. The derived variables are: inductance, flux and EMF. The torque-speed curve can be divided in 5 regions.

As shown in Figure 1, below the speed base (smallest speed where you can extract the maximum power) the torque remains constant. These regions (below the speed base) offer flexibility for the current control; allow getting the desired performance for the motor. It is important to know that in regions 1 and 2, the counter EMF is smaller that the DC bus voltage and can be neglected. In these regions, 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 the phases. Another restriction is that this strategy produces a significant braking torque.

More recent works present this technique combined with observers [1]. Another work proposes a techinique that uses an amplitude modulation [2], however it has the disadvantage to need an external circuit, which adds cost and complexity to the system.

In [3], a voltage measurement method is presented. The operation principle is based on the induced voltage measurement in one of the non energized phases. This voltage is induced by the current that circulate in the energized phase. Depending on the rotor position, this voltage varies and so, an electronic circuit captures this signal, which is processed by a microcontroller, in order to determine the commutation time.

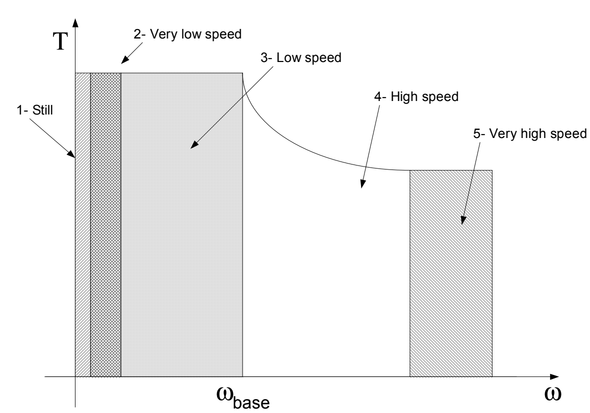


Figure 1 - Operation modes in sensorless control.

In region 3, techniques based on diagnosis signals start to have some limitations about acurancy and precision in this speed level [4]. Therefore, the use of techniques that work in the energized phases became suitable above this speed level.
The method presented in [5] to estimate the rotor position is based on the flux and current measurements. It presents an wide operation band in such a way being applicable for low speeds and high sppeds. It compares the measured signal with the value stored in a look-up table to obtain the position value. A drawback is the necessity to inject a current pulse diagnosis during the inductance fall period of the phase in question. In recent works, we have the use of this look-up table represented in a fuzzy logic system or neural nets [6].
When the speed increases, the EMF raises and become greater than the DC bus voltage. In this situation, the motor must operate in single pulse operation (region 4). In this way, the current is limited by EMF and it does not reach the desired value. Therefore, the current control is not possible and the torque is maintained in the desired value by the turn-on and turn-off angle control. This region is called “constant power region”. The operation in region 5 (very high speeds) requires high efficiency time algorithms due to physical limitation control to operate it in so high speed. In this situation definetely the motor is operating in single-pulse. The use of observers in this speed level is rare, only having exceptions in the flux estimation in induction motor and position estimation in PM motors.
In [7] is presented a proposal of nonlinear model of the reluctance motor. The voltage terminals are considered as input, the currents are considered as the output and flux, speed and position are the states. A disadvantage is the need of a powerful computational equipment. However, with the development of faster DSPs, this problem will be surpassed easily and with possible low costs. For these cases, the acquisition of aligned and unaligned positins using the EMF or flux variation is recommended.

II. TRAINING AND OPERATION

As shown in last section, many strategies of elimination of position sensor in SRM has been investigated. Currently, the use of identification techniques using neural nets [8],[9],[10] and fuzzy logic [11] is growing up. They have capacity 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 article [12], we developed a new strategy to estimate the rotor angular position. It is based on a neuro-fuzzy system, with 4 inputs: the voltage in all 3 phases and the reference of the control current, and as output, motor speed that, after integrated, produces the rotor position.
The use of the voltage and current measured signals to estimate the rotor position is sufficiently common, however this methodology always have some restrictions. To understand how to model an estimator, we must remember the equation that describes the system dynamically.

$$v = R.i + \frac{d\lambda}{dt} \qquad (2)$$

We know that flux is a function of θ and i

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

If we replace: λ in equation (2). The result is indicated by:

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

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

As seen in the equation (5), we can create a relation between the position variation, current, voltage and resistance of the machine. There are works that use this technique, presented in Figure 2. The inputs are phase voltage and phase current. The values of λ are obtained by the integration of the voltage and current, as shown in the Figure 2.
However, due to voltage and current measurement errors, and resistance variation associated to temperature variation, the error estimation can increase. Another situation that occurs is that in extreme points, (aligned position and unaligned position) the estimation errors are higher. Particularly, small errors in the current measurement and in the flux calculation generate an important estimation error for larger angles (regarding to the next unaligned zone). With the estimation proposed in this work, including the non-linearity of the flux inside the estimator prevents these errors. The inputs as shown in Figure 3 are: voltage variation at each phase and respective reference current. The reason of using voltage variation is based on the necessity to include the non-linearity, related to the flux, inside the estimator. This necessity is due to the time dependence existent between the voltage and the flux and, consequently, the relation between the position and the flux.

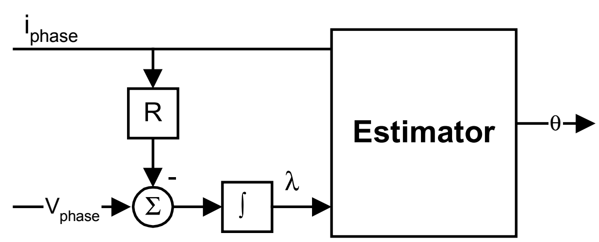


Figure 2 – Conventional estimator

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

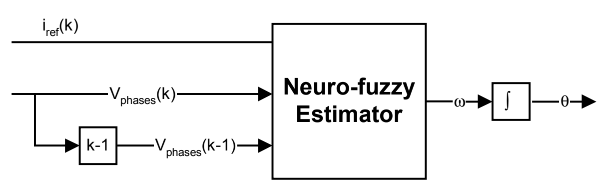


Figure 3 – Proposed Estimator

It is important to remember that the voltage values have discrete values of -150V, 0V and 150 V, as shown in Figure 4. So, to obtain adequate values of tension for the training, it is necessary the use of a low pass filter of second order since for the same voltage values, one would get different position values. Using this filter we get continuous values of the tension allowing the training. Figure 5 presents the voltage signal before and after the filtering.

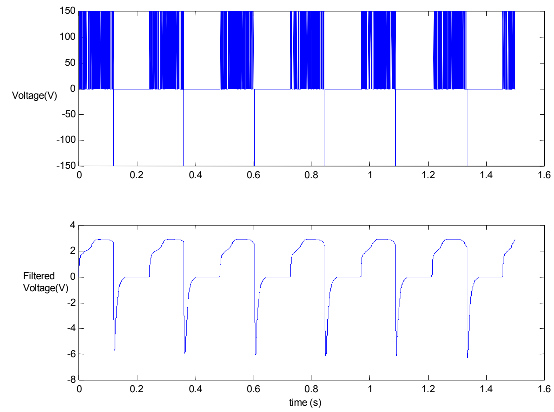


Figure 4 – Voltage in phase 1, before (up) and after(down) the filter

Therefore, the Figure 3 is better represented when it is included a low pass filter (Butterworth second order filter, equation (6)) is included, as Figure 5).

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

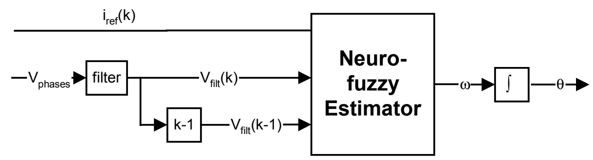
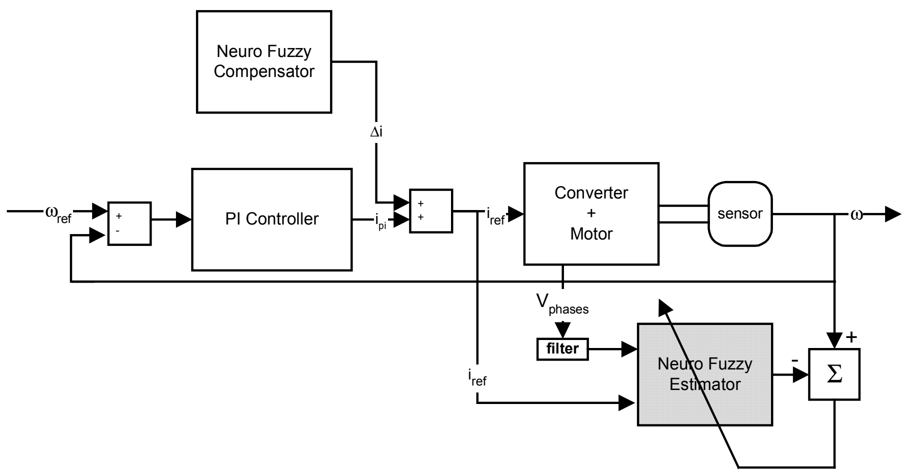
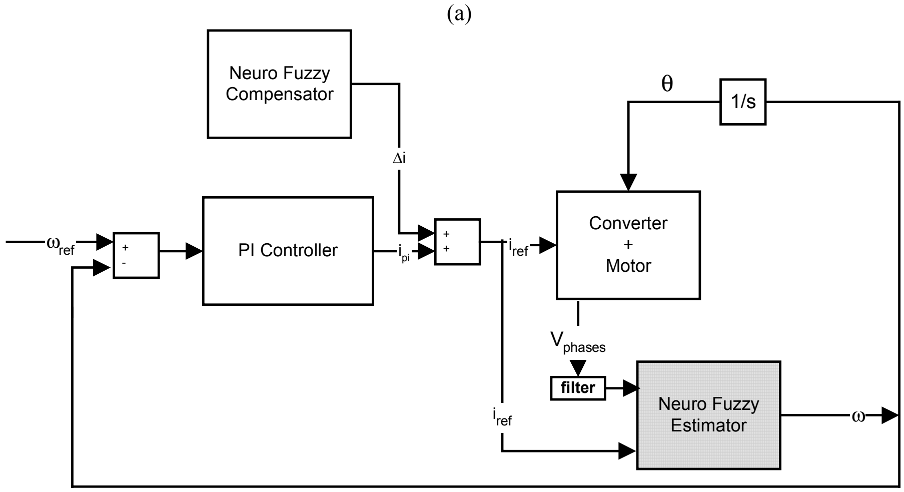


Figure 5 – Neuro-fuzzy estimator with filter

Through these measurements, the neuro-fuzzy net is capable to estimate the speed, thus facilitating the elimination of the position sensor.
With a representative amount of data for the training, the system can generate a 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

III SIMULATED AND EXPERIMENTAL RESULTS

The first step to train the neuro-fuzzy net is generating a training data set, initially with a constant value in reference current (in case 1,5A). For this current value, the equivalent speed is 62 rpm (
Figure 8). Initially the estimator was trained for only one point of operation. 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 then present in the position curve shown in Figure 7 but with no significant magnitude.

For the experimental results acquisition, a signal conditioner based in a voltage sensor (LEM) was developed; the voltage filter was generated using operational amplifiers (Figure 10).

The training data is obtained with 1000 points and the test data is 500 distinct points, with a different data set.

For the reference speed of 100 rpm the acquisition of the voltage signals, current and speed was made. Voltage and current signals are presented in Figure 9 and Figure 11

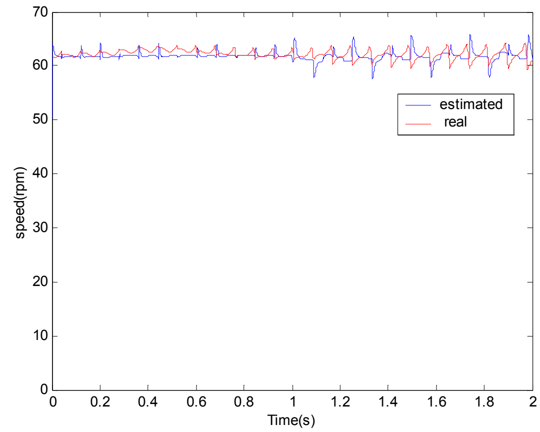


Figure 8 – Estimated and real speed

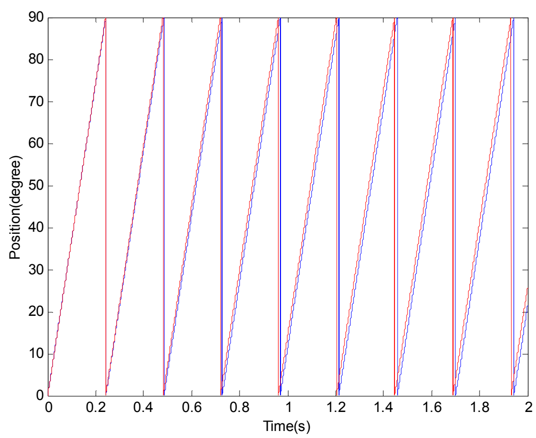


Figure 7 – Estimated and real position

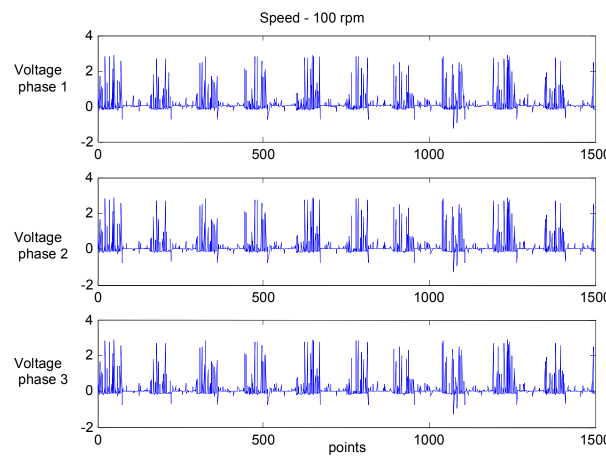


Figure 9 – filtered voltage (all phases)

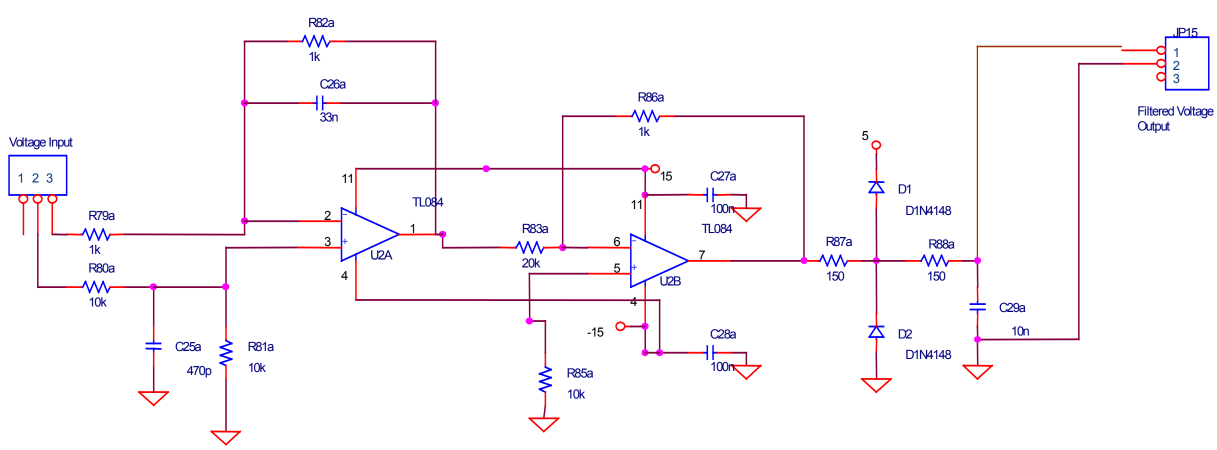


Figure 10 – Filter

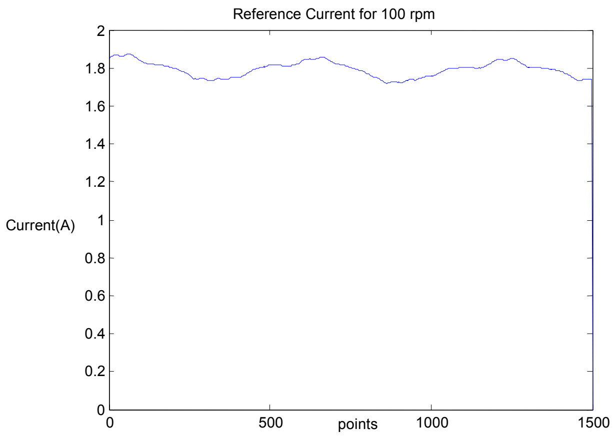


Figure 11 – Reference current

After the training, we got the following output signal (Figure 13).

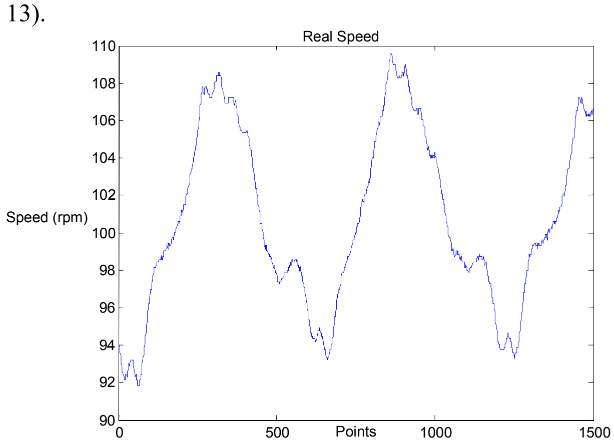


Figure 12 – Reference speed

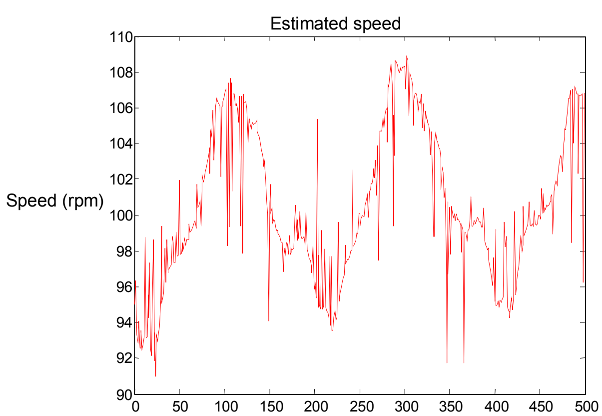


Figure 13 – Estimated speed

IV CONCLUSION

Simulated and experimental results demonstrated the feasibility to use this technique to eliminate the encoder of the SRM.

The next step, currently being developed, is the estimator training for a wide band of speed, to allow the operation for all conditions. A difficulty observed until this moment is to find a good criteria for finishing the learning and the ideal number of membership functions to be used.

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