

DEVELOPMENT AND IMPLEMENTATION 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 speed/position estimation. Experimental and simulation results are presented showing its good performance.

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:

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

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 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 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 the phases.

More recent works present this technique combined with observers [1], another work proposes a technique that uses an amplitude modulation [2], [3].

In region 3, techniques based on diagnosis signals start to have some limitations about accuracy and precision in this speed level [4],[5] and [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. 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 definitely 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.

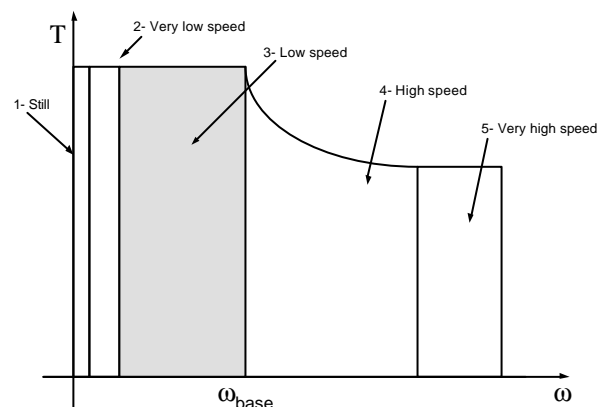


Figure 1 - Operation modes in sensorless control.

In [7] is presented a proposal of nonlinear observer 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 positions 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 have 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 [13], 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 neuro-fuzzy estimation is presented in this item as a rule learning method through examples. It use a representative mathematical model of a neural net whose neurons represent membership functions of fuzzy logic system.

The inputs are voltage in the three phases and the reference current. The system have five membership function for each one of the 4 entrances. The shape of the membership function is gaussian. The choice of the gaussian shapes comes of the fact to allow that for any value of entrance all the rules of the function will be activated.

The first stage activity of the training is 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 center of gravity method.

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.

$$v = R \cdot i + \frac{d\mathbf{l}}{dt} \quad (2)$$

We know that flux is a function of θ and i

$$\mathbf{l} = f(\mathbf{q}, i) \rightarrow \frac{d\mathbf{l}}{dt} = \frac{\partial \mathbf{l}}{\partial \mathbf{q}} \cdot \frac{d\mathbf{q}}{dt} + \frac{\partial \mathbf{l}}{\partial i} \cdot \frac{di}{dt} \quad (3)$$

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

$$v = R \cdot i + \frac{\partial \mathbf{l}}{\partial \mathbf{q}} \cdot \frac{d\mathbf{q}}{dt} + \frac{\partial \mathbf{l}}{\partial i} \cdot \frac{di}{dt} \quad (4)$$

$$\frac{d\mathbf{q}}{dt} = \frac{1}{\frac{\partial \mathbf{l}}{\partial \mathbf{q}}} \cdot \left(v - R \cdot i - \frac{\partial \mathbf{l}}{\partial i} \cdot \frac{di}{dt} \right) \quad (5)$$

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. The inputs are phase voltage and phase current. The values of θ 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.

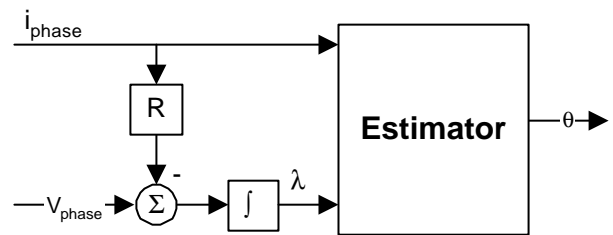


Figure 2 – Conventional estimator

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).

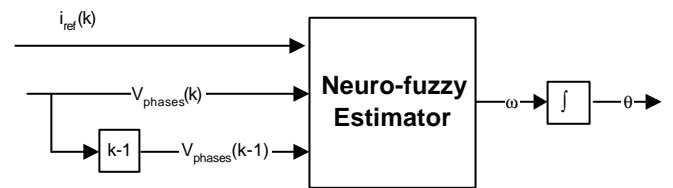


Figure 3 – Proposed Estimator

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.

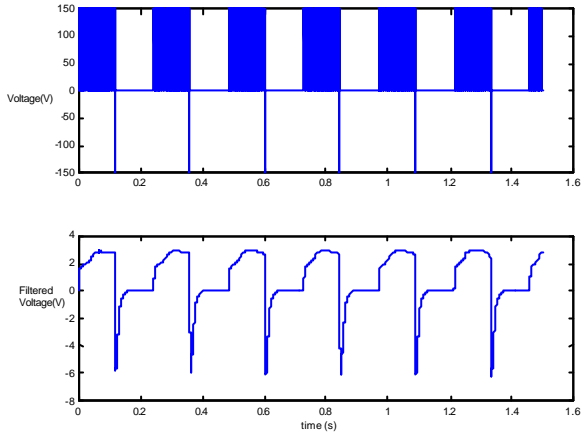


Figure 4 – Voltage in phase 1, before (up) and after (down) the filter

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).

$$\frac{1}{\frac{s^2}{(100p)^2} + \frac{\sqrt{2}s}{50p} + 1}$$

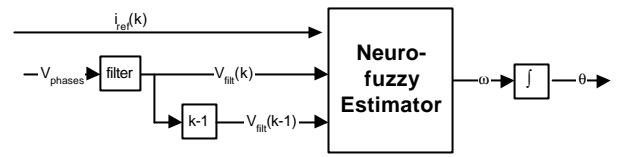
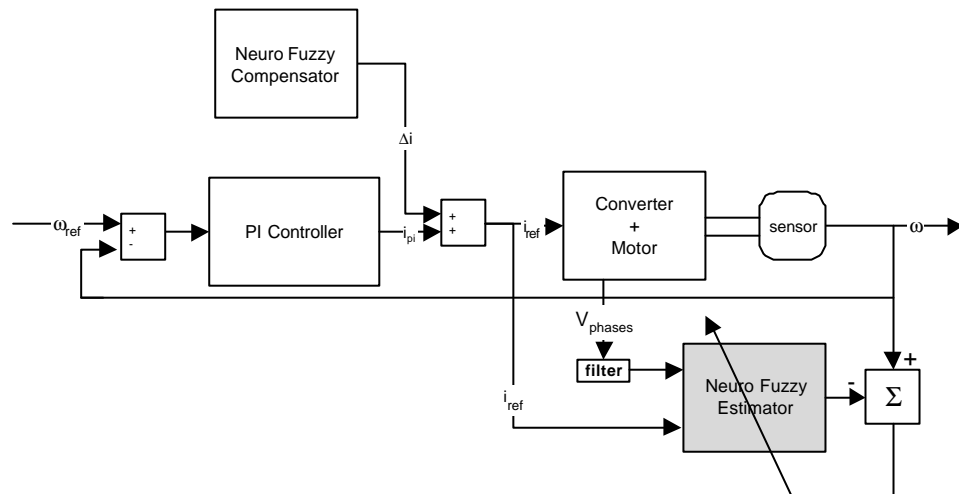


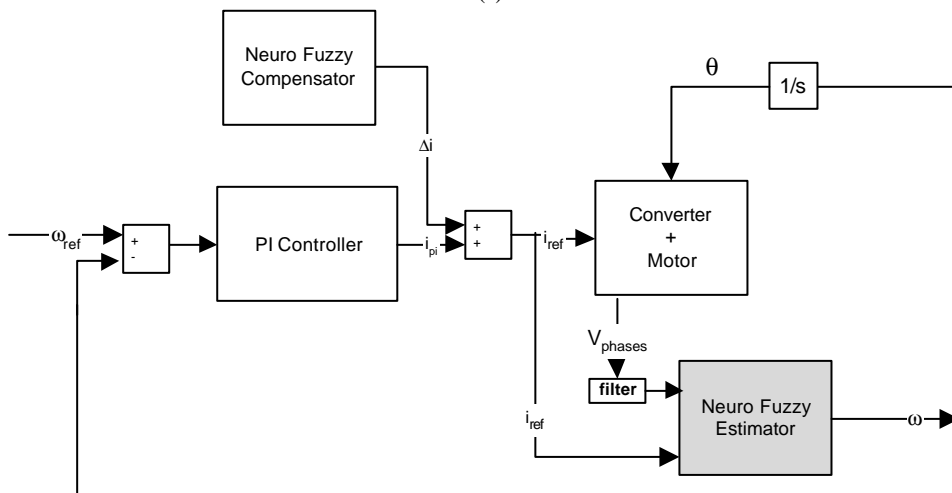
Figure 5 – Neuro-fuzzy estimator with filter

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 ?. 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

A. OFFLINE OPERATION

The first step to guarantee the neuro fuzzy operation 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

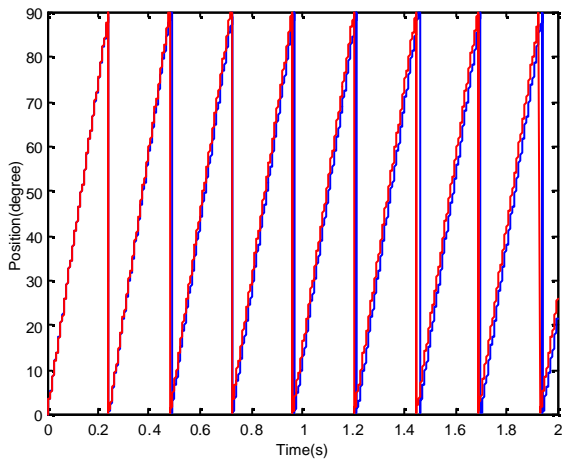


Figure 7 – Estimated and real position

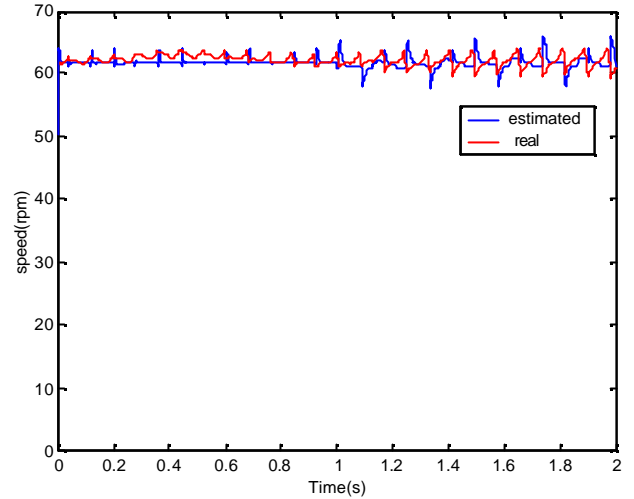


Figure 8- Estimated and real speed

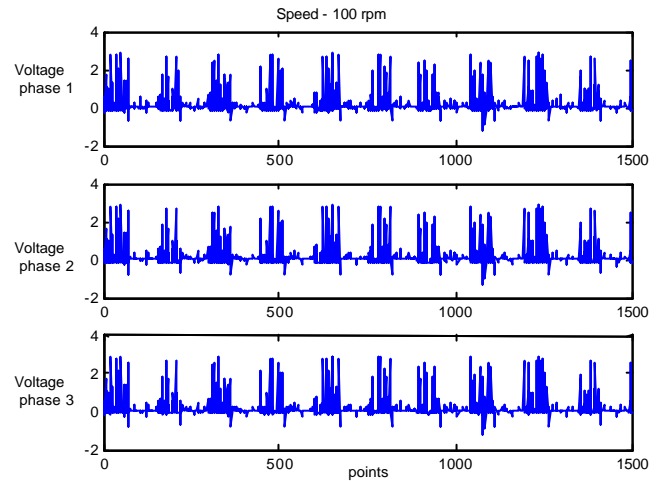


Figure 9 – Filtered voltage (all phases)

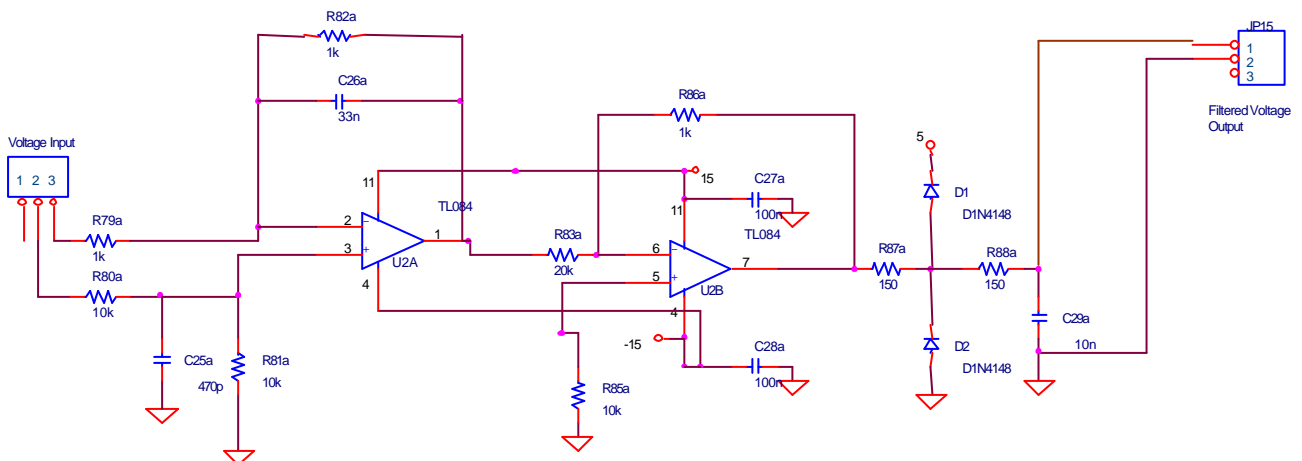


Figure 10 – Filter

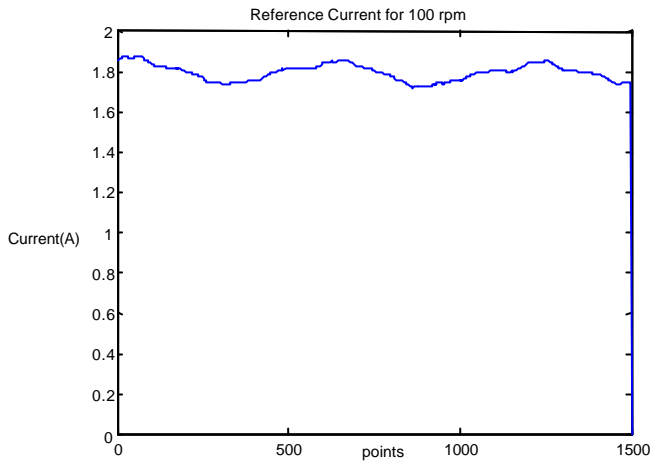


Figure 11 – Reference current

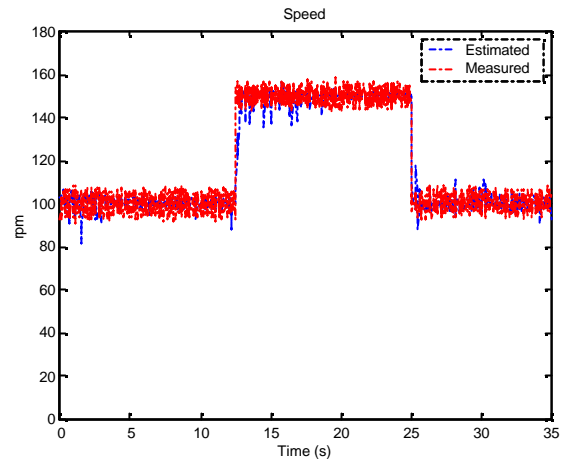


Figure 13 – Measured and estimated speed

After the training, we got the following output signal (Figure 12).

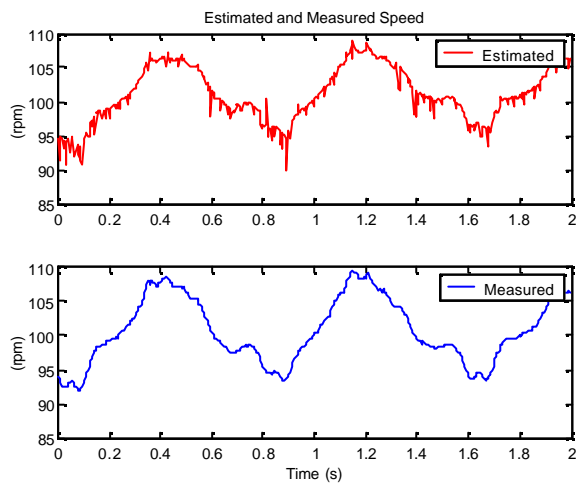


Figure 12 – Estimated and measured speed simulation

B. ONLINE OPERATION

After the correct operation in an offline mode, the next step is the online training and operation. For a long-term operation, we obtain a training data set each second. The system train while the acquisition is made. This online acquisition is produced in the same way of the offline acquisition.

Figure 13 shows the result for 35 seconds. Until 12.5 seconds, the neuro fuzzy system train in 100 rpm speed reference. At 12.5 seconds, the speed reference changes to 150 rpm, and the training persist 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 works. The least mean square speed error of this operation is show in Figure 14.

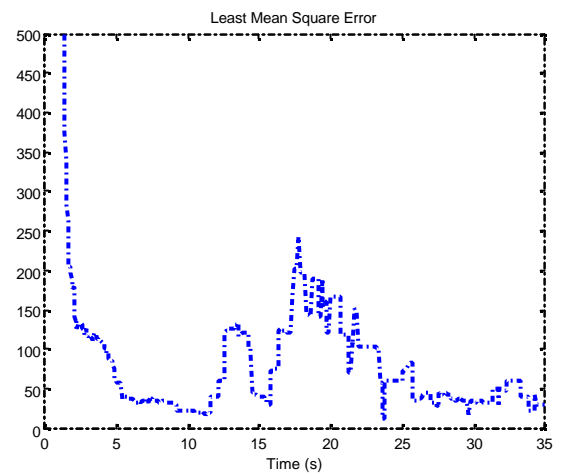


Figure 14 – Least mean square speed error

To conclude the presentation of the experimental results, we present the operation of the motor without the position sensor in closed loop speed control using the Neuro-fuzzy estimator in real time. The system operates with training for all the time and in $t=20$ seconds, the net stops the online training and only the estimator operates without encoder. The speed signal in Figure 15 show the moment that the estimator began to operate alone without the sensor.

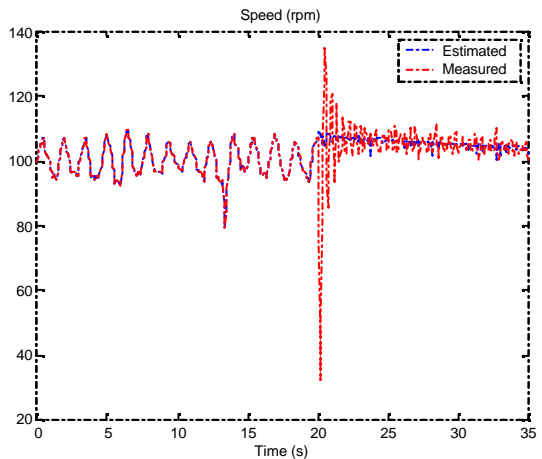


Figure 15 – Estimated and Measured Speed

Figure 16 present the current shape in one phase when the motor is operating without sensor. The imperfection in current signal is due the small estimation error, but the performance of the machine does not decrease.

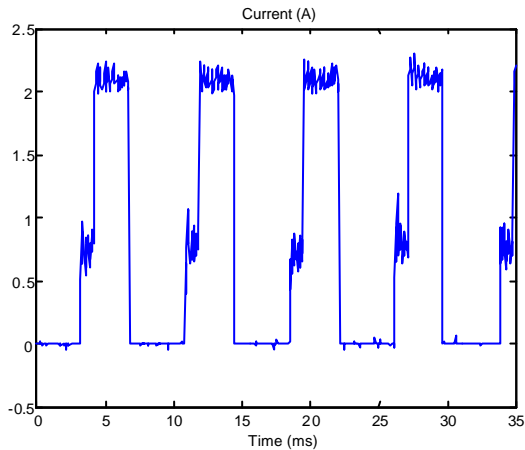


Figure 16 – Estimated speed

Figure 17 shows a zoom of the estimated/measured position signal when switched reluctance motor operates without sensor.

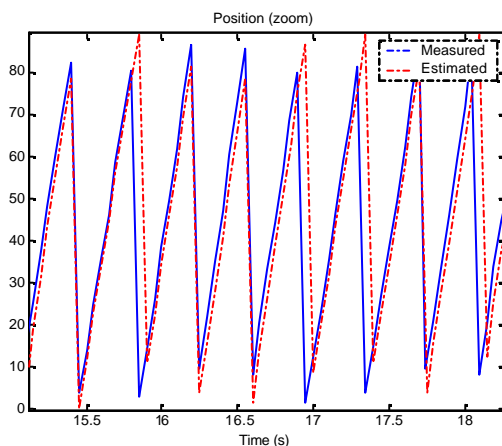


Figure 17 – Estimated/measured position

IV 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 demonstrated the feasibility to use this technique to eliminate the encoder of the SRM. Online and offline training/operation was developed, and good results were achieved.

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