NEURO-FUZZY COMPENSATION STRATEGY TO MINIMISE TORQUE RIPPLE IN SWITCHED RELUCTANCE MOTOR DRIVES

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Abstract: Simple power electronics and fault tolerance are advantages of SRM drives. However, excessive torque ripple has limited their application. This paper presents a novel method of controlling the motor currents to minimise the torque ripple based on a neuro-fuzzy compensator. In the proposed controller, a compensating signal is added to the output of a PI controller, in a current-regulated speed control-loop. The compensating signal is learned prior to normal operation, in a self-commissioning run, but the neuro-fuzzy methodology is also suitable for on-line self-learning implementation, for continuous improvement of the compensating signal.

Keywords: Switched reluctance motors, Learning control, Compensation, Electrical machines, Fuzzy control, Actuators, Fuzzy systems, Speed control

1. INTRODUCTION

In the last years, some works (Belfore and Arkadan, 1997; Bolognani and Zigliotto, 1996) have been proposed on modelling and control of SR motors using soft-computing techniques. Artificial intelligence-based fuzzy, and/or neural, and/or genetic controllers have demonstrated a number of advantages over conventional ones and, more significantly, helping to incorporate "some intelligence" into them (Costa Branco and Dente, 1998). Fuzzy control of a SR drive has been implemented with success by Rodrigues *et al.* (1997), and has shown to be effective for speed control in applications where some degree of torque ripple is tolerated, as is the case in many industrial applications. Nevertheless, in servo control applications or when smooth control is required at low speeds, elimination of torque ripple becomes the main issue for an acceptable control strategy of the SRM. In this case, even using a fuzzy PI-like control, is not satisfactory because the controller response, which is used as reference signal for current control, gives rise to sustained torque pulsations. Furthermore, the magnitude of these pulsations changes with the motor speed and with its load. Results (Husain and Ehsani, 1996; Lovatt and Stephenson, 1994; Wallace and Taylor, 1992) have been published, which use many different compensating strategies. Some works (Lovatt and Stephenson, 1994) use the inverse of the static torque-current-rotor position relationship that are tabulated previously and stored in memory. However, these methods are quite laborious and mainly sensitive to parameter variations. A novel compensation method is proposed in this paper, which is based upon a self-tuning neuro-fuzzy compensator with adaptation capacity to motor parameters change. The compensating signal is added to the output of a PI controller. Therefore, the compensator has the objective of to learn how modulate the currents to reduce the torque ripple.

2. THE PROBLEM: TORQUE RIPPLE

With only a PI-speed controller, it is not possible to obtain a ripple-free motor speed at any speed range because it would require a ripple-free output torque for this purpose. If it is supposed that the speed is constant and equal to the reference one in steady state, then the PI controller's signal (i.e. the reference current) would be constant. Figure 1 shows, however, that a constant current reference produces a pulsating torque, rendering the ripple-free speed control unfeasible. The results shown correspond to the current-regulated, full-load operation of a 750W SR motor, at rated speed (1800rpm). At high speeds, torque pulsation occurs at higher frequencies, thus causing less speed ripple due to the natural filtering provided by the mechanical load inertia.

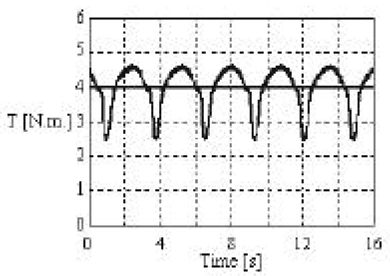


Fig. 1. Torque ripple from constant current reference.

SR drives are operated in single-pulse mode at high speeds, without current control. In this case, the most effective way of reducing the torque pulsations is by way of turn-off angle control (Mir *et al.*, 1999). At lower speeds, it is more convenient to compensate for the torque pulsation through phase current wave shaping. In this case, the current reference signal should vary as a function of position, motor speed, and load torque, to produce the desired ripple compensation.

3. NEURO-FUZZY CURRENT COMPENSATOR

To attenuate the torque ripple, it is proposed to add a compensating signal to the PI controller as shown in Figure 2. This signal can be dependent of the rotor position, the motor speed, and the torque load value. In fact, it is a function that possesses high mathematical complexity and therefore the production of this signal is quite complicated. In this work, by the learning capabilities of the compensator, the control shows large operation flexibility. The learning mechanism makes the compensator more independent of the motor characteristics. If the system has some load modification and/or change of speed, the compensator will have the ability of to adapt itself to this new operating point, searching for the required torque ripple minimisation. The strategy to produce the compensating signal is to incorporate to the PI speed controller some learning mechanism through the new "intelligent" methodologies as the neuro-fuzzy systems.

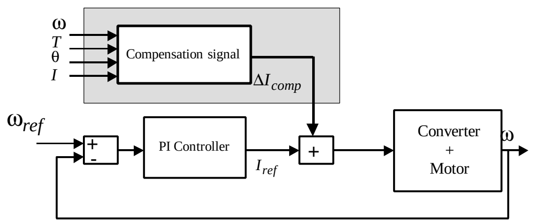


Fig. 2. SR drive with the compensating signal.

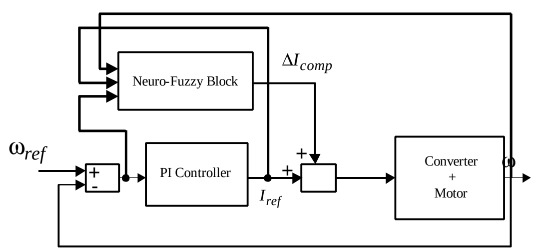


Fig. 3. PI control and the neuro-fuzzy compensator.

3.1 The Neuro-Fuzzy System.

The ANFIS neuro-fuzzy system (Jang, 1993) was used to implement the compensator. First, it uses the training data set to build the fuzzy system, which membership functions are adjusted using the backpropagation algorithm, allowing that the compensator learns with the data that it is modelling. Figure 4 shows the network structure of the ANFIS that maps the inputs by the membership functions and their associated parameters, and so through the output membership functions and corresponding associated parameters. These will be the synaptic weights and bias, and are associated to the membership functions that are adjusted during the learning process. The computational work to the obtain the parameters (and their adjustments) is helped by the gradient descendent technique.

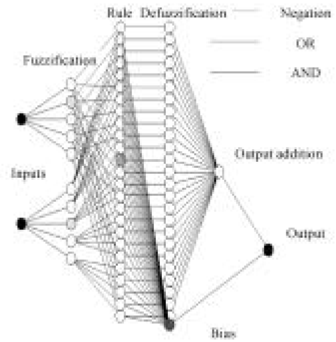


Fig. 4. ANFIS network structure.

We have used the ANFIS system at the MATLAB®. Its operation can be resumed in two steps:
1) The set of membership functions has to be chosen: their number and corresponding shape.
2) The input-output training data is used by the ANFIS. It starts making a clustering study of the data to obtain a concise and significant representation of the system's behaviour. It is important to note that the system has a good modelling if the training set is enough representative, i.e., it has a good data distribution to make possible to interpolated all necessary values to the system's operation. The clustering technique used was the fuzzy c-means. After set the number of clusters that are estimated to compose the data, the cluster's centres are searched in an iterative way based on minimising an objective function. This represents the distance between a data value to the cluster's centre. As we do not know how much clusters exist, or the number of rules composing the neuro-fuzzy compensator, we used the technique of subtractive clustering to estimate the number of clusters.

3.2 Compensator: Operation and Training.

The compensator considers two inputs: rotor position θ and the PI controller's reference current I_{ref}. These are used by ANFIS to generate the compensating function $\Delta I_{comp} = f(\theta, I_{ref})$ summed to I_{ref}. A second phase corresponds to the iterative training of the neuro-fuzzy compensator. The presence of this iteration comes from the capability of the training program in simulate the system and, after a pre-defined simulation time, to obtain the simulation results and use them to the training.

Training data was obtained from simulations of steady-state operation of the complete SR drive. At each training iteration, the dc component of the torque signal is removed, so that just remains the ripple. This ripple data is then tabulated against the mean value of the PI reference current and the rotor angle. Next, this data set is passed to the ANFIS algorithm so that the torque ripple is interpreted by the compensator as error information for each current-angle pair. The compensator is readjusted to reduce the error (which is in fact the torque ripple), being this process repeated until some minimum torque ripple limit is reached.

Figure 5 shows the flowchart of the training process. The output of the training block is the compensating signal ΔI_{ref} , and only θ and I_{ref} are reloaded in the system to train it again. The compensated current reference is produced and loaded in the system (shown in dotted line). The stopping criterion is, in this case, the maximum number of iterations (**N**). When the iteration counter **i** reaches **N,** the training program stops. The choice of stopping criteria is very important for the stability of the method, since the converter may not be able to produce the required compensated currents at any speed or load. In this case, persisting on training may lead to output windup at the compensator. The training process using the two variables, reference current and rotor position, occurs in the following way. The neuro-fuzzy network is trained using as membership functions to the position and current the function set shown in Figure 6.

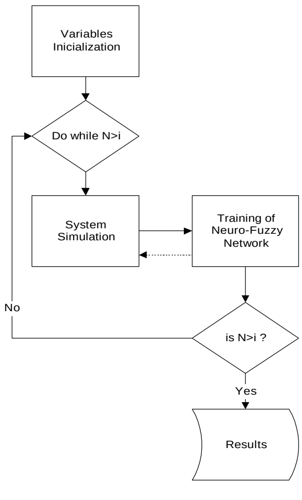
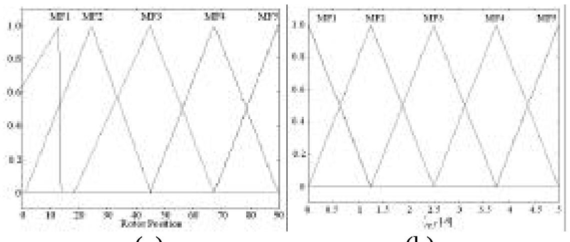


Fig. 5. Training program flowchart.



(a) (b)

Fig. 6. Rotor position (a) and reference current (b).

The ANFIS has two options to the optimisation of the fuzzy system: the backpropagation only and a hybrid technique that uses the back propagation and the mean squared. This last was used since it was more efficient in its operation. Varying all values of the reference current and rotor position, the compensating function $\Delta I_{comp} = f(I_{ref}, \theta)$ shown in Figure 7 is obtained.

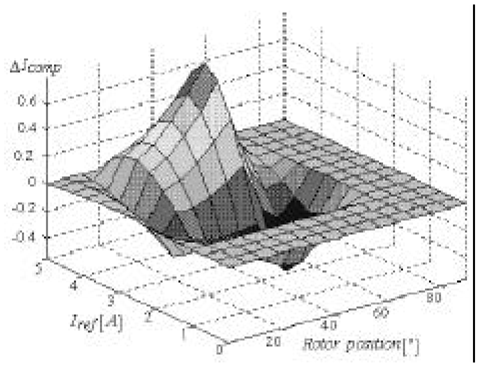


Fig. 7. Compensating function.

4. RESULTS

4.1 Initial Tests.

For comparison purposes, the system has been simulated without compensation, at full-load torque (4 Nm), and 500 rpm. The motor rated speed is 1800 rpm. The torque signal is plotted in Figure 8, and its harmonic components are shown in Figure 9. Since the motor has a 6/4 structure, the converter produces 12 current pulses per rotor turn. Therefore, the torque pulsations occur at a frequency 12 times higher than the rotating frequency. For this reason, the harmonic spectrum in Figure 9 exhibits non-zero components only for orders multiple of 12. The magnitudes of the harmonics are expressed as percentage of the mean value. It should be noticed that the first non-zero harmonic (12th) exhibits a quite high magnitude (approximately 13%).

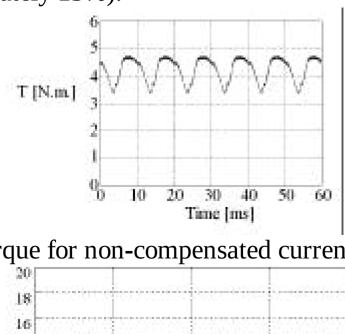


Fig. 8. Torque for non-compensated current 500 rpm.

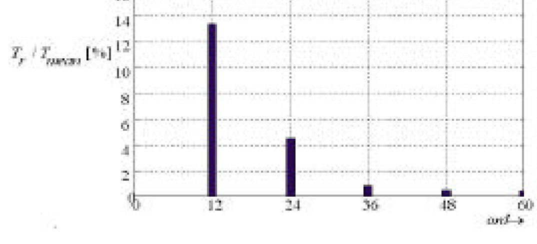


Fig. 9. Harmonics of non-compensated torque.

After one training iteration, the torque harmonic content is already significantly lower, as shown in Figures 10 and 11. The 12th harmonic has a relative magnitude of only 3% approximately.

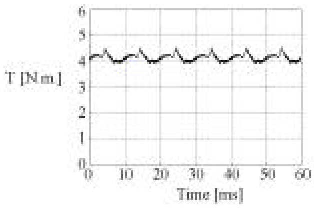


Fig. 10. Torque after the first learning iteration.

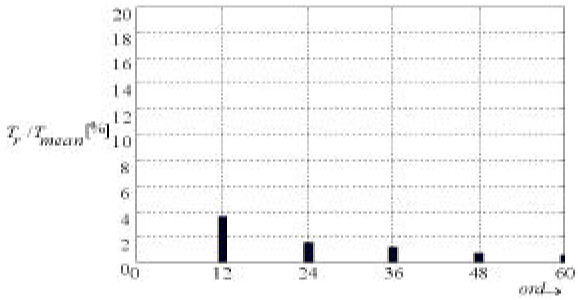


Fig. 11. Harmonic content in torque signal.

Figures 12 and 13 show the torque and its harmonics for a compensated current after 10 learning iterations. The total harmonic content is very low, and the 12th harmonic is now lower than 0.5% of the mean torque. The compensated current produces phase current pulses like those shown in Figure 14. As expected, the current values are higher at the beginning and at the end of the current pulse. This pulse shape is consistent with the torque characteristics of the machine, which produces less torque at the beginning of pole overlapping and before the aligned position.

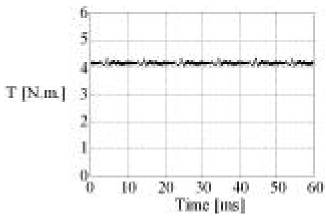


Fig. 12. Compensated torque after 10 iterations.

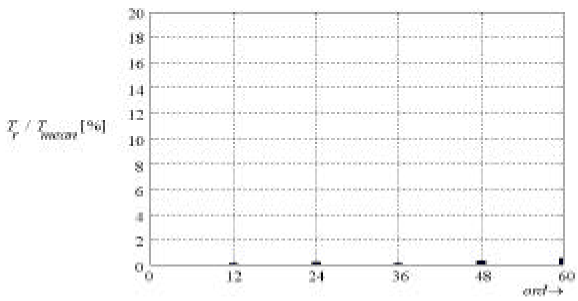


Fig. 13. Harmonic content in torque signal.

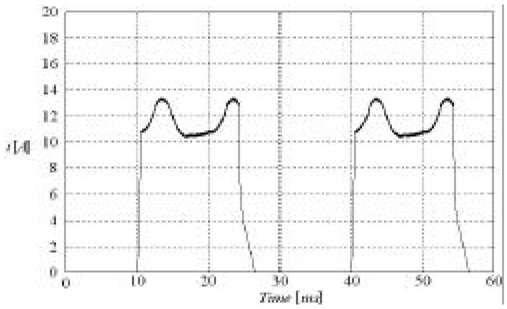


Fig. 14. Current pulses after 10 iterations.

4.2 Generalisation Tests

We show the compensator action for different motor speeds. The signals shown in items (a) have no additional compensating current signal. In items (b), the compensation is shown after 100 learning epochs and with the motor already in its reference speed.

Current in Phase A. Figures 15 to 17 show the current signal before (a) and after (b) the addition of the compensating signal for a nominal speed operation (1800 rpm), a speed of 1000 rpm, and a speed of 500 rpm. One notices better in the current centre in Figure 17b that there is a reduction in the current value that causes the ripple attenuation.

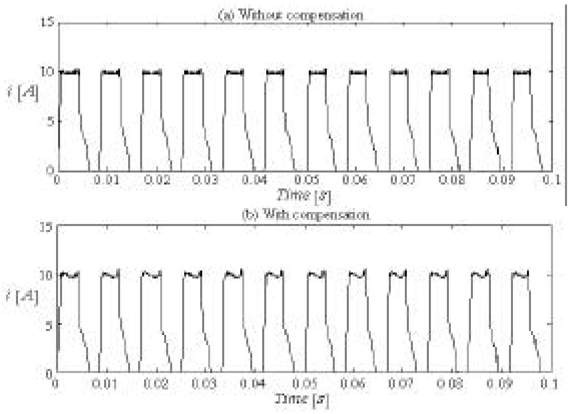


Fig. 15. Phase current A – 1800 rpm.

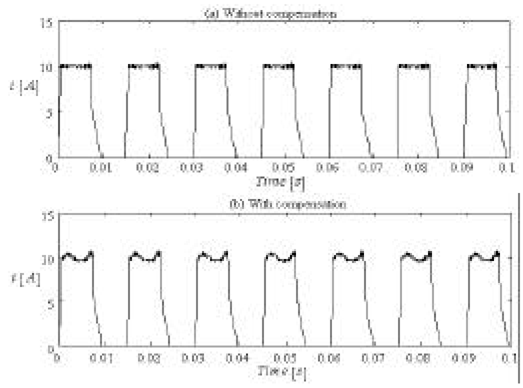


Fig. 16. Phase current A – 1000 rpm.

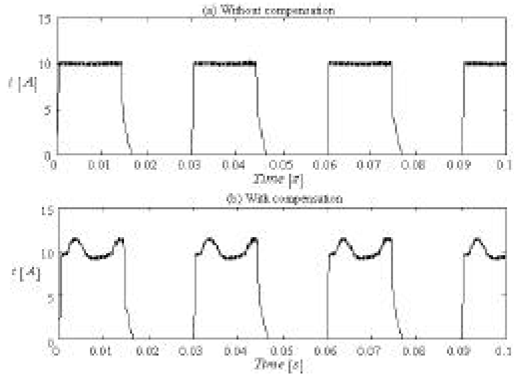


Fig. 17. Phase current A – 500 rpm.

Torque in Phases A and B. Figures 18 to 20 show the torque for 1800 rpm, 1000 rpm, and 500 rpm. Graphics in Figure 18 show similar behaviour. On other hand, the compensator action is better shown in figures 19 and 20 for lower speeds.

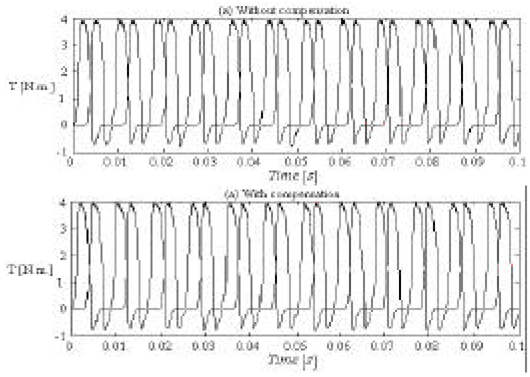


Fig. 18. Torque in phases A and B – 1800 rpm.

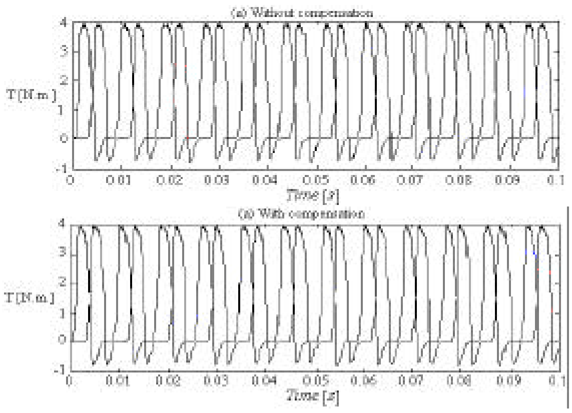


Fig. 19. Torque in phases A and B – 1000 rpm.

Total Torque. The total torque before and after compensation is shown in figures 21 to 23. The variance of the torque values (var) was used as a quantitative measurement of torque ripple. The results show clearly the effects of the compensating signal, mainly Figure 23 showing the efficiency of this technique to low speeds.

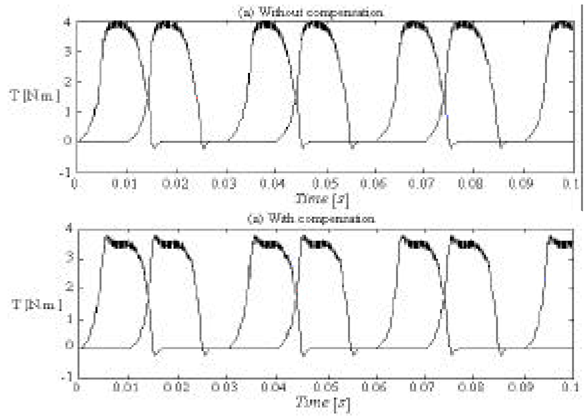


Fig. 20. Torque in phases A and B – 500 rpm.

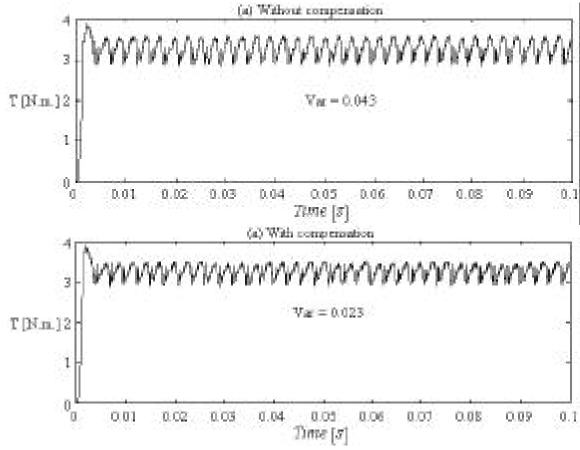


Fig. 21. Total torque – 1800 rpm.

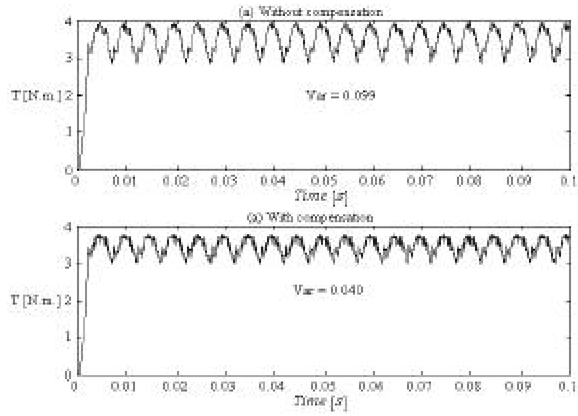


Fig. 22. Total torque– 1000 rpm.

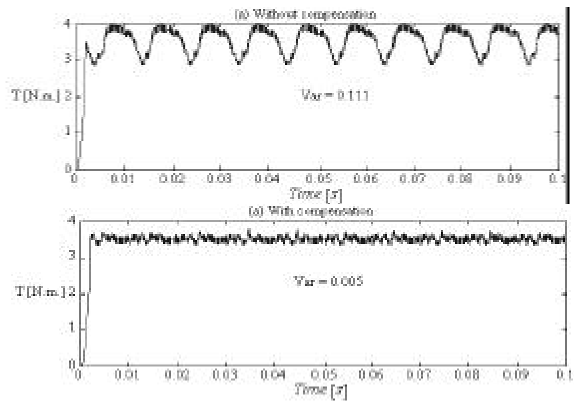


Fig. 23. Total torque – 500 rpm.

Torque Spectrum. Figures 24 to 26 show the torque frequency spectrum. As the converter gives 12 pulses by turn, the predominant harmonic is of 12 order, being reduced after the compensation process.

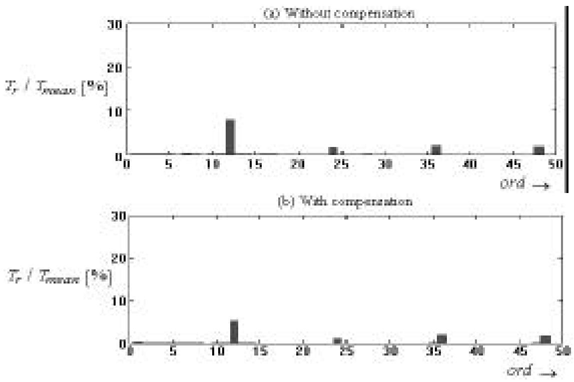


Fig. 24. Torque frequency spectrum – 1800 rpm.

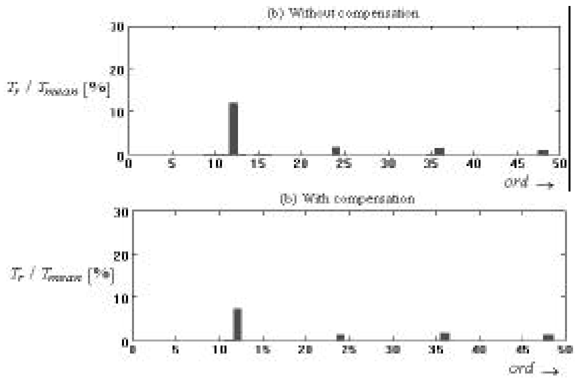


Fig. 25. Torque frequency spectrum – 1000 rpm.

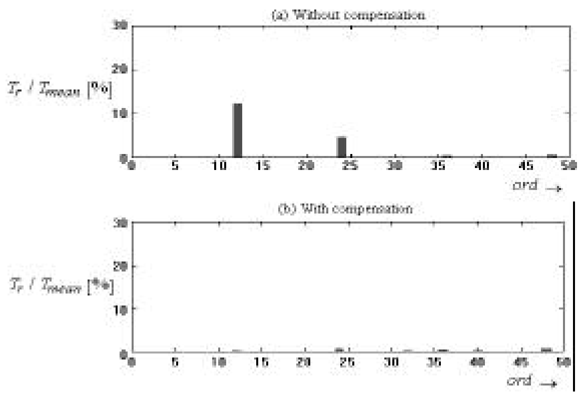


Fig. 26. Torque frequency spectrum – 500 rpm.

Different learning epochs. Figure 27 shows the influence of the learning epochs in the compensation for 25, 50, 75 e 100 iterations. For more than 75 iterations, the torque quality remains. Therefore, all simulations were done until 100 iterations.

5. CONCLUSION

The neuro-fuzzy modelling and the learning mechanism to ripple reduction in SR motor were investigated. The simulations of the switched reluctance drive show that it is possible to incorporate a compensating signal in the current waveform to minimise the torque ripple. Next steps will be to use this concept in an experimental drive and incorporate another signal to be trained.

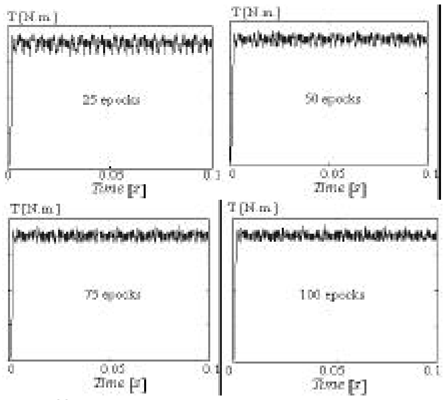


Fig. 27. Different learning epochs.

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