Fuzzy Model based on 3D FEM Simulation Data applied to Torque Ripple Minimization in a Switched Reluctance Motor

J. Vicuña*, A. Martínez-Iturbe, F. Pérez-Cebolla, B. Martín del Brío, E. Laloya, T. Pollán, J. Lladó**, B. Sánchez-Tabuenca**

** Dpto. Ingeniería Eléctrica, ETSII Universidad de La Rioja,*

*Dpto. Ingeniería Electrónica y Comunicaciones, ** Dpto. Ingeniería Mecánica, Universidad de Zaragoza*

javier.vicuna@die.unirioja.es, amiturbe@posta.unizar.es

***Abstract*—A fuzzy model to minimize torque ripple in a Switched Reluctance Motor is presented. Motor has been built as a flat profiled direct drive in a domestic washing machine [1]. The method uses the characteristic relation between torque, current and rotor position from data that have been obtained by 3D electromagnetic simulation of Finite Elements. The fuzzy controller uses these static data by an off-line modeling method and the dynamic information incorporated on-line through an adaptation mechanism in a previous training course stage to modeling this non-linear relation.**

Keywords-component; Switched Reluctance Motors; Fuzzy modeling; Torque-ripple minimization, Current profiling.

I. Introduction

Switched Reluctance Motor (SRM) has a simple geometry without coils in mobile parts and with low ratio Cu/Fe. They are robust low cost drives with a high tolerance to faults, which can be used in a wide range of tasks. SRMs have resulted adequate in high and medium power level applications due to its high starting torque and high performance. In lower power applications, such as the auxiliary automotive industry or electrical household market, its low cost and wide range of operation result specially appreciated. However it also has certain inconveniences that have limited their use in this application range. Their main limitations are, on the one hand, that they are hard to control given their highly non-linear behavior. On the other hand, the need to know the angular position of the rotor, which forces to use position sensors. A final problem is the oscillation in torque ripple [1, 2]. This last inconvenience is a determining limitation in applications in which an elevated stability in torque ripple is required. Several techniques have been developed to relieve these drawbacks. Some of them are focused on motor controlling without position sensors. In general these different methods can be classified in intrusive and non intrusive methods, attending on the injection or not of test signals in the motor. Especially interest has suscited the artificial intelligence based methods, like Neural Networks and Fuzzy Logic systems in sensorless control [3].

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Other techniques have been developed to minimize as much as possible torque ripple in SRMs. These methods act in two different ways: the first one consists in an optimal design of the machine through an adequate selection of the geometric parameters: pole number, phase number, repetitions number, etc. [1, 2]. The second one is an adequate electronic control of the machine [4-8].

The torque ripple produced in SRM is owing to the salient two-pole geometry of the machine and by the successive relays in the activation of the phases. The essential factors are the characteristic torque-current-position of the motor and the overlapping angle of the torque between consecutive phases [4].

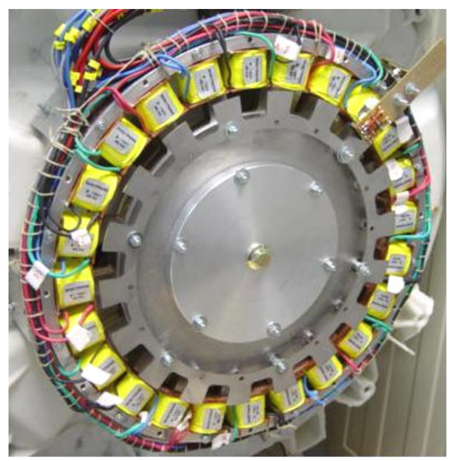

Fig. 1: Photography of the switched reluctance motor designed with a flat profile to adapt to the space available in a domestic washing machine.

In terms of machine design, different tasks have obtained improvements in the minimization of torque ripple, based on the increase in the number of motor phases or on an increase in the number of repetitions or the number of poles of the rotor [9]. These aspects have an impact on the cost or cause an increase in the losses of the motor and, in some cases, may be unfeasible with the physical dimensions of the motor and the windings to assemble.

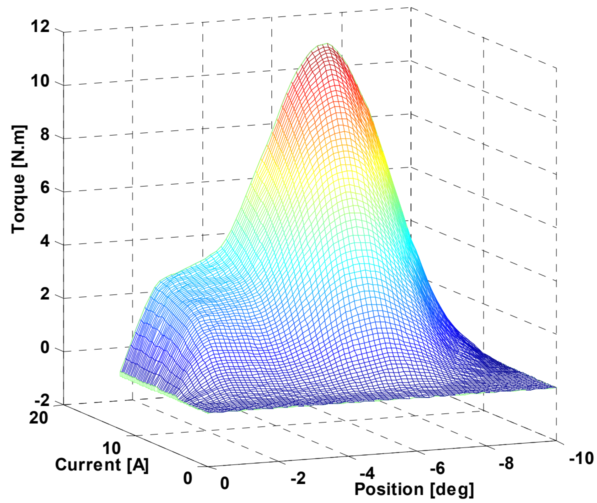

Fig. 2: Surface $T = f(i, \theta)$ of the 8/6, 3 rep. SRM flat-shaped generated from 3D FEM simulation data.

Methods focused on the electronic control and using the torque-current-position relation usually obtain it through static trials of the motor or starting from an analysis by finite elements with electromagnetic simulation software. Then, this relation is stored statically on memory tables or is analytically modeled. One of the inconveniences of storing information on a table is that data are static and may not consider the differences among phases or losses during the dynamic operation of the motor, given that this information corresponds to the state and form of the tested or simulated motor.

On the other hand, on account of the capacity of fuzzy systems to model on-line non-linear relations acquired from real-time data, the use of a fuzzy system is proposed to adjust this non-lineal relation, modifying the parameters obtained in off-line training. This dynamic information obtained on-line should improve the minimization of torque ripple when considering the state and real behavior of the motor in operation.

II. SRM PROTOTYPE

The prototype of the motor designed has a flat profile to be able to adapt to the rear part of the tank of a domestic washing machine. This is formed by an 8/6 polar structure (8 poles in the shaft for every 6 poles in the rotor) repeated 3 times. The motor has q=4 phases and each phase includes 6 coils connected in a series configuration. Overall, there are Ns=24 poles in the shaft and Nr=18 poles in the rotor. For the convenience of assembly, the shaft has been placed in the exterior. The polar pitch of the rotor is 360/Nr=20 mechanical degrees. The number of motor pitches are $q * Nr = 72$. As a consequence, the energizing angle of a phase is $360/(q * Nr) = 5$ mechanical degrees.

After the magnetic characterization of the iron panels used to build the motor which provide the B-H diagram, a 3D electromagnetic analysis of finite elements has been carried out to obtain the torque ripple in terms of intensity and angular position of the motor.

Keeping in mind the symmetry of the motor, it has only been necessary to obtain data from the aligned position among the poles to the misaligned position, namely, half pitch of the rotor (=10 mechanical degrees). The axis abscissa represents the density of the current applied to the section of copper of the coil.

Given the non-linear relation among the variables shown in Fig. 2, the generation of a constant torque involves using a current reference that should follow a specific profile. So that the speed regulator does not have to supply a profiled current reference, a fuzzy model is inserted between speed controller and the current mode controller. This one generates the reference profile of the current using the information of the position and desired torque reference. This reference torque is supplied by the speed regulator.

III. CONTROL MODEL PROPOSED

The control model proposed can be seen in Fig. 3. It is made up of a speed loop regulator through a proportional-integral controller that transforms the speed reference into a torque reference, together with an adaptable fuzzy model that has been initially characterized *off-line* in relation to $i = f(T, \theta)$. The on-line adaptation to the real characteristics of the motor in operation is executed by an adapter block with the additional information of a torque estimator and a sensorless position estimator block.

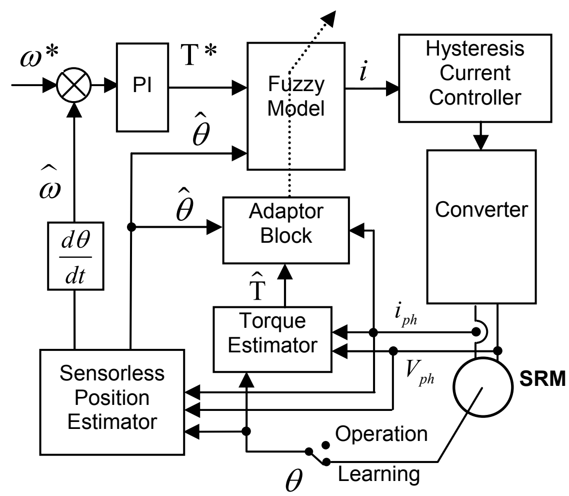

Fig. 3: Diagram of the speed closed loop proposed for torque minimization.

A. Adaptable fuzzy block

Due to its simple implementation in hardware, an adaptive MISO, two inputs TSK-type controller with fuzzy partitions uniformly spread through of triangular membership functions has been chosen. The overlapping degree has been set to a constant value at 50%. The consequents used were singleton ones and the rules were all the possible ones for the cartesian product of the number of fuzzy partitions of both entries ($R = N_{torque} \times N_{\theta}$). The inference method was the T-norm

Product. The aggregation method was the S-norm Sum, and the defuzzifier method was the Fuzzy Mean, according to (1).

$$Z(T,\theta) = \frac{\sum_{i=1}^{r} \alpha_i \cdot z_i}{\sum_{i=1}^{r} \alpha_i} \tag{1}$$

Where α_i is the degree of activation of the *i-th* rule involved and z_i its corresponding singleton consequent. The parameter r is the maximum number of rules simultaneously activated.

This TSK model has been initially characterized with the relation $i = f(T,\theta)$ by mean of an off-line learning method which is described below.

1) Off-line learning

From the torque data, a grid of D training points of the inverse characteristic has been generated according to the position and phase current. With these points, the singleton consequents of the fuzzy control rules have been adjusted [10]. In this case, a multiple linear regression method has been used, which is described below.

The expression (1) can be written as:

$$\vec{d} = P\vec{Z} + \vec{e} \tag{2}$$

Being $\vec{d}$, a column vector of dimension D that contains the model outputs at each point. P is a matrix of dimension (D,R) with that represent the activation degree of each rule for each training point, $\vec{Z}$ is the vector column containing the R parameters of consequents to estimate, and $\vec{e}$ is a column vector that contains the error. Operating and deriving with matrices, we obtain:

$$\vec{Z} = (P^T P)^{-1} P^T \vec{d} = P^{+} \vec{d} \tag{3}$$

Where, the term P^{+} is the pseudo inverse matrix of P.

B. On-line Adaptor Block

The estimated torque, the real position and current are the inputs of this block. With this information, the block adapts the rule consequents, using an iterative algorithm based on the descent of the gradient to minimize the differences which is described below.

1) On-line learning

Starting from the entries of the estimated torque, real current and real position, the adaptor block forms a $\{d_1, d_2, ...d_D\}$ batch of training data. With them, the accumulated difference between the real output controller and the desired model output is obtained. This difference is taken as the function to minimize:

$$\min\left[e = \frac{1}{2}\sum_{d=1}^{D} (Z|_d - f|_d)^2 \right] \tag{4}$$

The consequents to update should minimize the previous function of cost. To this aim, a descending gradient is used in an iterative way.

$$z_i^j = z_i^{j-1} - \eta \left.\frac{\delta e}{\delta z_i}\right|_d \tag{5}$$

Where i, is the *i-th* activated rule. The index j, is the number of iteration and η corresponds to the learning rate.

C. Torque Estimator Model

This block presents the torque for each phase of the motor and is available for simulation. It belongs to the Simulink model and uses the interpolation of the torque values in the table obtained from the electromagnetic simulator. For the control implementation, this torque value can be obtained through a robust estimator torque block, as developed in [11].

IV. Simulation Results

In Fig. 4, the wave of the phase currents is shown for a PI closed loop with constant speed reference of 1000 rpm, without the fuzzy corrector block for the ripple. The ripple torque index (RT) obtained according to (8) was, in this case, 98%.

$$RT = \frac{T_{inst}(\max) - T_{inst}(\min)}{T_{avg}} \times 100 \tag{6}$$

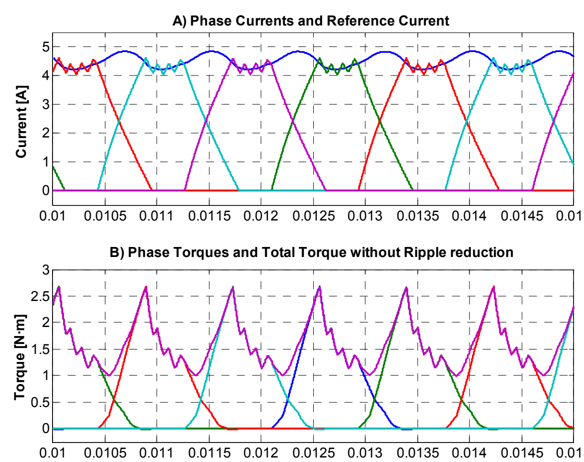

Fig. 4: A) Phase currents for 1000 rpm of speed reference in closed loop without torque minimization block. B) Instantaneous torque ripple per phase and total torque for above operational conditions.

From a grid of 4.900 points uniformly distributed on the surface shown in Fig. 1, 2.700 points were chosen for training, leaving out 2.200 points for validation. Different values of learning rate and number of iterations were tried in different controllers with the various N_{Torque} and N_θ parameters. Enough approximation precision training these data was obtain with $N_{torque} = 41$ and $N_\theta = 17$.

To check the efficiency of the model in minimizing torque ripple, a Simulink motor model and its control were designed according to the diagram shown in Fig. 3. Different speed and operation values were tested. An example of the results obtained is shown in Fig. 5 and Fig. 6.

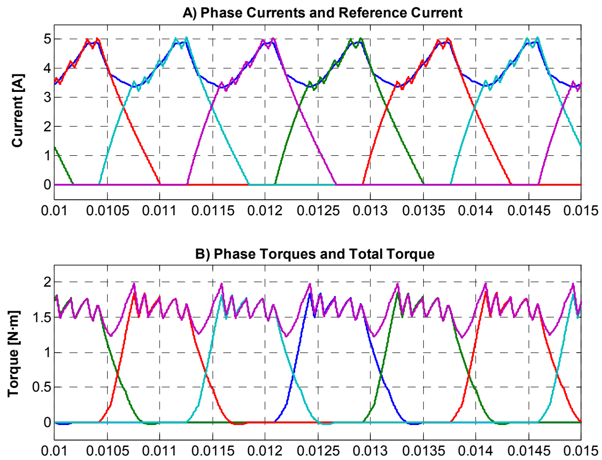

Fig. 5: A) Phase currents for same 1000 rpm of constant speed reference, with torque minimization block after off-line learning stage, in this case. B) Instantaneous torque ripple per phase and total torque for above conditions.

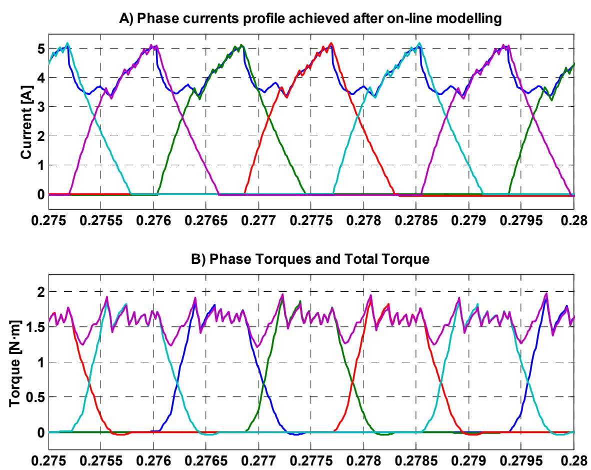

Fig. 6: A) Phase currents for same speed reference, after 200 learning cycles with only the on-line method, 20 iterations and learning rate of 0.25. B) Instantaneous torque ripple per phase and total torque for above conditions.

Fig. 5. shows the improvement obtained in torque ripple with the wave current forms generated by the correction proposed control, at a speed of 1000 rpm, only with the off-line learning method.

Fig 6. shows the torque ripple obtained from the same fuzzy model only trained with the on-line method, starting with parameters non-trained. Note the similar results obtained in both cases by phase current profiling and how it produces a global minimization of torque ripple at about of 40%.

V. CONCLUSIONS

It has been used 3D Finite Element electromagnetic simulation data of a SRM to characterize the flat shaped SRM. With this data, a Fuzzy model has been trained using a linear regression off-line method. Then an adaptive block has been designed to train on-line the fuzzy model to incorporate dynamic information. The results obtained shown the significant improvements obtained in the minimization of the ripple in the motor built. The minimization obtained with the proposed method was about 60%. Moreover, given the characteristics of the fuzzy controller chosen -triangular membership functions, 50% overlapping degree, the simplicity of the defuzzifier method and the adaptive mechanism incorporated- make possible updating the modeled characteristic with low hardware cost. These characteristics let incorporate dynamic information or for instance, consider differences among phases.

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