3D FEM Simulation Data Applied to ANN to Sensorless Position Estimation and Torque Ripple Minimization in a Switched Reluctance Motor.

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Abstract. Due to the non-linear electrical characteristics of Switched Reluctance Motors (SRMs), Artificial Neural Networks (ANNs) perform a good tool to sensorless control of these machines. In this paper are shown some simulation results to prove the efficiency of a multilayer perceptron (MLP) to estimate the rotor position and to reduce the ripple torque of flat shaped SRM, designed as a direct drive in a domestic washing machine, where data employed to train the network has been obtained by a 3D Finite Element simulation.

Keywords-component. Switched Reluctance Motors, Artificial Neural Networks, Ripple Minimization, Sensorless Control.

1. Introduction.

Switched Reluctance Motor (SRM) is well known due to its robustness, easy assembly, good performance and low manufacture costs [1, 2]. Nevertheless owing to its non-linear electrical behaviour, it provides a high torque ripple. Moreover it needs position sensors to be controlled. Artificial Intelligence techniques have been widely used as a way to eliminate position sensors providing good results [5-11]. In this paper will be presented some simulation results, which prove the efficiency of artificial neural networks (ANNs), working in a closed loop system to provide both information of rotor position and torque ripple minimization for these machines[1].

Due to the non-linear electrical characteristics and the inherent capability of ANN for identification [3, 4], a multilayer perceptron (MLP) becomes a suitable architecture to solve this problem [5-11]. However, to train the network it is used experimental data or approximated analytic equations. Thus, the SRM behaviour is not known until the motor has been built or it is only approximated. In this paper it has been used 3D Finite Element electromagnetic simulation and the behaviour can be foreseen at the design stage.

In what follows it is first shown the data obtained by 3D Finite Element electromagnetic simulation, then the relative and absolute position is estimated by a MLP to set the phase activation pulses and, finally, a second MLP is added between the speed current controller to reduce the torque ripple.

2. 3d Finite Element Simulation Data.

For this study it has been used a flat shaped SRM depicted in Fig. 1 and designed as a direct drive in a domestic washing machine. This SRM follows an 8/6 basic structure repeated three times. This means a four phases motor with 24 poles in an external stator and 18 poles rotor placed inside.

Fig. 1: Prototype of a Flat shaped Switched Reluctance Motor fitted to a tub of a washing machine.

As the rotor pitch is 20 deg mechanical (360deg/18poles), the phase inductance versus rotor position has this rotor pitch periodicity and is shown in Fig 2.

After characterizing the B-H curve of the iron sheets used to assemble the rotor and stator, it has been carried out a 3D Finite Element electromagnetic simulation of the motor.

Taking into account the symmetry, only 11 angular positions, from 0º (rotor and stator poles aligned) to 10º (mechanical), (rotor and stator unaligned) has been analyzed. Each of these angular positions has been simulated for 10 current values within the range of 0A to 12.5A.

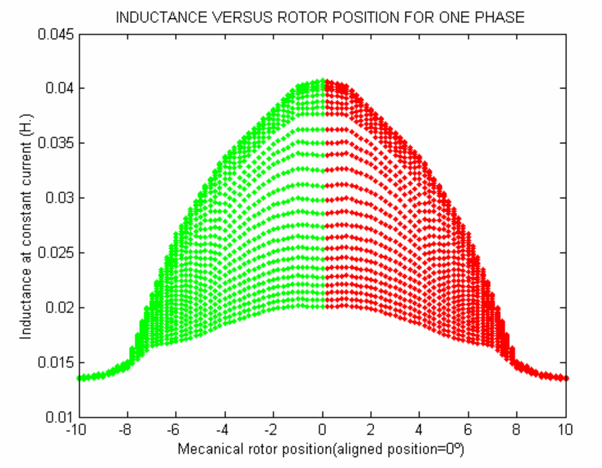

Fig. 2: Inductance versus rotor position (aligned=0º) taking current as a parameter.

By post processing simulation data, many other electrical and mechanical parameters can be obtained as torque or incremental inductance. Although simulation provides a table of discrete values, intermediate data values can be obtained by interpolation using the algorithm proposed in [12].

3. Case I: Position Estimation.

In this section an ANN, working in a closed loop system, is used to set the phase activation pulses by the rotor position estimation.

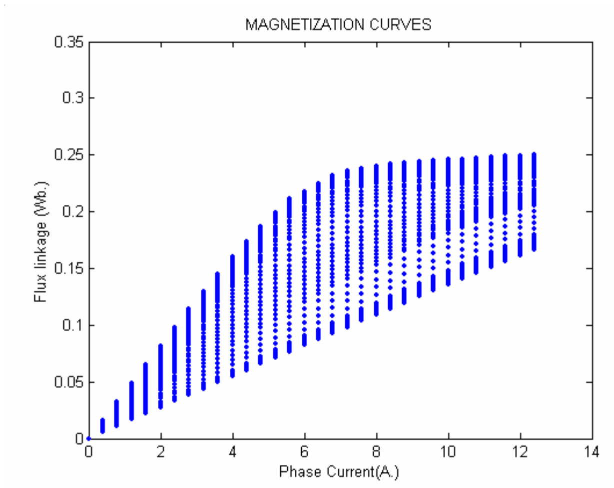

Fig. 3: Phase flux linkage vs. current taking rotor position as parameter. Maximum value is with poles aligned and minimum value is for poles unaligned.

Position estimator for one phase has as inputs the current, i, and the flux-linkage λ(θ,i). In this case the mechanical position has been chosen as output between the unaligned and the aligned position (θ) for one phase.

Since flux-linkage cannot be measured directly, it is necessary to estimate its value through the measurement of voltage and current. For one phase flux-linkage and current are related according to the equation:

$$\lambda = \int (V_s - Ri)dt \qquad (1)$$

By using, the aforementioned interpolating algorithm they have been collected 1632 patterns, where 2/4 have been used for training, 1/4 for testing and 1/4 for validating. These patterns are shown on Fig. 3. The current has been increased from zero to 12.5A with a step of 0.4A. The targets, have been selected from unaligned (-10º) to aligned rotor position (0º) every 0.2º.

The architecture selected for the ANN is a 2-10-1 MLP, with a sigmoidal activation function for the neurons on the hidden layer, and a linear activation function for the output neuron. Probed different methods for training, the Levenberg-Marquadt (LM) algorithm has resulted the most suitable.

Taking the validation patterns subset as inputs, in Fig.4.b it is shown a linear regression between the networks outputs and the corresponding targets. A problem appears, if it is tried to estimate the rotor position for a zero current value. For this current value, flux-linkage is also zero, and that point is associated to all possible rotor positions. This could be solved by setting a fixed output value for zero current.

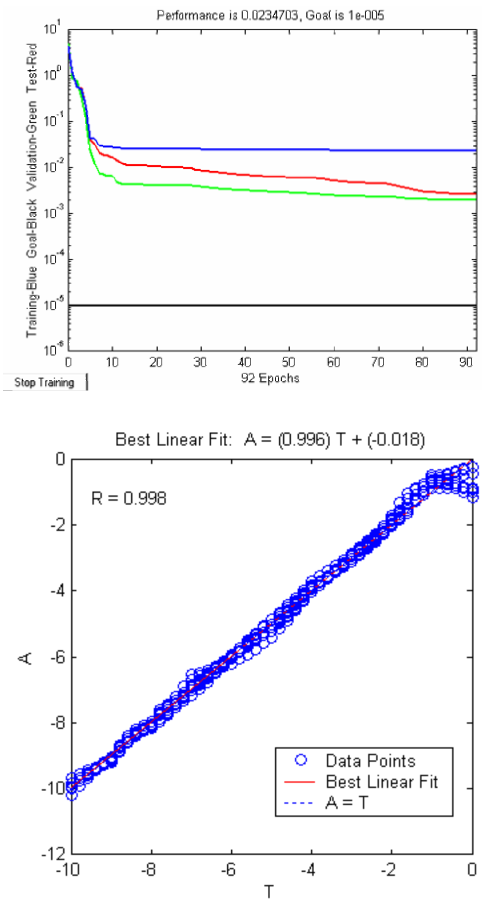

Fig. 4: From top to down: a) Error measure trajectory; b) Linear regression between outputs and targets for position estimator

The behaviour of the trained network for one phase can be seen in Fig. 5. For a better understanding, it should be taken into account the following premises: a) The dwell angle, θ_D, for each phase is constant and equal to motor step (5º); b) The switch on angle, θ_{ON}, for a phase is defined from the aligned position (see Fig. 2) as θ_{ON}=-(5º+θ_A), where θ_A is the advance angle; c) At the beginning of simulation the SRM model starts with one phase over the aligned position, so, the next switched phase is on only for an angle of 5º-θ_A.

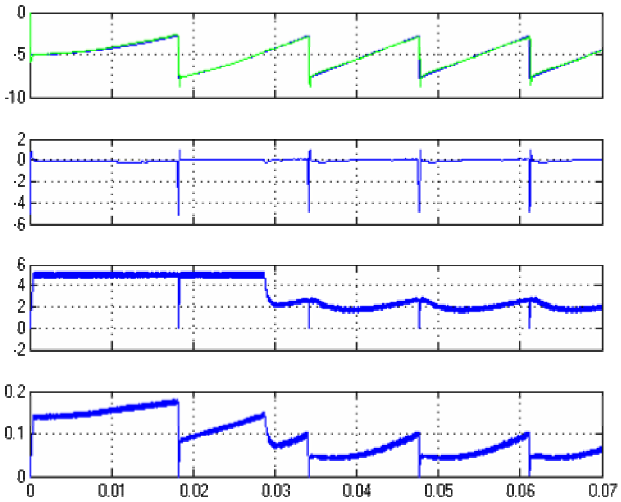

Fig. 5. From top to down: a) Estimated and real relative position for each phase: b) Difference between the estimated and real relative rotor position; c) Phase Currents with different current command values; d)Flux-linkage for each phase due to the previous currents

To carry out this experiment, it has only been used a neural network, where its two inputs were the current and flux-linkage for the active phase (see fig.6). Respect to the SRM, it have been subjected to different current command values and advance angles, until it reaches a speed of 60 rpm.

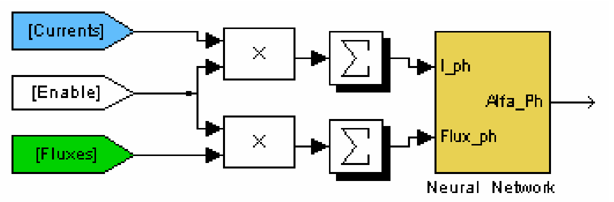

Fig. 6: Block diagram of the subsystem used to estimate the real rotor position with a simple neural network

The previous experiment shows that it is possible to obtain the relative rotor position for each phase with a non significant error (between commutations the maximum error is 0.3º).

As was mentioned before, at the beginning of the simulation the SRM starts following a protocol, which establishes the phase that will be excited for the first time, and guarantees that this phase will be at its aligned position. Besides, the initiation algorithm allows determining the adequate phase excitation sequence that will be carried on.

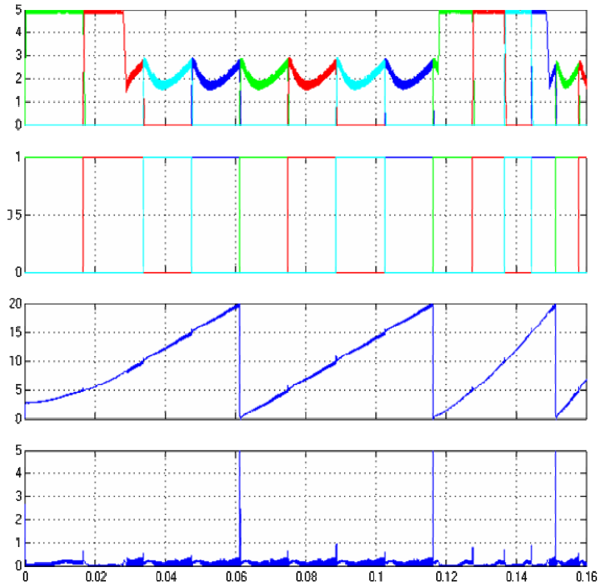

Fig. 7: Simulation for a close loop system working with a neural network per each phase. From top to down: a) Phase Currents with different current command values: b) Excitation pulses sequence obtained from the estimated position; c) Estimated rotor position for a complete mechanical cycle between two poles; d) Absolute error between the estimated and real rotor position

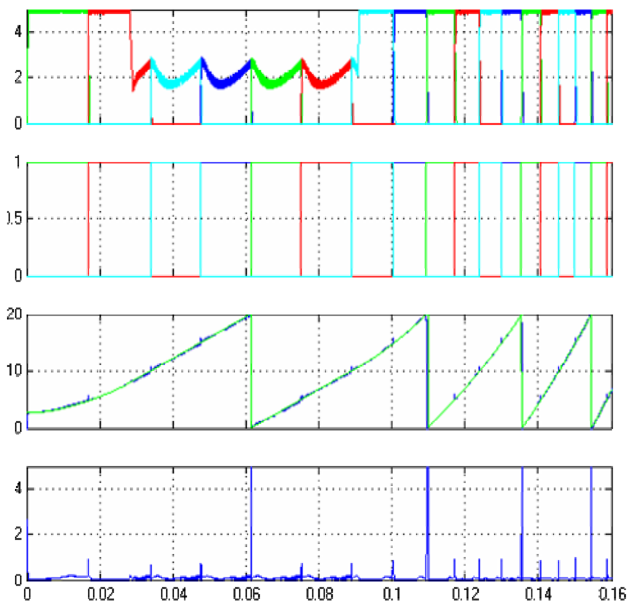

Fig. 8: Simulation for a close loop system working with a neural network for all phases. From top to down: a) Phase Currents with different current command values: b) Excitation pulses sequence obtained from the estimated position; c) Estimated and real rotor position for a complete mechanical cycle between two poles; d) Absolute error between the estimated and real rotor position

Thus, if the phase relative position (θ_{REL}) and the phases excitation sequence are available, the absolute rotor position for a complete mechanical cycle between two poles (θ_{ABS}), can be determined by the following algorithm:

$$\theta_{ABS} = n * \theta_D + \theta_{REL} \qquad (2)$$

Where n=0,1,2,3 according to the active phase.

In order to implement a close loop system able to obtain a correct sequence of excitation pulses, two control systems have been developed. The first one with four neural networks, one per phase, and another one with just a neural network where its inputs are associated to the active phase (see Fig. 6). The results are shown in Fig. 7 and Fig. 8, respectively. They show that both systems offer a similar performance but the second one has less computational work.

4. Case II: Torque Ripple Minimization.

In order to minimize the SRM ripple torque it is necessary to establish a proper current command for the current controller. This can be achieved by an ANN whose inputs are a torque command signal and the rotor position, and its output is the desired command current.

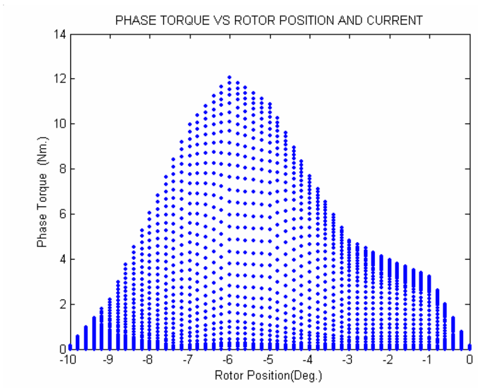

Fig. 9: Torque produced by a phase vs. rotor position (aligned=0º) for different current values.

These network inputs are generated, respectively, by a position estimator and a speed controller. The speed controller output is taken as a torque command. In this experiment the position estimator will be the network proposed in the case I.

Once again, the architecture selected for the ANN is a MLP. One hidden layer with ten neurons looks enough, nevertheless, due to the fast current changes that the SRM is subjected by the hysteresis switching controller, better results have been reached adding to the network a second hidden layer with five neurons.

For training process, it has been followed the same procedure that for the position estimator. Another 1623 patterns has been generated, choosing 2/4 for training, 1/4 for testing, and 1/4 for validating. Levenberg-Marquadt algorithm has been applied for training.

It should be taken into account, that for a correct training of the network as position estimator it was needed an important number of patterns, however, for this network with only a tenth of the patterns is enough.

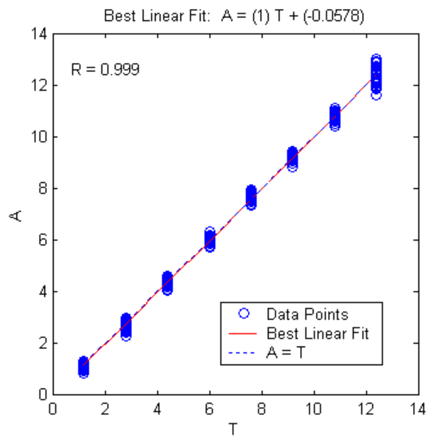

Fig. 10: Linear regression between outputs and targets for current estimator

To prove the efficiency of the network as current estimator, once again, it has been used just a neural network for all phases, being the inputs the torque and the relative rotor position for the active phase (see fig.6). The behaviour of the training network is shown in Fig. 11 where the estimated current by the network match fairly well the real SRM phase currents.

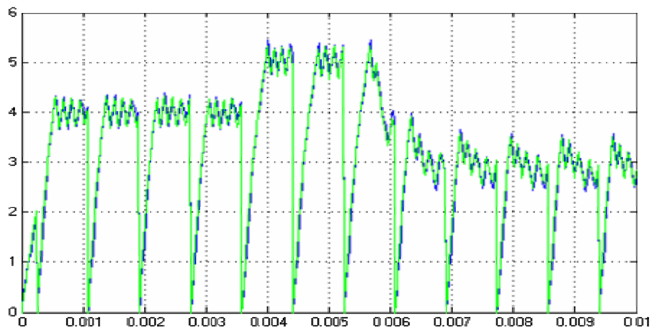

Fig. 11: Estimated and real SRM phase currents

Once the network has been validated, it has been included between the speed controller and current mode controller to guarantee a small torque ripple (see Fig. 12).

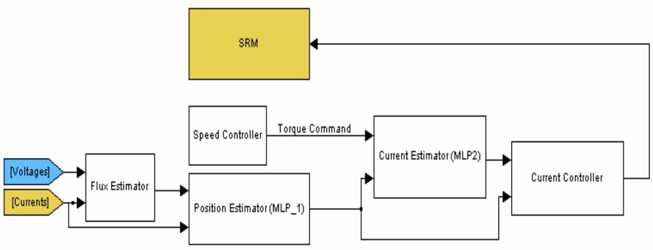

Fig. 12: Block diagram of the SRM drive system

The simulation results of the proposed method are shown in Fig.13 where the SRM speed is 1000 rpm and the torque demand is 1,6 Nm. The current mode controller is of hysteresis type with a tolerance band of 0.3A.

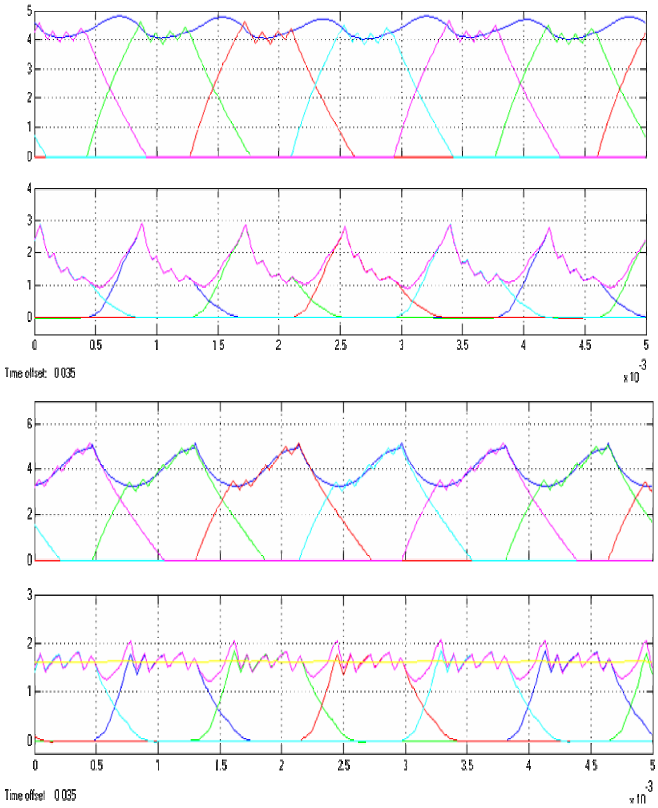

Fig. 13: From top to down, for a SRM speed of 1000 rpm and a torque demand of 1,6 Nm: a) SRM phase currents and command current without including the current estimator in the control loop; b) Torque per phase and total torque produced by the above currents; c) SRM phase currents and command current including the current estimator in the control loop d) Improvement of torque per phase and total torque figures obtained when the current estimator is included in the control loop and the current command is as depicted in c)

5. Conclusions.

It has been used 3D Finite Element electromagnetic simulation data of a SRM to characterize its electrical and mechanical behaviour.

Then a multilayer perceptron has been trained to estimate the rotor angular position which is used to enable the excitation of motor phases. Further, a second MLP playing the role of a torque controller sets the current command for a current mode controller. The results show how ANNs can be used to avoid position sensors (between commutations the maximum error is 0.3º) and to minimize the SRM torque ripple. The later is performed by providing a current command profile which maintains a constant torque.

As future work, it is expected to validate the simulation results applying the proposed method to control the flat shaped SRM, designed as a direct drive, in a domestic washing machine.

Acknowledgments.

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