Artificial Neural Networks applied to Sensorless Control in a Switched Reluctance Motor

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Abstract: - This work analyzes the advantages of Artificial Neural Networks applied to sensorless control for Switched Reluctance Motors. Due to the non-linear electrical characteristics of Switched Reluctance Motors, Artificial Neural Networks perform a good tool and for torque ripple minimization in Switched Reluctance Motors. The simulation results to prove the efficiency of a multilayer perceptron in order to estimate the rotor position and to reduce the ripple torque of this machines. The data employed to train the network has been obtained by numerical simulation.

Key-Words: - Artificial Neural Networks, Modeling, Multilayer Perceptron, Ripple Minimization, Sensorless Control, Switched Reluctance Motors.

1 Introduction
Power electronic technology has made the Switched Reluctance Motor (SRM) an attractive for many applications. The SRM is a doubly salient, singly excited synchronous motor. The rotor and stator are comprised of stacked iron laminations with copper windings on the stator. The motor is excited with a power electronic inverter that energizes appropriate phases based on shaft position. The excitation of a phase creates a magnetic field that attracts the nearest rotor pole to the excited stator pole in an attempt to minimize the reluctance path through the rotor. The excitation is performed in a sequence that steps the rotor around. The SRM is similar in structure to the stepping motor, but it is operated in a manner that allows for smooth rotation. Because there are no permanent magnets or windings on the rotor, all of the torque developed in the SRM is reluctance torque. While the SRM is simple in principle, it is rather difficult to develop performance predictions.

This is due to the nonlinear magnetic characteristics of the motor under normally saturated operation. Switched Reluctance Motor (SRM) is well known due to its robustness; easy assembly and good performance [1], [2]. Nevertheless owing to its nonlinear electrical behavior, 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 [1]. Artificial neural networks (ANN) are working in a closed loop system to provide information about the rotor position and torque ripple minimization, for these machines.

2 Problem Formulation
Due to the non-linear electrical characteristics and the inherent capability of ANN for identification [1], [2] a
multilayer perceptron (MLP) becomes a suitable architecture to solve this problem [2], [4]. However, to train the network it is used numerical data or approximated analytic equations.

MLP is a feedforward artificial neural network model that maps sets of input data onto a set of appropriate output. It is a modification of the standard linear perceptron in that it uses three or more layers of neurons (nodes) with nonlinear activation functions, and is more powerful than the perceptron in that it can distinguish data that is not linearly separable, or separable by a hyperplane.

The multilayer perceptron consists of an input and an output layer with one or more hidden layers of nonlinearly-activating nodes. Each node in one layer connects with a certain weight to every other node in the following layer.

If a multilayer perceptron consists of a linear activation function in all neurons, that is, a simple on-off mechanism to determine whether or not a neuron fires, then it is easily proved with linear algebra that any number of layers can be reduced to the standard two-layer input-output model (see perceptron). What makes a multilayer perceptron different is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain. This function is modeled in several ways, but must always be normalizable and differentiable.

On used an 8/6 SRM, for this analysis.

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 Figure 1.

![Fig. 1. Inductance versus rotor position (aligned=0°) taking current as a parameter.](image)

It is shown that the data obtained by numerical analysis, is estimated by a MLP to set the phase activation pulses and a second MLP is added between the speeds current controllers to reduce the torque ripple.

3 Problem Solution

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 a numerical algorithm.

3.1 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.

Position estimator for one phase has as inputs the current, $i$, and the flux-linkage $\lambda(\theta, i)$. In this case the mechanical position has been chosen as output between the unaligned and the aligned position ($\theta$) 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 these equations:

$$\lambda(\theta, i) = L(\theta, i) \cdot i \quad (1)$$

$$p \cdot \lambda(\theta, i) = L(\theta, i) \frac{di}{dt} + iL' \quad (2)$$

Where $p$ is the derivative operator, $\frac{d}{dt}$. The inductance $L$ is the self inductance of the machine phase and it is available as a function of excitation current and rotor position.

![Fig. 2. Phase flux linkage versus current taking rotor position as parameter.](image)
By using an interpolating algorithm they have been collected the patterns. These patterns are shown on Figure 2. Maximum value for phase flux linkage versus current is with poles aligned and minimum value is for poles unaligned. The behavior of the trained network for one phase can be seen in Figure 3. 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. For this analysis, on used a neural network, where its two inputs were the current and flux-linkage for the active phase.

The phase relative position is $\theta_{rel}$ and the absolute rotor position for a complete mechanical cycle between two poles is, $\theta_{abs}$.

### 3.2 Torque Ripple Minimization

Controlling a constant value of current will result in torque ripple because of the non linearity of the relationship between torque and current for a SRM. Torque ripple is undesirable because it contributes to the problem of audible noise, it contributes to vibrations and it introduces torque disturbances which manifest as velocity errors. A solution to the problem of torque ripple in SRM is to profile the current such that torque is the controlled variable. Since torque cannot be controlled directly, due to the lack of adequate torque sensors, this can only be accomplished using information about the motor’s torque-current-angle characteristics. Additionally these characteristics must be known fairly accurately in order to achieve the best results.

The torque control strategy is based on following a contour for each of the phases of the SRM such that the sum of torque produced by each phase is constant and equals the desired torque. The desired total torque is calculated from the velocity loop, and this total torque is split into desired phase torque via shaping function. Some torque ripple will remain if the torque shaping function do not fully address the torque non linearity. Nevertheless, this control structure allows a much smoother torque production than with the constant winding current control.

The torque control method is generally not useful for high speed applications, however, because the torque ripple increases rapidly with degraded ability to arbitrarily regulate the motor current. 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. These network inputs are generated, respectively, by a position estimator and a speed controller. The speed controller output is taken as a torque command. The position estimator is the network analyzed in the 3.1.

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 (Figure 4).
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For training process, it has been followed the same procedure that the position estimator.

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.

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 active phase [3].

After the network has been validated, it has been included between the speed controller and current mode controller to guarantee a small torque ripple (Figure 5).

The simulation results of this method are shown in Figure 6 where the SRM speed is 1000 rpm and the torque demand is 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.

The simulations shows that ANN is a good tool for torque ripple minimization in Switched Reluctance Motors

4 Conclusion

The numerical simulation of a SRM on used for 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.

A second MLP playing the role of a torque controller sets the current command for a current mode controller. The results show how ANN can be used to avoid position sensors and to minimize the SRM torque ripple.

References: