PREDICTING ROTOR POSITION OF SWITCHED RELUCTANCE MOTOR WITH THE USE OF NEURAL NETWORKS

Ferhat Daldaban
e-mail: daldaban@erciyes.edu.tr

Nurettin Üstkoyuncu
e-mail: nurettinu@erciyes.edu.tr

Erciyes University, Faculty of Engineering, Department of Electronic Engineering,38039 Melikgazi, Kayseri,Turkey

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ABSTRACT

In this presented study the control of switched reluctance motors which are widely used in recent years using with neural networks is pointed out. The trained neural network which doesn't need any position sensor, has an ability of prediction of rotor position of the switched reluctance motor.

I. INTRODUCTION

The switched reluctance motor (SRM) is an electrical machine and it has a simple structure compared other electrical machines. The first of variable reluctance motors which is basic in this field is proposed in 1969 [1]. SRM drives for industrial applications are of recent origin. Even though this machine is a type of synchronous machine, it has certain novel features. It has wound field coils of a dc motor for its stator windings and has no coils or magnets on its rotor. Both the stator and rotor have salient poles, hence the machine is referred to as a doubly salient machine [2]. An important characteristic of the SRM drive is its inherent nonlinearity. The inductance of the magnetic circuit is a nonlinear function of both phase current and rotor position [3]. The cross-sectional picture of 6/4 SRM is shown in Figure 1.

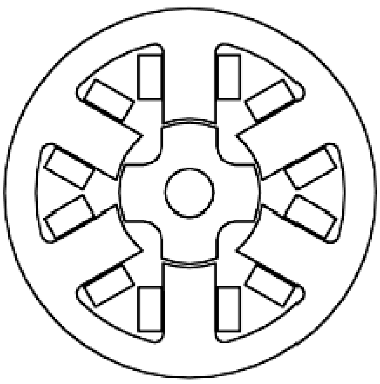

Figure 1. The 6/4 SRM with a doubly-salient structure.

It can be concluded that in contrast to other types of ac and dc motors, the SRM can not run directly from ac or dc (the stator flux is not constant), but the stator flux must be established from zero every step and the converter must supply unipolar current pulses, which are timed accurately by using information on the rotor position. In a conventional SRM, this information is obtained using a position sensor, but in position-sensorless SRM drives, it is possible to use different techniques to extract this information. One of these techniques is artificial intelligence based position estimator [4].

The usage of artificial intelligence techniques in the field of automatic control, has been very popular in the last few years. Ability and adaptability to learn, generalisation, less information requirement, fast real time operation and ease of implementation have made ANNs popular. Especially, because of nonlineer modeling capability of ANNs, they are quite suitable for automatic control.

In this presented study, an artificial neural network application which is aimed to control of SRMs is realized. With this ANN structure the prediction of rotor position is provided when the phase current and voltage values were applied to the system. The trained ANN is tested by test values. Real rotor position angles and the results of ANN is shown graphically to evaluate performance of the ANN. The rotor position experimental data for 8/6 SRM are taken from [5]

The ANN which is realized in this study has a feed-forward multi layer perceptron (MLP) structure and is trained by using Levenberg-Marquardt algorithm. Presented application is very important to make redundant the dependence of position sensors which are disadvantages of SRMs.

II. SRM FUNDEMENTALS

SRMs have a doubly-salient structure and there aren't any windings on the rotor. The principle of working of the motor is based on reluctance force and realizes by pulling the rotor which has doubly-salient structure to the least reluctance position where is the easiest and most suitable way to flow flux linkages. SRMs have a nonlinear characteristic and are widely worked on saturation field, otherwise the torque which is obtained from the motor will be very little values.

The equivalent electrical circuit of the one phase of the SRM is shown in Figure 2.

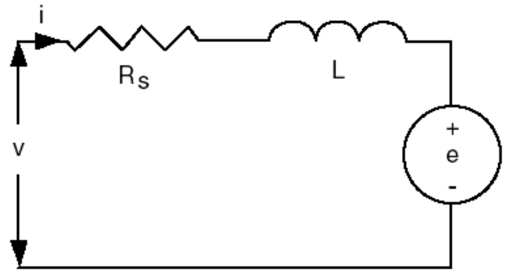

Figure 2. The equivalent electrical circuit of the one phase of the SRM.

Where, R_s is resistance of each stator windings and L is inductance value. The applied voltage to a phase is equal to the sum of the resistive voltage drop and the rate of the flux linkages and is given as:

$$V = R_s i + \frac{d\lambda(\theta,i)}{dt} \tag{1}$$

Where λ is the flux linkage per phase given by:

$$\lambda = L(\theta,i)i \tag{2}$$

Substituting for the flux linkages in the voltage equation and multiplying with the current results in instantaneous input power given by:

$$p_i = vi = R_s i^2 + i^2 \frac{dL(\theta,i)}{dt} + L(\theta,i)i\frac{di}{dt} \tag{3}$$

Here, the last term is physically uninterpretable; to draw a meaningful inference, it may be cast in terms of known variables as in the following:

$$\frac{d}{dt}\left(\frac{1}{2}L(\theta,i)i^2\right) = L(\theta,i)i\frac{di}{dt} + \frac{1}{2}i^2\frac{dL(\theta,i)}{dt} \tag{4}$$

and instantaneous input power given by:

$$p_i = R_s i^2 + \frac{d}{dt}\left(\frac{1}{2}L(\theta,i)i^2\right) + \frac{1}{2}i^2\frac{dL(\theta,i)}{dt} \tag{5}$$

As will be shown from Equation 5 that the input power is the sum of the winding resistive losses given by $R_s i^2$, the rate of change of the field energy given by $p[L(\theta,i)i^2/2]$ and the air gap power, p_{ag}, which is identified by the term $[i^2 pL(\theta,i)]/2$.

Substituting for time in terms of the rotor position and speed, with;

$$t = \frac{\theta}{w_m} \tag{6}$$

in the air gap power results in:

$$p_{ag} = \frac{1}{2}i^2\frac{dL(\theta,i)}{dt} = \frac{1}{2}i^2\frac{dL(\theta,i)}{d\theta}\frac{d\theta}{dt}$$
$$p_{ag} = \frac{1}{2}i^2\frac{dL(\theta,i)}{d\theta}w_m \tag{7}$$

The air gap power is the product of the electromagnetic torque and rotor speed given

$$p_{ag} = Tw_m \tag{8}$$

from which the torque is obtained by equating these two equations as:

$$T = \frac{1}{2}i^2\frac{dL(\theta,i)}{d\theta} \tag{9}$$

This completes development of the equivalent circuit and equations for evaluating electromagnetic torque, air gap power, and input power to the SRM both for dynamic and steady-state operations [2].

III. THE ANN MODEL OF SRM

ANNs are systems that are deliberately constructed to make use of some organizational principles resembling those of the human brain [6] and are widely used a lot of engineering fields after the developments of computer technologies. ANNs have a nonlinear, adaptive and parallel distributed memory. Because of learning, generalization and highly computing ability, ANNs are widely used many fields. One of these fields is automatic control.

In general, SRMs are worked in saturation, consequently there are nonlinear relationships among the rotor parameters. The relationship between flux linkages and current in SRM is shown in Figure 3.

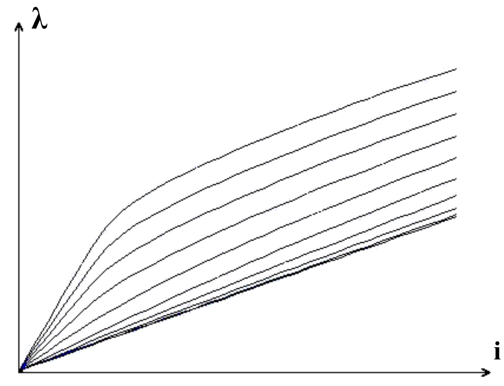

Figure 3. The relationship between flux linkages and current in SRM.

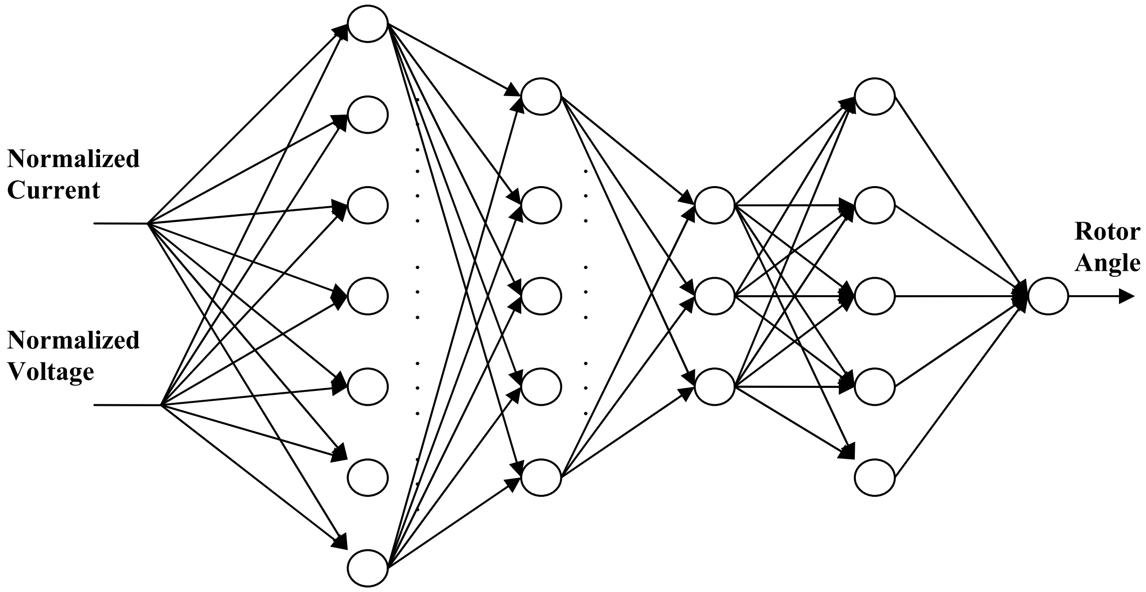

Figure 4. Realized ANN structure to predict the rotor position of SRM.

The realizing of mathematical modeling of the SRMs is quite difficult because of nonlinear characteristic of the SRMs as will be shown in Figure 3. Many researchers are studied in this field to solve the problem. For example, Stephanson and Corda model the flux linkages as a function of current and rotor position [3].

Because of using the artificial intelligence techniques in control fields for recent years, many studies which have capability of modeling of the SRM characteristics are realized. Especially, these studies are based on ANN and fuzzy inference system [7-12].

The ANN which is realized in this study has a feed-forward multi layer perceptron (MLP) structure and is trained by using Levenberg-Marquardt learning algorithm. The ANN has an input layer, four hidden layers with in order seven-five-three-five neurons and an output layer with a neuron as will be shown in Figure 4. In order for each layers tangent sigmoid, purelin, purelin, tangent sigmoid and purelin transfer functions are used respectively. The training of the ANN is realized by using a data set which has 80 values for each voltage, current and rotor position. Normalized voltage and current values are given as input and rotor position values are given as output to the ANN.

The trained ANN is tested by a test data set which has also 80 normalized voltage and current values and the real rotor angle values are compared with obtained rotor position values from the ANN in Figure 5. Obtained error tolerance at the end of the test process is among the acceptable degrees.

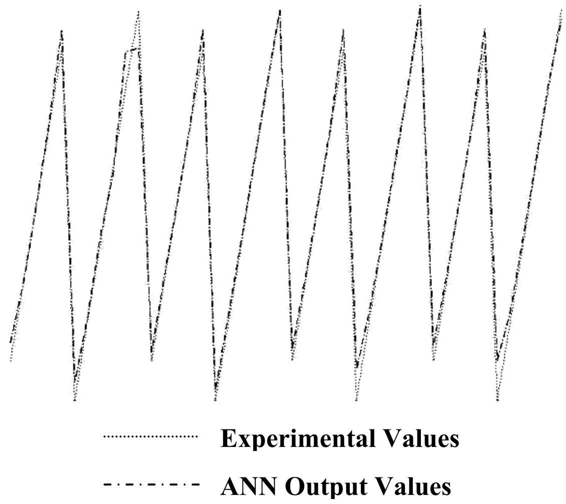

Figure 5. Comparing the trained ANN outputs and real rotor position values.

IV. CONCLUSION

Although SRMs have many advantages, they don't have usage fields so much in practical application especially in industry. One of the important reasons is necessity of being known of the rotor position to control the motor and product maximum torque. Consequently, a position sensor must be used. The present neural modal provides flexibility and eliminates the use of position sensors by using the phase voltage and current values which can be obtained easily. Obtained error tolerance at the end of the test process is among the acceptable degrees. In studies which will be realized in future, when used the other artificial intelligence techniques better values may be obtained.

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