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Sensorless speed control of switched reluctance motor using brain emotional learning based intelligent controller

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ABSTRACT

In this paper, a brain emotional learning based intelligent controller (BELBIC) is developed to control the switched reluctance motor (SRM) speed. Like other intelligent controllers, BELBIC is model free and is suitable to control nonlinear systems. Motor parameter changes, operating point changes, measurement noise, open circuit fault in one phase and asymmetric phases in SRM are also simulated to show the robustness and superior performance of BELBIC. To compare the BELBIC performance with other intelligent controllers, Fuzzy Logic Controller (FLC) is developed. System responses with BELBIC and FLC are compared. Furthermore, by eliminating the position sensor, a method is introduced to estimate the rotor position. This method is based on Adaptive Neuro Fuzzy Inference System (ANFIS). The estimator inputs are four phase flux linkages. Suggested rotor position estimator is simulated in different conditions. Simulation results confirm the accurate rotor position estimation in different loads and speeds.

1. Introduction

The switched reluctance motor (SRM) is a doubly salient and singly excited machine with an unequal number of rotor and stator poles to avoid magnetic locking between the stator and rotor poles [1,2]. Because of simple rugged construction, they have considerable benefits like lower shopping and maintenance costs. Despite of higher efficiency and ability to produce high torques at very low speed in contrast with other conventional motors, they have not been used widely in industrial applications. The main reasons are nonlinearity nature of SRM and therefore difficult control of them [3]. However, some methods for SRM control are presented [4–6].

Generally, the classic control theory is model based. Since nonlinear system modeling is a complex task, SRM control is difficult using classic controllers. Additionally, the plants parameters change due to wear and tear and also when the motor is replaced by a new motor. In these circumstances, the designer is forced to recalculate the controller parameters for new condition. Recently, intelligent controllers have shown great results in various industrial controllers such as SRM drives [7–9]. In these controllers information of the dynamic equations of the plant is not required and these methods are independent of plant model. Although these controllers are model free and useful for nonlinear system control, additional work is needed when they are being used. In fuzzy method, suitable set of rules are needed. So, an expert person who is familiar with plant behavior and fuzzy system, should design the fuzzy controller and define the rules. Also, the type and the number of membership functions should be selected properly. Furthermore the optimization of membership function parameters and tuning of the scaling factors are not simple. Thus, to apply fuzzy system, experience of designer is an important parameter. The requirements are different when the ANFIS or neural network is used. Lots of data from plant input–output is needed to train these controllers. Therefore, initially the plant should be controlled by another controller and the plant input–output should be measured and saved. Then, the measured data should be used to train the controller. It is noticeable that the trained controller cannot control the system better than the initially applied controller. Recently, a novel computational model, inspired by emotional learning in mammalians brain has been proposed [10–13]. Using this model, a control method is developed [14]. This new intelligent controller does not need the plant model, rule base and data base for training. Control of Washing Machine using BELBIC is discussed in [15]. In [16], BELBIC is used as a controller for speed control of interior permanent magnet synchronous motor. Power management by brain emotional learning algorithm is discussed in details in [17]. The results show satisfactory performance of BELBIC to control

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nonlinear dynamic systems. In this paper, SRM is controlled using both BELBIC and FLC. Moreover, system responses in different operating points and its stability and robustness against speed measurement noise, motor parameter changes, open circuit fault in one phase and asymmetric phase are investigated.

Another serious problem in SRM drives is position sensor cost and error. Position sensor is needed for detecting rotor position and synchronizing it with the SRM phases excitation. But industrial environments pollution reduce the position sensor accuracy. As a result, SRM drives with the position sensor are not reliable. Some methods are introduced to eliminate the position sensor [18–27]. In [18] current change is used to estimate the rotor position. Measuring mutually induced voltages is another method [19].

Intelligent system based predictors have been used recently to predict the rotor angle and phase inductance [21–27]. In [21] a method is presented to estimate the rotor position. This method is based on Adaptive Neuro Fuzzy Inference System. Motor currents and fluxes are used as estimator inputs.

However this method is complex. A fuzzy predictive filter is used to predict the flux linkage. A decision block determines the correct flux linkage using predicted and estimated flux linkage. Using the four phase flux linkages and current, rotor position is estimated. For this purpose, fuzzy model of SRM and optimal phase selector are used. Angle fuzzy predictive filter and another decision block are necessary for accurate rotor position estimation.

In [22] rotor position is estimated using ANFIS and ANN and the results are compared. The results presented in this paper show that the ANFIS can estimate the rotor position more accurately.

Rotor position estimation has considerable errors in completely aligned and completely unaligned regions. So, an improved fuzzy optimal phase selector is developed in [23]. Rotor position estimation in switched reluctance motors by using a cerebellum model articulation controller is described in [24].

In this paper, a new method is used to predict the rotor position. This method is based on ANFIS and four phase flux linkages, which constitute the intelligent system inputs. Low prediction error, simplicity and good performance in different speeds and torques are the advantages of this estimator. This paper is organized as follows:

Section 2 shows the structure of SRM, equations and flux curve versus current in different rotor angles. The foundation of BELBIC is described in Section 3. Simulation results are presented in Section 4 which contains simulation results with position sensor and also rotor position estimation method.

2. Mathematical model of SRM

The SRM is a variable reluctance stepping motor that is designed to convert energy efficiently. This motor has a very simple structure. Its rotor is brushless and has no winding of any kind. The motor is singly excited from stator windings which are concentric coils wound in series on diagonally opposite stator poles. Both rotor and stator are made of laminated iron. In spite of the simple structure of the motor, an accurate analysis of the SRM is very difficult and conserving. This complexity is because of working in saturation condition. Several methods are reported for the analysis of the SRM, such as finite element method, improved magnetic equivalent circuit method [28], and piecewise linear model. Furthermore, in [29] modeling of a 6/4 switched reluctance motor using ANFIS and in [30] a nonlinear full model of switched reluctance motor with artificial neural network are presented. In [31] Modeling faulted switched reluctance motors using evolutionary neural networks is described.

The voltage equation in the motor phases is:

$$V_k = Ri_k + \frac{d\lambda_k(\theta, i_k)}{dt} + \frac{d\lambda_l}{dt} \tag{1}$$

In which, V_k stands for Kth phase voltage, i_k for Kth phase current, λ_k for Kth flux linkage, R for one phase resistance and λ_l leakage flux.

Using the chain derivation, (1) can be written as:

$$V_k = Ri_k + \frac{\partial\lambda_k(\theta, i_k)}{\partial i_k}\cdot\frac{di_k}{dt} + \frac{\partial\lambda_k(\theta, i_k)}{\partial\theta}\cdot\frac{d\theta}{dt} + \frac{d\lambda_l}{dt} \tag{2}$$

Thus:

$$V_k = Ri_k + L\cdot\frac{di_k}{dt} + C_\omega\cdot\omega + L_k\frac{di_k}{dt} \tag{3}$$

The electrical torque on shaft can be obtained from (4).

$$T(i,\theta) = \sum_{k=1}^{3}\left(\frac{\partial W'}{\partial\theta}\right)\Bigg|_{i_k=cte} \tag{4}$$

where the co-energy is defined as follows:

$$W'(i_k,\theta) = \int_0^{i_k}\lambda_k(i_k,\theta)di_k \tag{5}$$

At last the mechanical equations will be:

$$\begin{aligned} &\omega = \tfrac{d\theta}{dt} \\ &\tfrac{d\omega}{dt} = \tfrac{1}{J}\cdot(T(i,\theta) - T_L - B\cdot\omega) \end{aligned} \tag{6}$$

In (6), ω, T_L, B and J show the angular velocity, load torque, friction coefficient and moment of inertia respectively.

In this paper, static characteristic of optimally designed SRM is used for simulations. This SRM is designed using fuzzy genetic algorithm [32,33].

3. BELBIC structure

Emotion has been considered as a negative factor in decision making process. But, recently positive effect of emotion in decision making is documented by psychologists. There are two functions of emotional system in decision making. The first one is evaluating the stimuli. When an environmental stimulus occurs, the emotional system will associate it with the same or similar emotional content that is experienced previously. The second function of emotional systems is to focus the attention of the system on the signals which have main role in desired response of system.

In mammalian's brain, limbic system is responsible for emotional processes. The main components of limbic system involved in emotional process are Amygdala, Orbitofrontal Cortex, Thalamus and Sensory Cortex. The first two play a key role in the processing of emotions while the rest function as preprocessors of sensory input. The main learning of this system occurs within the Amygdala and Orbitofrontal Cortex.

The primary affective conditioning of the system occurs in the Amygdala. Amygdala communicates with all other sensory cortices and areas within the limbic system parts. Emotional consequences and stimulus are associated in Amygdala. The role of the Amygdala is in fact to assign emotional value to each stimulus that is paired with a primary reinforcement signal. The Orbitofrontal Cortex is another component interacts with the Amygdala reciprocally. It performs as Inhibitory Controller. Inhibitory control is the selective suppression of areas that may be inappropriate in the current situation. More specifically, the Orbitofrontal Cortex reacts to omit the expected reward or punishment and control the extinction of the learning in the Amygdala. Thalamus is a way-station between subcortical and cortical structures. The task of Thalamus is usually simulated by passing the maximum signal, over all sensory signals, to the Amygdala.