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"ROTOR POSITION ESTIMATION AND CONTROL OF SWITCHED RELUCTANCE MOTOR DRIVES USING NEURO-FUZZY TOPOLOGY"

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ABSTRACT

This paper presents a new approach to the sensor less control of the switched-reluctance motor (SRM). Generally, the switched reluctance drive controllers require rotor position feedback, because excitation of the switched reluctance motor phases needs to be synchronized with the rotor angle. Position sensors are commonly used to obtain the rotor position measurements. However there are many disadvantages in using the rotor position sensors due to the necessity of extra electrical connections. Hence, the proposed approach aims at overcoming the above disadvantages by sensing the position of the switched reluctance motor using neuro-fuzzy technique. Through measurement of the phase flux linkages and phase currents the

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network is able to estimate the rotor position, thereby facilitating the elimination of the rotor position sensor.

KEYWORDS

Switched Reluctance Motor, Position Sensors, Sensorless Operation, Neuro-Fuzzy

INTRODUCTION

The switched reluctance motor (SRM) has been receiving attention for industry applications due to its low cost in mass production, reduced maintenance requirements, rugged behavior and large torque output over very wide speed range. This makes them well suited for many commercial applications. On the other hand, torque ripple, acoustic noise and rotor position sensor requirements are often-cited disadvantages of the motor[1]. In an SR drive, the rotor position must be known, because excitation of the SR motor phases needs to be synchronized with the rotor position. Position sensors are commonly employed to obtain rotor position measurements, however, in many systems advantages can be found in eliminating these sensors. These benefits include the elimination of electrical connections to the sensors, reduced size, low maintenance, and insusceptibility to environmental factors. Hence, a diverse range of indirect or sensorless position estimation methods has previously been proposed. These estimation methods can be classified into two major groups. In one group, low-amplitude test signals are inserted into the motor phase windings to derive rotor position information, while, in the other group, the actual motor excitation waveforms are monitored without the use of

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additional signals in the motor. Mathematical model based schemes are also classified under the latter group[2].

However, some practical implementation problems exist in the previous estimation methods. This is due to the fact that the methods, which use test signals or monitor the motor excitation waveforms, have some limitations and problems in providing accurate rotor position measurements continuously in both high and low operating speeds and various transient conditions found in SR motor drives. Also, the most sophisticated of the previously developed estimation schemes, which are the model-based methods, use simplified linear motor models and involve complex mathematical computations, or require large numerical lookup tables. This makes the schemes practically difficult to implement due to the fact that the motors normally operate under magnetic saturation and, thus, can only be completely described by a nonlinear model[3]. Moreover, complex mathematical computations are disadvantageous because of the demand for a fast real-time processor, which may not be suitable for all motor drives Numerical lookup tables are also not desirable, because they have the disadvantage of a large memory requirement, and require accurately measured inputs which brings about sensitivity to noise and error.

In addition, motor drives are usually electrically noisy environments and, therefore, practical measurement systems are normally subject to error and inaccuracy. Thus, estimation schemes may not be useful in practical drives, if their reliability and robustness against noise and error are not proven. If the reliability of a sensorless position detection scheme is low, then this lessens or cancels any advantages of replacing the mechanical sensor[4]. Hence, artificial

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intelligence techniques are receiving attention for position sensor elimination in SRM. Recently, many publications have appeared in the literature based on using artificial intelligence techniques for position estimation. Application of artificial neural networks and Fuzzy logic for position estimation in SRM drives is being studied by many researchers and proven to give a robust sensorless operation of SRM. In this paper is developed a new strategy to estimate the rotor angular position with the use of identification technique using neural/fuzzy logic. They have the capacity to estimate values from a set of inputs, mapping in a satisfactory way an output signal.

SRM FEATURES

In construction, the SRM is the simplest of all electrical machines. The switched reluctance motor (SRM) is a doubly salient machine with independent phase windings on the stator and a solid laminated rotor. Only the stator has windings. The rotor contains no conductors or permanent magnets. It consists simply of steel laminations stacked onto a shaft. It is because of this simple mechanical construction that SRMs carry the promise of low cost, which in turn has motivated a large amount of research on SRMs in the last decade. The mechanical simplicity of the device, however, comes with some limitations. Like the brushless DC motor, SRMs cannot run directly from a DC bus or an AC line, but must always be electronically commutated. Also, the saliency of the stator and rotor, necessary for the machine to produce reluctance torque, causes strong non-linear magnetic characteristics, complicating the analysis and control of the SRM. Not surprisingly, industry acceptance of SRMs has been slow[5]. This is due to a combination of perceived difficulties with the SRM, the lack of commercially available electronics with which to operate them, and the entrenchment of traditional AC and DC

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machines in the marketplace. SRMs do, however, offer some advantages along with potential low cost. For example, they can be very reliable machines since each phase of the SRM is largely independent physically, magnetically, and electrically from the other motor phases. Also, because of the lack of conductors or magnets on the rotor, very high speeds can be achieved, relative to comparable motors.

Disadvantages often cited for the SRM; that they are difficult to control, that they require a shaft position sensor to operate, they tend to be noisy, and they have more torque ripple than other types of motors; have generally been overcome through a better understanding of SRM mechanical design and the development of algorithms that can compensate for these problems[6].

By varying the number of phases, the number of stator poles, and the number of rotor poles, many different SRM geometries can be realized. The stator windings on diametrically opposite poles are connected in series to form one phase of the motor. Fig. 1(a) and Fig. 1(b) shows a four phase 8/6 switched reluctance motor and a three phase 6/4 switched reluctance motor respectively. Theoretically it is possible to have a number of stator and rotor pole combinations. However, certain combinations, such as 4/4 or 2/2, will have problems during start up operation. With combinations like 2/2 or 4/4 it will be impossible to develop a starting torque with rotor and stator pole exactly aligned. Although, the configurations with higher number of stator/rotor pole combinations have less torque ripple and do not have the problem of starting torque, 6/4 or 8/6 combinations are typically used. Because, increasing the number of SRM phases reduces the torque ripple, at the expense of requiring more electronics with which to

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operate the SRM[7]. At least two phases are required to guarantee starting, and at least three phases are required to insure the starting direction.

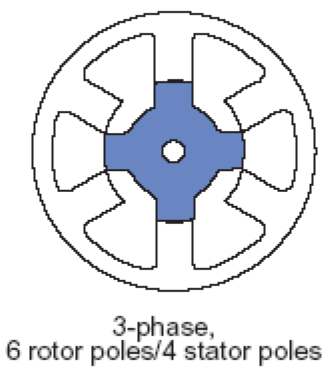

Fig. 1 (a)

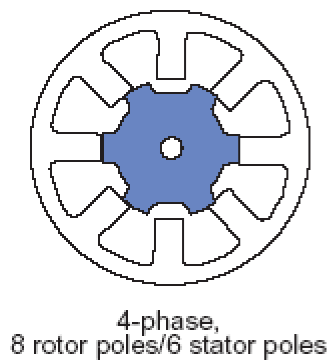

Fig. 1 (b)

Moreover, higher number of poles will decrease the maximum inductance ratio obtainable for a good torque per ampere. These practical issues limit stator and pole ratio to 6/4 or 8/6 in most applications of Switched Reluctance motor drives. A well designed Switched reluctance motor will minimize the core losses, will offer good starting capability, and will also minimize the unwanted effects due to varying flux distributions and saturation and to eliminate mutual coupling.

SRM OPERATING PRINCIPLE

The basic operating principle of the SRM is quite simple; when a stator phase is energized, the most adjacent rotor pole-pair is attracted towards the energized stator in order to

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minimize the reluctance of the magnetic path. Therefore, by energizing consecutive phases in succession it is possible to develop constant torque in either direction of rotation[8]. The direction of torque generated is a function of the rotor position with respect to the energized phase, and is independent of the direction of current flow through the phase winding. Continuous torque can be produced by intelligently synchronizing each phase's excitation with the rotor position.

The phase voltage equation of Switched reluctance motor can be written as:

$$V = iR + \frac{d\lambda}{dt}$$

where, V is the dc bus voltage, 'i' is the instantaneous phase current, R is the phase winding resistance and l is the flux linking the phase coil. Ignoring stator resistance, the above equation can also be written as:

$$V = L(\theta)\frac{di}{dt} + i\frac{dL(\theta)}{d\theta}\omega$$

where, w is the rotor speed, q is the rotor angular position, and L (θ) is the instantaneous phase inductance. The rate of flow of energy can be obtained by multiplying the voltage with current and can be written as:

$$Vi = Li\frac{di}{dt} + i^2\frac{dL}{d\theta}\omega$$

Or

$$P = \frac{d}{dt}\left(\frac{1}{2}Li^2\right) + \frac{1}{2}i^2\frac{dL}{d\theta}\omega$$

The first term of the above equation represents the rate of increase in the stored magnetic field energy while the second term is the mechanical output. Thus, the

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

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instantaneous torque can be written as:

OVERVIEW OF SENSORLESS TECHNIQUES

A large number of methods have been introduced to accomplish position sensorless operation of the SRM during the last fifteen years. The fundamental principle used in position estimation is the extraction of rotor position information from stator circuit measurements or their derived parameters. The operation of the SRM is based on the variation of the flux as a function of the angular position of the rotor. The basic equation of phase voltage is given by:

$$V_j = Ri_j + d/\,dt\sum_{k=1}^{n}\lambda_{kj}$$

Where, n is the total phase numbers, V_j is the voltage applied in phase j, R is the winding resistance per phase, λ represents the flux in the stator and t is the time[9].

The dependence of the flux with the position is the key point for the operation without sensors. Flux linkage is a function of the rotor position and the current through the phase winding. Compared to other types of electric machines, it is an advantage for an SRM not to have a rotor field disturbing the stator field. On the other hand, the nonlinear relationship between the electrical and mechanical terminals of the machine makes analytic calculation of rotor position impossible for a given flux linkage and current value. Moreover, accurate measurement would be much more difficult if more than one phase winding carries current simultaneously and the mutual coupling is not negligible. Inevitably, the great majority of the existing techniques of sensors elimination are based on this basic principle to obtain the position information. The typically measured variable are: voltage, current, current rising time or current

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falling time. The derived variables are: inductance, flux and EMF. The torque speed curve can be divided into five regions.

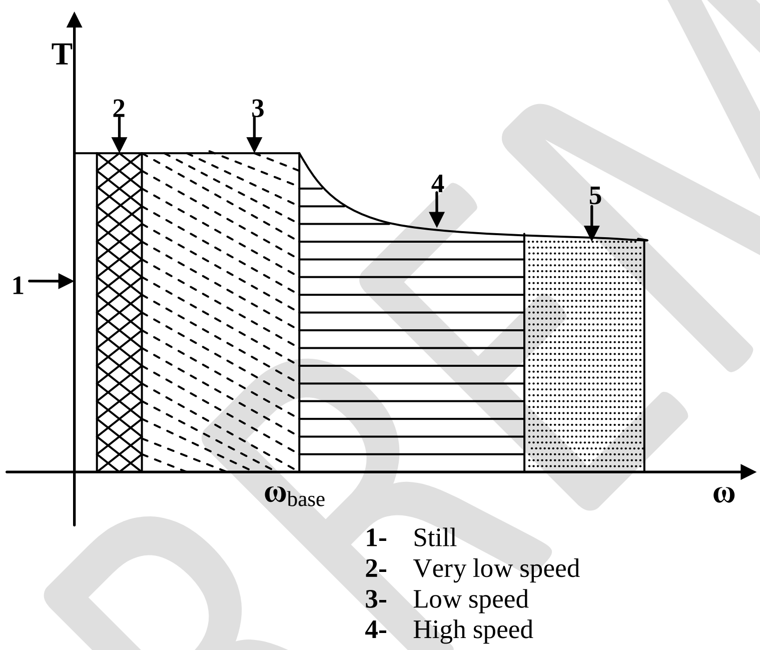

Fig. 2-Operation modes in sensorless control.

As shown in Fig.2, below the speed base (smallest speed where you can extract the maximum power) the torque remains constant. These regions (below the speed base) offer flexibility for the current control, allow getting the desired performance for the motor. It is important to know that in regions 1 and 2, the counter EMF is smaller than the DC bus voltage and can be neglected. In these regions, there is always a moment, during the commutation

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sequence, when a determined phase is not energized. At this moment, one voltage pulse signal is injected in this phase with objective to measure the inductance. Depending on the current time fall and its value, the position can be estimated. Some limitations to this estimation strategy are the eddy current effects in the iron and mutual magnetic linkage between the phases. Another restriction is that this strategy produces a significant braking torque[10]. More recent works present this technique combined with observers. Another work proposed a technique that uses amplitude modulations; however it has the disadvantage to need an external circuit, which adds cost, and complexity to the system.

Then a voltage measurement method is presented. The operation principle is based on the induced voltage measurement in one of the non energized phases. This voltage is induced by the current that circulate in the energized phase. Depending on the rotor position, this voltage varies and so, an electronic circuit captures this signal, which is processed by a microcontroller, in order to determine the commutation time.

In regions 3, techniques based on diagnosis signals start to have some limitations about accuracy and precision in this speed level. Therefore the use of techniques that work in the energized phases became suitable above this speed level. The other method presented is to estimate the rotor position based on the flux and current measurements. It presents a wide operation band in such a way being applicable for low speeds and high speeds. It compares the measured signal with the value stored in a look-up table to obtain the position value. A drawback is the necessity to inject a current pulse diagnosis during the inductance fall period of the phase in question. In recent works, we have the use of this look-up table represented in a fuzzy logic system or neural nets.

When the speed increases, the EMF raises and become greater than the DC bus voltage. In this situation, the motor must operate in single pulse operation (region 4). In this way, the current is limited by EMF and it does not reach the desired value. Therefore, the current control is not possible and the torque is maintained in the desired value by the turn-on and turn-off angle control. This region is called "constant power region". The operation in region 5 (very high speeds) requires high efficiency time algorithms due to physical limitation control to operate it in so high speed. In this situation definitely the motor is operating in single-pulse. The use of observers in this speed level is rare, only having exceptions in the flux estimation in induction motor and position estimation in PM motors. In another method, magnetization data are used for position estimation. The data are stored in a look-up table and interpolation is used to estimate rotor position. The major difficult in this approach is the accurate modeling of SRM since simulated data are used instead of real-time experimental data.

All of the proposed techniques try in one way or another to use the SRM as its own sensor. Many of these techniques require manipulating the unexcited phase. In the method using state observers, is presented a proposal of nonlinear model of the reluctance motor. The voltage terminals are considered as input, the currents are considered as the output and flux, speed and position are the states. A disadvantage is the need of powerful computational equipment. However, with the development of faster DSPs, this problem will be surpassed easily and with

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possible low costs. For these cases, the acquisition of aligned and unaligned positions using the EMF or flux variation is recommended.

Many strategies of elimination of position sensor in SRM have been investigated. Currently, the use of identification technique using neural nets and fuzzy logic is growing up. They have capacity to estimate values from a set of inputs, mapping in a satisfactory way an output signal. Recently, many publications have appeared in the literature based on using artificial intelligence techniques for motion control. Application of artificial intelligence for position estimation in SRM drives is also studied by many researchers. It is also suggested that fuzzy-logic be used along with a coarse position estimator based on the dynamic equations of the system. This alleviates large memory requirements when the fuzzy-logic controller is the only estimator in the system. In another fuzzy reasoning based method, measured magnetization data for several rotor positions are stored in fuzzy rule-base tables; the position information is then retrieved from the tables during online operation. Furthermore, the performance of the estimator is improved by some additional features like fuzzy phase selection, fuzzy flux linkage and angle predictors in order to maintain robust sensorless operation of SRM.

From the ideas employed in these methods, a new strategy has been developed to estimate the rotor angular position. It is based on the neuro-fuzzy system with current and flux linkage as inputs and as output, the rotor position.

NEURO-FUZZY BASED POSITION ESTIMATION

The basic premise of the proposed method is that a Neuro-Fuzzy estimator forms a very efficient mapping structure for the SRM[11]. Through measurement of the phase flux linkages

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and phase currents, the network is able to estimate the rotor position, thereby facilitating elimination of the rotor position sensor. The training data set is comprised of magnetization data for the SRM of which flux linkage (λ) and current (i) serve as inputs and the corresponding position (θ) as output in this set. Given a sufficiently large training data set, the Neuro-Fuzzy estimator can build up a correlation among λ, i and θ for an appropriate network architecture.

Construction Of The Training Data Set

There are two possible ways to generate training data for a neuro-fuzzy estimator: model-based data generation and experiment-based data generation. The method of model based data generation is used in this paper. Here, the training data set is constructed using a Fuzzy logic based SRM model.

SR Motor Fuzzy-Logic-Based Model

A major component of the neuro-fuzzy based angle estimation algorithm is the fuzzy-logic-based SR motor model. This model is used to construct the training data set for the neuro-fuzzy estimator. The main advantages of developing a fuzzy-logic-based model of the SR motor are as follows.

a) No Mathematical Model is Required

Fuzzy logic system identification provides a mathematical model-free estimation and modeling approach. The SR motor is difficult to define in a precise and accurate manner with a conventional mathematical model. This is because the motor has nonlinear magnetization characteristics and complex magnetic coupling interactions between the motor phases. Hence, fuzzy techniques are well qualified in providing a model of the SR motor.

b) Fuzzy Models Are Universal Approximators

Although fuzzy modeling does not require any mathematical model, it has been proven that fuzzy models are universal approximators. Therefore, a fuzzy model can approximate any continuous function to any degree of accuracy using arbitrary fuzzy sets. In other words, for any continuous function f(x1, x2 ..., xn) and for every error bound, Є>0, there exists a fuzzy model F(x1, x2 ..., xn), which uniformly approximates and is always Є close to f. The SR motor model is a nonlinear continuous function and, therefore, it is possible to model this function using fuzzy sets without the requirement for mathematical-based modeling.

c) No Requirement for Large Lookup Table

In some previous schemes, a numerical table of measured static motor characteristics is used to describe the motor. The measured motor data provide a numerical model of the static angle versus flux linkage and current characteristics. These methods are commonly called table lookup methods and, although they have the advantage of being fast, they have the disadvantage of needing a large memory to store the table. However, in systems where numerical data is learned by a fuzzy system, it is found that the memory requirement of the stored fuzzy model is much lower than that required by the equivalent lookup table.

d) Fuzzy Models Allow Fast Computation

Fuzzy logic does not need a complex mathematical model and, thus, has the advantage of relatively simple mathematical calculations used for the rule processing. In addition, it has been shown that the fastest possible universal computation scheme corresponds exactly to the operations in fuzzy logic methods using Max–Min composition. Therefore, in terms of real-time

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sensorless SR motor operation, it could be said that fuzzy logic techniques represent an ideal choice.

SR MOTOR MODEL TRAINING SCHEME

To create a fuzzy-rule-based model of the SR motor characteristics, a training scheme is used which trains a fuzzy logic model based on measured numerical information about the SR motor[12]. The information is derived from the static flux linkage versus current and position curves of the motor, which provide important information about the electromagnetic characteristics of the SR motor phases. (fig.3)

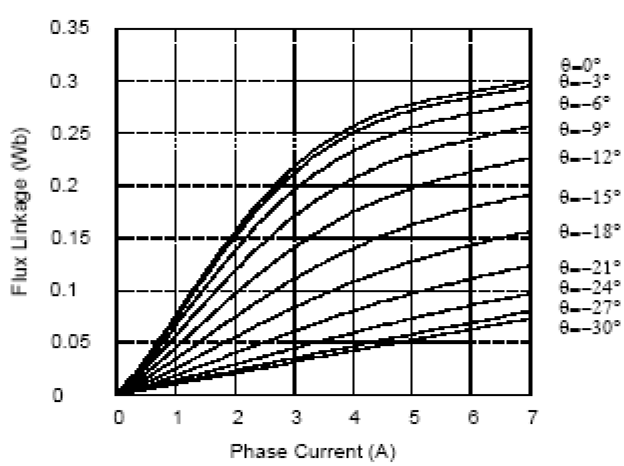

Fig. 3

Magnetization curves of an SRM

In this case, the measured data are defined as a two-input one-output input–output pair such that flux linkage (ψ) and current (i) are defined as the inputs, and the rotor position (θ) is

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defined as the output. Each datum presented to the training system is defined as ($\psi^{(n)}$, $i^{(n)}$, $\theta^{(n)}$), where n is the n^{th} data pair.

The datum is defined in this manner because the SR motor characteristics are defined as a two-input–one-output nonlinear function that relates flux linkage and current to rotor angle. Hence, the training task involves creating a fuzzy model of this function from the training data. After the training is completed, the generated fuzzy logic rule base defines a function 'f' mapping input values of flux linkage and current to output values of rotor position

$$\{f: (\psi, i) \rightarrow \theta\}$$

Various methods can be used to train the fuzzy model from the measured data, such as using neural networks, genetic algorithms, and classical adaptive control techniques[13]. However, due to its suitability to practical applications (fast, simple, and accurate), the table lookup scheme was used.

The training scheme consists of the following steps.

Step A—Dividing the Input and Output Domains into Fuzzy Regions:

In this initialization step, which is performed only once before the algorithm is executed, the range of intervals of the input and output variable domains are defined. Each domain is then divided up into fuzzy regions. The choice of the number of regions is a compromise between the number of resultant rules that are generated in the rule base and the desired accuracy. However, to increase accuracy, the number of fuzzy regions can be increased and optimized. Each region is assigned a fuzzy membership function.

Step B—Generating Fuzzy Rules from Input Data of Flux, Current, and Angle:

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After the fuzzy membership functions in each of the input and output domains are defined, the measured training data can be used to generate fuzzy rules in order to create the fuzzy rule base model. During the training phase, each input–output data pair, which consists of a crisp numerical value of measured flux linkage, current, and angle, is used to generate the fuzzy rules which model the system. To determine a fuzzy rule from each input–output data pair, the first step is to find the degree of each data value (flux, current, angle) in every membership region of its corresponding fuzzy domain. The variable is then assigned to the region with the maximum degree.

Step C—Assigning Rule Degrees: When each new rule is generated from the input–output data pairs, a rule degree or truth is assigned to that rule, where this rule degree is defined as the degree of confidence that the rule does, in fact, correlate to the function relating flux linkages and current to angle. In the developed method, a degree is assigned which is the product of the membership function degree of each variable in its respective region. The purpose of this assignment is to choose between data sets that produce the same antecedents but different consequents. This would arise because when there is a large amount of measured data, some data pairs will produce rules that have the same antecedent but a different consequent (due to errors or noise in the measured data). This would mean that there are conflicting rules in the system. These are resolved by choosing the rule that has the highest degree to be placed in the fuzzy rule base.

Step D—Adaptive Rule Base Modification:

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As can be seen from the above, every training data set produces a corresponding relating flux linkage and current to rotor position. Each new rule is stored on the fuzzy rule base unless there is a conflicting rule already existing that has a higher degree of truth. In this manner, the fuzzy rule base is adaptive in nature.

Results of Training with Static Curves

As was stated previously, the fuzzy knowledge base is generated using the static magnetization curves of the motor. Each point on the motor's magnetization curve represents an input data set of flux linkage and current and an output value of angle. The static flux linkage curves will characterize the motor to a good degree. After the learning tasks are performed, the generated fuzzy rules in the fuzzy rule base determine a fuzzy logic system mapping input flux and current to angle according to the modeled nonlinear function.

NEURO-FUZZY ESTIMATOR

Every intelligent technique has particular computational properties (e.g. ability to learn, explanation of decisions) that make them suited for particular problems and not for others. For example, while neural networks are good at recognizing patterns, they are not good at explaining how they reach their decisions. Fuzzy logic systems, which can reason with imprecise information, are good at explaining their decisions but they cannot automatically acquire the rules they use to make those decisions[14]. These limitations have been a central driving force behind the creation of intelligent hybrid systems where two or more techniques are combined in a manner that overcomes the limitations of individual techniques. Hybrid systems are also important when considering the varied nature of application domains.

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Many complex domains have many different component problems, each of which may require different types of processing. If there is a complex application which has two distinct sub-problems say a signal processing task and a serial reasoning task, then a neural network and an expert system respectively can be used for solving these separate tasks. The use of intelligent hybrid systems is growing rapidly with successful applications in many areas including process control, engineering design, financial trading, credit evaluation, medical diagnosis, and cognitive simulation. Neural networks are used to tune membership functions of fuzzy systems that are employed as decision making systems for controlling equipment. Although fuzzy logic can encode expert knowledge directly using rules with linguistic labels, it usually takes a lot of time to design and tune the membership functions which quantitatively define these linguistic labels. Neural network learning techniques can automate this process and substantially reduce development time and cost while improving performance [15].

In theory, neural networks, and fuzzy systems are equivalent in that they are convertible, yet in practice each has its own advantages and disadvantages. For neural networks, the knowledge is automatically acquired by the back propagation algorithm, but the learning process is relatively slow and analysis of the trained network is difficult (black box). Neither is it possible to extract structural knowledge does not (rule) from the trained neural network, nor can we integrate special information about the problem into the neural network in order to simplify the learning procedure[16]. Fuzzy systems are more favorable in that their behavior can be explained based on fuzzy rules and thus their performance can be adjusted by tuning the rules. But since, in general, knowledge acquisition is difficult and also the universe of discourse of each input variable needs to be divided into several intervals, applications of fuzzy systems are restricted to the fields where expert knowledge is available and the number of input variables is small. To overcome the problem of knowledge acquisition, neural networks are extended to automatically extract fuzzy rules from numerical data.

After the learning phase is complete, the fuzzy model encapsulates the nonlinear function relating the SR motor rotor position to the flux linkage and current[17]. The training data obtained from the model is then utilized during the operation of the sensorless rotor position estimation scheme using neuro-fuzzy estimator to calculate the rotor position. The sensorless system essentially operates as follows: While the motor is running, the phase currents and voltages in each of the phases are measured and the flux linkages are estimated by trapezoidal integration using the motor voltage equation given below. Trapezoidal integration was used due to its relatively high accuracy and simple calculations, which made it well suited for real-time implementation.

$$\psi(n+1) = \psi(n) + \Delta T[v(n) - Ri(n) + v(n-1) - Ri(n-1)]/2$$
$$\psi(0) = 0$$

where n is the sample number, ΔT is the sampling period, ψ is the winding voltage, and R is the resistance.

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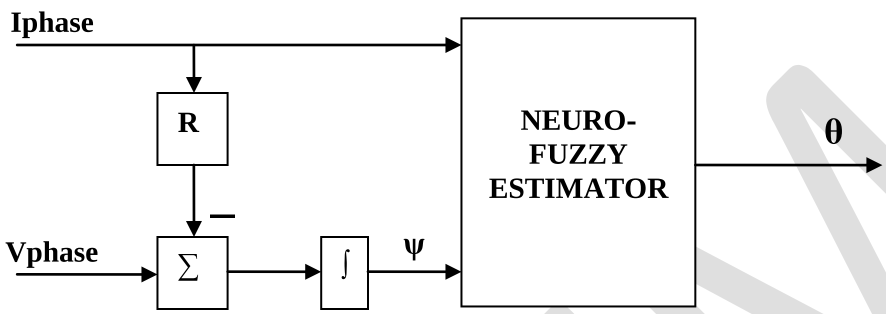

Fig. 4 Neuro-Fuzzy Position Estimator.

Fig. 4 shows the simplified block diagram of a Neuro-Fuzzy Position Estimator. The phase voltage and phase current are measured and the flux linkage is calculated by the trapezoidal integration method. This calculated flux linkage is given as one of the input to the estimator and current the other input. The angular position of the rotor is the output of the estimator. The neuro-fuzzy estimator is trained using the data constructed with the fuzzy logic based SRM model. With a representative amount of data for the training, the system can generate a correlation between current (I), flux linkage (ψ) and position (θ).

The multilayer feed forward network is chosen with the so called error back propagation training algorithm to train the network[18]. Then, the performance of the trained network is tested against different operating points. The first task in this process is to obtain flux linkage and current waveforms. After capturing the waveforms by means of an SRM simulation program, flux linkage and phase current are normalized. At the last step of the verification, normalized flux linkage and phase current values are fed into the trained network to estimate rotor position. Then the estimated rotor positions are compared with real values of the rotor position.

SIMULATION RESULTS

The captured waveforms of rotor angle, voltage, current, and the flux linkage by SRM simulation for one phase of the motor are shown in Fig. 5.

In the waveform of the actual rotor position given in Fig. 5(a), it can be seen that the rotor position accelerates from standstill to zero speed. The voltage and the corresponding phase current of the motor are detailed in Fig. 5(b) and 5(c). The phase flux linkage waveform is found from the numerical integration of the phase voltage and current. Fig. 5(d) plots the flux linkage waveform corresponding to the currents and voltages.

Fig. 6 shows the simulated results of actual and estimated rotor angles. One can see from the results in Fig. 6(a) and 6(b) that the estimated angle is very close to the actual rotor position at all times including the acceleration and stand still. The angle error between actual and estimated angle can also be seen in fig. 6(c). The position error could be reduced by increasing the amount of fuzzy sets in the variables domain, but an increase in the number of fuzzy sets would lead to more rules being required, and a corresponding increase in memory or storage requirements.

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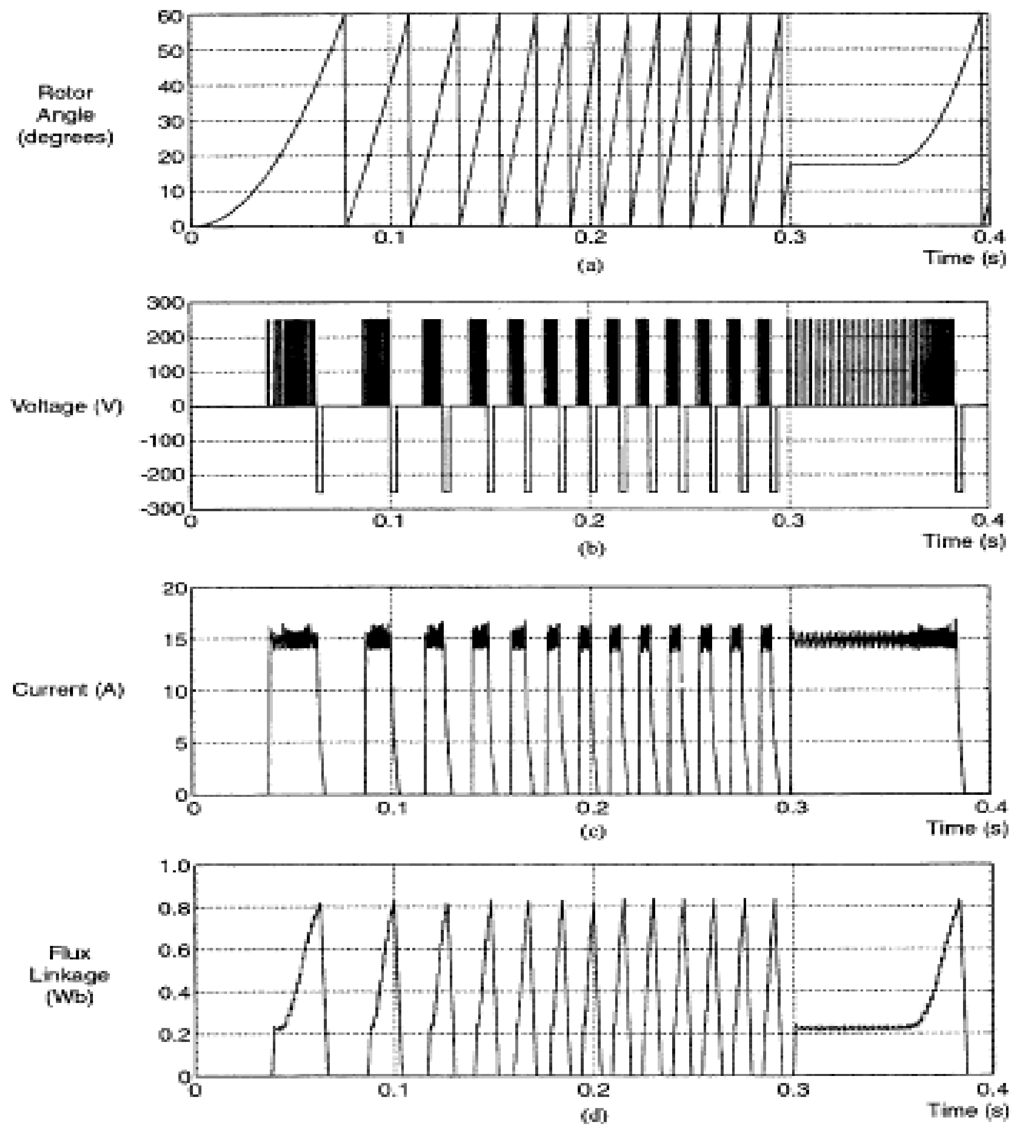

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Fig. 5 Waveforms for (a) Actual rotor angle (b) Phase voltage (c) Phase current (d) Phase flux linkage.

CONCLUSION

This paper proposes an approach for sensorless rotor position estimation in switched reluctance motors. The suggested method relies on the magnetization characteristic of the SRM which is a relation between electrical variables and mechanical variables. The electrical variables in this relation are flux linkage λ and phase current i and the mechanical variable is given as rotor position θ. The main goal is to estimate rotor position for given flux linkage and phase current values. A Neuro-Fuzzy Position Estimator is conceived to be the appropriate solution to construct a map between the electrical and mechanical variables of SRM. Simulation results show that the Neuro-Fuzzy estimator can be used as a position estimator for the SRM with acceptably small estimation error. The investigations conducted throughout this paper show that a properly trained and utilized Neuro-Fuzzy Position Estimator is capable of estimating rotor position of SRM within acceptable accuracy limits. The estimation method presented in this paper addresses the restrictions of previous sensorless schemes, as it can be used in both high and low operating speeds and does not assume linear characteristics of the SR motor. Thus, this system is well suited to a wide range of practical motor drives, where the accuracy of the measurements cannot be always be guaranteed.

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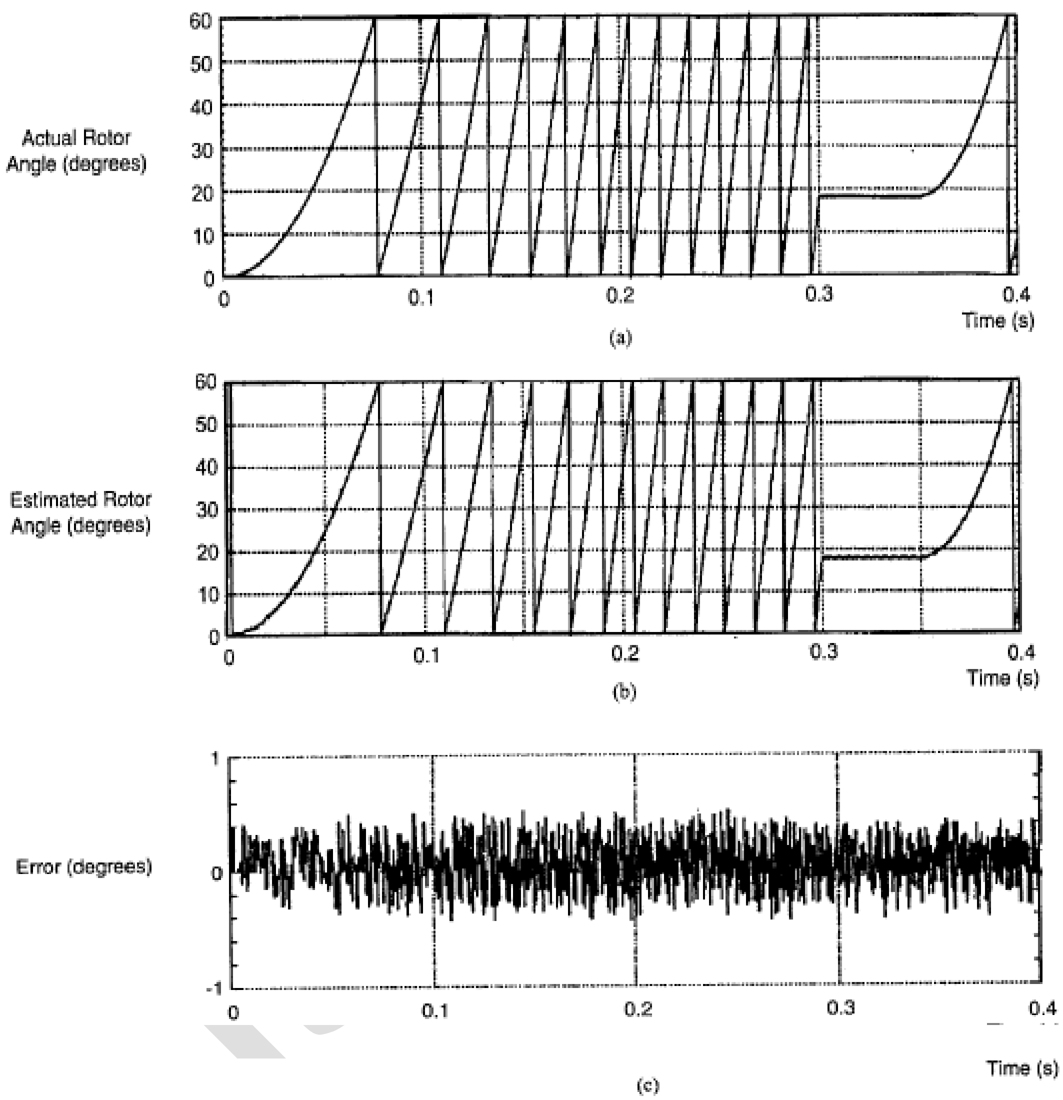

Fig. 6 Angle Waveforms. (a) Actual Rotor Angle (b) Estimated Rotor Angle (c) Angle Error

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