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Adaptive Neuro-Fuzzy Controller of Switched Reluctance Motor

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Abstract: This paper presents an application of adaptive neuro-fuzzy (ANFIS) control for switched reluctance motor (SRM) speed. The ANFIS has the advantages of expert knowledge of the fuzzy inference system and the learning capability of neural networks. An adaptive neuro-fuzzy controller of the motor speed is then designed and simulated. Digital simulation results show that the designed ANFIS speed controller realizes a good dynamic behaviour of the motor, a perfect speed tracking with no overshoot and a good rejection of impact loads disturbance. The results of applying the adaptive neuro-fuzzy controller to a SRM give bettter performance and high robustness than those obtained by the application of a conventional controller (PI).

Keywords: Switched reluctance motor, PI, Adaptive neuro-fuzzy (ANFIS), Speed control.

1 Introduction

Switched reluctance motors (SRMs) can be applied in many industrial applications due to their cost advantages and ruggedness. The switched reluctance motor is simple to construct. It is not only features a salient pole stator with concentrated coils, which allows earlier winding and shorter end turns than other types of motors, but also features a salient pole rotor, which has no conductors or magnets and is thus the simplest of all electric machine rotors. Simplicity makes the SRM inexpensive and reliable, and together with its high speed capacity and high torque to inertia ratio, makes it a superior choice in different applications.

The FIS forms are a useful computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules and fuzzy reasoning. The ANFIS [1, 2] is a FIS implemented in the framework of an adaptive fuzzy neural network. It combines the explicit knowledge representation of a FIS with the learning power of ANNs. Usually, the transformation of human knowledge into a fuzzy system (in the form of rules and membership functions) does not give the target

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response accurately. So, the parameters of the FIS should be determined optimally

However, the motor is highly nonlinear and operates in saturation to maximize the output torque. Moreover, the motor torque is a nonlinear function of current and rotor position. This highly coupled nonlinear and complex structure of the SRM make the design of the controller difficult [3].

In this paper the application of adaptive neuro-fuzzy in switched reluctance motor speed control is described. The organization of this paper is as follows: in section 2, the control principle for switched reluctance motor drive is presented; in section 3, the proposed controller is described, and used to control the speed of the switched reluctance motor. Simulation results are given to show the effectiveness of this controller. Conclusions are summarized in the last section.

2 SRM Model

2.2 Description of the system

In a switched reluctance machine, only the stator presents windings, while the rotor is made of steel laminations without conductors or permanent magnets. This very simple structure reduces greatly its cost. Motivated by this mechanical simplicity together with the recent advances in the power electronics components, much research has been developed in the last decade.

The switched reluctance machine motion is produced because of the variable reluctance in the air gap between the rotor and the stator. When a stator winding is energized, producing a single magnetic field, reluctance torque is produced by the tendency of the rotor to move to its minimum reluctance position [4]. A cross-sectional view is presented in Fig. 1.

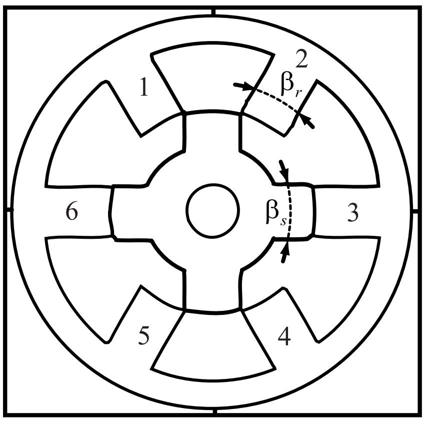


Fig. 1 – *Switched reluctance motor.*

The schematic diagram of the speed control system under study is shown in Fig. 2. The power circuit consists of the *H*-bridge asymmetric type converter whose output is connected to the stator of the switched reluctance machine [5, 6].

The ANFIS inputs are obtained by manipulating the speed reference and feedback, while the ANFIS output is integrated to produce the current reference.

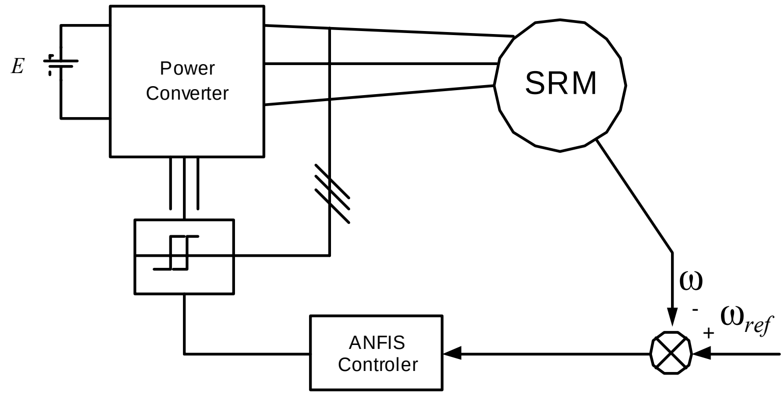


Fig. 2 – *Control of SRM.*

2.2 Machine equation

The switched reluctance motor has a simple construction, but the solution of its mathematical models is relatively difficult due to its dominant non-linear behaviour. The flux linkage is a function of two variables, the current I and the rotor position (angle θ).

The mathematical model from the equivalent circuit is:

$$V_j = RI_j + \frac{\mathrm{d}\Psi_j(i,\theta)}{\mathrm{d}t}, \tag{1}$$

with $j = 1, 2, \ldots, 3$.

The motion equation is:

$$J\frac{\mathrm{d}\omega}{\mathrm{d}t} = T_e - T_l - f\omega, \tag{2}$$

where are

$$\omega = \frac{\mathrm{d}\theta}{\mathrm{d}t},$$

$$T_e = \frac{1}{2}\frac{\mathrm{d}L(\theta,i)}{\mathrm{d}\theta}i^2. \tag{3}$$

The average torque can be written as the superposition of the torque of the individual motor phases:

$$T_e = \sum_{phase=1}^{n} T_{phase}, \tag{4}$$

where V – the terminal voltage, I – the phase current, R – the phase winding resistance, Ψ – the flux linked by the winding, J – the moment of inertia, f – the friction, $L(\theta, i)$ – the instantaneous inductance and T_e is the total torque.

3 Adaptive Neuro-Fuzzy MODE Speed Controller

3.1 Adaptive neuro-fuzzy principle

A typical architecture of an ANFIS is shown in Fig. 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. For simplicity, we consider two inputs *x*, *y* and one output *z*. Among many FIS models, the Sugeno fuzzy model is the most widely applied one for its high interpretability and computational efficiency, and built-in optimal and adaptive techniques. For a first order Sugeno fuzzy model, a common rule set with two fuzzy if–then rules can be expressed as:

$$\begin{aligned}&\text{Rule 1: if } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } z_1 = p_1 x + q_1 y + r_1\\&\text{Rule 2: if } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } z_2 = p_2 x + q_2 y + r_2\end{aligned}, \tag{5}$$

where A_i and B_i are the fuzzy sets in the antecedent, and p_i, q_i and r_i are the design parameters that are determined during the training process. As in Fig. 3, the ANFIS consists of five layers:

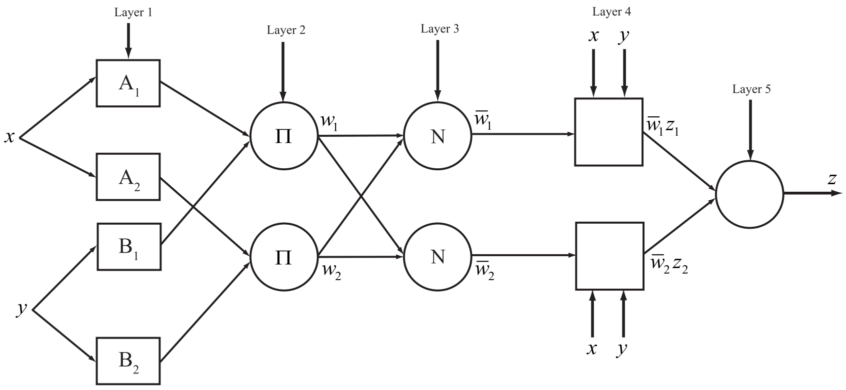


Fig. 3 – *Architecture of ANFIS.*

Layer 1: Every node i in the first layer employs a node function given by:

$$O_i^1 = \mu_{A_i}(x), \quad i = 1,2$$
$$O_i^1 = \mu_{B_{i-2}}(y), \quad i = 3,4 \tag{6}$$

where μ_{A_i} and μ_{B_i} can adopt any fuzzy membership function (MF).

Layer 2: Every node in this layer calculates the firing strength of a rule via multiplication

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{7}$$

Layer 3: The i-th node in this layer calculates the ratio of the i-th rule's firing strength to the sum of all rules firing strengths:

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{8}$$

where $\overline{w}_i$ is referred to as the normalized firing strengths.

Layer 4: In this layer, every node i has the following function:

$$O_i^4 = \overline{w}_i z_i = \overline{w}_i(p_i x + q_i y + r_i), \quad i = 1,2 \tag{9}$$

where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. The parameters in this layer are referred to as the consequent parameters.

Layer 5: The single node in this layer computes the overall output as the summation of all incoming signals, which is expressed as:

$$O_i^5 = \sum_{i=1}^{2} \overline{w}_i z_i = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2}. \tag{10}$$

The output z in Fig. 3 can be rewritten as [7- 9]:

$$z = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}_2 x)p_2 + (\overline{w}_2 y)q_2 + (\overline{w}_2)r_2. \tag{11}$$

3.2 Adaptive neuro-fuzzy controller

The ANFIS controller generates change in the reference current (I_{ref}), based on speed error (e) and derivate in the speed error ($\mathrm{d}e$) defined as:

$$e = \omega_{ref} - \omega, \tag{12}$$

$$\mathrm{d}e = \frac{\mathrm{d}(\omega_{ref} - \omega)}{\mathrm{d}t}, \tag{13}$$

where ω_{ref} and ω are the reference and the actual speeds, respectively.

In this study first order Sugeno type fuzzy inference was used for ANFIS and the typical fuzzy rule is:

$$\text{if } e \text{ is } A_i \text{ and } \mathrm{d}e \text{ is } B_i \text{ then } z = f(e, \mathrm{d}e), \tag{14}$$

where A and B are fuzzy sets in the antecedent and $z = f(e, \mathrm{d}e)$ is a crisp function in the consequent.

The significances of ANFIS structure are:

Layer 1: Each adaptive node in this layer generates the membership grades for the input vectors A_i, $i = 1, \ldots, 5$. In this paper, the node function is a triangular membership function:

$$O_i^1 = \mu_{Ai}(e) = \begin{cases} 0, & e \le a_i \\ \dfrac{e - a_i}{b_i - a_i}, & a_i \le e \le b_i \\ \dfrac{c_i - e}{c_i - b_i}, & b_i \le e \le c_i \\ 0, & c_i \le e \end{cases}. \tag{15}$$

Layer 2: The total number of rule is 25 in this layer. Each node output represents the activation level of a rule:

$$O_i^1 = w_i = \min((\mu_{Ai}(e), \mu_{Bi}(\mathrm{d}e)), \quad i = 1, \ldots, 5. \tag{16}$$

Layer 3: Fixed node i in this layer calculate the ratio of the i-th rule's activation level to the total of all activation level:

$$O_i^3 = \overline{w}_i = \frac{w}{\sum_{j=1}^{n} w_j}. \tag{17}$$

Layer 4: Adaptive node i in this layer calculate the contribution of i-th rule towards the overall output, with the following node function:

$$O_i^4 = \overline{w}_i z_i = \overline{w}_i (p_i e + q_i \,\mathrm{d}e + r_i). \tag{18}$$

Layer 5: The single fixed node in this layer computes the overall output as the summation of contribution from each rule:

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} z_i = \frac{w_1 z_1 + w_2 z_2}{w_1 + w_2}. \tag{19}$$

The parameters to be trained are a_i, b_i, and c_i of the premise parameters and p_i, q_i, and r_i of the consequent parameters. Training algorithm requires a training set defined between inputs and output [10 - 12]. Although, the input and output pattern set have 150 rows. Fig. 4 shows optimized membership function for e and de.

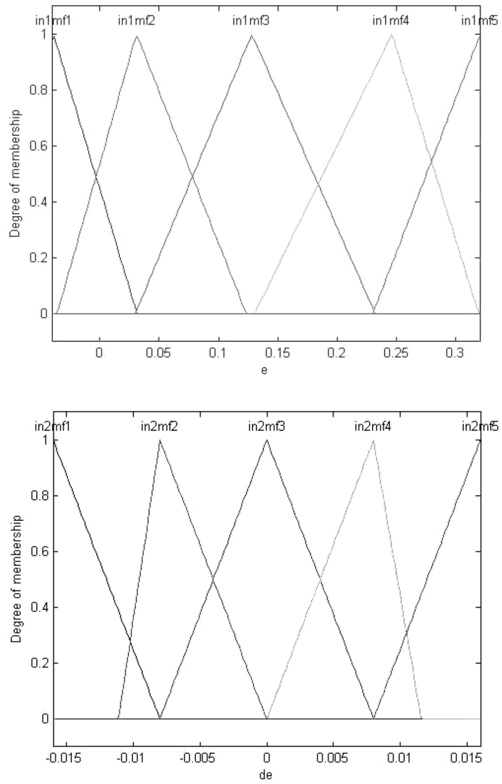


Fig. 4 – *Membership functions for e and de after trained.*

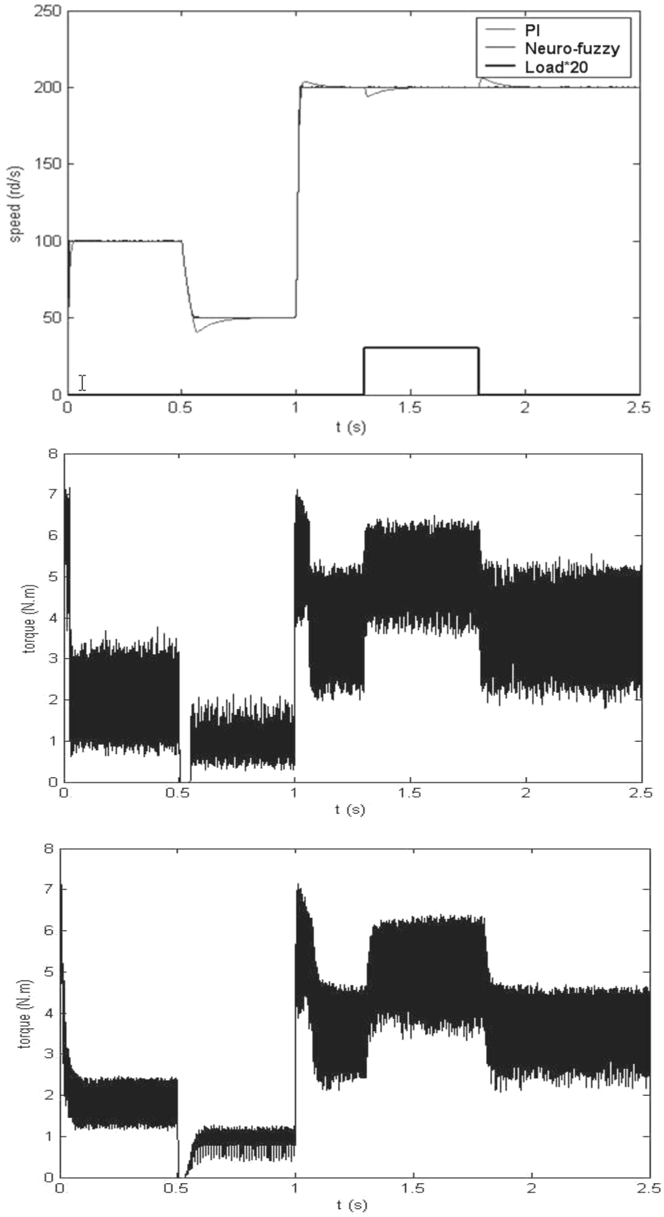
The number of epochs was 100 for training. The number of MFs for the input variables e and de is 5 and 5, respectively. The number of rules is then 25 ($5 \cdot 5 = 25$). The triangular MF is used for two input variables. It is clear from (15) that the triangular MF is specified by two parameters.

Therefore, the ANFIS used here contains a total of 95 fitting parameters, of which 20 ($5 \cdot 2 + 5 \cdot 2 = 20$) are the premise parameters and 75 ($3 \cdot 25 = 75$) are the consequent parameters.

The training and testing root mean square (RMS) errors obtained from the ANFIS are $4.7 \cdot 10^{-6}$ and $5.3 \cdot 10^{-6}$ respectively.

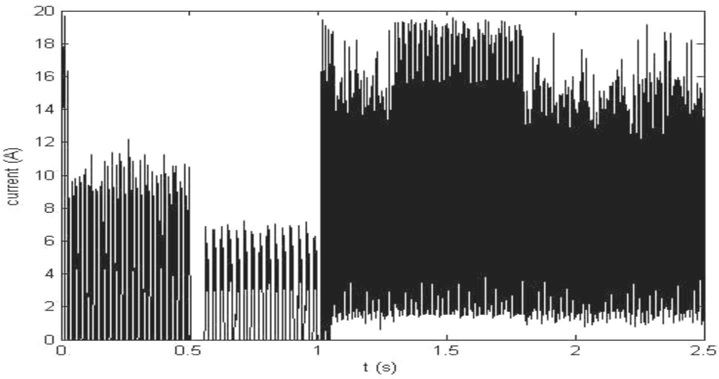
4 Simulation Result

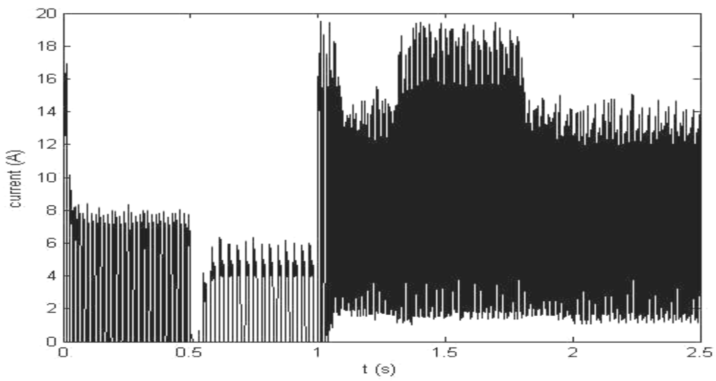
To show the Anfis mode controller performances we have simulated the system described in Fig. 1.



a) PI

Fig. 5 – *Simulation results of speed control.*





b) neuro-fuzzy

Fig. 5 – *Simulation results of speed control.*

Using a PI controller, a good compromise for K_p and K_i parameters has been found in order to have weak speed oscillations. The simulation of the starting mode without load is done. A simulation test was achieved for three speed reference signals, respectively: $+100$, $+50$ and $+200\,\text{rad/s}$. These results have been obtained with a load of $T_r = 1.5\,\text{Nm}$ applied at $t = 1.3\text{s}$ and eliminate at $t = 1.8\text{s}$.

The simulation is realized using the SIMULINK software in MATLAB environment. Fig. 5 shows the performances of the adaptive neuro-fuzzy controller.

When $t = 1.3\text{s}$, torque load passes from zero to $+1.5\,\text{Nm}$. To continue the speed regulation at $t = 1.3\text{s}$, the reference current is increased by the PI controller. The PI controller lacks flexibility regarding changes of the SRM operating point, which means that parameters K_p and K_i are only valid for a certain operating region Fig. 5.

Fig. 5 shows the very good performances reached by the adaptive neuro-fuzzy controller. Indeed, one notes that the overshoot is less important in the case of the neuro-fuzzy regulator, with a best response time without increasing the overshoot. For this test, the adaptive neuro-fuzzy controller proves to be well more robust because the speed curve is hardly of its reference. On the other hand, the speed signal evolution obtained with the PI controller deviates about 10% from its reference value (Fig. 5). The speed tracking is satisfactory, and the torque ripple is low. These results demonstrate the robustness of the drive under unpredictable load conditions.

Robustness

In order to test the robustness of the proposed control, we have studied the speed performances. Two cases are considered:

1. Inertia variation,

2. Stator resistance variation.

The Fig. 6a shows the robustness tests concerning the variation of the resistances and Fig. 6b shows the robustness tests in relation to inertia variations.

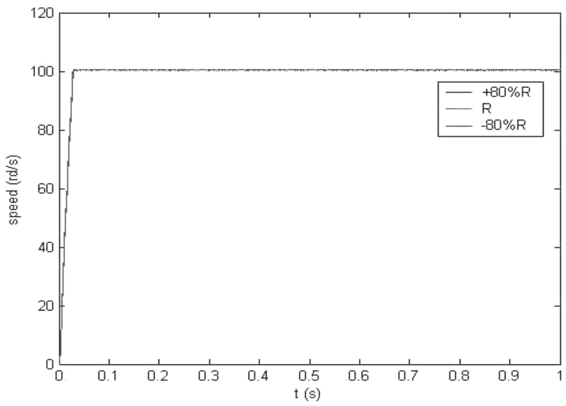
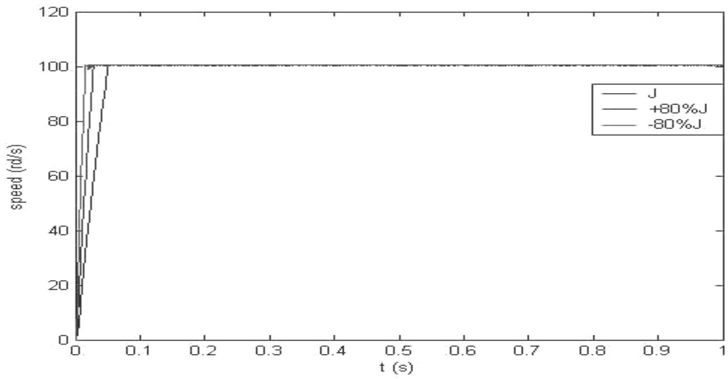


Fig. 6a – *Test of robustness- different values of resistance of stator.*

Fig. 6b shows the parameter variation does not allocate performances of proposed control. The speed response is insensitive to parameter variations of the machine, without overshoot and without static error. The other performances are maintained.



Different values of moment of inertia

Fig. 6 – *Test of robustness.*

5 Conclusion

The paper presents a new approach to robust speed control for switched reluctance motor. It develops a simple robust controller to deal with parameters uncertain and external disturbances and takes full account of system noise, digital implementation and integral control. The control strategy is based on ANFIS approaches.

The simulation results show that the proposed controller is superior to conventional controller in robustness and in tracking precision. The simulation study clearly indicates the superior performance of adaptive neuro-fuzzy control, because it is inherently adaptive in nature. It appears from the response properties that it has a high performance in presence of the plant parameters uncertain and load disturbances. It is used to control system with unknown model. The control of speed by ANFIS gives fast dynamic response without overshoot and zero steady-state error.

6 Appendix

Phase number 3;

Number of stator poles 6; 30° pole arc;

Number of rotor poles 4; 30° pole arc;

Maximum inductance $60\,\text{mH}$ (unsaturated);

Minimum inductance $8\,\text{mH}$;

Phase resistance $R = 1.3\Omega$;

Moment of inertia $J = 0.0013\,\mathrm{Kg}\cdot\mathrm{m}^2$;

Friction $f = 0.0183\,\mathrm{Nm/s}$;

Inverter voltage $V = 150\,\mathrm{V}$.

7 References

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