International Journal of Electrical and Power Engineering 1 (2): 215-221, 2007

Nonlinear Modelling of Switched Reluctance Motors Using Soft Computing Techniques

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Abstract: Switched Reluctance Motors (SRM) is almost always operated within the saturation region for very large operation region. This yields very strong non linearity, which makes it very difficult to derive a comprehensive mathematical model for the behavior of the machine. This study develops and compares fuzzy logic, neuro- fuzzy logic and neural network techniques for the modelling of a Switched Reluctance Motor (SRM) in view of its nonlinear magnetisation characteristics. All the models are simulated and applied for nonlinear modelling, especially for finding the rotor angle positions at different currents, from a suitable measured data set for an associated SRM. The data comprised flux linkage, current and rotor position. The model evaluation results are compared with the measured values and the error analyses are given to determine the performance of the developed model. The error analyses have shown great accuracy and successful modelling of SRMs using soft computing techniques.

Key words: Error analysis, fuzzy logic, neuro-fuzzy, neural network SRM

INTRODUCTION

The switched reluctance motor has a simple design with a rotor without windings and stator with windings located at the poles. The inherent simplicity, ruggedness and low cost of SRM make it possess strong competition in many adjustable speed and servo-type applications. The simplicity of the motor construction promised low cost in manufacturing which, in turn, has motivated researchers' interest. The switched reluctance motor has a simple design with a rotor without windings and stator with windings located at the poles. Figure 1 shows the configuration of a four-phase SRM with eight poles in the stator and 6 poles in the rotor, alternatively called a 8:6 SRM. The simplicity of the motor construction, however, has a crucial disadvantage due to the double saliency of the SRM causing its highly nonlinear magnetic characteristics. Hence, understanding the motor's magnetic property is essential for a proper control operation. It is important to have knowledge of the rotor position for the good performance of the SRM and traditionally it was achieved by some form of rotor position sensor. There has been extensive research to eliminate direct rotor position sensors, simply by indirectly determining the rotor position. Recently, many publications based on magnetization characteristics of the SRM have been studied by many researchers (Mese and Torrey, 2002; Zhan *et al*., 1998; Eyguesier *et al*., 1999; Miller and McGlip, 1990; Lyons *et al*., 1991; Elmas and Zelaya, 1993). Some models, as those based on "gage curve" (Lyons *et al*., 1991; Miller *et al*., 1998) use empirical knowledge and need only a few recalculated points of the magnetization curves. However they are unable to include effects of mutual interaction between two or more simultaneously excited phases, which are important in designing SRM drive with four or larger number of motor phases (Michaelides and Pollock, 1996; Pillay *et al*., 1998).

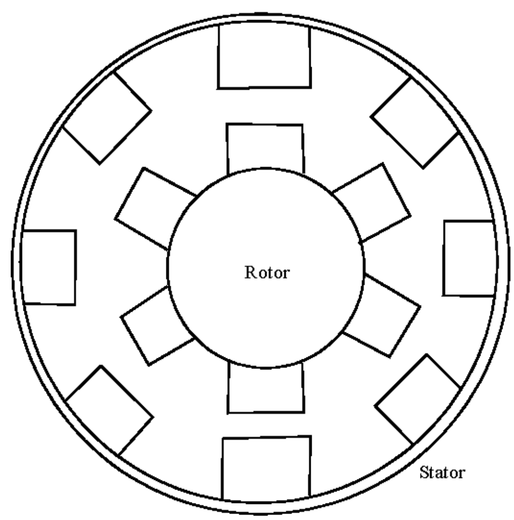

Fig.1: SRM with 8/6 poles

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A number of nonlinear SRM models, using magnetic theory (Faiz and Finch, 1993; Radun, 1995) have been developed. However, where there is no pole overlap, the model in (Radun, 1995) does not include saturation. In contrast to the above methods, there have been many attempts to generate the necessary static magnetisation curves by Finite Element Analysis (FEA) (Elmas and Zelaya, 1993). The methods above have some disadvantages, namely; the complex, modelling, the computation time and the lack of accuracy. In this study, model based on fuzzy logic, is used to develop optimised model that represent the nonlinear characteristics of the switched reluctance motor. Thus, the ultimate goal is to develop such models using artificial intelligence technique that demonstrate the nonlinear magnetization characteristics of SRM without ignoring motor saturation or behavior.

MAGNETISATION CHARACTERISTICS

The nonlinear characteristic of the SRM lies between the relationship of flux linkage with stator currents and rotor angles. Therefore, it is essential to develop a model based on magnetisation characteristics, which show the nonlinear behaviors of the SRM. In general, the nonlinear magnetic characteristics of an SRM can be appropriately modelled by equations defining the nonlinear flux-current-angle and torque-flux-angle characteristics. However, instead of using only complex mathematical equations in the modelling, artificial intelligence techniques provide a simple way of modelling, which can take into consideration the static and dynamic effects of the motor. The models of switched reluctance motor developed in this study use the measured magnetisation data sets obtained from (Miller and McGilp, 1990). The data comprise flux linkage, current and rotor angle. The magnetisation data set does not have to have huge measured values, but instead it is important to have the magnetisation values in the region that is critical to the modelling such as the aligned and unaligned values. However, the accuracy of the models depends on the amount of the data sets available. With the data sets, two models were presented. Both models define a two inputs and one output nonlinear function where flux linkage and stator currents are assigned as the inputs, with rotor angle as the output. The fuzzy model developed uses measured magnetization data set to generate the magnetisation model curve. The curve plotted with respect to the measured data set with polynomial curve fitting is as shown in Fig. 2. In this figure, the flux linkages against current curves for different rotor angles ranging from 30° (unaligned position) to 60° (aligned position) for 8:6 SRM are given. The magnetisation curve is important for modelling, because it provides the basis for measured numerical information about the SRM and also allows knowing about the magnetisation characteristics of it. It is easier to understand the graphical presentation than the numerical data values.

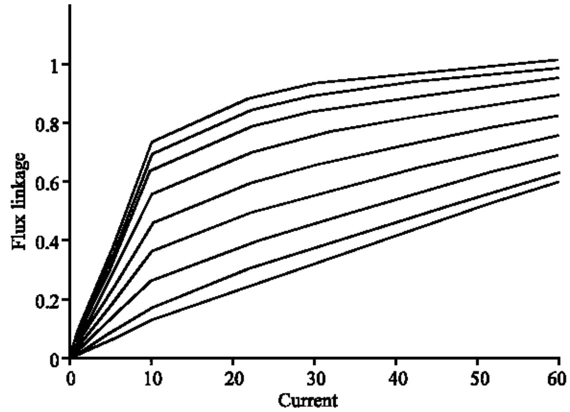

Fig. 2: Magnetisation curve for SRM

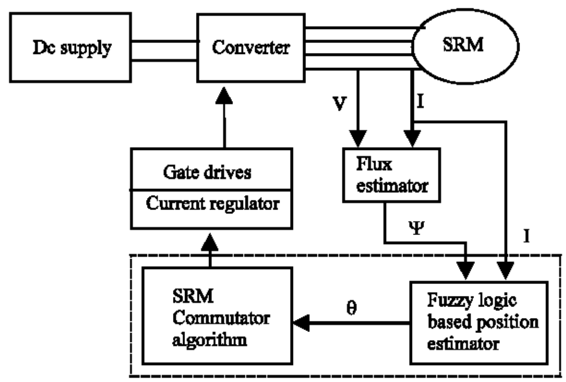

Fig: 3: Block diagram of development of SRM model

DEVELOPMENT OF SOFT COMPUTING BASED SR MOTOR MODEL

The basic premise of the proposed method is that a soft computing technique forms a very efficient mapping structure for the nonlinear SRM. Through measurement of the phase flux linkages and phase currents the soft computing technique is able to estimate the rotor position, thereby facilitating elimination of the rotor position sensor. The soft computing technique training data set is comprised of magnetization data for the SRM of which flux linkage (•) and current (i) serve as inputs and the corresponding position (•) as output in this set (Fig. 3).

Construction of the training data set: There are 2 possible ways to generate training data: model-based data generation and experiment-based data generation.

Model based data generation: A suitable magnetization model for the associated SRM is used to generate the data. Given a proper model, flux linkage values are computed for randomly generated phase current and rotor position values so that the resulting flux linkage, phase current and rotor position values will judiciously cover the intended operating region. This method is used during the simulation study.

Experiment based data generation: In this approach the motor is run for certain operating points with a shaft encoder so that the magnetization characteristic is swept over certain regions, or, in a better approach, the motor is run from zero speed to full speed and every electric cycle of the flux linkage, phase current and rotor position is captured with a certain sampling rate. This allows more judicious coverage of the magnetization characteristic. This method is used during the experimental study.

FUZZY MODELLING

To create a fuzzy model of SRM, the SRM magnetization model curve is termed a fuzzy rule base. This rule base is used to provide a value of rotor position from the inputs of the fuzzy model.

The generated fuzzy rule base defines a function for mapping input values of flux linkages and current to output values of rotor position. Initially, the input and output domains are divided into fuzzy regions, before the algorithm is executed, as shown in Table 1. Here, the input domains are flux linkages and current and have a range of 0-1 and 0-60 A, respectively for the motor drive used in this research. Likewise, the range of the angle is 30-60°. Table 1 shows the corresponding input and output variable domains with their respective range of interval, number of fuzzy regions assigned and the linguistic variable assigned for the regions. The selection of the number of regions is based on the need to provide a degree of accuracy to the system, since there is a compromise between the number of resultant rules that are generated in the rule base and the desired accuracy. More regions would mean more accuracy in such systems, but will cause more memory requirement due to

Table 1: Input and output domains for fuzzy model

Input/ Output	Range	Number of regions	Fuzzy Linguistic term
Current, I(A)	0-60	21	s10-m-b10
Flux linkage,• (Vs)	0-1	21	s10-m-b10
Angle, •(°)	30-60	11	s5-m-b5

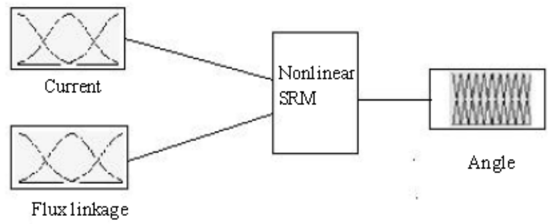

Fig. 4: FIS block diagram

the greater number of fuzzy sets and rules in the system. From the table, the range of the interval for inputs and output is divided equally into regions. Each region is assigned a Membership Function (MF) and a linguistic variable term as shown in Table 2,where 's' is denoted as 'small' ,'m' denoted as 'medium' and 'b' denoted as 'big'. It is understood that s11<s5<m<b5<b11. For each region between 2 different inputs, there will be a corresponding output that has been assigned with output variable ranging from s5-to-m-to-b5.Once MPs are defined, the magnetisation curve is used to generate fuzzy rules in order to create the fuzzy rule base model. A correct interpretation of the rule base from the magnetisation curve is important, as each rule assigned will influence the final output of the overall fuzzy model that will be constructed later. To determine a fuzzy rule, the first step is to find the degree of each data value (flux-linkages, current, angle) in every membership region of its corresponding fuzzy domain. The variable is then assigned to the region with the maximum degree. The rule base interpreted from the magnetisation curve into the rule base table form is shown in Table 2. The 'xx' in the table shows the empty rule for the correspond inputs, or in others words, there is not such a condition for that particular input. Thus, these inputs will not be included in the model. The types of MF were chosen to have the same simple triangular shape when each region (fuzzy set) was assigned to a fuzzy membership function. Each fuzzy set is denoted with fuzzy linguistic term ranging from s10-m-b10 for both of the inputs and from s5-m-b5 for the output. Figure 4 shows the Fuzzy Inference System (FIS) block diagram constructed. Since the variables have been named and the membership functions have appropriate shapes and names, the next step will be constructing the rules. The rules are in the form of if-then rule statements that are used to formulate the conditional statements that comprise fuzzy logic. The rules are set accordingly to the fuzzy rule base table construct previously shown in Table 2.

Table 2: Fuzzy rule base table (s: small, m: medium, b: big, xx: empty rule)

	•	0	0.05	0.1	0.15	0.2	0.25	0.3	0.35	0.4	0.45	0.5	0.55	0.6	0.65	0.7	0.75	0.8	0.85	0.9	0.95	1
1		s10	s9	s8	s7	s6	s5	s4	s3	s2	s1	m	b1	b2	b3	b4	b5	b6	b7	b8	b9	b10
0	s10	b2	b1	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx
3	s9	xx	s3	s2	s1	m	m	b1	b2	b2	b3	b4	b5	xx	xx	xx	xx	xx	xx	xx	xx	xx
6	s8	xx	s4	s3	s2	s1	s1	m	m	b1	b1	b2	b2	b3	b5	xx	xx	xx	xx	xx	xx	xx
9	s7	xx	s5	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b3	b3	b5	xx	xx	xx	xx	xx
12	s6	xx	xx	s5	s3	s3	s2	s1	s1	s1	m	m	b1	b1	b2	b2	b3	b5	xx	xx	xx	xx
15	s5	xx	xx	xx	s4	s3	s2	s2	s1	s1	m	m	m	b1	b1	b2	b3	b3	b5	xx	xx	xx
18	s4	xx	xx	xx	s5	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b2	b3	b4	xx	xx	xx
21	s3	xx	xx	xx	xx	s4	s3	s2	s2	s1	s1	m	m	m	b1	b1	b2	b2	b3	b4	xx	xx
24	s2	xx	xx	xx	xx	s5	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b1	b2	b3	b3	xx	xx
27	s10	xx	xx	xx	xx	xx	s5	s3	s2	s2	s1	s1	s1	m	m	b1	b1	b2	b2	b3	b5	xx
30	m	xx	xx	xx	xx	xx	xx	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b1	b2	b3	b4	xx
33	b1	xx	xx	xx	xx	xx	xx	s5	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b2	b3	xx
36	b2	xx	xx	xx	xx	xx	xx	xx	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b2	b3	xx
39	b3	xx	xx	xx	xx	xx	xx	xx	s5	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b3	b5
42	b4	xx	xx	xx	xx	xx	xx	xx	xx	s5	s3	s3	s2	s2	s1	s1	m	m	b1	b2	b3	b4
45	b5	xx	xx	xx	xx	xx	xx	xx	xx	xx	s4	s3	s2	s2	s1	s1	m	m	b1	b1	b2	b4
48	b6	xx	xx	xx	xx	xx	xx	xx	xx	xx	s5	s3	s3	s2	s2	s1	s1	m	b1	b1	b2	b3
51	b7	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	s4	s3	s3	s2	s1	s1	m	m	b1	b2	b3
54	b8	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	s5	s4	s3	s2	s2	s1	m	m	b1	b2	b3
57	b9	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	s5	s3	s3	s2	s1	s1	m	b1	b1	b3
60	b10	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	xx	s4	s3	s2	s2	s1	m	m	b1	b2

Table 3: Error analysis table for fuzzy SRM model

I	• (vs)	• m	• f (°)	•
10	0.1500	33	36.000	3.0000
10	0.1600	36	36.77300	0.7730
10	0.2400	39	38.227	0.7730
10	0.3100	42	42.0000	0.0000
10	0.4530	45	45.2757	0.2757
10	0.5500	48	48.0000	0.0000
10	0.6200	51	51.1462	0.1462
10	0.7200	54	54.2115	0.2115
10	0.7470	57	55.9468	1.0532
20	0.1970	33	32.9798	0.0202
20	0.2310	36	34.7917	1.2083
20	0.3070	39	39.0000	0.0000
20	0.4250	42	42.0000	0.0000
20	0.5410	45	45.0000	0.0000
20	0.6600	48	48.7730	0.7730
20	0.7690	51	52.1202	1.1202
20	0.8470	54	54.8352	0.8352
20	0.8810	57	55.7917	1.2083
30	0.2920	33	33.0000	0.0000
30	0.3350	36	34.9959	1.00410
30	0.4220	39	39.0000	0.0000
30	0.5330	42	42.0000	0.0000
30	0.6390	45	45.0000	0.0000
30	0.7500	48	48.0000	0.0000
30	0.8470	51	50.7524	0.2476
30	0.9160	54	55.0559	1.0559
30	0.9510	57	57.0000	0.0000
40	0.3930	33	32.7896	0.2104
40	0.4430	36	35.3263	0.6737
40	0.5340	39	37.9359	1.0641
40	0.6360	42	41.0229	0.9771
40	0.7340	45	43.9359	1.0641
40	0.8400	48	47.2270	0.7730
40	0.9100	51	51.7730	0.7730
40	0.9670	54	55.3730	1.3730
40	0.9940	57	57.1151	0.1151
50	0.4930	33	34.0317	1.0317
50	0.5470	36	35.7243	0.2757
50	0.6310	39	37.7917	1.2083
50	0.7240	42	42.0000	0.0000
50	0.8110	45	45.8268	0.8268

Table 3: Continued

50	0.8900	48	47.2270	0.7730
50	0.9580	51	52.5215	1.5215
50	1.0000	54	54.0000	0.0000
50	1.0190	57	54.0000	3.0000
60	0.5880	33	33.0000	0.0000
60	0.6410	36	35.3377	0.6623
60	0.7190	39	39.0000	0.0000
60	0.7990	42	41.9145	0.0855
60	0.8700	45	46.2581	1.2581
60	0.9500	48	48.0000	0.0000
60	0.9940	51	50.5326	0.4674
60	1.0130	54	54.0000	0.0000
60	1.0380	57	51.0000	3.0000
			2458.34	37.839

Example Rule 1: (refer to Table 2)

If current; I is s8 and flux linkage; • is b2; then angle; • is b3: When a rule is generated, a rule degree is assigned to that rule, where this rule degree is defined as the degree of confidence that the rule does, actually, correlate with the function relating flux linkages and current to angle. Each rule has a degree i, which is the product of the membership function degree of each variable in the respective region.

The fuzzy model in this study consists of 264 rules. Modification and tuning were performed against the fuzzy model by varying the rules or membership functions of both the inputs and outputs. Once the modification and tuning are complete, the SRM fuzzy model encapsulates the nonlinear function relating the SRM rotor angle to the flux linkage and current.

From the error analysis table as shown in Table 3, the error analysis for Fuzzy SRM model:

- N number of data points = 54
- *I* phase current, A

- • flux linkage at various rotor angle, V.s
- $\bullet_m$ measured rotor angle, °
- $\bullet_f$ fuzzy model rotor angle, °
- Calculated total • m = 2458.341
- Calculated total error =37.8392
- Mean $\bullet_m$ = 2458.341 / 54 =45.5248
- $$\text{average\%error} = \left[\frac{\sum \varepsilon}{\text{mean}\theta_m \text{xN}}\right] * 100$$

  =37.8392*100/2458.341

  =1.5411 %

ARTIFICIAL NEURAL NETWORK MODELLING

The multilayer back propagation feed forward neural network is used to develop a model that provides a good estimate of rotor position and the idea of using neural network is normally useful when the main position estimation algorithms degrade at low speeds. The main task behind the modelling is to determine the unknown rotor position from the provided magnetisation curve. A total of 30 neurons in multilayer hidden layer1 and 20 neurons in multilayer hidden layer1, 2 neurons in input layer and 1 neuron in output layer are found to be a good balance between rotor position estimation and ANN complexity. However, if large neurons are applied in the hidden layer, the network will get an over fit whereby the network will have problems to generalize. A supervised learning method is used here, in which weights are randomly arranged into small values (both positive and negative) to ensure that the network is not saturated by large values of weights and will be reshuffled as the network is told how close it is to achieve the goal. If all the weights are started at same value, but the desired output value requires unequal weights, the network would not be trained. The comparison of ANN structures is based on minimizing the least-squared estimation error over the training data set .The neural model applied to 8/6 SRM has 54 sets of data, with a conduction period of 30°<=•<=60°. In the network, two sets of data have been using flux linkages, current and rotor angle.

From the error analysis table as shown in Table 4, the error analysis for Neuro SRM model:

- N number of data points = 54
- *I* phase current, A
- • flux linkage at various rotor angle, V.s
- $\bullet_m$ measured rotor angle, °
- $\bullet_n$ Neuro- model rotor angle, °
- Calculated total • m = 2430
- Calculated total error =0.02284
- Mean $\bullet_m$ = 2430 / 54 =45

Table 4: Error analysis table for Neuro SRM

I	• (V.s)	$\bullet_m$°	$\bullet_n$°	•
10	0.1288	33	33	-4.8054e-005
22	0.2493	33	33	-0.0003425
30	0.3236	33	33	-0.00027559
42	0.434	33	33	-0.00018942
50	0.5123	33	33	-0.00023049
60	0.5981	33	33	-3.5379e-006
10	0.165	36	36	-4.0538e-005
22	0.2995	36	36	-0.00021502
30	0.372	36	36	-0.00021411
42	0.4768	36	36	-0.00032624
50	0.5506	36	36	-0.00012857
60	0.6314	36	36	-0.00020361
10	0.26	39	39	-2.9127e-006
22	0.3876	39	39	0.00019935
30	0.4568	39	39	0.00017528
42	0.552	39	39	7.194e-005
50	0.6177	39	39	0.00014345
60	0.6896	39	39	-0.00019768
10	0.3583	42	42	-1.5854e-005
22	0.4912	42	42	-0.00022917
30	0.5565	42	42	-0.000182
42	0.6403	42	42	0.00010208
50	0.6967	42	42	-0.00016332
60	0.7581	42	42.002	0.0020559
10	0.4565	45	45	-0.00015855
22	0.5949	45	45	-0.00010647
30	0.6562	45	45	8.2374e-005
42	0.7287	45	45.001	0.0013257
50	0.7757	45	45	-0.00017393
60	0.8266	45	45.001	0.00060861
10	0.5548	48	48	-2.4835e-005
22	0.6985	48	48.001	0.00053053
30	0.7559	48	48.001	0.00064644
42	0.817	48	48.001	0.00072376
50	0.8547	48	48.001	0.00086654
60	0.8951	48	48.003	0.0032707
10	0.6358	51	51	9.4489e-006
22	0.7839	51	51	0.00037005
30	0.8381	51	51	-0.00012048
42	0.8899	51	51	-7.1775e-005
50	0.9198	51	51.001	0.00094201
60	0.9516	51	50.999	-0.00089118
10	0.6897	54	54	-5.9357e-006
22	0.8408	54	54	2.5238e-005
30	0.8928	54	54.001	0.00051314
42	0.9384	54	54	-0.00024687
50	0.9631	54	53.999	-0.00096819
60	0.9892	54	54	-0.00040733
10	0.7282	57	57	-1.3802e-005
22	0.8814	57	56.999	-0.00063726
30	0.9318	57	57	0.00019828
42	0.973	57	56.999	-0.0010064
50	0.994	57	56.999	-0.001056
60	1.016	57	56.999	-0.0010816
			2430	0.02284

- $$\text{average\%error} = \left[\frac{\sum \varepsilon}{\text{mean}\theta_m \text{xN}}\right] * 100$$

  =0.02284*100/2430

  =0.0094 %

NEURO-FUZZY MODELLING

The neuro-fuzzy model in this study uses the Adaptive Neuro-Fuzzy Inference System (ANFIS)

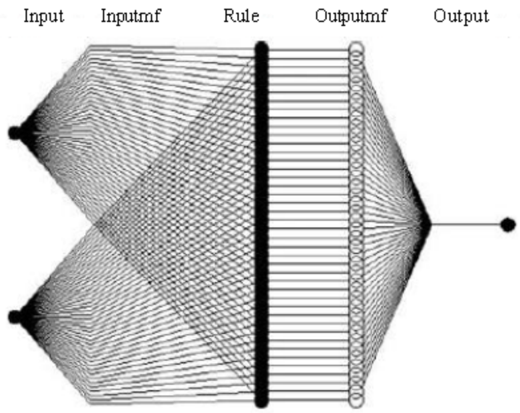

Fig. 5: Neuro-fuzzy architecture

techniques, which provide a method for the fuzzy modelling procedure to earn information about a data set, in order to compute the membership function parameters that best allow the associates fuzzy inference system to track the given input/output data. (Fig. 5). This learning method works similarly to that of neural networks (Jang, 1993; Takagi and Sugeno, 1985).

ANFIS modelling description

Number of inputs: 2
Number of outputs: 1
Method: Subtractive-clustering
Number of MFs : 3
Number of rules: 9
Optimised method: Hybrid
Epochs :100

From the error analysis table as shown in Table 5, the error analysis for Neuro-Fuzzy SRM model:

- N number of data points = 54
- *I* phase current, A
- • flux linkage at various rotor angle, V.s
- $\bullet_m$ measured rotor angle, °
- $\bullet_{nm}$ Neuro-fuzzy model rotor angle, °
- Calculated total • m = 2426
- Calculated total error =3.9606
- Mean $\bullet_m$ = 2426 / 54 =44.93
- $$\text{average\%error} = \left[\frac{\sum \varepsilon}{\text{mean}\theta_m \text{xN}}\right]*100$$

=3.9606*100/2426
=0.1632 %

From the error analysis, average, percentages of the modeling error are obtained for each of the models.

Table 5: Error analysis table for Neuro-fuzzy SAM model

I	• (V.s)	$\bullet_m$°	$\bullet_{nm}$°	•
10	0.1288	33	33.072	-0.07173
22	0.2493	33	33.644	-0.64417
30	0.3236	33	33.117	-0.11737
42	0.434	33	33.15	-0.1503
50	0.5123	33	33.039	-0.03903
60	0.5981	33	33.259	-0.25878
10	0.165	36	34.848	1.1524
22	0.2995	36	36.078	-0.07783
30	0.372	36	35.743	0.25655
42	0.4768	36	35.903	0.097199
50	0.5506	36	35.755	0.24521
60	0.6314	36	35.721	0.27859
10	0.26	39	39.022	-0.02244
22	0.3876	39	39.335	-0.33461
30	0.4568	39	39.123	-0.1228
42	0.552	39	39.218	-0.21833
50	0.6177	39	39.093	-0.09253
60	0.6896	39	39.041	-0.04069
10	0.3583	42	42.314	-0.31355
22	0.4912	42	42.106	-0.10586
30	0.5565	42	42.078	-0.07802
42	0.6403	42	42.118	-0.11773
50	0.6967	42	42.102	-0.10155
60	0.7581	42	42.13	-0.12982
10	0.4565	45	44.941	0.058757
22	0.5949	45	44.845	0.15509
30	0.6562	45	44.925	0.075094
42	0.7287	45	44.859	0.14076
50	0.7757	45	44.888	0.1123
60	0.8266	45	44.867	0.13278
10	0.5548	48	44.907	0.092727
22	0.6985	48	47.893	0.1074
30	0.7559	48	47.983	0.017093
42	0.817	48	47.777	0.22251
50	0.8547	48	47.846	0.15353
60	0.8951	48	47.788	0.21236
10	0.6358	51	51.165	-0.16466
22	0.7839	51	50.779	0.22122
30	0.8381	51	51.039	-0.03928
42	0.8899	51	50.821	0.17855
50	0.9198	51	51.025	-0.02529
60	0.9516	51	51.056	-0.05577
10	0.6897	54	54.125	-0.12528
22	0.8408	54	53.349	0.65113
30	0.8928	54	53.925	0.074981
42	0.9384	54	53.68	0.31959
50	0.9631	54	53.997	0.003179
60	0.9892	54	54.058	-0.05842
10	0.7282	57	56.968	0.031922
22	0.8814	57	55.968	1.0318
30	0.9318	57	56.801	0.19921
42	0.973	57	56.361	0.63944
50	0.994	57	56.703	0.29666
60	1.016	57	56.692	0.30841
			2426	3.9606

The table, analysis shows that the neuro approach has a higher accuracy than the fuzzy and neuro-fuzzy approach. This is due to the advantage of neuro network modelling with learning characteristics, which avoids dependency of human knowledge on systems or plant, learning from data values through the training scheme instead.

CONCLUSION

This study has successfully developed fuzzy, neuro fuzzy and neural network -based models for the nonlinear modelling of switched reluctance motors. The soft computing approach presented in this work addresses the restriction and complexity of analytical modelling for nonlinear characteristics of switched reluctance motor. All developed models constructed in this study have been successfully modelled with a low modelling error and are compared with one another so that a better choice of models for further work can be made.

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