Optimal Parameters Estimation of a Switched Reluctance Motor by Kohonen's Self Organizing Feature Map Method

B.Jaganathan
Assistant Professor
EEE Department
SRM University

R.Brindha
Assistant Professor
EEE Department
SRM University

Sumit Kumar Sah
UG Scholar
EEE Department
SRM University

ABSTRACT
SRM drives are the upcoming drives nowadays as these have many advantages such as simplicity , low manufacturing and operating costs, fault tolerance, high torque/inertia ratio and efficiency. The estimation of SRM drive parameters is an important consideration in their field. Many methods are available for this. However the estimation of the optimal parameters is normally preferred. Making use of neural networks is one of the best ways to achieve this. This paper proposes an unsupervised learning method i.e., Kohonen's Self Organizing Feature Map method of estimation of SRM drives. Since the method makes use of 'winner takes all' of a neuron, the values obtained by this, will be the optimal values. The drive is first simulated and the parameters obtained are used for training the ANN. The Unsupervised learning method is the Kohonen's Self Organizing Feature Map method, which is used for the estimation of the SRM drive parameters. The parameters estimated are the currents and fluxes in the two axis . Because of the unsupervised learning, it can be stated that the estimated values are the best or the optimal values. MATLAB/Simulink is used for the simulation and the results are shown.

Keywords
Artificial Neural Network, d-q control, Epoch, Estimation, KSOFM, SRM, Optimal Parameters, Unsupervised Learning, Unit Vectors, Weight Matrix.

1. INTRODUCTION
The Switched Reluctance Motor (SRM) is a form of stepper motor that uses fewer poles. Switched Reluctance Motor (SRM) is well known due to its robustness; easy assembly and good performance. The main principle used in the position estimation is the derivation of rotor position information from the stator circuit measurements or their derived parameters.[1],[2]. The Common usages for an SRM include applications where the rotor must be held stationary for long periods and in potentially explosive environments such as mining because it lacks a mechanical commutator. The phase windings in a SRM are electrically isolated from each other, resulting in higher fault tolerance compared to inverter driven AC induction motors. During online operation, the model structures and parameters of SRMs may differ from the standstill ones because of saturation and losses, especially at high current [3].

The optimal drive waveform is not a pure sinusoid, due to the non-linear torque relative to rotor displacement, and the highly position dependent inductance of the stator phase windings. SRM's are used in some washing machine design and in the control rod drive mechanisms of nuclear reactors. Two main models of SRM have been suggested in the literature—the flux model [4] and the inductance model [5]. But in this paper we preferred SRM model. NN is powerful empirical modeling tools that can be trained to represent complex multi-input multi-output nonlinear systems. NN have many advantageous features including parallel and distributed processing and an efficient non-linear mapping between inputs and outputs. Artificial Intelligence techniques have been widely used as a way to eliminate position sensors providing good results.

A self-organizing map (SOM) or self-organizing feature map (SOFM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two-dimensional), discretized representation of the input space of the training samples, called a map. Self-organizing maps are different from other artificial neural networks in the sense that they use a neighborhood function to preserve the topological properties of the input space. ANN architecture is most suitable to identify the online parameters required for the production of torque [6-8]. Like most artificial neural networks, SOMs operate in two modes: training and mapping. Training builds the map using input examples. It is a competitive process, also called vector quantization. Mapping automatically classifies a new input vector.

2. BLOCK DIAGRAM
The block diagram of the proposed method is shown in figure 1. DC input is given to a three phase inverter, which converts DC to AC. Inverter's AC output is fed to Switched Reluctance Motor (SRM).

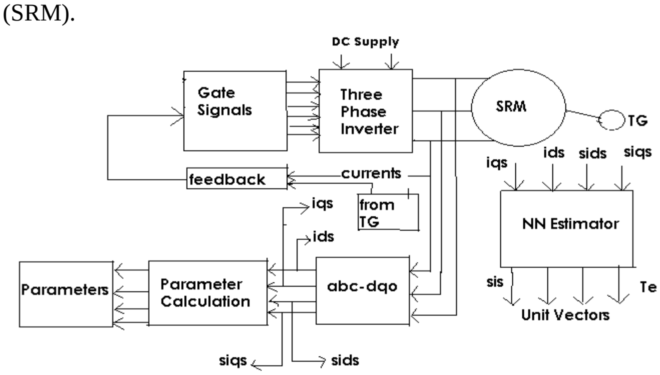

Fig. 1 Block Diagram of the Proposed Scheme

From here three phase currents are sensed and fed to the abc-dqo block. Output of this block is the transformed two phase currents which are i_{ds} and i_{qs}. Parameter calculation is the other block in which parameters such as stator flux, unit vectors ($\cos\theta_e$, $\sin\theta_e$), electromagnetic torque are calculated. Also the speed and the current are sensed and fed as input to the feedback element. In feedback the gating signals are produced and fed to the switching devices of the inverter. A range of values of i_{ds}, i_{qs}, Ψ_{ds}, Ψ_{qs} are fed as input to the neural network estimator. This NN estimator has the structure of KSOFM which estimates the optimal parameters of the SRM.

3. KOHONEN’S SELF-ORGANIZING FEATURE MAP

Fig. 2 shows the network architecture of a KSOFM. The Input layer accepts multidimensional input pattern from the environment. An input pattern is represented by a vector. Each neurode in the input layer represents one dimension of the input pattern. An input neurode distributes its assigned element of the input vector to the competitive layer.

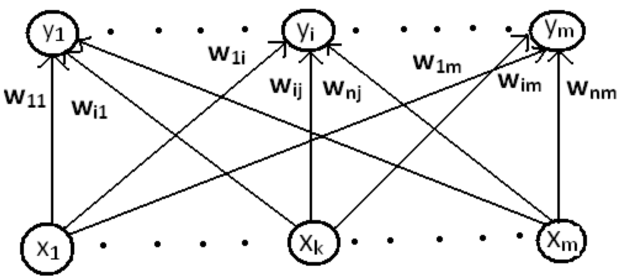

Fig. 2 Network Architecture of KSOFM

The Competitive layer consists of neurode each of which receives a sum of weighted inputs from the input layer. Every neurode in the competitive layer is associated with a collection of other neurodes which make up its 'neighbourhood’. A competitive Layer can be organized in 1 dimension, 2 dimensions, in general in n dimensions. The typical implementations are 1 or 2 dimensions. Upon the receipt of a given input, some of the neurodes will be sufficiently excited to fire. This event can have either an inhibitory, or an excitatory effect on its neighbourhood. The model has been copied from biological systems, and is known as 'on-center, off-surround' architecture, also known as lateral feedback inhibition.

The output layer can be organized and this organization is application-dependent. Strictly speaking, it is not necessary for the proper functioning of a Kohonen network. The "output" of the network is the way it is chosen to view the interconnections between nodes in the competitive layer. If the nodes are arranged along a single dimension, output can be seen as a continuum.

3.1 COMPETITION IN KSOFM

Each neurode in the competitive layer receives a (complex) mixture of excitatory and inhibitory signals from the neurodes in its neighbourhood, and from the input layer. The lateral inhibition is used to stabilize the network and prevent the "meltdown" due to over - excitation in the competitive layer, or starvation due to poor selection of the threshold value. For a given input, the neurode which responds most strongly will be permitted to adjust the weights of the neurodes which make up its neighbourhood, including itself. This is a "winner takes all" strategy to the learning process. The neurodes in this layer are competing to 'learn' the input vectors.

4. SIMULINK CIRCUIT

In Fig.3 is shown the Simulink circuit of a SRM drive which is used for obtaining the training data used for training the KSOFM network.

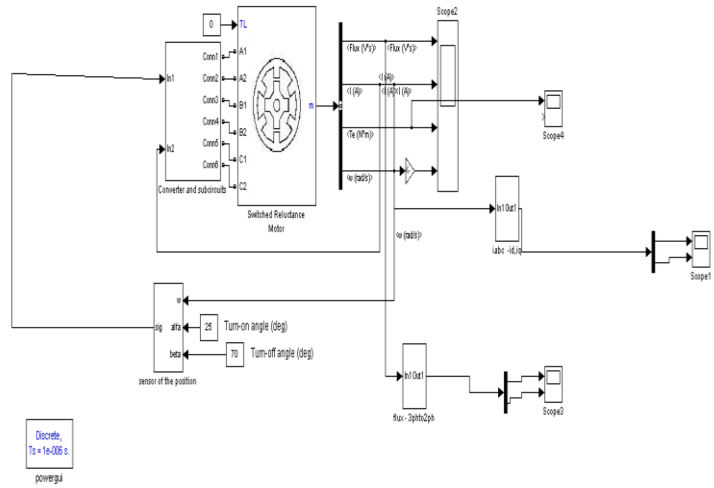

Fig. 3 Simulation diagram of SRM drive.

The turn on angle and turn off angle is given to the rotor position sensor whose output is given to gating circuit which provides the necessary gating pulses to the SRM drive and its corresponding outputs like current, flux, torque and speed is obtained. Three phases to two phase transformation is done to current and flux quantities thereby, their transformed two phase currents and fluxes i_{ds}, i_{qs}, Ψ_{ds} and Ψ_{qs} are obtained.

5. WAVEFORMS AND OBSERVATIONS FROM THE SIMULINK CIRCUIT

The waveforms obtained with the discussed simulink circuit and the observations are discussed in this section.

The transformed two phase currents i.e., the d and q axes currents i_{ds} and i_{qs}, and the d and q axes fluxes Ψ_{ds} and Ψ_{qs} are shown in fig. 4 and fig. 5 respectively. These quantities are plotted against time.

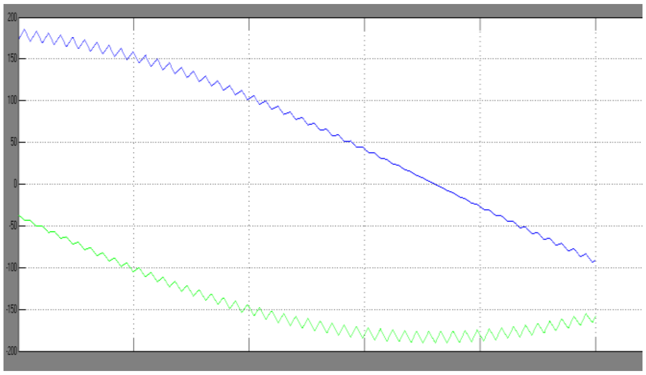

Fig. 4 d-q axes currents of the Drive

It can be observed that the average value of i_{ds} and i_{qs} are -115 and 35, respectively.

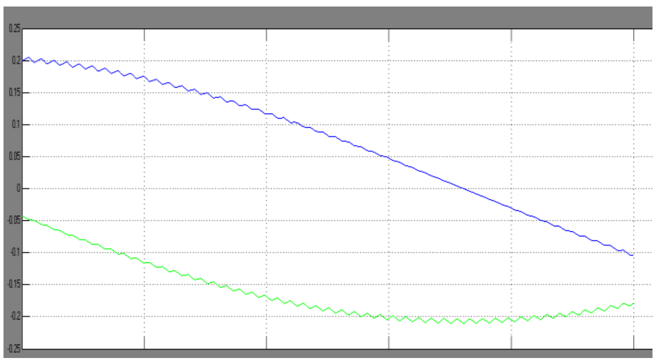

Fig. 5 d-q axes fluxes of the Drive.

It can be observed that the average value of Ψ_{ds} and Ψ_{qs} are -0.125 and 0.05, respectively.

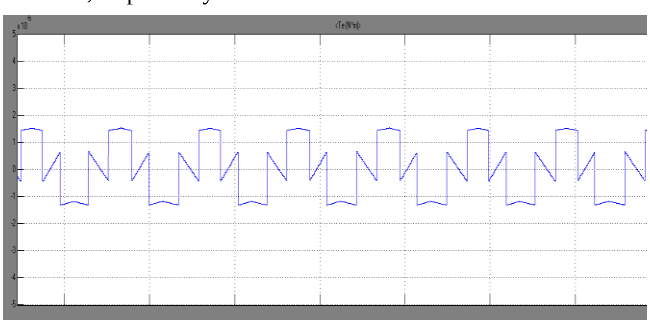

Fig. 6 Torque waveform of the SRM Drive.

The average torque value is zero since SRM drive is at no load.

6. KSOFM OUTPUT-OBSERVATIONS

The coding for the Kohonen's Self Organizing Feature Map is written and simulated in MATLAB. Coding is written for the determination of values of i_{ds}, i_{qs}, Ψ_{ds}, Ψ_{qs}. Since this concept works on the 'winner takes all' principle, the output is optimal. The program is written in MATLAB and is run. Four different programs are written for the determination of i_{ds}, i_{qs}, Ψ_{ds} and Ψ_{qs}.

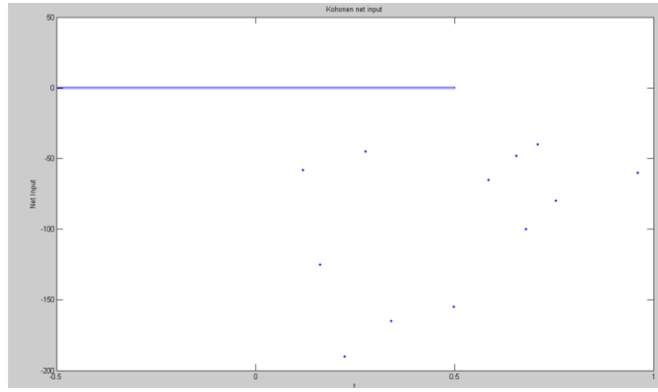

Fig.7 Kohonen's Net Input for ids.

The input distribution for i_{ds} is shown in Fig. 7. It is plotted against the time.

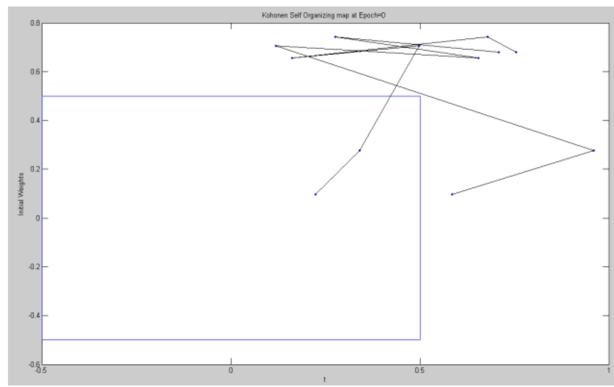

Fig. 8 Initial Weights for ids at Epoch=0

Initial weight matrix at epoch=0 for i_{ds} in fig. 8 is plotted against time. It can be observed that the plot is scattered.

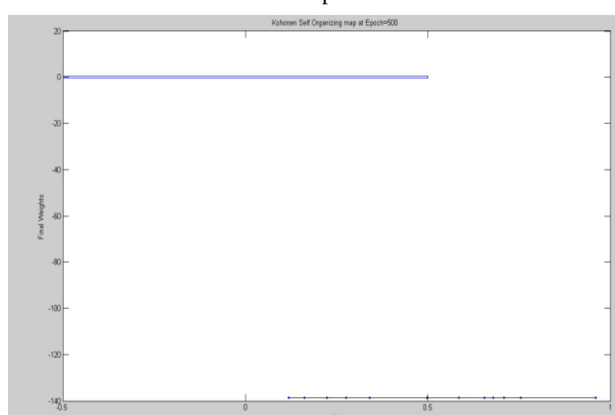

Fig. 9 Final Weights for ids at Epoch=500

Final weight matrix at epoch=500 for i_{ds} is plotted against time in fig.9. It can be observed that the plot is much smoother; it means that the output is converging.

The output data set obtained as the result of running the program is discussed below:

```
weight matrix after 500 epochs:
    0.6787    0.7431    0.6555  -28.0530 -138.6553    0.0971
    0.7577    0.3922    0.1712  -28.3969 -138.6742    0.8235

The Winner Neuron is:
     5

The value of ids is:
     1
```

Table 1. The data set, winner neuron and the output of ids

The final weight matrix at epoch=500 is displayed in the table.1, also the winner neuron for ids is 1. The output of i_{ds} is 1.

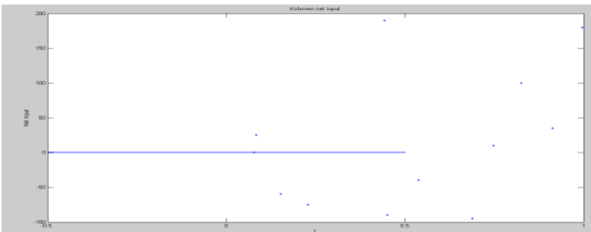

Fig. 10 Kohonen's Net Input for iqs.

The input distribution for i_{qs} is shown in Fig. 10. It is plotted against the time 't'.

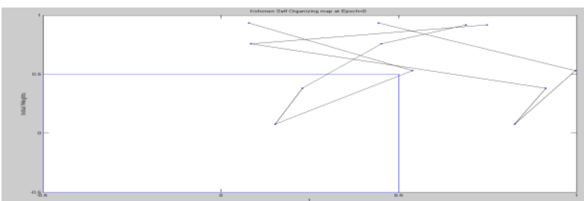

Fig.11 Initial Weights for iqs at Epoch=0

Initial weight matrix at epoch=0 for iqs is plotted against time in fig.11. It can be observed that the plot is scattered.

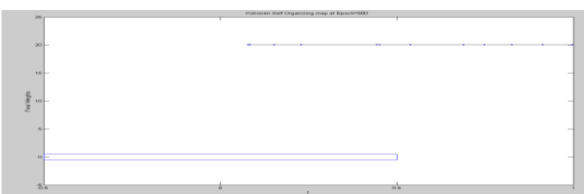

Fig. 12 Final Weights for iqs at Epoch=500

Final weight matrix at epoch=500 for i_{ds} is plotted against time in fig.12. It can be observed that the plot is much smoother; it means that the output is converging.

The output obtained as the result of running the above programs are discussed below:

```
weight matrix after 500 epochs:
    8.1043    0.2760    0.6551   -47.7329    0.9597    0.5853
    8.1135    0.6797    0.1626   -47.6555    0.3404    0.2238

The Winner Neuron is:
     1

The value of iqs is:
     1
```

Table 2. The data set, winner neuron and the output of i_{qs}

The final weight matrix at epoch=500 is displayed in the table.2, Also the winner neuron for i_{qs} is 1 and the output of i_{qs} is 1.

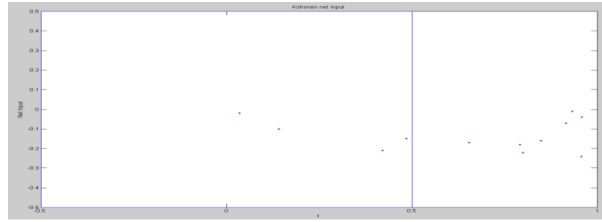

Fig.13.Kohonen's Net Input for Ψds.

The input distribution for Ψ_{ds} is shown in Fig. 13. It is plotted against the time 't'.

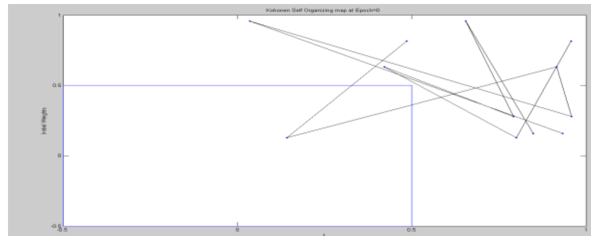

Fig. 14 Initial Weights for Ψds at Epoch=0

Initial weight matrix at epoch=0 for Ψ_{ds} is plotted against time in fig. 14. It can be observed that the plot is scattered much.

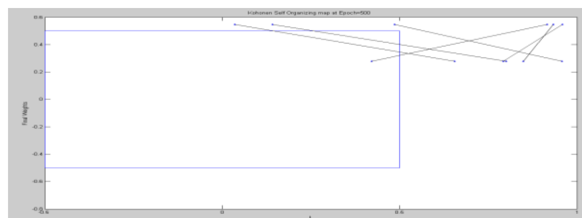

Fig. 15 Final Weights for Ψds at Epoch=500

Final weight matrix at epoch=500 for Ψds is plotted against time. In fig.15.It can be observed that the plot is much smoother; it means that the output is converging.

The output obtained as the result of running the above programs are discussed below:

```
weight matrix after 500 epochs:
    0.8147    0.1270    0.6324    0.2785    0.9575    0.1576
    0.9058    0.9134    0.0975    0.5469    0.9649    0.9706

The winner Neuron is:
     4

the output of sids is:
   -0.0219
```

Table 3. The data set, winner neuron and the output of Ψ_{ds}

The final weight matrix at epoch=500 is displayed in the table.3, also the winner neuron for Ψ_{ds} is 4. The output of Ψ_{ds} is-0.0219.

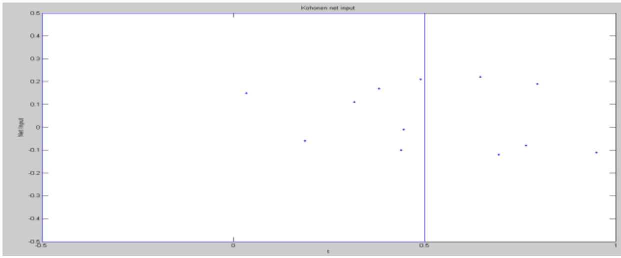

Fig. 16 Kohonen's Net Input for Ψqs

The input distribution for Ψ_{qs} is shown in Fig. 16. It is plotted against the time 't'.

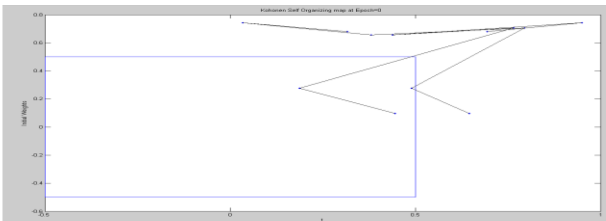

Fig. 17 Initial Weights for Ψqs at Epoch=0

Initial weight matrix at epoch=0 for Ψ_{qs} is plotted against time in fig. 17. It can be observed that the plot is scattered much.

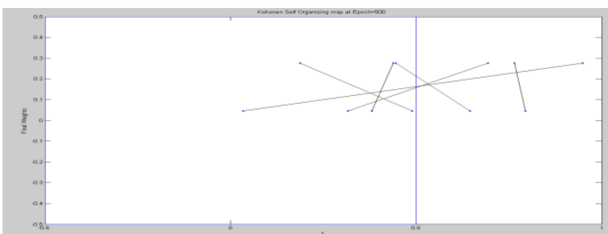

Fig. 18 Final Weights for Ψqs at Epoch=500

Final weight matrix at epoch=500 for Ψ_{qs} is plotted against time. In fig. 18.It can be observed that the plot is much smoother; it means that the output is converging.

The output obtained as the result of running the above programs are discussed below:

```
weight matrix after 500 epochs:
    0.6787    0.7431    0.6555    0.7060    0.2769    0.0971
    0.7577    0.3922    0.1712    0.0318    0.0462    0.8235

The winner Neuron is:
     5

the output of siqs is:
    0.0097
```

Table 4. The data set, winner neuron and the output of Ψ_{qs}

The final weight matrix at epoch=500 is displayed in the table.4, also the winner neuron for Ψ_{qs} is 5. The output of ids is 0.0097.

7. CONCLUSION

The estimation of SRM drive parameters is an important consideration in their field. Many methods are available for this. However the optimal way to estimate the parameters is normally preferred. Making use of neural networks is one of the best ways to achieve this. This paper makes use of Kohonen's Self Organizing Feature Map method which is an unsupervised learning method that estimates the best solution of the parameters of the SRM. Since the method makes use of 'winner takes all' of a neuron, the values obtained by this, will be the optimal values. The drive is first simulated and the parameters obtained are used for training the ANN. The parameters estimated are the currents and fluxes in the two axis model which Because of the unsupervised learning, it can be stated that the estimated values are the best or the optimal values. MATLAB/Simulink is used for the simulation and the results are shown**.**

8. REFERENCES

[1] K.M. Rahman, S. Gopalakrishnan, Optimized Instantaneous Torque Control of Switched Reluctance Motor by Neural Network, *IEEE IAS*, Vol. 37, 2001, pp. 904-913.

[2] E. Mese, D. A. Torrey, An approach for Sensor less Position Estimation for Switched Reluctance Motors Using Artificial Neural Networks, *IEEE Trans. Power Electronics*; Vol.17: No. l, 2002, pp. 66-75.

[3] Wenzhe Lu, Ali Keyhani, and Abbas Fardoun. Neural Network-Based Modeling and Parameter identification of Switched Reluctance Motors, *IEEE transactions on energy conversion.* June 2003;vol. 18:no. 2.

[4] S. Mir, I. Husain, and M. E. Elbuluk, "Switched reluctance motor modeling with on-line parameter Identification," *IEEE Trans. Ind. Applicat.*, vol. 34, July/Aug. 1998:pp. 776–783,

[5] B. Fahimi, G. Suresh, J. Mahdavi, and M. Ehsani, "A new approach to model switched reluctance motor drive application to dynamic performance prediction, control and design," in *Power Electron. Specialists Conf.*,vol. 2, 1998.

[6] Garside, J.J.; Brown, R.H.; Arkadan,A.A.; Identification of switched reluctance motor states using application specific artificial neural networks, Industrial Electronics, Control, and Instrumentation, 1995., Proceedings of the 1995 *IEEE IECON 21st International Conference on*, Volume: 2 , 6-10 Nov. 1995 Pages: 1446 -1451 vol.2

[7] Elmas, C.; Sagiroglu, S.; Colak, I.; Bal, G.; Modelling of a nonlinear switched reluctance drive based on artificial neural networks Power Electronics and Variable-Speed Drives, 1994. *Fifth International Conference* on, 26-28 Oct 1994 Pages: 7 – 12

[8] Reay, D.S.; Green, T.C.; Williams, B.W.; Minimisation of torque ripple in a switched reluctance motor using a neural network, *Third International Conference* on , 25-27 May 1993 Pages:224 – 228.