Genetic Neuro Controller Based Direct Torque Control for Switched Reluctance Motor Drive.

[1]Veena P & Jeyabharath R, [2]Rajaram M, [3]S.N.Sivanandam
[1]K.S.Rangasamy College of Technology, [2]Govt.College of Engg., [3]P.S.G.College of Technology
[1]Tiruchengode-637 215, [2]Tirunelveli, [3]Coimbatore
Tamil Nadu,India
veena_gce@yahoo.co.in

Abstract **- Direct torque control (DTC) of Switched reluctance motor is known to have simple control structure with comparable performance. However, the role of optimal selection of the voltage space vector is one of the weakest points in a conventional DTC drive. In this paper optimal selection of voltage space vectors is achieved using GA based neural network. Simulations results validate the proposed intelligent system with fast torque and flux response with minimized torque and flux ripple.**

Keywords **- Direct torque control, Flux control, Genetic Algorithm, Neuro controller, Switched Reluctance Motor.**

I. INTRODUCTION

Switched Reluctance Motor (SRM), the doubly salient, singly excited motor has simple and robust construction. Although, the induction motor is still the workhorse of the industries, the promising feature of the high torque to mass ratio, high torque to inertia ratio, low maintenance, high specific output and excellent overall performance of SRM make it an efficient competitor for ac drives. The simplified converter topology and switching algorithm due to the unipolar operation avoiding shoot through faults makes SRM advantageous in applications of aerospace, which require high reliability. Also it finds wide application in automotive industries, direct drive machine tools etc [1].

However, significant torque ripple, vibration and acoustic noise are the main drawbacks of SRM to achieve high performance. As the control of SR motor is being the recent trend of research, schemes were developed involving linear and non-linear models to control torque ripple [2]. But due to inaccuracy in linear models and complexity involved in non-linear control, the Direct Torque Control (DTC) was proposed which provided simple solution to control the motor torque and speed and minimized torque ripple.

The direct torque control techniques were proposed in the middle of the 1980's for induction motor [3],[4]. The basic idea of DTC is slip control which is based on the special relationship between the slip and torque. Compared with field orientated control, the DTC has many advantages such as less

machine parameter dependence, simple construction and fast dynamic torque response [5], [6]. There is no current controller needed in DTC, because it selects the voltage space vectors according to the errors of flux linkage and torque. The switching states of the inverter are updated in each sampling time. Introducing adaptive controllers instead of conventional hysteresis controllers can eliminate all the difficulties of classical DTC.

But with the development of intelligent control and its research the target complexity and the complexity of control objective are further reduced. A spurt of activity in the intelligent control methods encompassing artificial neural network and fuzzy control found application in SRM control. Intelligent techniques like fuzzy were developed [7] which were model independent. Fuzzy logic is well suited for dealing with ill-defined and uncertain systems. In [8][9][10] the DTC has also been used with "feed-forward neural networks" in order to substitute for the "optimal switching table". Since direct torque control scheme proved more robust and precise controls for SRM [11], this along with a neuro-fuzzy can achieve better performance with high reliability. In this paper, viable intelligent controllers in DTC scheme are discussed to improve the performance in low speed operations and to minimize the torque ripples. Intelligent controls using expert systems, fuzzy logic, neural networks and genetic algorithms have been recently recognized as important tools to enhance the performance of the power electronic systems [12][13]. The combination of intelligent control with adaptive and robust control appears today the most promising research accomplishment in the drive control area and in the meantime, as the best approach for the optimal exploitation of intelligent control prerogatives and practical realization of adaptive and robust ac motor drives. Artificial neural network theory has remarkable characteristics as: (a) good map approximation ability; (b) self-learning and self-organization ability; (c) association ability; (d) containing fault ability; (e) parallel dispose ability.

In this paper, the control algorithm implemented is the

integration neural network with the direct torque control (DTC) and optimized using GA for SRM drive. Controllers based on direct torque control do not require complex coordinate transformations. Adaptive intelligent techniques are applied to achieve high performance decoupled flux and torque control. This paper contributes:

(i) Neural network algorithm for voltage state selection for DTC:

(ii) Development of new algorithm for state selection using Genetic Algorithm principle.

In this paper, detailed investigations on viable intelligent torque control schemes are carried out by simulation and the results are compared.

II. NEURAL NETWORK DTC FOR SRM

DTC is based on theories of field oriented (FOC) control and torque vector control. Field Oriented Control uses space vector theory to optimally control magnetic field orientation. The DTC principle is to select stator voltage vectors according to the differences between the reference torque and stator flux linkage with exact value. Voltage vector are so chosen to limit the torque and flux errors within hysteresis bands. The required optimal voltage vectors are obtained from the position of the stator flux linkage space vector, the available switching vectors and the required torque and flux linkage [9]. To drive the control scheme for the SR motor, the non-uniform torque characteristics will first be examined. The motor torque output can be found using the motors electromagnetic equation.

$$v = Ri + \frac{d\psi(\theta,i)}{dt} \qquad (1)$$

The instantaneous torque expression is

$$T = \frac{dW_m}{d\theta} \qquad (2)$$

Hence by substitutions torque expression is derived considering the variation of magnetic co-energy and is given by

$$T \approx i\frac{d\psi(\theta,i)}{d\theta} \qquad (3)$$

Neural networks have the inherent capability for identification. The neural network has been used for torque ripple minimization control to find the current command from the torque reference and rotor position, which is a three-dimensional relationship. A similar approach is used here. The direct torque neuro controller is shown in Fig. 1. The neural network consists of basic elements of neurons modeled as a nonlinear combination of inputs with added bias. The gain in the path of each input, known as the synaptic weight, is given as $k_1, k_2, \ldots, k_n$ and shown in Fig. 2. In this control strategy, torque and flux errors are given as inputs along with the flux position information to the neural network controller. Output of the controller is compared with the previous switching states of inverter. Feed forward artificial neural networks are universal approximators of nonlinear functions [14-16].
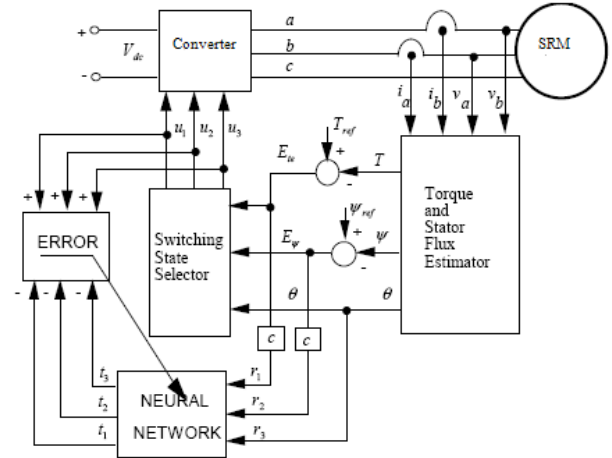

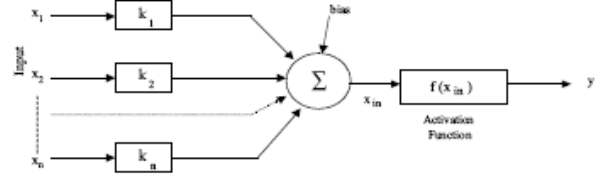Fig. 1. Schematic diagram of DTC using neural network controller

Fig. 2. Neuron model

Here a logarithmic sigmoidal activation function is used and the output is given by

$$y = \frac{1}{1 + \exp\left(\sum_{i=1}^{N} \omega_i x_i - b\right)} \qquad (4)$$

A feed forward neural network is organized in layers: an input layer, one or more hidden layers, and an output layer. No computation is performed in the input layer and the signals are directly supplied to the first hidden layer through input layer. Hidden and output neurons generally have a sigmoid activation function. The knowledge in an ANN is acquired through a learning algorithm, which performs the adaptation of weights of the network iteratively until the error between the target vectors and output of network falls below a certain error goal. The most popular learning algorithm for multi-layer networks is the back propagation algorithm, which consists of a forward and backward action. In the first, the signals are propagated through the network layer by layer. An output vector is thus generated and subtracted from the desired output vector. The resultant error vector is propagated backward in the network and serves to adjust the weights in order to minimize the output error. The time required to train an ANN depends on the size of the training data set and training algorithm.

An improved version of back propagation algorithm with adaptive learning rate is proposed and which permits a reduction of the number of iterations. Fig. 3 shows the proposed neural network for DTC scheme in which, input, output and hidden layers are shown. The error signals and

stator flux angle are given to input layer. Switching state information is taken from the output layer.
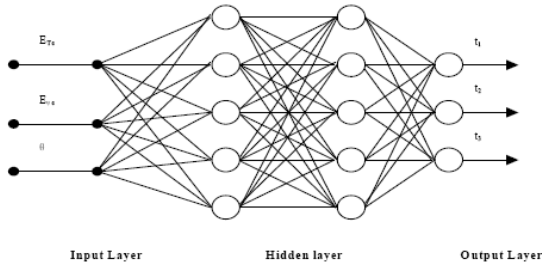

Fig. 3. Structure of Neural network proposed for DTC scheme.

III. DTC USING GENETIC ALGORITHM

Genetic algorithms are stochastic global search algorithms. They mimic processes observed in natural evolution and use a vocabulary borrowed from the natural genetic [17]. A GA considers individuals in a population quite often called strings or chromosomes. A genetic algorithm is constructed as follows:
i) Initialize a population of chromosomes;
ii) Evaluate each chromosome in the population;
iii) Select chromosomes in the population as parent chromosomes to reproduce;
iv) Apply the genetic operators to the parent chromosomes to produce children;
v) Evaluate the new chromosomes and insert them into the population;
vi) If the termination condition is satisfied, stop and return the best chromosome. If not go to step (iii).
For executing genetic algorithm to train the neural networks, detailed procedures were followed. It gives an algorithm to select best chromosome from the total population of chromosomes. To select best chromosome, parent selection is prominent. Steps for parent selection are summarized as follows:
i) Selection of parents for reproduction is stochastic;
ii) Selection of parents with higher fitness value;
iii) Roulette wheel technique for parent selection. A roulette wheel shown in Fig. 4 has slots, which are sized according to the fitness of each chromosome;
iv) Selection process is to spin the roulette wheel.
In Fig. 6, $f1, f2, f3, f4, f5$ are fitness of chromosomes 1, 2, 3, 4 and 5,respectively. Pop represents the total population size; that is, if total number of chromosomes is 50, population size is also 50. Therefore,
$f pop = f50 =$ Fitness of 50th chromosome
Total fitness is given by $F =$ Sum of the fitness of the population

$$F = \sum_{j=1}^{pop} eval_j \, . \tag{5}$$

Probability function for each chromosome is
$$p_i = eval_i / F , \quad i = 1, 2, 3, \ldots, pop \, .$$

Accumulative probability function for each chromosome is

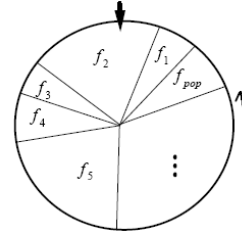$$q_i = \sum_{j=1}^{i} p_i, \quad i = 1, 2, 3, \ldots, pop \, .$$

Fig. 4. Roulette Wheel.

IV. NEURAL NETWORKS TRAINED BY GENETIC ALGORITHMS

In neural networks, genetic algorithms are used to determine the weights and threshold values. Fig. 5 shows the structure of neural networks trained using GA [17]. The respective error vectors between the state selector of conventional DTC and the neural networks outputs are $e1, e2, e3$. To achieve minimum value of performance index, the groups of threshold values and weights have to be determined.
Performance index $E(W)$ can be given by:

$$E(W) = \frac{1}{2} \sum_{j=1}^{N} e^T(j) \Lambda e(j), \tag{6}$$

where: $e^T = \begin{bmatrix} e1 & e2 & e3 \end{bmatrix}^T$ is error vector;
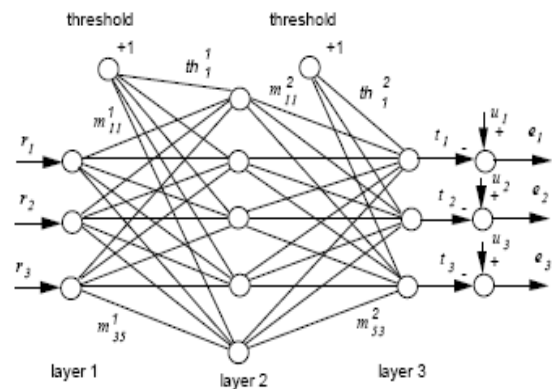Λ is symmetric positive definite matrix; and N is sample size.

Fig. 5. Structure of neural networks trained using GA.

Implementation of the genetic algorithm described in this paper has three stages:
i) Fitness evaluation
ii) Selector
iii) Breeding

The genetic operators used in this work are quite different from the classical ones used in [17].

The main differences between the proposed work and existing work are described as follows:

i) The real valued space are dealt in this paper, where a solution is coded as a vector with floating point type components

ii) Some genetic operators are non-uniform, that is, their action depends on the age of the population.

The contents of the algorithm are listed below:

(a) Chromosome Encoding

Let the total number of thresholds and weights of the neural network shown in Fig. 5, be packed in the n-dimensional vector *W*,

$$W = \left[th_1^2 m_{11}^2 \ldots m_{51}^2 \ldots th_5^1 m_{15}^1 \ldots m_{35}^1 \right] = \left[w_1 w_2 \ldots w_{38} \right] \quad (7)$$

where: *th* is threshold vector, *m* is weight vector and n = 38. Here, the weights vector *W* as a chromosome (individual). In other words, each chromosome vector is coded as a vector of floating point numbers of the same length as the solution vector. Each element is initially selected as to be within the desired domain.

(b) Evaluation Function

The evaluation function for chromosomes '*W*' is

$$eval(W) = \frac{100}{1 + E(W)}, \quad (8)$$

where, the chromosome vector *W* is a real weights vector, and $E(W)$ is defined by equation (7). The evaluation function is used to rate a chromosomes in terms of their "fitness". The higher fitness chromosome will perform better.

(c) Genetic Operators

In this paper, binary encoding are used as genetic operators to train the neural networks in DTC technique. The binary operators are one point crossover, two points crossover and bit mutation.

V. DTC USING GENETIC ALGORITHM

Neural network trained with genetic algorithm is implemented in such a way that the total number of thresholds and weights of the neural network be packed in n - dimensional vector 'w' as given in equation (6).To represent the values of weights *w*, binary encoding is used as a chromosome. Genetic operators used for binary representation are one point crossover, two-point crossover and bit mutation. Table I shows the parameters used for simulation.

In binary encoding algorithm, Lower number of chromosomes was used than floating point encoding algorithm. The performance of the system is affected if number of chromosomes reduced. To improve the performance and to overcome this drawback, the best member of each generation must be copied into the succeeding generation. Crossover probability can be chosen from 0.5 to 0.9. Convergence rate becomes slower with the higher crossover probability values. Convergence rate should be in high bias level. Fine tuning capabilities of genetic algorithm were achieved by using these operators and performance of the algorithm was also improved.

TABLE I
PARAMETERS USED FOR GENETIC ALGORITHM BASED DTC

Parameters used	Binary representation
Number of chromosomes	50
Crossover probability	0.8
Mutation probability	0.005

VI. RESULTS AND DISCUSSIONS

A Matlab/Simulink closed loop model was constructed for the SR motor GA based neuro-DTC control system. The motor parameters such as torque, phase flux and position are obtained from the 3Φ SRM. Adaptive neuro-DTC is used for voltage space vector generation is constructed. Sampled flux and torque errors, multiplied by weights, and the output of neuron is optimized to get the best voltage space vector. Based on the present position of motor, torque error and flux error the optimal selection of voltage space vector is done with the help of neuro-GA. Thus the converter switches and hence the motor is controlled by DTC scheme.

In this simulation test, the motor reference flux and torque were maintained at a constant of 0.3Wb and 5Nm respectively. The torque results in Figs.6-8. shows lower ripple content and constant amplitude nature for GA based neuro-DTC control compared to classical DTC.

(a) DTC using Neural Network

The algorithm used to train the neural network is back propagation with momentum factor. The time taken to train the neural network using this algorithm is 2000s. The simulations that have been performed in this paper were obtained using a trained state selector neural network. The desired outputs are taken from the outputs of the conventional DTC. Thus, the training time is basically the time used in the simulation by the conventional DTC with the induction motor. All training algorithms were used to train the 3-5-3 neural-network structure using sigmoids. The temperature coefficient of all the neurons was fixed to one, which gives reasonable weight magnitudes.

An increase in the learning rate produces a faster learning, but a certain point it could become unstable, in the sense that the performance index begins oscillating around some local minimum, which make the weights not settle to their final values. A small learning rate is convenient even though it requires more training time in order to get a safety weights convergence. The results of the simulations given by back propagation are almost the same given by the

conventional DTC, which shows that the neural network has been fully trained.

(b) DTC using Genetic Algorithm with Binary representation

In binary representation, elitist strategy is used to fix the potential source of loss by copying the best member of each generation into the succeeding generation. The crossover rates of 0.5, 06, 0.7 and 0.9 in the problem are tried; the results show that convergence rate is slower with the high crossover rate, maximum fitness values never get as high as with the setting of 0.8. In addition, mutation rates of 0.1, 0.05, 0.01, 0.001 and 0.0001 in the problem are tried. Fig. 8 shows the actual torque developed using DTC by neural network trained with genetic algorithm The results showed that the low mutation rate lead to poorer solutions but faster convergence. The higher mutation rate allows better solutions to be found, but it prohibits convergence to a high bias level. These results also showed that the GA procedure is not highly sensitive to parameter changes.
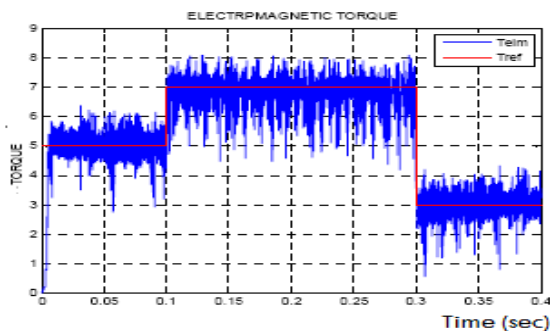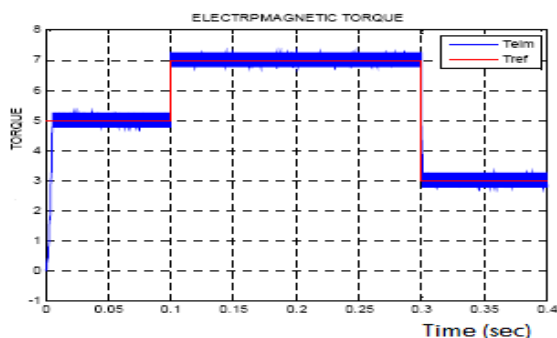

Fig. 6. Torque developed in conventional DTC.

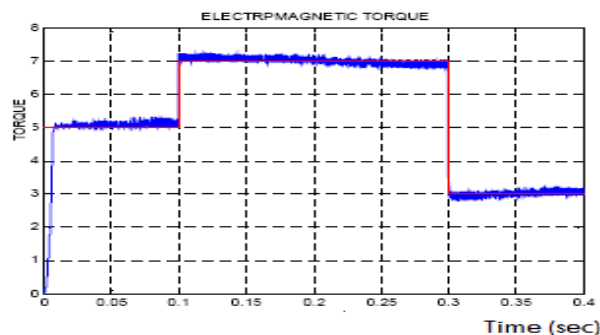Fig. 7. Torque developed in DTC using neural network.

Fig. 8.. Torque developed in DTC using neural network trained with genetic algorithm

VII. CONCLUSION

Direct torque neuro controller trained with genetic algorithm has been evaluated for switched reluctance motor drive and which have been compared with the conventional direct torque control technique. Since the conventional DTC presents some disadvantages such as difficulties in torque and flux control at very low speed, high current and torque ripple, variable switching frequency behavior, high noise level at low speed and lack of direct current control, an adaptive torque controller is proposed for high performance applications. In this paper, genetic algorithm based direct torque neuro controller shows better response. By using this controller, parameters of switched reluctance motor are also tuned and parameter variations are much reduced. When compared to other adaptive controllers precise results have been obtained using genetic algorithm based direct torque neuro controller.

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