# Artificial Neural Network and Adaptive Neuro Fuzzy Control of Direct Torque Control of Induction Motor for Speed and Torque Ripple Control

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*Abstract*- This paper presents Artificial Neural Networks (ANN) and Adaptive Neural-Fuzzy Inference System (ANFIS) for reduction of torque and flux ripples in transient and steady state response of Direct Torque Control (DTC) for Induction Motor drive. The Flux and Electromagnetic torque can be controlled by using efficient Direct Torque Control (DTC) scheme This proposed technique is to improve the torque, speed and flux response with the Artificial Neural Network (ANN) and then with the Adaptive Neuro-Fuzzy Inference (ANFIS). This paper shows implementation of DTC system using ANN and ANFIS on three phase induction motor to optimize the flux and to improve the performance of fast stator flux response in transient state. To improve the performance of DTC with the modern technique using ANN and ANFIS approach is implemented and performance of ANN DTC compared with CDTC and ANN DTC with ANFIS is done, conclusion is about the ANN approach shows the better performance than CDTC and ANFIS shows superior performance than ANN. The performance has been tested by using MATLAB/SIMULINK and NEURAL NETWORK toolbox.

*Keywords:* Direct torque Control, Induction Motor, Fuzzy Logic Controller, ANN, ANFIS

## 1. Introduction

Squirrel cage induction motors find applications in motor driven pumps, washing machines, air conditioning and heating systems, servo drives, hybrid electric vehicles, domestic appliances etc. Low price, small size and weight, rugged and robust construction, the absence of commentators and brushes are some of the distinct advantages that make induction motors the most preferred motors in electric drive systems. The speed variation of induction motors remains constant. With the use of power electronic converters, induction motors can be employed in variable speed applications. To interface between the fixed voltage and frequency utility supply with motors, power electronic converters are used. High frequency and low loss power semiconductor devices are being increasingly used for manufacturing efficient converters. Compared to the control of dc motors, the control of induction motors is difficult owing to the fact that the induction motor is a dynamic, nonlinear system. Unpredictable disturbances such as noise and load changes and the uncertainties in the machine parameters further complicate the control problem. To reduce the complex nonlinear structure, advanced control techniques such as field oriented control (FOC) [1], [2] and direct torque control (DTC) [3], [4] have been developed offering fast and dynamic torque response. The direct control of the torque and flux of the machine can be improvise by using the DTC scheme. The electromagnetic torque and the flux generated in the machine is compared to the reference values of the torque and flux in hysteresis comparators. The lookup table helps the voltage vector to be determined by comparing the output of stator flux position and comparators [15]. For controlling the various states of the inverter, control pulses are generated. The output of the inverter is eventually fed to the induction motor. Even though FOC and DTC methods have been effective, a number of drawbacks are observed (distortions in currents and torque due to change in the flux sector, the need for high sampling frequency for digital implementation of the comparators, sensitivity to variations in the machine parameters etc). To mitigate the shortcomings in the DTC scheme, intelligent control techniques using human motivated techniques, pattern recognition and decision making are being adopted [5], [6]. Some of the methods based on the concept of Artificial intelligence (AI) are Artificial Neural Network (ANN)[21], Expert System (ES), Fuzzy Logic Control (FLC) to mention a few. AI based techniques when implemented in motor control have shown improved performance [7]. Generally, motor control drives rely on the use of PI controllers. These controllers, however, are sensitive to system non-linearities, variations in parameters and any unwanted disturbances. These disadvantages can be overcome by the use of AI based intelligent controllers. Fuzzy logic and artificial neural networks are two of the most popular systems for use as intelligent controllers and have shown an improved performance over conventional controllers [8], [9], [10]. ANFIS (Adaptive Neural network based Fuzzy Inference System)[18], a hybrid of ANN and FLC is another popular control scheme being used in high performance drives, having superior design and performance characteristics [6]. This paper presents direct controlled induction motor drive using speed controller using ANFIS technique. The PI controller used in the conventional DTC scheme is replaced with the ANFIS based speed controller. The complete paper is organized as follows: Section 2 explains Neural Network with DTC Controller . Section 3 discusses about Adaptive Neuro Fuzzy Inference System (ANFIS) . The simulation results, comparison and discussion are presented in Section 4. Section 5 concludes the work.

## 2. Neural Networks DTC Controller

ANN refers to the computational/information-processing paradigm which fetches its inspiration from the densely interconnected parallel structure of the mammalian brain processes the information. Adaptive biological learning plays a vital role in circumcising the mathematical model of ANN using the properties of the biological nervous systems by emulating & drawing it's analogies. This novel structure related to the information processing system plays the vital substituent element of the ANN paradigm. ANNs consists of a large number of highly interconnected processing elements which are analogous to neurons and are tied together with weighted connections forming an analogy with the synapses. The biological systems can be understood with the relation between the Synaptic system's adjustments which exist for ANN also. The second way of learning can be mitigated by exposure to a set of input/output data or through an example of training where the connection weights (synapses) for the training algorithm is adjusted iteratively. The complexity existing in real world problems are being sorted out using ANNs as a method. One advantage of ANNs over simple lookup table approaches is the reduced amount of memory and computation required. In addition ANNs can provide interpolation between training points with no additional computational effort.

### 2.1 Neuron Model and Network Architectures

An Artificial neuron simply is a model of a biological neuron. A single input neuron is shown in the figure 1, Wp is produced by the multiplication of the scalar input p to scalar weight w, one of the terms that is sent to the summer. The next input 1 is multiplied by a bias (offset) b that is passed to the summer. The scalar neuron output a is generated by an activation function (transfer function) f when the summer output n is passed through it. is calculated as

$$a = f(W_p + b) \quad (1)$$

The actual output depends on the particular activation function that is chosen. Here, w and b are known as the adjustable parameters of the neuron. The neuron input/output relationship is being established to achieve the goal by choosing the activation function & adjusting the parameters w & b with learning rule

The neuron helps in satisfying the problem specification by initiating a selected activati

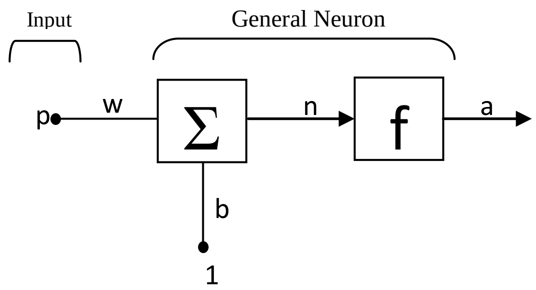


Fig 1. Simple Neuron

on function which can be of linear or non-linear nature. This paper consists of different types of transfer functions. The functions used commonly are given below.

- Hard limit activation function given by,
  a = 0, n<0
  1, n>=0
- Linear activation function given by, a = n
- Log-sigmoid activation function given by, $a = 1 / (1+ e^{-n})$
- Tan-sigmoid activation function given by, $a = (e^{n} - e^{-n}) / (e^{n} + e^{-n})$

### 2.2 Multiple Input Neuron

Typically, a neuron has more than one input. A neuron with R inputs is shown in the figure 2. The individual inputs $p_1$, $p_2$... $p_R$ are each weighted by corresponding elements $w_{1,1}$, $w_{1,2}$, …., $w_{1,R}$ of the weight matrix W. the neuron has the bias b, which is summed with the weighted inputs to form the net input n.

$$n = WP + b \quad (2)$$

where the matrix W for the single neuron case has only one row. Now the output can be written as

$$a = f\,(WP + b) \quad (3)$$

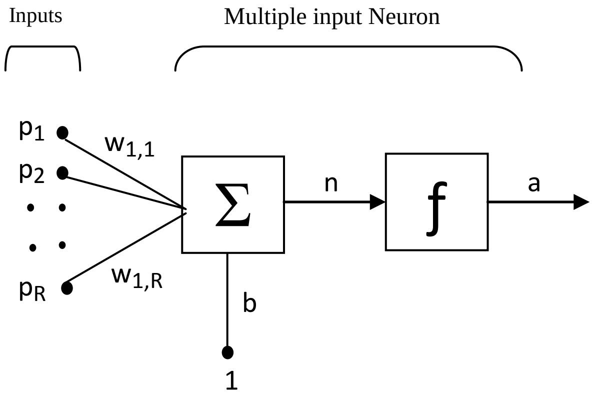


Fig.2 Multiple Neuron Structure

The neural networks can generally be classified as feed forward and feedback (or recurrent) types. In feed forward network, signals from neuron to neuron flow only in the forward direction, whereas in a recurrent network, the signals can flow in forward as well as backward direction. In this project, a Feed forward Back propagation type of network model is used for training the networks.

### 2.3 Direct Torque Control of Induction Motor Using Neural Controller

The back-propagation-training algorithm is used for this type of feed-forward neural networks. The training is automated with Matlab simulation program that uses a certain number of input–output sample patterns. The sample patterns were derived by simulation using the computer program. Part of the generated data is used to train the neural network. At the end of the training process (when the target mean squared error is reached), the model obtains the weight and the bias vectors. The newly generated sets of speed error and torque patterns are I/O to the Matlab neural net model and the corresponding pattern of firing angle is calculated systematically. The input to the program is the speed error. Based on the setting of the initial conditions, the program can simulate for speed control. Neural Control for dtc of induction motor is shown in Figure 3.

Figure 4, shows the schematic diagram of ANN for this experiment. The ANN has single input and single output. The input is speed error and the output is the torque $T^*$ of output. The training method is chosen Back propagation, introduced at previous section, because of its highly efficient performance and simplicity.

The input layer speed error, the neural network designed for the speed control of this drive is with single input layers, 5 hidden layers and one output layer. For the hidden layers either tansig function or logsig function can be used and for the output layer purelin is taken. The neural network is trained for specific number of epochs to obtain the target. For this the neural network is trained for 15000 epochs.

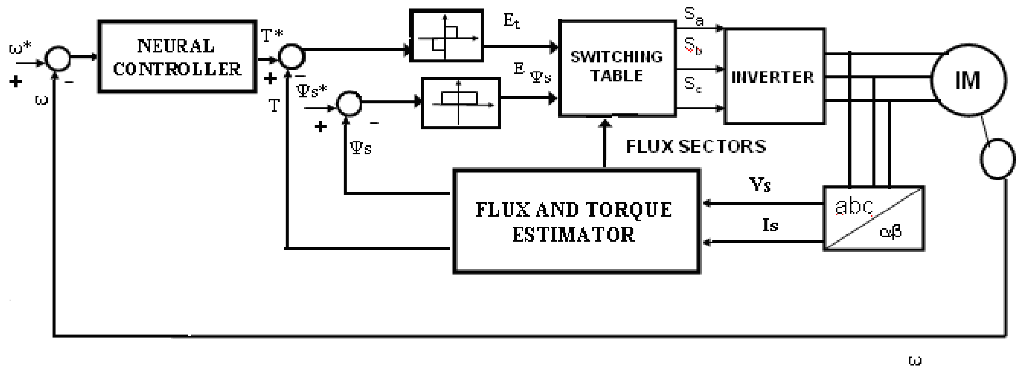


Fig 3. Neural Control for DTC of induction motor

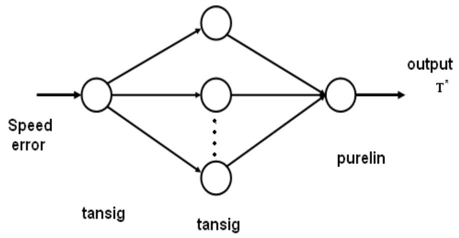


Fig 4. Neural Control Design

The steps for ANN based speed controller for the induction motor drive are summarized as follows:

- The sample data are collected from open loop operation for training the network.
- Speed error is the inputs to the ANN and output of the network is the desired Torque command.
- The training algorithm used is Back propagation.
- Network is trained until desired the target mean squared error is reached.

## 3. Adaptive Neuro Fuzzy Inference System

The complex problems can be solved extensively using Neuro Fuzzy (NF) computing framework. The FIS can be build with the knowledge of linguistic rules whereas ANNs can be used to learn from a simulation if we have the availability of data. The fuzzy sets, fuzzy operators and the knowledge base are specified by the user to build the FIS and architecture and learning algorithm are being specified for constructing an ANN for an application. An integrated system is build and analysis is being done using the concepts to overcome the drawbacks pertaining to these approaches. The FIS provides an advantage of learning capability whereas ANN relates to the advantage of the formation of the linguistic rules. The different parameters of FIS can be calculated using ANN learning algorithm in a fused NF architecture. Fused NF systems share data structures and knowledge representations. A learning algorithm can be applied to a fuzzy system by representing it in a special ANN like architecture. Since the functions used in inference process are non-differentiable, we cannot apply the conventional ANN learning algorithms (gradient descent) directly to such a system. The problem can be resolved by not using the standard neural learning algorithm or by using the inference system with differentiable functions.

### 3.1 ANFIS Architecture

Consider a Sugeno type of fuzzy system having the rule base of,

Input: 1. If x is A1 and y is B1, then $f_1=p_1x+q_1y+r_1$

2. If x is A2 and y is B2, then $f_2=p_2x+q_2y+r_2$

Output: 1. $O_i=w_i\,(p_ix+q_iy+r_i)$

Let the membership functions of fuzzy sets $A_i$, $B_i$, i=1, 2, be, $\mu_{Ai}$, $\mu_{Bi}$.

In evaluating the rules, choose product for T-norm (using logical 'and')

1. Evaluating the rule premises results in

$$W_i=\mu_{Ai}(x)\,\mu_{Bi}(y), \quad \text{where } i=1,2$$

2. Evaluating the implication and the rule consequences gives

$$f(x,y)=\frac{w_1(x,y)\,f_1(x,y)+w_2(x,y)\,f2(x,y)}{w_1(x,y)+w_2(x,y)}$$

Or leaving the arguments out

$$f=\frac{w_1f_1+w_2f2}{w_1+w_2}$$

This can be separated to phases by first defining

$$\overline{w_i}=\frac{w_f}{w_1+w_2}$$

Then f can be written as

$$f=\overline{w_1}f_1+\overline{w_2}f_2$$

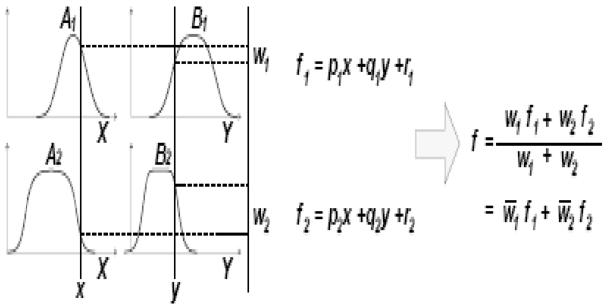


Fig 5 . A two input first order Sugeno fuzzy model with two rules

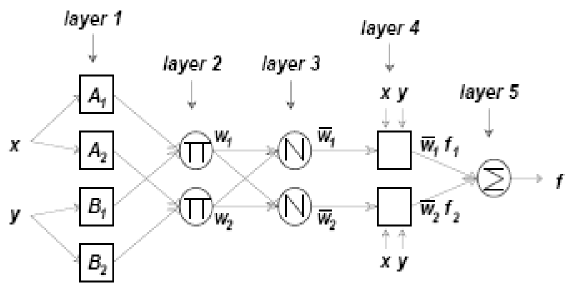


Fig. 6 Equivalent ANFIS architecture

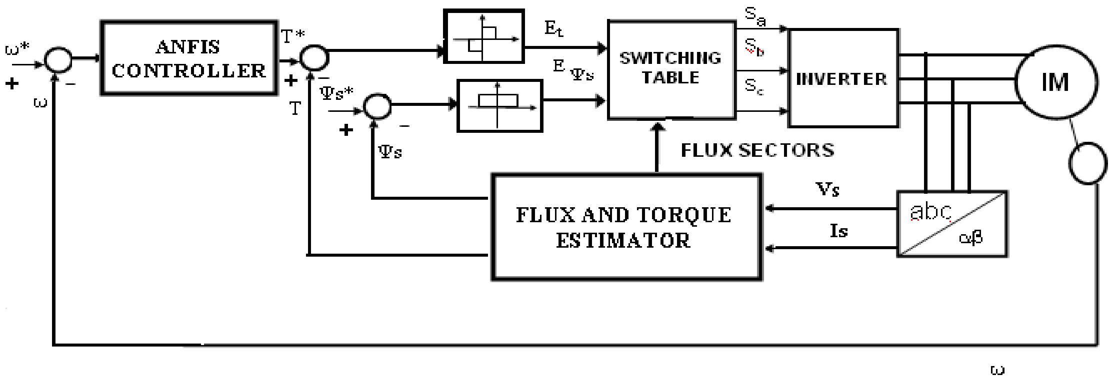


Fig. 7 Basic Block Diagram of ANFIS Controller

### 3.2 Design of ANFIS Controller for DTC of Induction Motor

The block diagram of the proposed ANFIS controller for DTC drive system is shown in figure 6. The error in speed controller will be initialized using well-known conventional methods, but these errors depend on the DTC of induction motor estimated model at rated operating conditions. Adaptive Neuro fuzzy Inference System (ANFIS) has been found to be excellent in dealing with systems that are imprecise, non-linear, or time-varying. ANFIS is relatively easy to implement, since it does not need any mathematical model of the controlled system. An automatic control strategy is being generated using linguistic control strategy of human experience and knowledge to provide a solution to it.

The steps for Neuro-fuzzy based, control of the speed for the induction motor are summarized as follows:

- The data is being loaded for training, testing, and checking by selecting appropriate radio buttons in the Load data portion of the GUI and then clicking Load Data. The output data is plotted in the region specified.
- Then an initial FIS model is being generated using the options in the Generate FIS portion of the GUI.
- successfully loaded by clicking on the Structure button.
- We selected the back propagation or a mixture of back propagation and least squares using the FIS model parameter optimization method.
- Thereafter the membership function parameters are adjusted w.r.t. training and plotted the training error plot(s) in the plot region.
- At last we click on the Test Now button to view the FIS model output versus the training, checking, or testing data output.
- Then the training error tolerance and the number of training epochs is being selected.

**Input Variable Membership Functions**

(i) Membership functions of Error

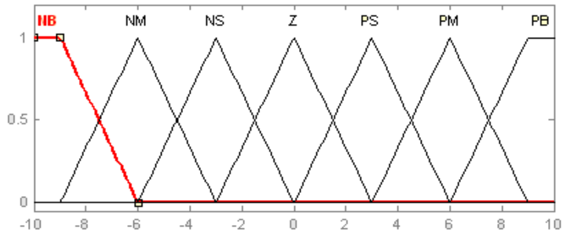


Fig.8 Input Variables (Error)

(ii) Membership functions of Change in Error

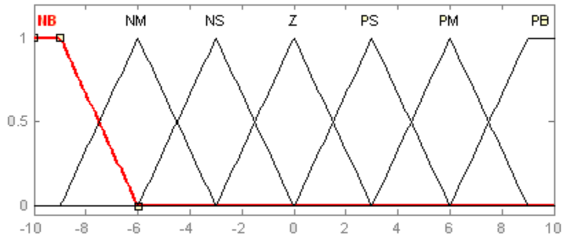


Fig. 9 Input Variables (Change in Error)

## 4. Simulation Results and Discussions

The neural and neuro-fuzzy controllers of DTC of induction motor drive system are simulated to investigate its dynamic performance and simulated results are shown in this chapter. The motor parameters used for simulation are given in appendix. The motor performance is tested under variation speed at constant load condition

## 4.1 ANN Controller

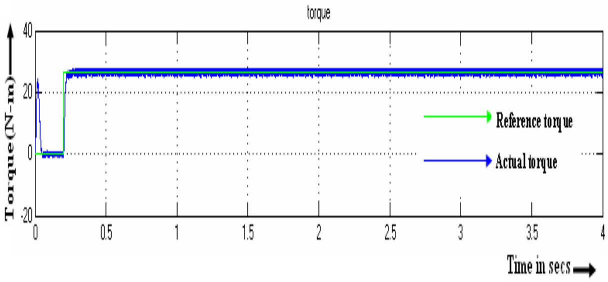


Fig: 10(a): torque response with neural controller

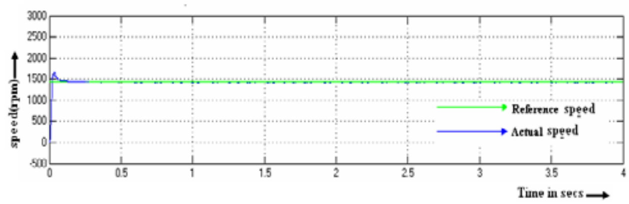


Fig: 10(b) Speed response with neural controller

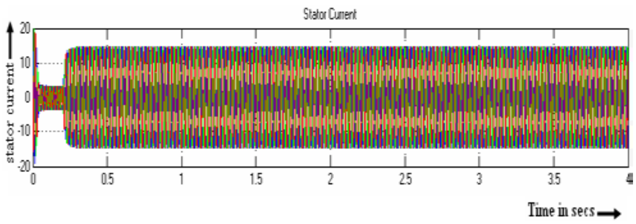


Fig: 10(c) Speed response with neural controller

Fig.10 .DTC response at full load with 100% speed

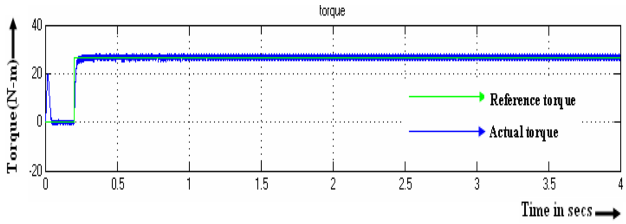


Fig: 11(a): torque response with neural controller

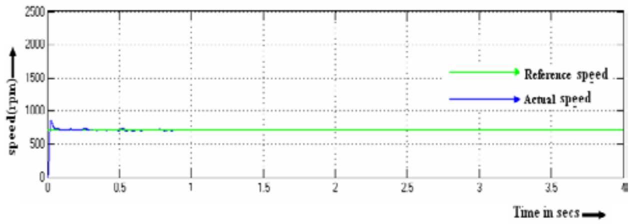


Fig: 11(b) speed response with neural controller

Fig.11. DTC response at full load with 50% speed

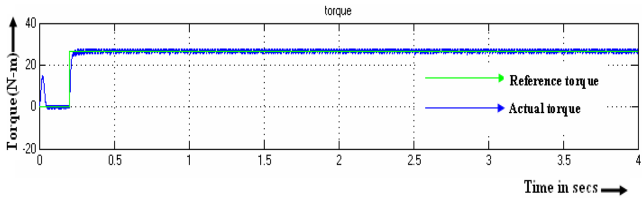


Fig: 12 (a): torque response wit neural h controller

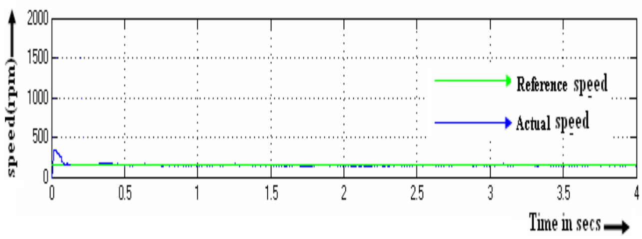


Fig: 12 (b) Speed response with neural controller

Fig.12. DTC response at full load with 10% speed

## 4.2. ANFIS Controller

The DTC of Induction motor is simulated in Simulink using ANFIS controller

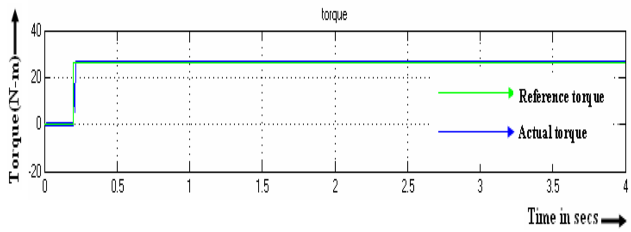


Fig: 13 (a): torque response with ANFIS controller

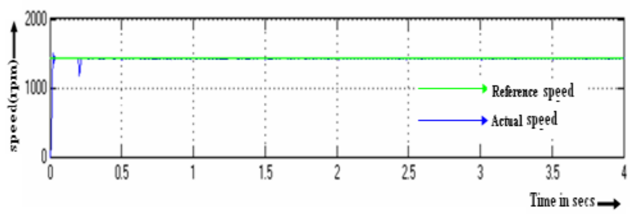


Fig: 13 (b) speed response with ANFIS controller

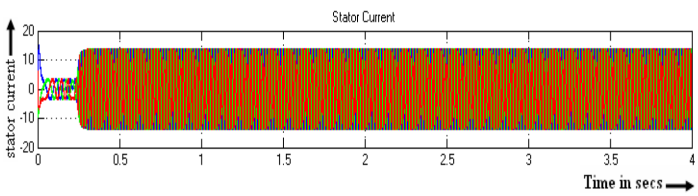


Fig.13 (c).three phase stator current

Fig.13. DTC response at full load with 100% speed

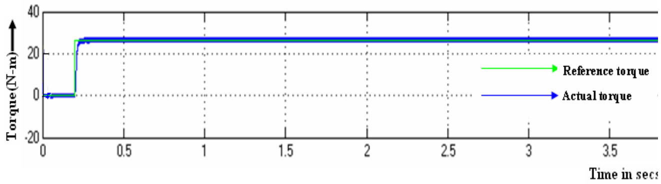


Fig 14 (a): Torque response with ANFIS controller

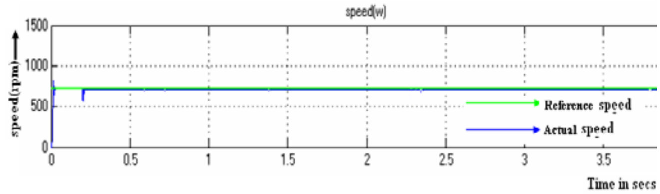


Fig14.(b).speed response with ANFIS controller

Fig.14. DTC response at full load with 50% speed

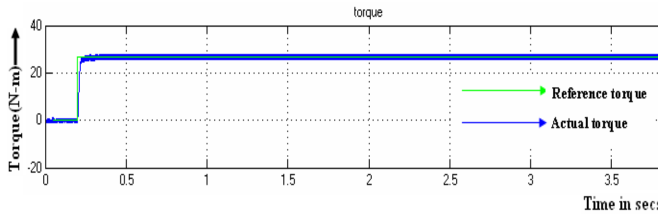


Fig.15 (a).torque response with ANFIS pi controller

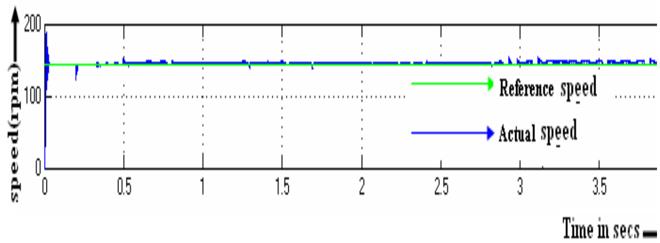


Fig.15 (b).speed response with ANFIS controller

Fig.15 DTC response at full load with 50% speed

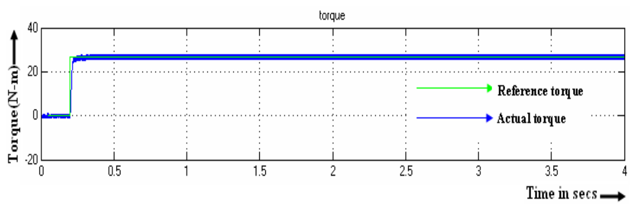


Fig.16(a).torque response with ANFIS pi controller

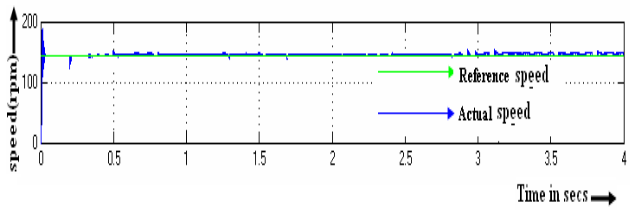


Fig.16 (b).speed response with ANFIS pi controller
Fig.16. DTC response at full load with 10% speed

| S. no | Variable Speed With Fixed Torque= 26.5Nm | Torque Ripple (%) | | | |
|---|---|---|---|---|---|
| | | Pi Controller | Fuzzy Controller | Neural Controller | ANFIS Controller |
| 1 | 1440 | 9 | 8.2 | 7.9 | 6.41 |
| 2 | 720 | 9.8 | 9.0 | 8.4 | 7.5 |
| 3 | 144 | 11.2 | 9.92 | 8.7 | 8.22 |

**Table 1.**Comparisons of Different Controller

## 5. Conclusion

This paper represents the performance of induction motor as a consequence of DTC method. In this, the torque is controlled by using conventional and non – conventional techniques which has been carried out and the comparative results of these techniques have been tabulated. This proposed technique is to improve the torque, speed and flux response with the Artificial Neural Network (ANN) and then with the Adaptive Neuro-Fuzzy Inference (ANFIS). This paper shows implementation of DTC system using ANN and ANFIS on three phase induction motor to optimize the flux and to improve the performance of fast stator flux response in transient state. The results are about the ANN approach shows the better performance than CDTC and ANFIS shows superior performance than ANN. This simulation process was carried out in MATLAB/SIMULINK.

The parameters and constants of the induction motor drives are shown below

| **Symbol** | **Parameter** | **Values** |
|---|---|---|
| n | Motor Speed | 1440rpm |
| f | Supply Frequency | 50Hz |
| $P_n$ | Power | 4kw |
| P | Pole pair | 4 |
| $R_s$ | Stator Resistance | 1.57Ω |
| $R_r$ | Rotor Resistance | 1.21 Ω |
| Ls | Stator Inductance | 0.17 H |
| $L_r$ | Rotor Inductance | 0.17 H |
| $L_m$ | Mutual Inductance | 0.165 H |
| J | Moment of Inertia | 0.06 Kg-m$^2$ |

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