ARTIFIACIAL NEURAL NETWORK CONTROLLED PMSM, DFIM AND IM DRIVES

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Abstract- *Recently, the Artificial Neural Network (ANN) can solve several problems in motor drives, this paper present a comparative study of Direct Torque Control (DTC)in closed loop based on ANN techniques in order to reduce torque and flux ripples producing by th hysteresis comparators in classical DTC, and to replace the traditional speed controlled Permanent Magnet Synchronous Motor (PMSM), Doubly Fed Induction Motor (DFIM) and Induction motor (IM). All techniques proposed in this paper are simulated and tested. Simulation results show that it is efficient and reliable .*

Keywords*- ANN ;DFIM ;DTC; IM; PMSM.*

1. Introduction

For a high-performance drive system, not only a fast response is required, but also the ability of quick recovery of the speed from any disturbances and insensitivity to parameter variation is essential [1]. To solve this problem, we propose a direct torque control which can provide a very quick and precise torque control response.

Since the first developments of direct torque control (DTC) concept, it has been used in many ac drives applications. This is thanks to its fast torque response and robustness against machine parameter variations [2]. DTC method introduced first by Depenbrok and Takhashi for induction machines (IM) in 1980's, then developed for PMSM and recently some research works on using it for BLDC machines [3] and DFIM.

The speed controller used in PMSM drive system plays an important role to meet all requires mentioned above. But conventional controllers such as proportional integral (PI) controller are unsatisfactory when the running conditions changed [1]. In the motor drive control, based on classical and modern control theory proposed control strategy is largely dependent on the motor model as IP speed controller, the dynamic changes when the model parameters or by external disturbance, the system performance will be affected [2]-[4]-[5].

Neural network has good nonlinear approximation and self-learning ability, nonlinear system modeling, identification and control has been widely used [5]-[6].

Using hysteresis comparators and the switching vector table for both flux and torque control is the origin of its simple structure. However, a direct torque controlled motor suffers from great torque ripples due to the fast torque response. Many control algorithms have been proposed to reduce the torque ripple in DTC [8].

In this paper, we propose two ANN estimators; the first is used to reduce high torque ripple of the traditional DTC, the second is proposed to replace the traditional IP speed controller of three types of motors, permanent magnet synchronous motor, induction and doubly fed induction motors.

2. Mathematical Motors Model

2.1 Permanent Magnet Synchronous Motor

PMSM mathematical model in d-q coordinate system is shown as follow [9]:

$$\begin{aligned} \varphi_d &= L_d I_d + \varphi_f \\ \varphi_q &= L_q I_q \end{aligned} \tag{1}$$

Where L_d is the d-axis inductance, φ_f is the flux-linkage due to the permanent magnets, and L_q is the q-axis inductance. As d-axis is aligned with magnet's axis, there is no contribution of the magnets to q-axis magnetic flux-linkage φ_f. The PMSM model is giving by:

$$\begin{cases} \dfrac{dI_d}{dt} = \dfrac{V_d}{L_d} - \dfrac{R_s}{L_d} I_d + \dfrac{L_q}{L_d}\omega_r I_q \\ \dfrac{dI_q}{dt} = \dfrac{V_q}{L_q} - \dfrac{R_s}{L_q} I_q - \dfrac{L_d}{L_q}\omega_r I_d - \dfrac{\varphi_f}{L_q}\omega_r \\ \dfrac{d\omega}{dt} = \dfrac{P^2\varphi_f}{J} I_q + \dfrac{P^2(L_d - L_q)}{J} I_d I_q - \dfrac{f\,\omega_r}{J} - P\dfrac{T_r}{J} \end{cases} \tag{2}$$

Where R_s is the stator resistance, I_d is the d-axis current, φ_d is the total flux in the d-direction, φ_q is the total flux in the q-direction, and I_q is the q-axis current.

The motor torque expression with d–q magnitudes is [10]:

$$T_e = P(\varphi_d I_q - \varphi_q I_d) \quad (3)$$

2.2 Doubly Fed Induction Motor

The state all-current of the DFIM is giving by [11]:

$$\begin{aligned}
\frac{dI_s}{dt} &= \frac{R_s}{\sigma L_s} I_s + \frac{M_{sr}R_r}{\sigma L_s L_r} I_r + \frac{1}{\sigma L_s} V_s - \frac{M_{sr}}{\sigma L_s L_r} V_r \\
\frac{dI_r}{dt} &= \frac{R_r}{\sigma L_r} I_r + \frac{M_{sr}R_s}{\sigma L_s L_r} I_r + \frac{1}{\sigma L_r} V_r - \frac{M_{sr}}{\sigma L_s L_r} V_s
\end{aligned} \quad (4)$$

With

$$(\sigma = 1 - \frac{M_{sr}^2}{L_s L_r})$$

This electrical model is completed by the mathematical equation.

$$\frac{J}{P}\frac{d\omega}{dt} = T_e - \frac{F\omega}{P} - T_r \quad (5)$$

with

$$\begin{cases} \omega = p.\Omega \\ T_e = pM_{sr} I_s I_r \end{cases} \quad (6)$$

2.3 Induction Motor

The dynamics of the induction motor in the d-q motor reference frame, which is rotating by the following nonlinear differential [12]:

$$\begin{aligned}
\frac{dI_{sd}}{dt} &= \frac{1}{\sigma L_s}\left[-(R_s + \frac{M_{sr}^2}{L_r T_r}) I_{sd} + \omega_s \sigma L_s I_{sq} + \frac{M_{sr}}{L_r T_r}\varphi_{rd} + \frac{M_{sr}}{L_r}\omega_r \varphi_{rd} + V_{sd}\right] \\
\frac{dI_{rq}}{dt} &= \frac{1}{\sigma L_s}\left[-\omega_s \sigma L_s I_{sd} - (R_s + \frac{M_{sr}^2}{L_r T_r}) I_{sq} - \frac{M_{sr}}{L_r}\omega_r \varphi_{rd} + \frac{M_{sr}}{L_r T_r}\varphi_{rq} + V_{sq}\right] \\
\frac{d\varphi_{rd}}{dt} &= \frac{M_{sr}}{T_r} I_{sd} - \frac{1}{T_r}\varphi_{rd} + (\omega_s - \omega_r)\varphi_{rd} \\
\frac{d\varphi_{rq}}{dt} &= \frac{M_{sr}}{T_r} I_{sq} - \frac{1}{T_r}\varphi_{rq} - (\omega_s - \omega_r)\varphi_{rd} \\
\frac{d\omega}{dt} &= \frac{P^2 M_{sr}}{L_r J}(I_{sq}\varphi_{rd} - I_{sd}\varphi_{rq}) - \frac{F}{J}\omega - \frac{P}{J}T_r
\end{aligned} \quad (7)$$

With

$$(\sigma = 1 - \frac{M_{sr}^2}{L_s L_r})$$

3. Classical Direct Torque Control

The scheme of the classical DTC consists of two hysteresis controllers as shown the figure1.

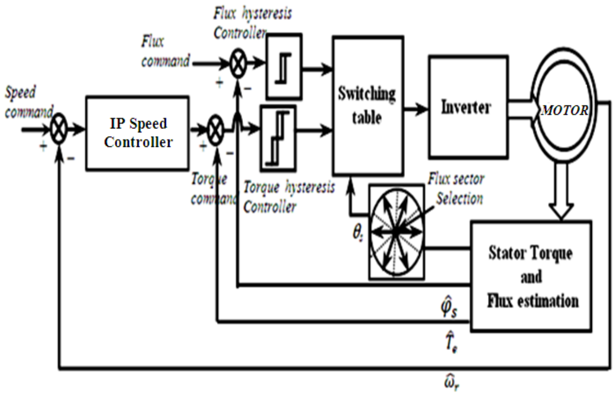

Figure 1
Schematic diagram of classical DTC control with speed regulation

In the DTC, the stator flux vector is estimated by taking the integral of difference between the input voltage and the voltage drop across the stator resistance given by [13]:

$$\varphi_s = \int_0^t (V_s - R_s i_s)dt \quad (8)$$

Lets us replace the estimate of the stator voltage with the true value and write it as:

$$V_s(S_a, S_b, S_c) = \frac{2}{3}U_o(S_a + S_b e^{\frac{j2\pi}{3}} + S_c e^{\frac{j4\pi}{3}}) \quad (9)$$

S_a, S_b, S_c represent the state of the three phase legs 0 meaning that the phase is connected to the negative and 1 meaning that the phase is connected to the positive leg.

The stator current space vector is calculated from measured currents i_a, i_b, i_c: [14]

$$i_s = \frac{2}{3}(i_a + i_b e^{\frac{j2\pi}{3}} + i_c e^{\frac{j4\pi}{3}}) \quad (10)$$

The component α and β of vector φ_s can be obtained:

$$\begin{aligned}
\varphi_{s\alpha} &= \int_0^t (V_{s\alpha} - R_s i_{s\alpha})dt \\
\varphi_{s\beta} &= \int_0^t (V_{s\beta} - R_s i_{s\beta})dt
\end{aligned} \quad (11)$$

Stator Flux amplitude and phase angle are calculated in expression (12):

$$\begin{cases} \varphi_s = \sqrt{\varphi_{s\alpha}^2 + \varphi_{s\beta}^2} \\ \angle\varphi_s = arctg\dfrac{\varphi_{s\beta}}{\varphi_{s\alpha}} \end{cases} \quad (12)$$

Once the two components of flux are obtained, the electromagnetic torque can be estimated from the relationship cited below:

$$T_{em} = \frac{3}{2} p \left(\varphi_{s\alpha} i_{s\beta} - \varphi_{s\beta} i_{s\alpha} \right) \qquad (13)$$

The voltage plane is divided into six sectors so that each voltage vector divides each region into two equal parts.
These vectors are shown in figure 2, where six active vectors of same magnitude are presented and two remaining vectors are zero.
The DTC is based on selecting one of the voltage vectors that maximizes the necessary change to correct the flux and torque error producing the smallest number of commutations in the bridge inverter.

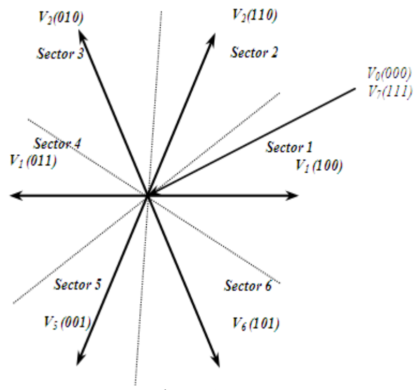

Figure 2
Spacial voltage vectors as function of the state inverter

The DTC is based on selecting one of the voltage vectors that maximizes the necessary change to correct the flux and torque error producing the smallest number of commutations in the bridge inverter.
Depending on the area where the stator flux vector is, each vector will have a different effect. In Table 1 is presented the DTC selection algorithm [15][16][17].

Table 1
Switching table

Flux	Torque	Voltage vectors					
		N=1	N=2	N=3	N=4	N=5	N=6
cflx=0	ccpl=1	V_5	V_6	V_1	V_5	V_6	V_1
	ccpl=0	V_7	V_0	V_7	V_0	V_7	V_0
	ccpl=-1	V_6	V_1	V_2	V_3	V_4	V_5
cflx=1	ccpl=1	V_3	V_4	V_5	V_6	V_1	V_2
	ccpl=0	V_0	V_7	V_0	V_7	V_0	V_7
	ccpl=-1	V_5	V_6	V_1	V_5	V_6	V_1

In this section, we propose an IP controller as presented the figure 3.

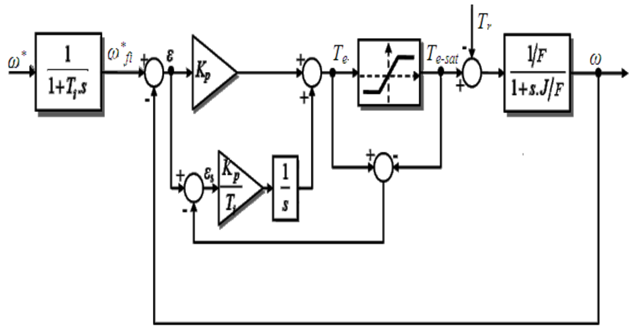

Figure 3
Diagram of speed controller (IP) with anti-windup [18]

4. Classical Direct Torque Control based on ANN

The use of hysteresis comparators in the conventional Direct Torque Control caused a considerable torque ripples. To get better performance and to reduce the torque and flux ripples, we propose in this paper two estimators based on ANN, the first is used to replace the hysteresis controller and switching table, the second is used to replace IP speed controller as shown figure 4.

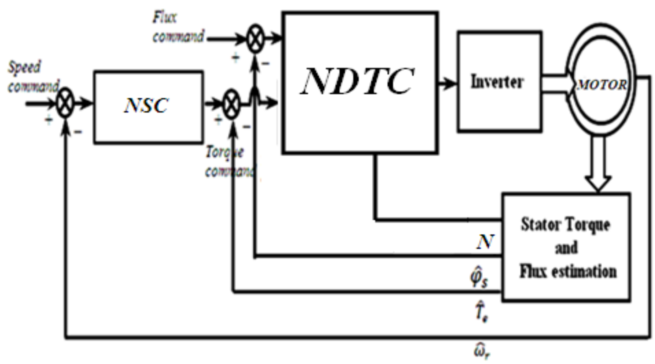

Figure 4
Schematic diagram of DTC control based on ANN

This estimator is designed to have three inputs control variable (E_ω, E_{Te}, N) and the output is the Boolean switching controls (S_a, S_b, S_c),
So structure of this first ANN of our work is 3-10-1: the first layer has three neurons that represent error of stator flux, error of electromagnetic torque and stator flux angle, the second layer has 10 neurons; and the last one with one neuron represents the output N (figure 5).
One of the most popular programs is the back-propagation. So for our application, we use an ANN with a single layer and tansig activation function type. We analyzing the performance of our system and execute several tests.
the second neural estimator is used to estimate rotor speed motor which has two inputs control variable the error between commanding value and real value, and its derivative (E_ω, ΔE_ω) and one output represent electromagnetic torque command (T_e^*).
So the structure of this estimator is 2-29-1: the first layer has two neurons that represent error of variation error of rotor speed as mentioned, the second layer has 10 neurons;

and the last one with one neuron represents the torque command as shown figure 5. This estimator is based on back propagation technique.

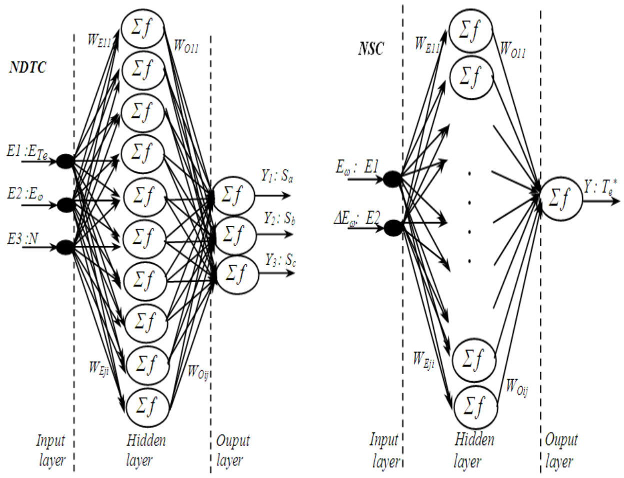

Figure 5
The structure of two estimators based on ANN

The training process is repeated until the error is minimum with desired output; the trained weights of the ANN are obtained by training the proposed ANN offline with data selected from simulation of highly performance DTC.

W_{Eij} means the weight between the input layer and the hidden layer, W_{Oji} means the weight between the hidden layer and the output layer.

$$E = \sum_{i=1}^{n} W_{Eij} E_i \qquad i = 1,\dots,n \tag{14}$$

$$Y_i = f(E) \tag{15}$$

$$Y_O = \sum_{i=1}^{m} W_{Oij} Y_i \qquad j = 1,\dots,m \tag{16}$$

$$Y = f(Y_O) \tag{17}$$

4. Simulation results

To verify the approaches proposed in this paper, digital simulation based on Matlab/Simulink have been implemented. In this simulation, the parameters of synchronous machine are: frequency: 50 Hz, stator resistance: 1.5 ohm, d-axis inductance : 0.05H, q-axis inductance : 0.05H, moment of inertia: 0.0030kg.m^2, Friction Coefficient: 0.0009Nm/rad/s, Magnetic flux linkage: 0.314Wb, and pole: 2.

The parameters of doubly fed induction machine are: frequency: 50 Hz, stator resistance: 1.75 ohm, rotor resistance: 1.68 ohm, moment of inertia: 0.01kg.m^2, Mutual inductance: 0.165, stator inductance: 0.295H, rotor inductance : 0.104H, Friction Coefficient: 0.002Nm/rad/s, power: 1.5 Kw, and pole: 2.

The parameters of induction machine are: frequency: 50 Hz, stator resistance: 4.85 ohm, rotor resistance: 3.805 ohm, stator inductance : 0.247H, rotor inductance: 0.247H, Mutual inductance: 0.258, moment of inertia: 0.031kg.m^2, Friction Coefficient: 0.001136Nm/rad/s, power: 1.5 Kw, and pole: 2.

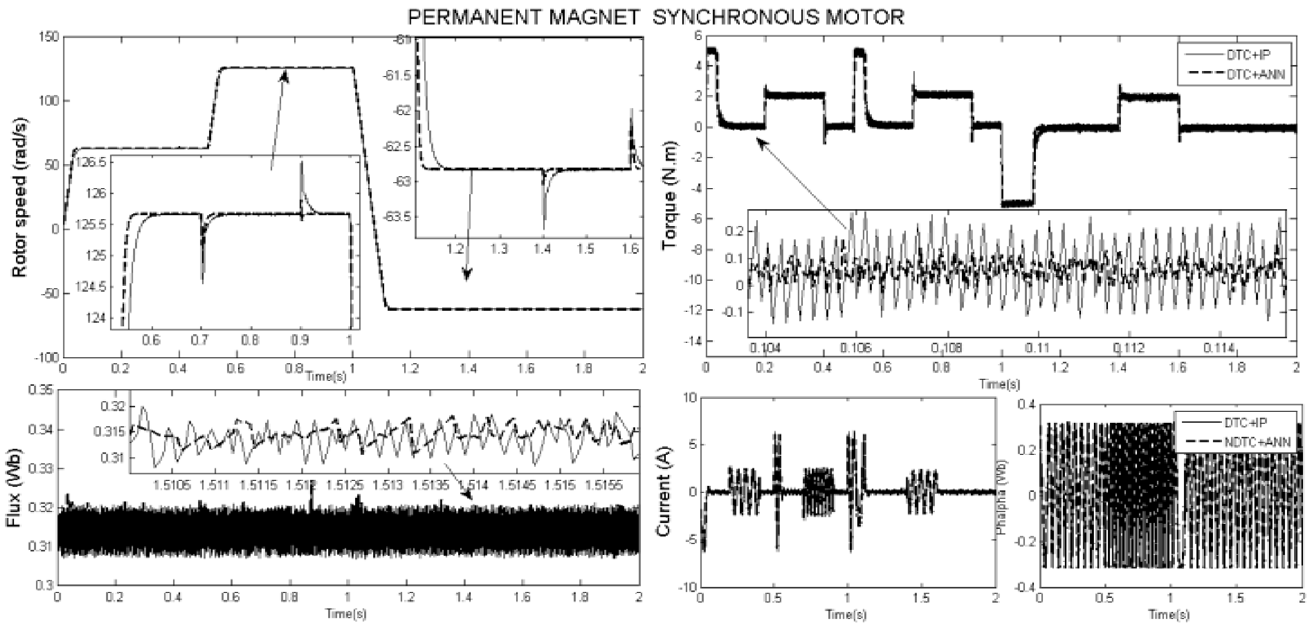

Figure 6
Comparative response using traditional and neural DTC of Permanent Magnet Synchronous Motor

To study the drive performance with a change in the command speed, a simulation test was achieved for three speed reference signals, respectively: +w/2, +w and –w rad/s with (w=126.66rad/sec applied to PMSM and IM, w=150rad/sec to FDIM). These results have been obtained with a load torque (Tr= 2N.m to PMSM and 10N.m to DFIM and IM) applied between 0.2sec and 0.4sec, between 0.7sec and 0.sec, and between 1.4sec and 1.6sec.

It can be seen in figure 6 that estimated value track their references, torque and flux ripple is less by using Neural DTC compared to traditional DTC, rotor speed response follows the reference, rejects the disturbance quickly and efficiently and with no overshoot compared to classical speed controller.

It can be also noticed that figures 7 and 8 have the same remarks; however, it can be found that estimators based on ANN gives better performance when we applied to PMSM compared to DFIM and IM

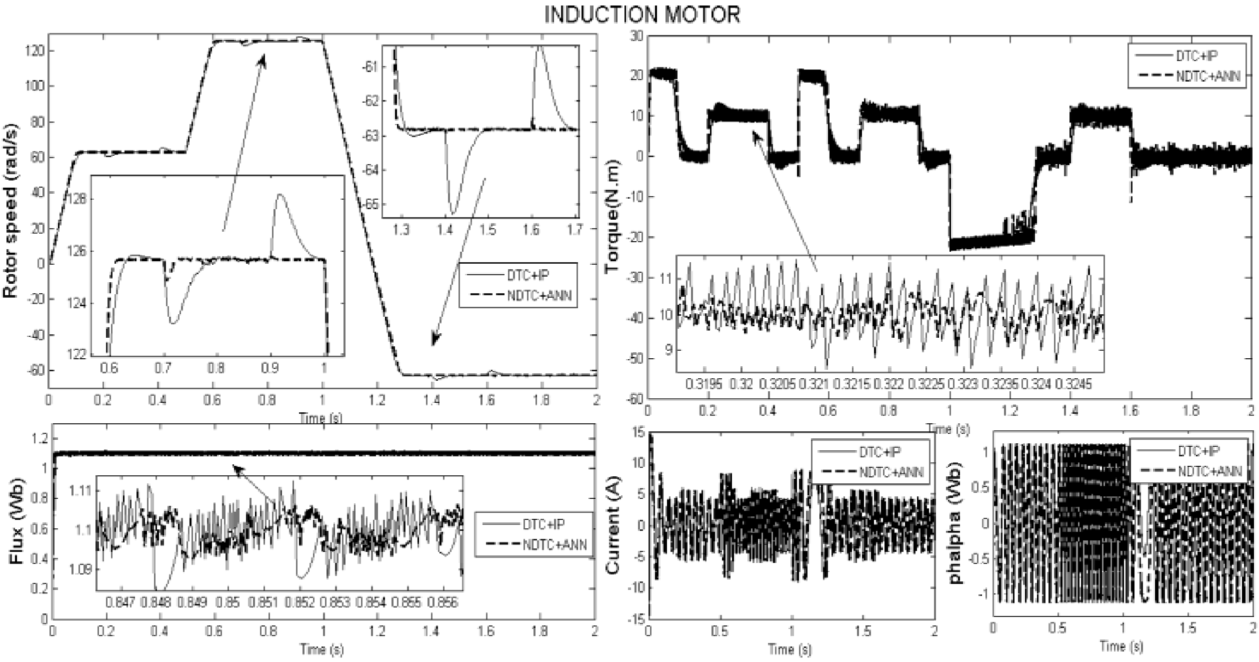

Figure 7
Comparative response using traditional and neural DTC of Induction Motor

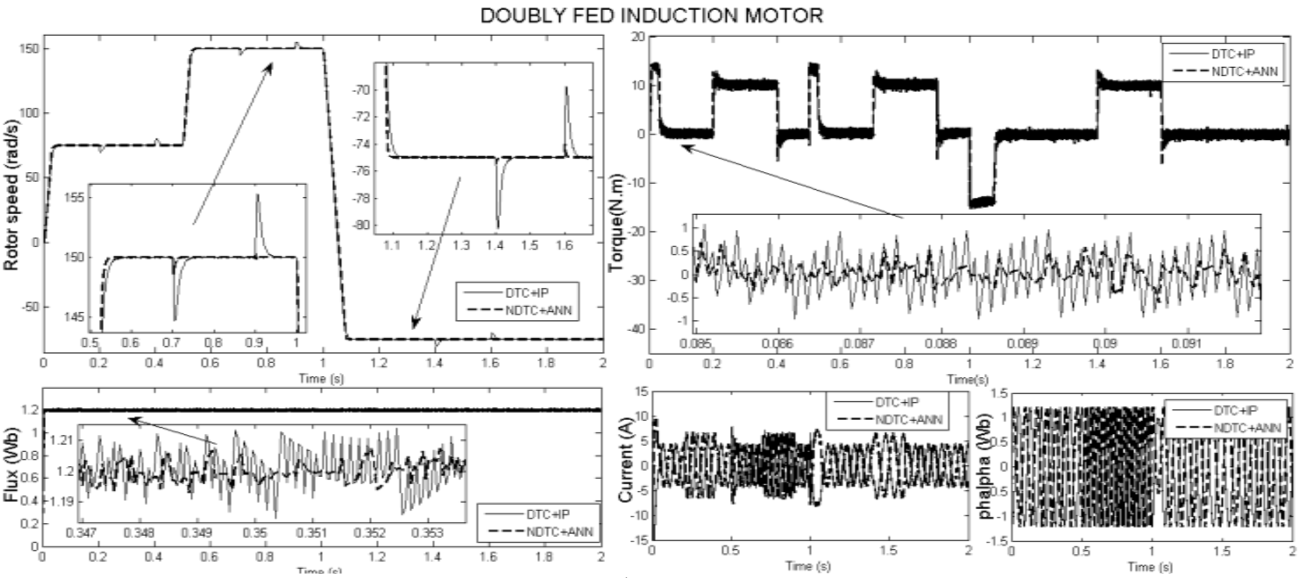

Figure 7
Comparative response using traditional and neural DTC of Doubly Fed Induction Motor

5. Conclusions

In this paper, we have developed a neural network technique combined with direct torque control of PMSM, FDIM and IM to show the feasibility of these approaches, and also to evaluate the computation time required by the neural network estimators. The obtained results show the feasibility of the proposed techniques.

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