Neural Network Based Predictive DTC Algorithm for Induction Motors

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Abstract—In this paper, a Neural Network based predictive DTC algorithm is proposed. This approach is used as an alternative to classical approaches. An appropriate Feedforward network is chosen and based on its value of derivative electromagnetic torque; optimal stator voltage vector is determined to be applied to the induction motor (by inverter). Moreover, an appropriate torque and flux observer is proposed.

Keywords—Neural Networks, Predictive DTC

I. INTRODUCTION

The use of the induction motor in servo drives is limited by its complex highly coupled nonlinear structure. This complexity implies certain control related problems. However, due to its ruggedness, maintenance free operation and many other advantages, squirrel cage induction motor are still ideal actuators for industrial applications (in some cases).

The basic problem of the induction motor control is the lack of the inverse model. Inverse model could be applied to calculate the desired applied stator voltage from the desired values of torque and flux. Hence, the FOC and later DTC methods were developed [1-5]. However, none of these methods analytically connects applied stator voltages to the torque (although some work has been done in that area [6]). A popular approach is using torque and flux derivative functions for the presentation and execution of DTC [7].

In most cases the PWM duty cycle is calculated to reduce the error of torque and flux from their desired values. In [14] the motivation was to use the Lyapunov stability function as a criteria function, which implies the inherent stability of control.

In this paper, a novel approach using Feedforward network is proposed. Torque and derivative functions are chosen as ANN inputs to calculate the optimal voltage vector.

II. INDUCTION MOTOR MODEL

In smooth rotor and stator (i.e. with constant air gap), phase windings are symmetrical. Both neutrals of the star connected winding are isolated. The permeability of fully laminated stator and rotor iron is infinite. Saturation, iron losses, end-winding and slot-effects are ignored. Hence, model of a three-phase squirrel cage induction motor in the stator reference frame can be expressed as [1, 2, and 8]:

$$\frac{d\psi_s}{dt} = \mathbf{u_s} - R_s \mathbf{i_s}$$  \hspace{1cm} (1)

$$\frac{d\psi_r}{dt} = L_{mr} R_s i_s - R_s \psi_s^g + \begin{bmatrix} 0 \\ -1 \end{bmatrix} p \omega \psi_r$$  \hspace{1cm} (2)

$$\frac{di_s}{dt} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \begin{bmatrix} u_s - \left(R_s + R_r \frac{L_m}{L_r} \right) i_s^g - \frac{L_m}{L_r} R_r \psi_s \\ \frac{1}{\sigma L_s} \left( u_s^g - e_s^g \right) \end{bmatrix}$$  \hspace{1cm} (3)

$$\begin{bmatrix} e_s^g \\ e_r^g \end{bmatrix} = \begin{bmatrix} R_s i_s^g + \frac{L_m}{L_r} \frac{d\psi_r}{dt} \\ \left( u_s - \frac{L_m}{L_r} R_r \psi_r \right) \end{bmatrix}$$  \hspace{1cm} (4)

$$\psi_s = \frac{L_m}{L_r} \psi_r + \sigma L_s i_s^g$$  \hspace{1cm} (5)

Where $\psi_s = \begin{bmatrix} \psi_s^g \\ \psi_r^g \end{bmatrix}$ is stator flux, $\psi_r = \begin{bmatrix} \psi_r^g \\ \psi_r^g \end{bmatrix}$ is rotor flux and $u_s = \begin{bmatrix} u_s^g \\ u_s^g \end{bmatrix}$ is the stator voltage, and $i_s = \begin{bmatrix} i_s^g \\ i_s^g \end{bmatrix}$ is the stator current, $\omega$ is the rotor axis speed, $\sigma$ is the total leakage factor ($\sigma = 1 - \frac{L_m^2}{(L_r L_s)}$) and $p$ is number of pole pairs. $R_s$ and $R_r$ are stator and rotor resistance; $L_s$ and $L_r$ denote stator and rotor self-inductance, whereas $L_m$ is mutual inductance. $T_e$ the torque produced by the drive is calculated as:

$$T_e = \frac{3p}{2} \begin{bmatrix} \psi_s^g i_s^g - \psi_r^g i_r^g \end{bmatrix}$$  \hspace{1cm} (6)

The mechanism can be presented with the following equation:

$$J \frac{d\omega}{dt} = T_e - T_L$$  \hspace{1cm} (7)
Where $J$ is the inertia and $T_L$ is the applied load torque including motor friction. However, the applied torque derivative can be calculated from (6):

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( \frac{d\psi^s_{ra}}{dt} \psi^s_{sb} + \frac{d\psi^s_{rb}}{dt} \psi^s_{ra} - \frac{d\psi^s_{sa}}{dt} \psi^s_{rb} \right)$$

With the use of (1), (2) and (3), the equation can be rewritten as:

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( \frac{\psi^s_{ra} \psi^s_{sb} - \psi^s_{rb} \psi^s_{sa}}{\sigma L_r} \right) - \frac{R_e}{\sigma L_r} \left( \frac{R_e}{\sigma L_r} \right)$$

$$= \frac{3pL_m}{2\sigma L_s L_r} \left( \frac{\psi^s_{ra} \psi^s_{sb} - \psi^s_{rb} \psi^s_{sa}}{\sigma L_r} \right) - p\omega_e \left( \psi^s_{ra} \psi^s_{sa} + \psi^s_{rb} \psi^s_{sb} \right)$$

(8)

Which result in:

$$\frac{dT_e}{dt} = \frac{R_e}{\sigma L_r} \left( \frac{R_e}{\sigma L_r} \right)$$

In a simpler form from (10) can be rewritten with the use of (4) as:

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( \psi^s_{ra} \psi^s_{sb} - \psi^s_{rb} \psi^s_{sa} \right)$$

(9)

With the use of (1), (2) and (3), the equation can be rewritten as:

$$\frac{dT_e}{dt} = \frac{3pL_m}{2\sigma L_s L_r} \left( \frac{d\psi^s_{ra}}{dt} \psi^s_{sb} + \frac{d\psi^s_{rb}}{dt} \psi^s_{ra} - \frac{d\psi^s_{sa}}{dt} \psi^s_{rb} \right)$$

(10)

III. DIRECT TORQUE CONTROL

The main idea of Direct Torque Control (DTC) is to directly control the torque and flux produced by the machine, without current control, as it is the case in FOC [4], [5]. Different approaches have been developed [12], [13]. However, in this paper only a basic approach and a new proposed algorithms will be presented.

Let us first present the basic conventional DTC control scheme, as described in [2],[3],[4]. The control scheme is presented in Fig.2, where in the presentation of sectors of the stator flux angle is included also(Fig.1). The applied switching table is presented in Table 1.

<table>
<thead>
<tr>
<th>$\phi_2$</th>
<th>$\phi_1$</th>
<th>$\phi_0$</th>
<th>$\phi_3$</th>
<th>$\phi_4$</th>
<th>$\phi_5$</th>
<th>$\phi_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tau = 1$</td>
<td>v2</td>
<td>v3</td>
<td>v4</td>
<td>v5</td>
<td>v6</td>
<td>v7</td>
</tr>
<tr>
<td>$\tau = 0$</td>
<td>v0</td>
<td>v1</td>
<td>v2</td>
<td>v3</td>
<td>v4</td>
<td>v5</td>
</tr>
<tr>
<td>$\tau = -1$</td>
<td>v6</td>
<td>v7</td>
<td>v0</td>
<td>v1</td>
<td>v2</td>
<td>v3</td>
</tr>
</tbody>
</table>

Table 1 Switching table - stator flux oriented DTC algorithm

IV. BASIC PRINCIPLE OF ARTIFICIAL NEURAL NETWORK USED FOR TRAINING

Neural networks have self-adapting compatibilities which makes them well suited to handle non-linearities, uncertainness and parameter variations. A multilayered feed forward neural network constructs a global approximations to non-linear input-output mapping [15]. Neural networks are capable of generalization in regions of the input space, where little or no training data are available. The structure of the proposed neural network used in this paper is shown in Fig.3.
The proposed neural networks have three layers, i.e. input layer, hidden layer and the output layer. Input layer has 10 neurons, output layer has only one neuron and hidden layer has 15 neurons. Momentum coefficient, learning rate and final error is 0.9, 0.09 and 1e-6 respectively. Neural network based predictive control scheme is present in Fig.4.

\[
\begin{align*}
\frac{d\hat{i}_s}{dt} &= \frac{1}{\sigma L_s}(u_s^e - \epsilon_s) \\
\hat{T}_s[k+1] &= \hat{T}_s[k] + T \frac{d\hat{T}_s}{dt}[k] \\
\hat{\psi}_s[k+1] &= \hat{\psi}_s[k] + T \frac{d\hat{\psi}_s}{dt}[k],
\end{align*}
\]

V. TORQUE AND FLUX OBSERVER

Torque and flux observer (Fig. 5) is based on (3), which is rewritten in following form [14]:

\[
\frac{d\psi_s^e}{dt} = u_s^e[k] - R_s i_s^e[k],
\]

Where

\[
\epsilon_s^e = R_s i_s + \left(\frac{L_m}{L_r}\right) \left(\frac{d\psi_s^e}{dt} + k(i_s - i_s^e)\right)
\]

and

\[
\frac{d\psi_s^e}{dt} = \frac{L_m}{L_r} R_s i_s - \frac{R_s}{L_r} \psi_s^e + k(i_s - i_s^e). 
\]

Stator flux is calculated with (5), whereas torque calculation is performed with (6).

In order to reach the best convergence behavior, the voltage vector is selected from the existing 8 (actually 7) choices. The equation 9 has two parts. Part 2 is independent of voltage vector. Values of the inputs of neural network are divided to 7 vectors according to 7 switching states. However, the following formulas are calculated (estimated values are denoted by \(\hat{\cdot}\)):

\[
\begin{align*}
\hat{\psi}_s[k+1] &= \psi_s[k] + T \frac{d\psi_s}{dt}[k] \\
\hat{T}_s[k+1] &= T_s[k] + \hat{T}_s[k] \\
\psi_s^e[k+1] &= \psi_s^e[k] + T \frac{d\psi_s^e}{dt}[k],
\end{align*}
\]

\[
\begin{align*}
\frac{dT_s}{dt}[k] &= \frac{3pL_m}{2\sigma L_s L_r} \\
&= \left(\hat{\psi}_s^e[k]e_{sl}[k] - \psi_s^e[k]e_{sl}^e[k]\right) \\
&\quad - \left(\hat{\psi}_s[k]e_{sh}[k] - \psi_s[k]e_{sh}^e[k]\right).
\end{align*}
\]
Fig. 6. Output after training network

Fig. 7. Difference between target and simulation result

Fig. 8. Simulation results – Neural network based DTC. Applied torque ($T_e$), its desired value ($T_{ed}$) and applied load torque ($T_L$).

Fig. 9. Simulation results – classic DTC. Applied torque ($T_e$), its desired value ($T_{ed}$) and applied load torque ($T_L$).

Fig. 10. Simulation results – Neural network based DTC. Stator flux ($\psi_s$) and its desired value.

Fig. 11. Simulation results – Neural network based DTC. Stator voltage.
VII. CONCLUSION

A neural network based predictive DTC for induction motors is presented in this paper. To control the motor, an appropriate torque and flux observer is proposed also. Torque and its derivative are chosen as ANN inputs to calculate the optimal voltage vector. It is shown in simulation results, that under identical conditions the results obtained by the use of proposed method, are improved compared to classical DTC, which is especially true for the torque ripple. Torque ripple is reduced by a considerable ratio due to soft interpolation property of ANN. A comprehensive simulation study in MATLAB shows satisfactory results.

REFERENCES