A DSIM Control Using Artificial Neural Network Controller

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Abstract. *This paper presents a vector control indirect (IFOC) of double –star induction machine (DSIM) based on artificial neural network (ANN). Double star induction machine are used in high-power applications because they are characterized by efficiency and their ability to power splitting. The objective of this work is the comparison between the CVI indirect vector control with the PI regulator and the CVI indirect vector control with the artificial neural network regulator (ANN) MULTI-LAYER (MLP) found us that the tuning by the neural networks is good and robust in comparison of the PI. Simulation results through MATLAB/Simulink are using for both controls, the results obtained showed a very satisfactory behavior of this machine*
.

Keywords: vector control indirect (IFOC), doubly stator induction machine (DSIM), Artificial neural network (ANN).

NOMENCLATURE

DSIM doubly stator induction machine
MLP The Multilayer Perceptron
ANN artificial neural networks
CVI control vector indirect
PI proportional integrator
V_{sd}, V_{sq} *d*- and *q*-axis components of the stator voltage.
V_{rd}, V_{rq} *d*-and *q* -axis components of the rotor voltage.
i_{sq}, i_{sq} *d*- and *q*-axis components of the stator current .
i_{rd}, i_{rq} *d*- and *q*-axis components of the rotor current.
R_s Stator phase resistance.
R_r Rotor phase resistance.
M_{sr} Mutual inductance between the stator and rotor.
L_s Stator inductance.
L_r Rotor inductance.
P Number of poles of the induction machine.
ω_s Stator pulsation.
ω_r Rotor pulsation.
C_{em} **Electromagnetic torque.**

1. Introduction

Nowadays, many industry segments need doubly star induction motors are one of widely used motor. Due to their advantages in power segmentation, reliability, and minimized torque pulsations. Such segmented structures are very attractive for high-power applications since they allow the use of lower rating power electronic devices at a switching frequency higher than the one usually used in three-phase AC machine drives. This machine has been used required in many applications, such as pumps, fans, compressors, rolling mills, cement mills, mine hoists[10].
In recent years, the multiphase machines, five-phase and six-phase induction are the most considered in the literature. The present study is focused on the doubly star Induction motor. This type of machine is composed by two three-phase windings shifted by 30 degrees and a standard simple squirrel-cage rotor [11].
In order to ensure an effective control of DSIM, several methods have been proposed [12]. An alternative solution is the use of indirect vector Oriented Control (IFOC) is modern technique for high-performance control of MLI inverter fed DSIM. To achieve a variable speed operation a power electronics inverter can be used.

The indirect vector control theory is the base of a special control method for doubly star induction motor drives. With this theory doubly star induction motors can be controlled like a separately excited DC motor. This method enables the control of field and torque of the DSIM independently (decoupling) by manipulating the corresponding field oriented quantities [13].

With the aim of improving the performance of traditional IFOC-based electrical drives, artificial neural network control is increasingly attracting the attention of many scientists to the configuration and design of the artificial neural network controller for control. The proposed neural network controller has been successfully simulated on a simulink model. The performance of ANN compared to conventional PI.
This paper is structured as follows: In Section II the model of the DSIM is presented, a suitable transformation matrix is used to develop a simple dynamic model. We will describe the indirect Field Oriented control.
In section III the control vector strategy for this system is proposed. In section IV, the controllor ANN is proposed.
At the end, in section V we shows simulation results for a comparison between the performances of controller ANN field oriented control DSIM with those obtained from conventional PI controller under various conditions operation

2. MATHEMATICAL MODEL OF THE DSIM

A . Three-phase model of MASDE on real axes

The schematic representation of the double star asynchronous machine in electrical space is given in the following figure (1)
The doubly star induction machine represented by two stators windings : As1, Bs1, Cs1 and As2, Bs2, Cs2 which are displaced by $\alpha = \frac{\pi}{6}$ electrical angle .and the rotor windings (Ar, Br, Cr) are sinusoidal distributed and have axes that are displaced apart by $\frac{2\pi}{3}$
The customary assumptions are adopted [2]:
1. Motor windings are sinusoidal distributed.
2. The saturation of magnetic circuit is neglected.
3. The two stars have same parameters.
4. The flux path is linear.
The windings of the DSIM are shown in Figure 1

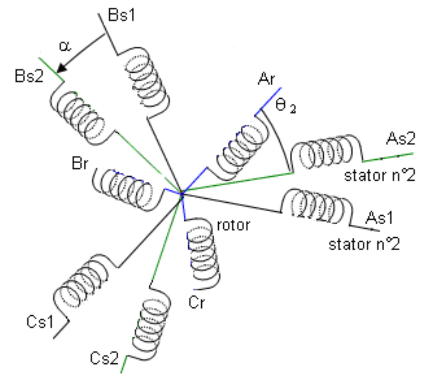

Figure 1. Doubly stator winding representation

The voltage equations for stator and rotor circuits for model of the DSIM motor have the following matrix form [4]:

$$\begin{cases} [V_{abc,s1}] = [R_{s1}][I_{abc,s1}] + \dfrac{d}{dt}[\psi_{abc,s1}] \\ [V_{abc,s2}] = [R_{s2}][I_{abc,s2}] + \dfrac{d}{dt}[\psi_{abc,s2}] \\ [V_{abc,r}] = [R_r][I_{abc,r}] + \dfrac{d}{dt}[\psi_{abc,r}] \end{cases} \quad (1)$$

With:

$[V_{abcs1}]$, $[V_{abcs2}]$, $[V_{abc,r}]$: stato and rotor voltages

$[I_{abc,s1}]$, $[I_{abc,s2}]$, $[I_{abc,r}]$: stator and rotor currents

$\psi_{abc,s1}$, $\psi_{abc,s2}$, $\psi_{abc,r}$:flux stator and rotor

$[R_{s1}]$, $[R_{s2}]$, $[R_r]$:Resistance matrices stator and rotor

B.Two-phase model

Park's transformation [6] is based on the transformation of a three-phase system of axes (a, b, c) into an equivalent two-phase system of axis (x, y) and vice versa, with the creation of a rotating electromagnetic field with magneto motive forces figure(2).

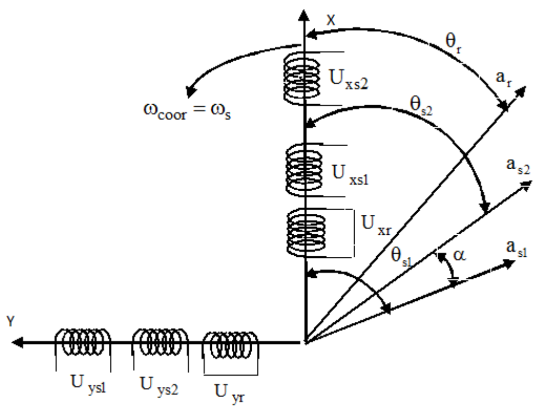

Figure 2: Schematic representation of the DSIM PARK model

Park's transformation [7] is based on the transformation of a three-phase system of axes (show Figure 2). The schematic representation of the DSIM PARK model (a, b, c) into an equivalent two-phase system of axis (x, y) and vice versa, with the creation of a rotating electromagnetic field with magneto motive forces.

$$\begin{cases} V_{xs1} = R_{s1} i_{xs1} + \dfrac{d\psi_{xs1}}{dt} - \omega_s \psi_{ys1} \\ V_{xs2} = R_{s2} i_{xs2} + \dfrac{d\psi_{xs2}}{dt} - \omega_s \psi_{ys2} \\ V_{ys1} = R_{s1} i_{ys1} + \dfrac{d\psi_{ys1}}{dt} + \omega_s \psi_{xs1} \\ V_{ys2} = R_{s2} i_{ys2} + \dfrac{d\psi_{ys2}}{dt} + \omega_s \psi_{xs2} \\ 0 = R_r i_{xr} + \dfrac{d\psi_{xr}}{dt} - \omega_{gl} \psi_{yr} \\ 0 = R_r i_{yr} + \dfrac{d\psi_{yr}}{dt} + \omega_{gl} \psi_{xr} \end{cases} \quad (2)$$

With:

$V_{s1,xy}$, $V_{s2,xy}$:Stator voltages *xy* components

$I_{s1,xy}$, $I_{s2,xy}$, $I_{r,xy}$:Stator and Rotor currents xy components

$\psi_{s1,xy}$, $\psi_{s2,xy}$, $\psi_{r,xy}$: Stator and Rotor flux xy components.

The relation flux and current are :

$$\begin{cases} \psi_{xs1} = L_{s1} i_{xs1} + L_m (i_{xs1} + i_{xs2} + i_{xr}) \\ \psi_{xs2} = L_{s2} i_{xs2} + L_m (i_{xs1} + i_{xs2} + i_{xr}) \\ \psi_{ys1} = L_{s1} i_{ys1} + L_m (i_{ys1} + i_{ys2} + i_{yr}) \\ \psi_{ys2} = L_{s2} i_{ys2} + L_m (i_{ys1} + i_{ys2} + i_{yr}) \\ \psi_{xr} = L_r i_{xr} + L_m (i_{xs1} + i_{xs2} + i_{xr}) \\ \psi_{yr} = L_r i_{yr} + L_m (i_{ys1} + i_{ys2} + i_{yr}) \end{cases} \quad (3)$$

Where:

Lm: Cyclic mutual inductance between stator 1, stator 2 and rotor.

Ls1,s2,r: the inductance of a stator 1, stator 2 and rotor respectively.

Ls1+Lm , Ls2+Lm, Lr+Lm: the total inductance of a stator 1, stator 2 and rotor respectively.

The electromagnetic torque and the mechanical equations can be written as:

$$C_{em} = \frac{3}{2} P \frac{L_m}{L_m + L_r} [\psi_{xr}(i_{ys1} + i_{ys2}) - \psi_{yr}(i_{xs1} + i_{xs2})] \quad (4)$$

$$J \frac{d\Omega}{dt} = C_{em} - C_r - k_f \Omega \quad (5)$$

3 . VECTOR CONTROL OF THE DSIM FLUX STRATEGY

The technique of vector control is based on a control law leading to a characteristic adjustment similar that of a DC machine with separate excitation. The vector control with rotoric flux oriented concerns.

The constraint of the rotor flux orientation can be written as, $\psi_{rq} = 0$ and $\psi_{rd} = \emptyset_r$, which consider that the assumption of the constant stator flux [5].

The expressions of the rotoric currents may be given as:

$$i_{dr} = \frac{1}{l_m + l_r} [\psi_r - l_m (i_{ds1} + i_{ds2})] \quad (6)$$

$$i_{qr} = \frac{-l_m}{l_m + l_r}\left(i_{qs1} + i_{qs2}\right) \quad (7)$$

$$\psi_{ds1} = \hbar 1 i_{ds1} + l_r \sigma i_{ds2} + \sigma \psi_r^* \quad (8)$$

$$\psi_{qs1} = \hbar 1 i_{qs1} + l_r \sigma i_{qs2} \quad (9)$$

$$\psi_{ds2} = \hbar 2 i_{ds2} + l_r \sigma i_{ds1} + \sigma \psi_r^* \quad (10)$$

$$\psi_{qs2} = \hbar 2 i_{qs2} + l_r \sigma i_{qs1} \quad (11)$$

where

$$\sigma = \frac{l_m}{l_m + l_r} \quad (12)$$

$$\hbar = l_{s1,s2} + \sigma l_r \quad (13)$$

We have

$$\psi_r^* = l_m\left(i_{ds1} + i_{ds2}\right) \quad (14)$$

$$i_{qr} = \frac{-\omega_g^* \psi_r^*}{R_r} \quad (15)$$

After replacement we find

$$\begin{cases} V_{ds1}^* = R_{s1} i_{ds1} + l_{s1}\frac{d}{dt} i_{ds1} - \omega_s^*\left(l_{s1} i_{qs1} + T_r \psi_r^* \omega_{gl}^*\right) \\ V_{qs1}^* = R_{s1} i_{qs1} + l_{s1}\frac{d}{dt} i_{qs1} + \omega_s^*\left(l_{s1} i_{ds1} + \psi_r^*\right) \\ V_{ds2}^* = R_{s2} i_{ds2} + l_{s2}\frac{d}{dt} i_{ds2} - \omega_s^*\left(l_{s2} i_{qs2} + T_r \psi_r^* \omega_{gl}^*\right) \\ V_{qs2}^* = R_{s2} i_{qs2} + l_{s2}\frac{d}{dt} i_{qs2} + \omega_s^*\left(l_{s2} i_{ds2} + \psi_r^*\right) \end{cases} \quad (16)$$

4 .CORRECTEUR WITH ARTIFICIAL NEURAL NETWORKS

The corrector with neural networks was originally proposed to identify the critical point of a system to be controlled.

The motivation was, by automating the measurement procedure, increase safety and reduce the experimental time required compared to conventional controllers.

A . definition

An artificial neural networks (ANN) (is a set of formal neurons (simple computing units, processor nodes) associated in layers (or subgroups) and operating in parallel. In a network, each subgroup does an independent treatment of the others and transmits the result of its analysis to the next subgroup. The information given to the network will therefore be propagated layer by layer. From the input layer to the output layer, passing either through none, one or more intermediate layers (known as hidden layers). It should be noted that depending on the learning algorithm, it is also possible to propagate information backwards ("back propagation"). Usually (except for the input and output layers), each neuron in one layer is connected to all neurons in the previous layer and the next layer. ANNs have the capacity to store empirical knowledge and make it available for use. The processing skills (and therefore the knowledge) of the network will be stored in the synaptic weights, obtained by adaptation or learning processes [5].

B.operation of ANN

The functioning of an ANN is based on the formal neuron which calculates the sum of its inputs and then this value passes through the activation function to produce its output (fig3).

As a rule, the calculation of the value of this function can behave in two stages [8]:

A linear combination of inputs:

$$v = \sum_{i=1}^{n} w_i x_i + b \quad (17)$$

The output of the neuron is

$$y = f(v) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \quad (18)$$

When input signals (x_i), Les (w_i) are called synaptic weights, (b) is called bias.

(f): is the activation function of the neuron (step, sigmoid, Gaussian ...).

Next in the backward phase, the error of each neuron is calculated, which is essentially: Target - Actual Output [1].

$$E(k) = \frac{1}{N}\sum_{n=1}^{k}\left(d_i(k) - y_i(k)\right)^2 \quad (19)$$

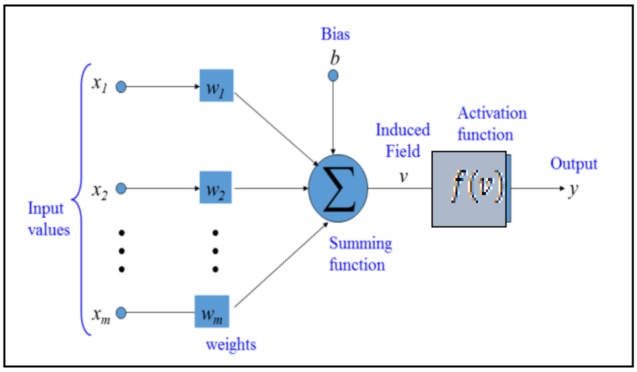

Fig.3: Model of an artificial neuron

C. The Multilayer Perceptron MLP

A Learning algorithm performs the adaptation of bias and weights of the network to minimize the error between the input vector and the neural output vector (fig4). The criterion of error minimization is:

$$\boldsymbol{e} = \sum_i \left(d_i - x_i\right)^2 \quad (20)$$

The learning algorithm used in our work is that of the error backpropagation because the latter is best suited to the learning of typMLP neural networks [3].

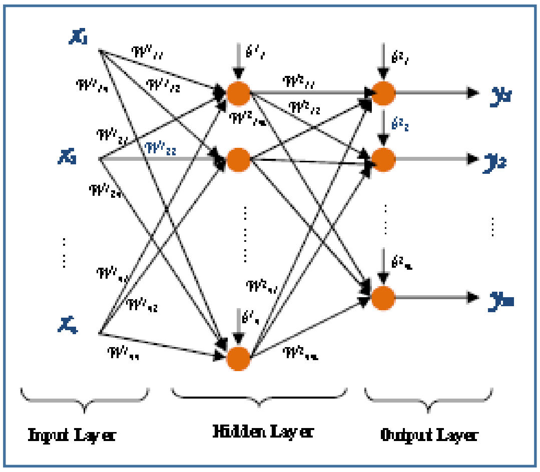

Fig.4:Example of a Multi-Layer perceptron network.

5. SIMULATION RESULTS

In order to know the best DSIM control technique, a comparative study is essential between the two previously mentioned controls (classical CVI-PI, and CVI -neuronal). The following figure shows the comparison between them:
The test: Wr = 300rad / s; Cr = 14N.m at time t = [1.5, 2.5] s.

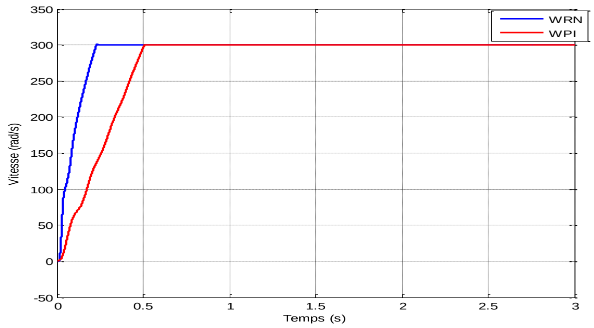

Fig-5: Comparison between CVI-NN and CVI-PI speeds.

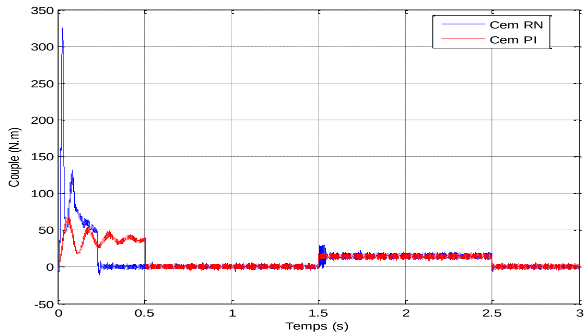

Fig-6: Comparison between the torque of the CVI –PI and CVI-NN

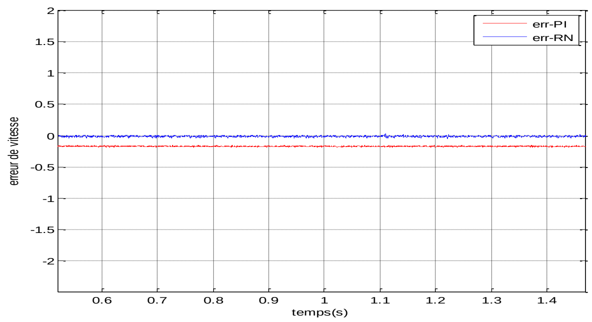

Fig-7 Speed error between CVI-PI and CVI-RN.

The figures show the comparison of dynamic speed response and electromagnetic torque and speed error for indirect vector control by neural regulation and classical PI regulator
We notice that the response time is faster and the speed follows the reference speed well in the case of CVI-NN in an instant t = 0.28sec On the other hand the CVI-PI in an instant t = 0.51sec
We also notice that the torque with the NN regulators at the start time of the large oscillations, but quickly returned to the value close to zero in a short time (t = 0.28sec). on the other hand in the CVI-PI of the oscillations until time (t = 0.51sec). Moreover after stabilization, the shape of the electromagnetic couple shows that follows the resistive couple. with great precision and a fast reaction.
In figure (7) (the error) shows the comparison of the speed error for CVI-RN and CVI-PI. It is noted that the error in speed of the neural regulation (CVI-NN) is almost non-existent, which indicates that the speed of rotation follows the reference speed well. the opposite for the speed error of the control by PI (CVI-PI) equal to 0.2. This indicates the divergence between the rotational speed and the reference speed, which means that there is an improvement in tracking accuracy and a decrease in error for indirect vector control by neural regulation.

CONCLUSION

This work has been the subject of the application of indirect vector control of the double star asynchronous machine based on neural regulation, the main objective being torque and speed regulation. In this context, we first presented a theoretical reminder on the double star machine.
The various simulations made show that the regulation system gives good static and dynamic performance.
From this fact, we conclude that the speed and torque adjustment by ANN regulator brings remarkable improvements compared to the vector control with PI regulator. Because the ANN regulator offers good static and dynamic performance with a time of shorter response and without overshoot.

Appendix

Parameter’s of DSIM

Pn= 4,5 kW
Vn= 220 V
In = 6.5 A
Rs1= 3,72 Ω
Rs2= 3,72
Rr = 2,12 Ω
Ls1= 0,022H
Ls2= 0,02H
Lr= 0,006 H
Lm = 0,3672 H
J = 0,0625 kg.m2
Kf= 0,001 N.m.s/rad
f = 50 Hz
P = 1

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