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A DTC Neurofuzzy Speed Regulation Concept for a Permanent Magnet Synchronous Machine

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Abstract: Based on Sugeno fuzzy logic system, this paper develops a Neuro-Fuzzy Direct Torque Control (NFDTC) for a Permanent Magnet Synchronous motor (PMSM). The main idea of DTC control is motivated by direct choosing the stators voltage vectors according to the differences between the references of the electromagnetic torque and the stators flux and their reels values calculated and related only on the actual-sizes of the stators. The neurofuzzy regulator is synthesized by using the Sugeno reasoning methods, where the consequences rules are a single order polynomial of inputs defined by three Gaussians fuzzy sets. The parameters of the premises and the conclusions of the fuzzy rules of Sugeno are determined on the base of the input-output data provided by a fuzzy regulator of the Mamdani type, where the linguistic variables of inputs-outputs of the torque, flux and position of the stator flux vectors are of triangular membership functions. The training is based on the extended Kalman filter concept, which allows the determining of the parameters vector of the fuzzy rules so that the output of the Sugeno regulator approaches will be the best possible output of the Mamdani regulator. The simulation results make it possible an effective evaluation of the Kalman extended based filters training algorithms.

Keywords: *DTC; PMSM; Inverter voltage; fuzzy sets; Sugeno methods; extended Mamdani and Kalman filter.*

Mathematics Subject Classification (2010): 03B52, 93C42, 94D05.

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1 Introduction

The use of the PMSM always continues to extend. The technological development made it possible that the permanent magnet synchronous machines are more essential in the field applications of a very high static and dynamic performances demands, especially in the embedded systems fields (aeronautical and aerospace) because of its high power/weight ratio. A noiseless linear process with a constant parameters concept can be controlled accurately by traditional PID regulators; these regulators proved to be sufficient, however the process is subjected to disturbances and its parameters variations are relatively less, especially if the requirements on the precision of adjustment and the dynamic response of the system are not strict. In the contrary case one can have recourse to an auto adaptative solution, which by readjustment of the parameters of the regulators, allows preserving performances fixed in advance in the presence of the disturbances and variation of parameters. Nevertheless, this solution presents the disadvantage of often complex implementation. It is thus possible to solve this problem by using the method of robust commands and neurofuzzy control.

In this paper we apply the neurofuzzy control by the method of Sugeno to the speed regulation of a Permanent Magnet Synchronous Machine. The objective is to synthesize neurofuzzy regulator of Sugeno to three fuzzy sets for each one of: torque, flux and position of the flux vector and whose consequences of the rules are the polynomials of order one. This neurofuzzy regulator is thus deduced by recopying the data inputs outputs provided by a fuzzy regulator of Mamdani to 132 fuzzy rules [1]. The method of copy is based on the approach by extended Kalman filter. In [1], the authors introduce a fuzzy logic controller in conjunction with direct torque control strategy for a permanent magnet synchronous machine. In this controller there are three inputs, which are the error of stator flux, the error of torque and the stator flux angle. The total rule number used is 132 rules. The rules base of the proposed approach contains only 27 rules. Consequently, this approach requires less computing time for its execution compared with the method that is proposed in [1].

2 Mathematical Model of a Permanent Magnet Synchronous Motor

The PMSM model is considered under the following assumptions.

1. The spatial distribution of stator winding is sinusoidal.
2. The saturation is neglected.
3. The damping effect is neglected.

Thus, in the synchronous $d-q$ reference form, the dynamics of PMSM is represented as follows [1, 4]

$$\begin{aligned} V_d &= R_s I_d + L_d \frac{dI_d}{dt} - w_r L_q I_q, \\ V_q &= R_s I_q + L_q \frac{dI_q}{dt} - w_r L_d I_d + w_r \varphi_f, \\ T_{em} &= p(\varphi_d I_q - \varphi_q I_d), \end{aligned} \tag{1}$$

with

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

L_d : direct stator inductance,
L_q : stator inductance in squaring,
φ_f : flux of the permanents magnets.

The total mathematical model is given in the form of space of following state:

$$\begin{aligned}\frac{dI_d}{dt} &= \frac{V_d}{L_d} - \frac{R_s}{L_d} I_d + \frac{L_q}{L_d} w_r I_q p,\\ \frac{dI_q}{dt} &= \frac{V_q}{L_q} - \frac{R_s}{L_q} I_q - p\frac{L_d}{L_q} w_r I_d - \frac{\varphi_f}{L_q} w_r p,\\ \frac{dw_r}{dt} &= p^2 I_q \frac{\varphi_f}{j} + \frac{1}{j}\left[p^2(L_d - L_q) I_d I_q f_m\right] - p\frac{c_r}{j},\\ \frac{d\theta_r}{dt} &= p w_r.\end{aligned} \tag{2}$$

3 General Principal of DTC

The direct torque control of the permanent magnet synchronous machine is based on the determination "direct" sequence of order applied to the switches of an inverter of tension. First, we use a fuzzy regulator. Secondly, we replace the latter by a neurofuzzy regulator, whose function is to control the state of the system (the amplitude of stator flux and electromagnetic torque).

3.1 Selection of the voltage vector V_s

The voltage vector V_s is delivered by a three-phase of the voltage source inverter and is given by [5,6]:

$$V_s = \sqrt{\frac{2}{3}}\left(a^0 V_a + a V_b + a^2 V_c\right) \tag{3}$$

with

$$a = \exp(j\frac{2\pi}{3}).$$

By using the logical variables representing the state of the switches, the voltage vector can be written in the form:

$$V_s = \sqrt{\frac{2}{3}} U_0 \left(S_a + a S_b + a^2 S_c\right). \tag{4}$$

As shown in Figure 2 the combinations of the three sizes (S_a, S_b, S_c) allow to generate 8 fixed positions of the vector V_s, two correspond to the null vectors:

$$(S_a, S_b, S_c) = (0,0,0) \quad \text{and} \quad (S_a, S_b, S_c) = (1,1,1). \tag{5}$$

Generally, the space of evolution of stator flux φ_s is delimited in the fixed reference frame

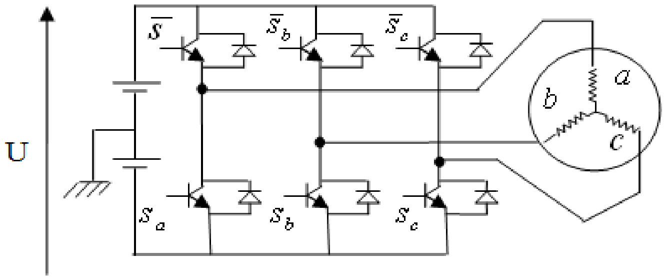

Figure 1: Scheme of the voltage source inverter.

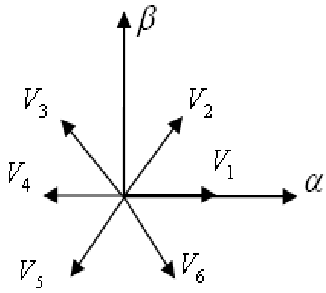

Figure 2: Development of the 8 vectors V_s $(\alpha\beta)$ Stationary reference frame.

V_0	(1 1 1)
V_1	(1 0 0)
V_2	(1 1 0)
V_3	(0 1 0)
V_4	(0 1 1)
V_5	(0 0 1)
V_6	(1 0 1)
V_7	(0 0 0)

Table 1: Development of the 8 possible configurations of the vectors V_s.

(stator) by breaking it up into 6 symmetrical zones compared to the directions of the nonnull voltage vectors. The position of the flux vector in these zones is determined from these components.

When the stator flux vector φ_s is in a numbered zone N, the control of flux and torque can be ensured by selecting one of the nonnull voltage vectors:

N				1	2	3	4	5	6
Tcont	1	flxC	1	V_2	V_3	V_4	V_5	V_6	V_1
			0	V_3	V_4	V_5	V_6	V_1	V_2
Tcont	0	flxC	1	V_0	V_7	V_7	V_0	V_7	V_0
			0	V_7	V_0	V_0	V_7	V_0	V_7

Tcont: Torque Control. flxC: flux Control.

Table 2: Table of commutation for the selection of the voltage vector.

4 Fuzzy Controller

In the hysteresis direct torque control, the errors of torque and flux are directly used to select the switching state of switches of the inverter voltage with any distinction between large or relatively small error. The large or small terms are vague terms containing the concept of fuzzy logic control which allows using a fuzzy controller [1–3]. On the other hand, the torque ripples will be reduced (Figure 3).

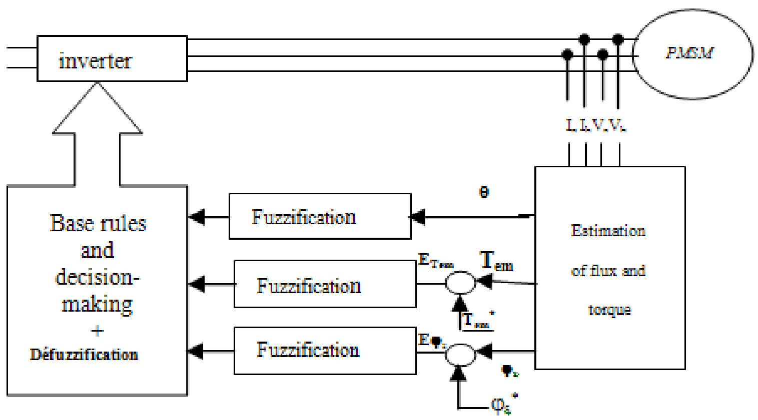

Figure 3: Synoptic scheme of the fuzzy controller of the PMSM.

The studied fuzzy controller has 3 state variables of input and one variable of command in output.

Each variable is represented by fuzzy set. The number of the fuzzy set for each variable is selected to obtain a powerful command with a minimal number of fuzzy rules.

The first fuzzy state variable is the difference between the reference stator flux φ_s^* (in Webers) and the estimated stator flux magnitude φ_s given by:

$$E_{\varphi_s} = \varphi_s^* - |\varphi_s|. \tag{6}$$

The grade of membership distribution is shown in Figure 4(a) which uses a triangular distribution.

The second fuzzy state variable is the difference between the command electromagnetic torque T_{em} and the estimated electromagnetic torque T_{em}^* (error in torque $E_{T_{em}}$) given by:

$$E_{T_{em}} = T_{em}^* - T_{em}. \tag{7}$$

The electromagnetic torque is estimated from the flux and current information which are given in [1]. The grade of membership distribution is shown in Figure 4(b).

The third fuzzy state variable is the angle between stator flux and their reference axis (stator flux angle θ) which is determined by the following relation

$$\theta = \tan^{-1}\left(\frac{\varphi_\beta}{\varphi_\alpha}\right). \tag{8}$$

The universe of discourse of this fuzzy variable is divided into 12 fuzzy sets (θ_1 to θ_{12}). The membership distribution of fuzzy variables is shown in Figure 4(c).

θ_1

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_1	V_2	V_2
PS	V_1	V_2	V_3
ZE	0	0	0
NS	V_6	0	V_4
NL	V_6	V_5	V_5

θ_2

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_2	V_2	V_3
PS	V_2	V_3	V_3
ZE	0	0	0
NS	V_6	V_0	V_5
NL	V_6	V_6	V_5

θ_3

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_2	V_3	V_3
PS	V_2	V_3	V_4
ZE	0	0	0
NS	V_1	0	V_5
NL	V_1	V_6	V_6

θ_4

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_3	V_3	V_4
PS	V_3	V_4	V_4
ZE	0	0	0
NS	V_1	0	V_6
NL	V_1	V_1	V_6

θ_5

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_3	V_4	V_4
PS	V_3	V_4	V_5
ZE	0	0	0
NS	V_2	0	V_6
NL	V_2	V_1	V_1

θ_6

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_5	V_4	V_4
PS	V_4	V_5	V_5
ZE	0	0	0
NS	V_2	0	V_1
NL	V_2	V_2	V_1

θ_7

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_4	V_5	V_5
PS	V_4	V_5	V_6
ZE	0	0	0
NS	V_3	0	V_1
NL	V_3	V_2	V_2

θ_8

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_5	V_5	V_6
PS	V_5	V_6	V_6
ZE	0	0	0
NS	V_3	0	V_2
NL	V_3	V_3	V_2

θ_9

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_5	V_6	V_6
PS	V_5	V_6	V_1
ZE	0	0	0
NS	V_4	0	V_2
NL	V_4	V_3	V_3

θ_{10}

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_6	V_6	V_1
PS	V_6	V_1	V_1
ZE	0	0	0
NS	V_4	0	V_3
NL	V_4	V_4	V_3

θ_{11}

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_6	V_1	V_1
PS	V_6	V_1	V_2
ZE	0	0	0
NS	V_5	0	V_3
NL	V_5	V_4	V_4

θ_{12}

$E_{tor} \diagdown E_{\varphi_s}$	P	Z	N
PL	V_1	V_1	V_2
PS	V_1	V_2	V_2
ZE	0	0	0
NS	V_5	0	V_4
NL	V_5	V_5	V_4

Table 3: Set of fuzzy rules for control of PMSM (E_{φ_s}: error of the stator flux, E_{tor}: torque error).

In Figure 5, the output has only one variable of command which is the state of ordering of the switch when the voltage vectors are discrete values.

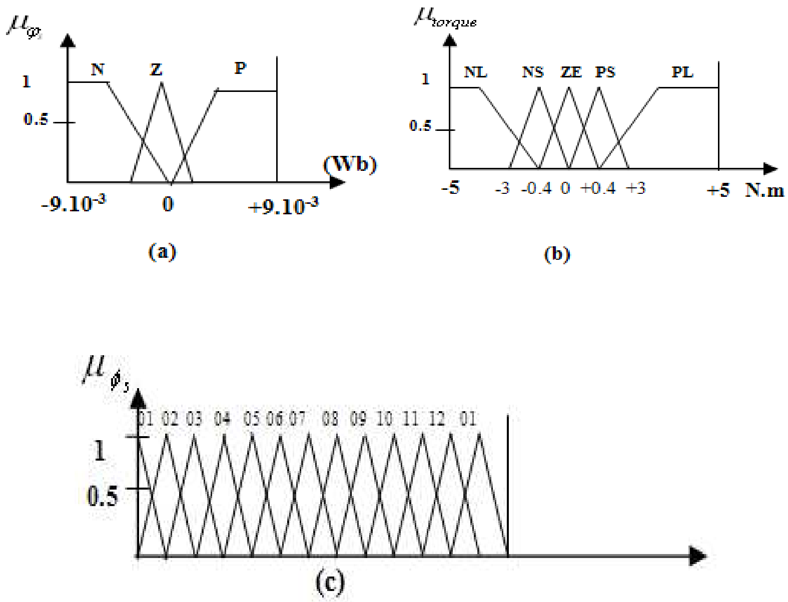

Figure 4: Membership distribution of fuzzy variables for fuzzy controller.

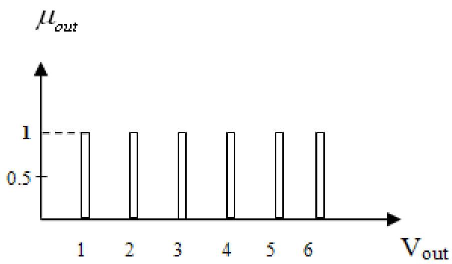

Figure 5: Membership functions variables of fuzzy output.

5 The Sugeno Method

The Sugeno fuzzy logic controller is proposed by Takagi and Sugeno [8], who develops a systematic method of generation of the fuzzy rules starting from a whole of data input-output. In this case, the consequences of the rules are numerical functions, which depend on the current values of the variables of inputs. Being given that each rule has a numerical conclusion, the total output of neurofuzzy controller is obtained by the calculation of a weighted average, and in this manner the time consuming by the procedure of defuzzification is avoided.

Let us designate by e, Δe and δ inputs of the neurofuzzy controller, and by Δu its output. The rules base of the neurofuzzy controller has: $M = m_1 \times m_2 \times m_3$ fuzzy rules of the form:

R_l : If e is F_e and Δe is $F_{\Delta e}$ and δ is F_δ, then

$$\begin{aligned}\Delta u &= f_l[e, \Delta e, \delta] \\ &= p_l e + q_l \Delta e + r_l \delta + z_l \end{aligned} \tag{9}$$

with $l = 1, 2, \ldots, M$, where m_1, m_2 and m_3 are the numbers of fuzzy set associate with e, Δe and δ, respectively. Thus, the output of the neurofuzzy controller is given by the following relation:

$$\Delta u = \frac{\sum\limits_{l=1}^{M} \alpha_l f_l}{\sum\limits_{l=1}^{M} \alpha_l}, \tag{10}$$

where α_l represents the confidence degree or activation of the rule R_l, and is given by:

$$\alpha_l = \mu_{F_e} \mu_{F_{\Delta e}} \mu_{F_\delta}. \tag{11}$$

In our case and for the Sugeno method, the input variables e, Δe and δ are characterized by neurofuzzy set of Gaussian type defined by the relation:

$$\mu(x) = \exp\left[-0.5(v_i(x - c_i))^2\right], \tag{12}$$

where c_i is the average and v_i is the reverse of the variance. Initially, the problem is to determine the parameters: p_l , q_l, r_l and z_l.

6 Determination by Training of the Parameters Sugeno Regulator

The determination of the parameters of neurofuzzy controller of Sugeno constitutes the most difficult phase in the design, taking into account a significant number of parameters to be determined (parameters of the premises and the consequences).

Methods of training, applied specially in neural networks, are more developed for the approximation of an application input output according to a criterion of training. For our case we use an algorithm of training based on Extended Kalman Filter which is usually used to estimate the neural networks parameters. Let us consider a neurofuzzy controller of Sugeno characterized by a vector of parameters θ. Let data set of input-output be $(x(k), d(k))$. Our objective is to find the vectors θ so that the output of neurofuzzy regulator approachs the best possible desired output $d(k)$, i.e. to have $\Delta u\,[x(k), \theta] = d(k)$. Extended Kalman filter approach consists in linearizing the output Δu at any time around the estimated vector $\widehat{\theta}$. This amounts to writing:

$$\begin{aligned} d(k) &= \Delta u\left[x(k); \widehat{\theta}(k-1)\right] + \Psi^T(k)\left[\theta - \widehat{\theta}(k-1)\right], \\ \Psi(k) &= \frac{\partial \Delta u\,[x(k); \theta]}{\partial \theta} / \widehat{\theta}(k-1). \end{aligned} \tag{13}$$

The well-known form of the relation (13) is:

$$\begin{aligned} \widehat{\theta}(k) &= \widehat{\theta}(k-1) + p(k)\Psi(k)e(k), \\ e(k) &= d(k) - \Delta u\left[x(k); \widehat{\theta}(k-1)\right], \end{aligned} \tag{14}$$

where $p(k)$ is the gain of the algorithm of estimate. In the method of the modified gradient, the gain $p(k)$ is selected as a variable. It is given by the following relation [9]:

$$p(k) = \frac{\alpha_1 I}{\alpha_2 \Psi^T(k)\Psi(k)}; \quad \alpha_1 > 0, \alpha_2 > 0. \tag{15}$$

We notice as well that this method requires the calculation of the gradient $\Psi = \frac{\partial \Delta u}{\partial \theta}$, this gradient is calculated by the method of the retropropagation used in the artificial neural network.

For our case, the vector of the parameters is $\theta = [c \;\; v \;\; p \;\; q \;\; r \;\; z]^T$. Consequently, we have:

$$\frac{\partial \Delta u}{\partial \theta} = \left[\frac{\partial \Delta u}{\partial c} \;\; \frac{\partial \Delta u}{\partial v} \;\; \frac{\partial \Delta u}{\partial p} \;\; \frac{\partial \Delta u}{\partial q} \;\; \frac{\partial \Delta u}{\partial r} \;\; \frac{\partial \Delta u}{\partial z}\right], \tag{16}$$

where

$$\frac{\partial \Delta u}{\Delta c_i} = \frac{v_i^2 (x_i - c_i) \sum\limits_{k \in I} \alpha_k (f_k - \Delta u)}{\sum\limits_{l=1}^{M} \alpha_l}, \tag{17}$$

$$\frac{\partial \Delta u}{\Delta v_i} = \frac{v_i (x_i - c_i)^2 \sum\limits_{k \in I} \alpha_k (f_k - \Delta u)}{\sum\limits_{l=1}^{M} \alpha_l}, \tag{18}$$

$$\frac{\partial \Delta u}{\Delta p_i} = \frac{\alpha_i e}{\sum\limits_{l=1}^{M} \alpha_l}, \quad \frac{\partial \Delta u}{\Delta q_i} = \frac{\alpha_i \Delta e}{\sum\limits_{l=1}^{M} \alpha_l}, \quad \frac{\partial \Delta u}{\Delta r_i} = \frac{\alpha_i \delta}{\sum\limits_{l=1}^{M} \alpha_l}, \tag{19}$$

$$\frac{\partial \Delta u}{\Delta z_i} = \frac{\alpha_i}{\sum\limits_{l=1}^{M} \alpha_l}, \tag{20}$$

with $x_i \in \{e, \Delta e, \delta\}$ and I represents the whole of the indices of the fuzzy rules of which appears the parameter. In our case, the input-output data are obtained by synthesizing a neurofuzzy regulator, while at exploiting the method of Mamdani the linguistic variables of inputs e, Δe, δ and the output variable Δu are described respectively in Figure 4 and Figure 5.

7 Control Algorithm

For the method of Sugeno, the input variables e, Δe, δ are characterized by three fuzzy set Gaussian type:

e: is the input of the electromagnetic torque,

Δe: is the input of the flux,

δ : is the input angles (position) of the stator flux vector.

The fuzzy rules, being used to induce the order for the case of the Sugeno neurofuzzy regulator, are grouped as follows:

if e is NB and Δe is NB and δ is NG, then Δu is f_1;

if e is PB and Δe is PG and δ is PB, then Δu is f_{27}.

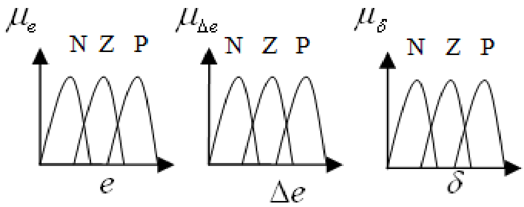

Figure 6: Membership functions of fuzzy input variables.

The training is carried out for the electromagnetic torque control and for speed control. The gains parameters of adaptation are fixed as follows:

$$\alpha_1 = 0.8, \qquad \alpha_2 = 1. \tag{21}$$

Parameters of consequences and premises are gathered in Tables 4 and 5.

8 Simulation Results

In order to test the effectiveness of the training algorithm, we carried out the following sets of control-machines simulation

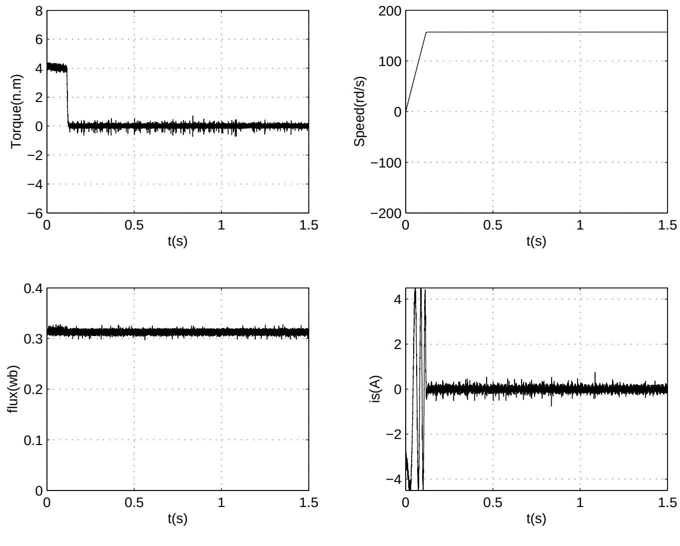

Figure 7: Dynamic behavior of the PMSM controlled by a fuzzy regulator (case of Mamdani).

In Figure 7 we use the following test with Mamdani fuzzy controler:

— No-load start of the process with a reference speed of 157rd/s. We applied load torque of (zero) O N.m. The waveforms obtained in this case show clearly that the revolutions of the machine are followed closely by their references. Both, torque T_{em} and stator current i_s cancel after the transient. And the magnetic flux remains stable by keeping its value with 0.314 Webes.

	p	q	r	z
f_1	-0.001787	$-8.62 * 10^{-5}$	0.0005546	0.0009657
f_2	-0.0001574	$-7.894 * 10^{-6}$	0.0007904	0.0001191
f_3	$-4.157 * 10^{-5}$	$-4.286 * 10^{-6}$	0.002469	$8.91 * 10^{-5}$
f_4	-0.739	-0.05672	0.149	3.921
f_5	0.5889	-0.02495	0.2139	0.3412
f_6	0.01215	-0.009218	0.1277	-0.02831
f_7	-0.4112	0.01933	0.6928	2.881
f_8	-0.215	0.02486	0.268	0.03967
f_9	-0.01169	0.01212	0.1612	0.01257
f_{10}	-0.0001059	$-7.292 * 10^{-6}$	0.0001513	0.000111
f_{11}	$-9.837 * 10^{-6}$	$-1.218 * 10^{-6}$	0.0004298	$3.403 * 10 - 5$
f_{12}	$-6.92 * 10^{-6}$	$-2.245 * 10^{-6}$	0.001392	$5.019 * 10^{-5}$
f_{13}	-0.9648	-0.1822	0.2086	3.159
f_{14}	-0.3653	-0.1021	0.1006	0.9569
f_{15}	0.1277	$9.767 * 10^{-5}$	0.07375	-0.2289
f_{16}	0.1187	-0.03402	-0.03536	0.5158
f_{17}	0.1603	-0.0358	0.003331	0.496
f_{18}	-0.2666	-0.05353	0.03755	-0.0825
f_{19}	$9.041 * 10^{-7}$	$-1.105 * 10^{-8}$	$1.19e - 006$	$4.109 * 10^{-7}$
f_{20}	$1.644 * 10^{-6}$	$-6.729 * 10^{-9}$	$5.699e - 006$	$4.074 * 10^{-7}$
f_{21}	$3.106 * 10^{-7}$	$-7.119e - 009$	$5.613e - 006$	$2.154 * 10^{-7}$
f_{22}	0.406	-0.00212	0.1018	0.1133
f_{23}	0.1034	-0.0006938	0.08979	0.01391
f_{24}	0.02006	$3.082 * 10^{-5}$	0.06282	0.002271
f_{25}	0.2008	-0.000487	-0.05291	0.0424
f_{26}	0.04644	-0.0004289	0.05497	0.001026
f_{27}	0.01833	-0.0001224	0.09209	0.003566

Table 4: The consequences values.

	e		
	NG	Z	PG
c	-2.152	2.403	6.785
v	0.2337	0.2652	0.6746

(a)

	Δe		
	NG	Z	PG
c	-0.1066	-0.01417	0.00829
v	0.00132	0.012	0.01495

(b)

	δ		
	NG	Z	PG
c	-0.2462	14.53	29.76
v	6.608	6.102	6.604

(c)

Table 5: The premises values.

By using the following test with Sugeno neurofuzzy controller in Figure 8:

— We obtain practically the same reponses of Figure 7.

By using the following test with Mamdani fuzzy controller in Figure 9:

— No-load start of the process with a reference speed of 157rd/s. Both, torque T_{em} and stator current i_s cancel after the transient. But from $t = 0.5s$ to $t = 1s$, it applied a nominal load torque of 3.5N.m. The waveforms obtained in this case show clearly by that the revolutions of the machine are followed closely their references.

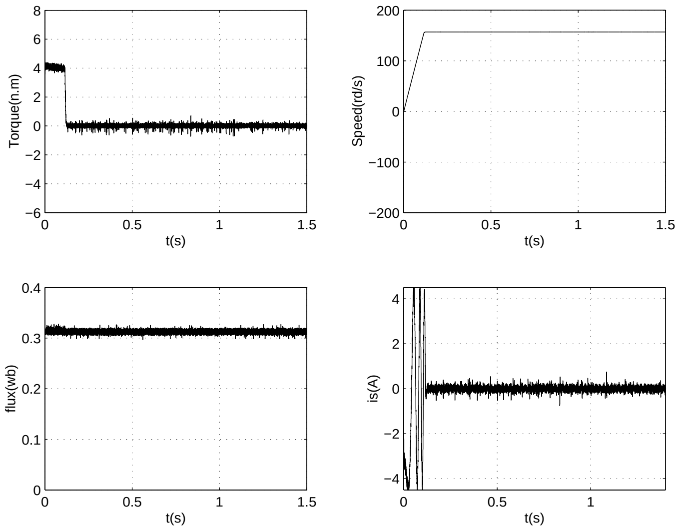

Figure 8: Dynamic behavior of the PMSM controlled by a neurofuzzy regulator (case of Sugeno).

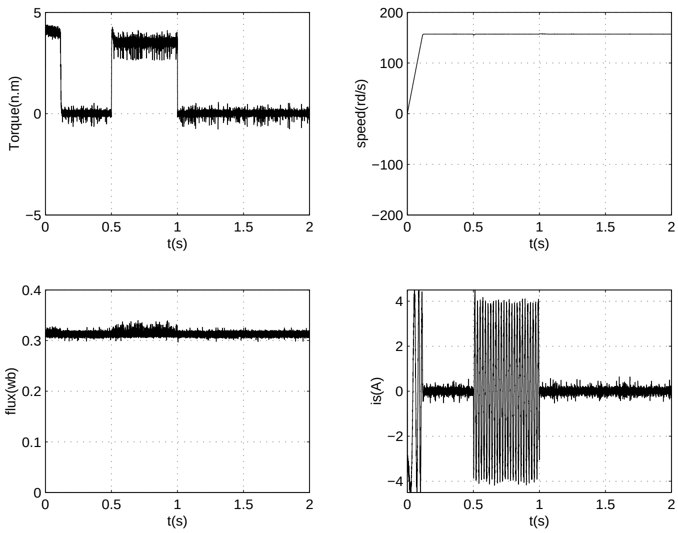

Figure 9: Dynamic behavior of the PMSM controlled by a fuzzy regulator (case of Mamdani).

Each one of torque T_{em}, stator flux and stator current i_s.

By using the following test with Sugeno neurofuzzy controller in Figure 10:

— We obtain practically the same reponses as in Figure 9.

In Figures 11 and 12, we carried out the inversion of direction speed of the PMSM in the two cases (fuzzy and neurofuzzy), with starting the reference of nominal speed of 157rd/s without a load torque at $t = 2s$, it's reversed the reference with -157rd/s.

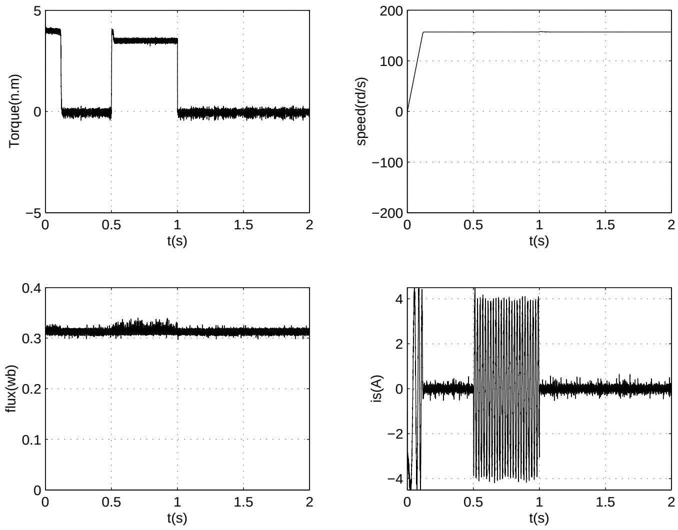

Figure 10: Dynamic behavior of the PMSM controlled by a neurofuzzy regulator (case of Sugeno).

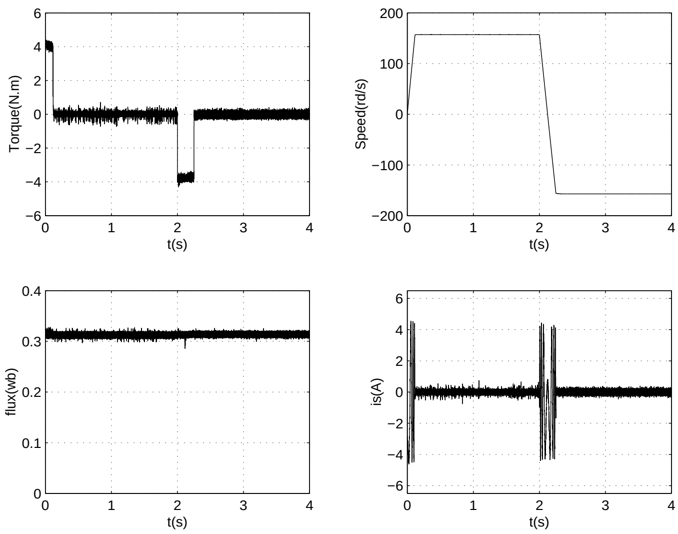

Figure 11: Inversion of direction speed of PMSM controlled by a fuzzy regulator (case of Mamdani).

We notice that the answers on the currents are almost identical too, this shows the effectiveness of the algorithm of training suggested. Learning has been made to keep the same dynamic speed regardless of the dynamics of the electromagnetic torque. Ideally the two results should be identical, but because of the error of learning the results appear different.

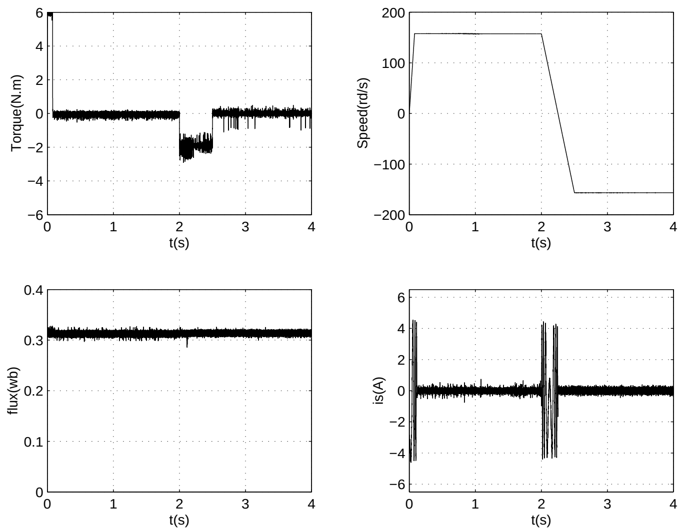

Figure 12: Inversion of direction speed of PMSM controlled by a neurofuzzy regulator (case of Sugeno).

9 Conclusion

In this paper we developed the adjustment of DTC neurofuzzy concept by exploiting the Sugeno methods applied to the PMSM. The DTC strategy is motivated by direct choosing the stators voltage vectors according to the differences between the references of the electromagnetic torque and the stators flux and their reels values calculated and related only on the actual-sizes of the stators. The Sugeno regulator is defined as a polynomial of order one, and the outputs of the regulator depend on its inputs. The Parameters of the premises and the consequences of the neurofuzzy rules of Sugeno are given by re-writing the input-output data obtained by a Mamdani regulator; and the linguistic variables of the inputs, by 3 fuzzy sets. e, Δe and δ are described by 5, 3 and 12 fuzzy sets, respectively. The re-writing concept is obtained by the training while using the extended Kalman filter shows better performance than Mamdani, and got a reduced algorithm tasks. The defuzzification time is less for Sugeno regulator, which is designed only with three membership functions.

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