ON THE DESIGN OF A NEURO-FUZZY CONTROLLER FOR THE VECTOR CONTROL STRATEGY. DATA PREPARING.

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Abstract – The paper deals with the synthesis of a neuro-fuzzy velocity controller for a vector control based structure associated with an asynchronous motor. The solution is found by input – output data generated from a model based on standard field oriented control. The conditions for having an appropriate such model are mainly presented in the paper, the right tuning of the initial model being a guarantee for good training data set. Different training conditions are taken into account. Some special operation conditions of the system, like a smooth motion for a transportation system, are considered too.

Keywords: neuro-fuzzy controller, vector control, asynchronous motor.

1. INTRODUCTION

The fuzzy logic controllers (FLC) and the artificial neural networks (ANN) represent now in electrical drives control much more than some exotic tools. Such an approach might concern both the process / plant, the motor, the power supply and the controllers or the whole system, including the interaction with the line. Many papers are dedicated to the applications of one or more of the artificial intelligence tools in the field of electrical drives with induction motor (IM) and associated power electronics - [2]. Some books and papers are oriented especially on applications - [2], [8] - the last one being dedicated to the robotics, drives / motion control. It seems that using FLC for the control of asynchronous motors is a not very new idea - [20]. But the variety of approaches is very big. [1] proposes a fuzzy controller for the speed control for an IM with constant flux. Some researches concern the modeling / identification of the system (complex, non-linear) by neural networks or using ANN for the asynchronous motor speed estimation in order to improve existing control strategies. Others try to find solutions by neuro-fuzzy models for detecting faults in the IM. Fewer papers are allowed for a vector control (FOC-Field Oriented Control) including FLC. However, some books and papers give more or less detailed guidelines for the IM and FOC: [5], [6], [10], [22]. Although stated as a high quality strategy for the IM control (one of the best, anyway - [12]), there are some important drawbacks related to the parameters sensitivity. The effort paid to overcome this problem is very important. In that meaning, [21] is a proof for how complex is any method trying to suppress the stator resistance sensitivity. Tuning for an optimized FOC by on-line procedures is a very challenging task, involving several difficulties and complex methods -[14]. [13] gives an ANN - based solution for the adaptive control for an induction servodrive. [4] proposes an ANN solution for the digital current regulation of inverter drives. [9] makes a study for a fuzzy supervisor for an optimal FOC in term of the best flux estimation. In [24], beside a modeling of induction motor using feed-forward neural networks (usable mainly in speed-sensorless estimation), a brief list of research directions and results is inserted. One of the most representative references in the field, especially in terms of a wide range of results using the Artificial Neural Network (ANN) for the induction motor control, is [25].

The author proved by some previous results - [15], [16], [17] that a well tuned fuzzy loop is able to compete and outrun the standard digital algorithms for DC servodrive and for the IM systems lead by FOC strategy. In some applications, an off-line preprocessing associated with FLC is justified by a high quality of the results; however, the top advantage of the fuzzy logic - its simplicity - is diminished. Another way is to use only input-output data. Then, a FLC design method is based on the training of an ANN. After some promising results in substituting the conventional speed controller in a FOC structure for the IM, the aim of the paper is to analyze now the abilities of the FOC - FLC - ANN control part to offer good or high quality solutions for a high demanding application in terms of torque and current ripple, fast transient response, smooth motion, limitation of the overcurrent. The results are compared with those associated with standard control algorithms. Not only that this kind of classical controllers (and their loops) are not robust, but their tuning (although stated as well settled) seems to be very difficult in complex conditions. [23] concerns a PID control robustness and shows some recent efforts, ideas and methods, revealing how difficult such a task is.

An initial standard vector control structure (rotor flux variant) was considered - [7], [9], [10]. In a previous work - [17], [19], the author performed the synthesis

of a neuro-fuzzy (N-F) speed controller. Unlike other studies and solution that implement a Mamdani controller, this one is a Sugeno type. Some basic elements concerning this stage will be briefly mentioned below. Then, the overall behavior of the system will be analyzed comparatively with the standard PI speed controller, for some new operating conditions: ramp type for the speed input signal, impulse torque perturbation, no shock speed references, simultaneously application of various conditions for the motor parameters deviations, the load torque, the speed reversal and the sampling period value.

2. THE INITIAL CONTROL STRUCTURE WITH MOTORS, MODELS AND ASSOCIATED VELOCITY LOOP PARAMETERS.

Obtaining a large amount of training data in various operating conditions from an experimental platform could mean a very hard work, a lot of wasted energy and time. Besides, some modifications for motor or system parameters are not possible in a controllable manner without a big cost. It is much more convenient to use a computer model and simulations. For having appropriate input-output data (for a good expected neuro-fuzzy controller), the first step is to make a good tuning of the initial FOC system. The current controllers by hysteresis are still kept for their simplicity (only one tuning parameter) and because such blocks are able to generate directly the control pulses for the inverter.

Fig. 1 gives the image of the initial model of the electrical drive system based on a FOC strategy. Some additional elements were added in order to perform the data acquisition for the training of the neural net involved in the fuzzy speed controller synthesis. The FOC block contains coordinates transformations, flux computation etc. The speed error and (electromagnetic) torque reference values (thousands data) provided by the PI speed controller are stored for the neuro-fuzzy controller synthesis.

By several tests, a single training set for all operating condition was, fortunately, found, corresponding to a reversal speed diagram. It is, indeed, a well suited training, the obtained neuro-fuzzy controller being able to ensure good performance even in operation conditions quite different from those of the training step. The study was made for several IM, accordingly to the power of the target applications, verifying by that too the ability of the solution to be valid for a quite large motor parameters range. Fig. 2 presents the considered IM data. Besides the standard and well-known notations, F means the friction factor.

2.1. The tuning of the initial model.

For the tuning of the initial FOC structure, the velocity loop is simplified in an equivalent form as in the fig. 3. From the motion equation, with a PI controller ($k_{p\omega}$ and $T_{i\omega}$ as tuning parameters), the next relations are derived:

$$\Omega = \frac{1}{J_{s+f}} \times (T - T_{load})$$
 (1)

$$\Omega = \frac{1}{J_{s+f}} \times \left(k_{p\omega} + \frac{1}{sT_{i\omega}} \right) \times (\Omega^* - \Omega) - \frac{1}{J_{s+f}} \times T_L$$
(2)

After some calculus, identifying the results with the standard form, the next algebraic system is obtained:

$$G(s) = \frac{1}{1 + \frac{2\xi}{\omega_{n}}s + \frac{s^{2}}{\omega_{n}^{2}}}$$
(3)
$$J \times T_{i\omega} = \frac{1}{\omega_{n}^{2}}$$
(4)
$$\frac{2\xi}{\omega_{n}^{2}} = (k_{p\omega} + f) \times T_{i\omega}$$



Fig. 1. The FOC structure used to perform the neural network training.

From $\xi \leftrightarrow \omega_n t_{resp}$ (t_{resp} is the response speed time of the system) – see the table 1 – [3], is considered an unit damping factor, so:

٤	$\omega_n t_{resp}$
0.4	7.7
0.5	5.3
0.6	5.2
0.7	3
1	4.75

Table 1. The response damping.

 $\omega_n t_{resp 5\%} \approx 4.75$ gives the tuning parameters:

$$\begin{cases} k_{p\omega} = J \times \frac{9.5}{t_{resp}} - f \\ T_{i\omega} = \frac{1}{J} \times \left(\frac{t_{resp}}{4.75}\right)^2 \end{cases}$$
(5)

2.2. The velocity reference block.

The first experiment used input-output data acquired from a system activated by a step function for the reference speed. The results were not able to ensure a good behavior in other different operation conditions. One of the best choices was a reversal speed diagram, as in the fig. 4. The mechanical shock limitation is an essential request for the transportation systems. In such applications, the training stage for the ANN involves other speed profiles. Fig. 5 gives some images for a generator model based on a trapezoidal diagram for the acceleration. In fig. 5a, the space is scaled for having an intelligible image when different kinematical variables have very different values range. Several results certifying a good tuning of the FOC structure are depicted in the fig. 6. The fig. 6.a is for M1 at ¹/₂ of its rated load torque for a velocity reference diagram without mechanical shock. The speed follows closely the reference. A similar (very good) behavior is shown by fig. 6.b for M2, where the electromagnetic torque ripple is much more reduced. Fig. 6.c is for M3 having no load, activated by a step velocity reference. After an acceptable transient regime (small overshoot), the steady state speed value is reached. A detailed (zoomed) view of the initial starting time - fig. 6.d, reveals another aspect certifying the quality of the control system: it can be seen a small reversal time just after the starting. Indeed, from the movement mechanical equation, there is an initial negative derivative:

$$\frac{d\omega}{dt}\Big|_{t = 0 +} = \frac{T_{\text{mot.}}^{(0) - T_{\text{load}}^{(0)}}}{J} = -\frac{T_{\text{load}}}{J} < 0 \quad (6)$$

	P_N	2.2	kW
	U_N	380	V
	f_N	50	Hz
	n_o	1500	r/min
	T_N	15	Nm
	R_s	0.435	ß
$\mathbf{M1}$	R',	0.816	Ω
	L_m	69.31x10 ⁻³	Н
	Ls	2 x10 ⁻³	Н
	L,	2 x10 ⁻³	Н
	J	0.089	kgm²
	F	0.005	Nms
	р	2	

	P_N	7.5	kW
	U_N	380	V
	ſN	50	Hz
	no	1500	r/min
	T_N	50	Nm
	R_s	0.63	Ω
M2	R',	0.4	ß
	L_m	9.1x10 ⁻³	Н
	Ls	9.7 x10 ⁻³	Η
	L,	9.1 x10 ⁻³	Н
	J	0.22	kgm²
	F	0.001	Nms
	n	2	

	P_n	37.3	kW
	U_n	460	V
	f_n	60	Hz
	Ω_0	1800	r/min
	Γ_n	200	Nm
	R_s	0.087	Ω
M3	R'_r	0.228	Ω
	L_m	34.7x10 ⁻³	Н
	L_s	$0.8 \text{ x} 10^{-3}$	Н
	L_r	0.8 x10 ⁻³	Н
	J	1.662	kgm²
	F	0.1	Nms
	n	2	

Fig. 2 The involved IM data.



Fig. 3. For the speed controller tuning.



Fig. 4. A first successful velocity reference.

The fig. 6.e proves that a bad tuning of the loop could not only lead to the lost of the performance but the control system is more useful. The fig. 6.f concerns a variant with speed dependent torque and the fig. 6.g gives a zoomed image during the steady-state regime. All this parts underlines the importance of having a very good source (model, control structure) for the in-out data necessary to the design of the neuro fuzzy controller. Also, a deep understanding of the system nature and functionality is advisable.

3. IN – OUT DATA FOR ANN TRAINING.

The "sampl training_1" block from fig. 1 makes the In–Out data acquisition for the initial (a PI) speed controller. Usually, the samplers are settled to a few ms; for most part of the scenarios, the number of data couples is several thousand. In fig. 7 are such data:

- a. step velocity reference the controller is most of the time saturated, so the expectations for good results are not very high;
- b. reversal speed reference, with more sensitive controller output, so predictable good results;
- c. speed reference diagram without mechanical shock (for a smooth motion), whit no saturation intervals.
- d. In-Out data from the FLC designed by training an ANN with data from b; the lack of any saturation interval make confidence in this controller.



Fig. 5a. The symetrical reduced shock kinematic.



Fig. 5b. The asymetrical reduced shock kinematic.

4. CONCLUSIONS

The paper made an analysis of an already successful electrical drive system (based on a vector control) with the intention to generate the best data for designing a neuro - fuzzy controller for the speed loop. Although the work could seem quite simple (training a neural network and then using the synthesized fuzzy controller in different operation modes), many problems arise for the controller and for the system. A first one concerns the choice for the training conditions as an essential factor for the robustness of the system. The author found an unique training set, able to deliver a good controller for different variants concerning the system parameters, perturbations, operating quadrants, input references and sampling time. Some very special (and difficult to analyze) aspects for the conventional approach – like the magnetic saturation of the motor, special design details and others, are no more significant for the neuro-fuzzy approach. Passing from two tuning parameters of a PI controller to multi-parameters tuning of a fuzzy controller (mainly by changing the fuzzy sets into infinite possibilities) is an interesting and big challenge. The new controller will be presented in a subsequent paper, as well as the tuning of the new structure, the results and some comparisons with the initial results set of the conventional control.

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Fig. 6. Some results for the initial FOC model.

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Fig. 7. Some bad (a), good (b, c) training data and the In / Out variables of the synthesized FLC (d).