Neuro-fuzzy DTC for an Electrical Drive System with Induction Motor. A SISO controller for the velocity loop.

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Abstract - **The paper presents some design aspects concerning the implementation of a neuro-fuzzy controller for the velocity loop of an electrical drive system with induction motor and a Direct Torque Control strategy. The approach is made comparatively with a similar control structure based on Field Oriented Control. The included results prove that even a quite simple structure for the fuzzy controller (Single Input - Single Output) is able to ensure a good global behavior of the system. Different parameters and operation conditions are analyzed in term of the gains for a fuzzy - continuous controller embedded into a control strategy having a quasi-discrete character by the choice of the vector control from a finite sectors number. The design of the fuzzy controller is performed by training a neural network by means of the ANFIS algorithm. Several aspects concerning the most relevant reference speed profile, the input – output acquisition data for the training, the neural network as well as the parameters associated with the training process are considered. A possible better approach, considering the speed error variation as the second input for the fuzzy controller does not necessarily improve the quality of the results when the same design procedure is put into operation.**

Keywords - *neuro-fuzzy design, DTC, electrical drive, induction motor*

I. INTRODUCTION

The best control strategies for the electrical drive systems, Field Oriented Control (FOC) and Direct Torque Control (DTC) brought high performance qualities for such systems, although each of them has some drawbacks. It is important to make a right option between these control strategies, upon the operation conditions – [5], [11] and [21].

During the last decades, many researchers focused their studies on the application of the artificial intelligence into the classic and modern control strategies. Most research works have been made for embedding fuzzy logic, artificial neural networks and genetic algorithms in different conditions and combinations. One of the most successful tools in that meaning became the neuro-fuzzy control – [8] and the paper goal is to design a fuzzy controller by training artificial neural networks.

The author obtained very good results in designing neuro-fuzzy controllers for the electrical drive systems based on the FOC strategy. A full process of the design for neuro-fuzzy controllers (both for the velocity and the current loops) is made in [12] and [13] and many aspects or methods are very inspiring for other application condition too.

The most interesting part of these studies is related to the substitution of the hysteresis current controllers, operating in a commutation manner, with fuzzy controllers, based on a continuous logic. But the design flow is not a direct one (application of the ANFIS algorithm and that's all) but several design procedures could lead to a useful controller.

Many other authors have contributions on this subject. A Mamdani neuro-fuzzy controller (three inputs: torque error, flux error and sector information, one output: the switching state) brings as main benefit a significantly reduced torque and flux ripple – [23].

An interesting approach is made by [6]. The flux and torque estimators in the conventional DTC system are replaced by fuzzy controllers and the Adaptive Neuro-Fuzzy Inference System (ANFIS) controller replaces the conventional fixed switching table pattern. Two fuzzy controllers are used to replace three level torque comparator and two level flux comparator in the conventional system. In the fuzzy torque comparator, the inputs are estimated torque value and reference torque values. The inputs for the flux comparators are reference flux values and estimated flux values from the torque and flux estimators. The third controller is a neuro-fuzzy one (ANFIS controller) having as inputs the torque error, flux error and stator flux linkage angle. The output of the ANFIS controller selects the appropriate switching configurations. This last controller eliminates the need of lookup table for selecting the switching states. Unfortunately, this complex control architecture is intended only for matrix converters and the authors present their ideas and a few results without a real design study for the intelligent controllers.

A SISO neuro-fuzzy controller replaces in [19] a classical PI speed controller and the main benefit revealed by the simulation results is a much lower overshoot. The lack of considerations about the design of the neuro-fuzzy controller makes, however the study less inspiring.

Improving the efficiency of the DTC strategy for light loads of the induction machine is made in [17] by an optimized flux controller that uses a neuro-fuzzy filtering to stator current estimation. A neuro-fuzzy noise cancellation algorithm (based on ANFIS method) is proposed to optimize the process to achieve fast dynamics and good steady state response.

In order to diminish some well-known disadvantages of the standard DTC strategy (like current and torque distortion caused by sector changes, start and low speed operation problems, high sampling frequency involved for digital implementation of hysteresis comparators), a Direct Torque Neuro Fuzzy Control scheme (DTNFC) has been proposed - [7].

A controller based on an adaptive NF inference system together with a space voltage modulator replaces the hysteresis comparators and the switching table.

A variable gain PI controller is used by [14] to replace the classical PI controller in the speed control of a modified direct torque neuro-fuzzy controlled induction machine drive where the ANFIS of the DTNFC acts on both the amplitude and the angle of space vector components.

The classical DTC-SVM (space vector modulation) flux and torque regulators are replaced in [3] by two SISO (Single Input – single output) fuzzy logic regulators; the outputs of flux and torque fuzzy logic regulators are used to produce the control signals for the SPWM voltage inverter. The authors state a good smooth circular trajectory of stator flux locus by that method.

The optimal selection of voltage space vectors is achieved by [22] using GA (genetic algorithm) based neural network. A genetic algorithm is used to determine the weights and threshold values for the neural network.

Paper [1] proposed a so-called self-tuned direct torque neuro-fuzzy controller (DTNFC) for a voltage source inverter fed induction motor, with an ANFIS logic controller having three variable input: the stator flux error, the electromagnetic torque error and angle of flux stator; the output is the voltage space vector. The neuro-fuzzy controller provides a lower ripple for both torque and flux. The authors make interesting consideration about the training procedures: it seems that a bigger data collection does not lead to better results!

An artificial neural network is applied in switching select voltage vector, keeping a PID speed controller – [20]. Two approaches to a controller design are presented and compared in [25]. Both of them are based o the assumption that control loop can be considered as quasi-continuous (fast sampling). The first method is based on simple symmetric criterion, the second one uses root locus technique.

Because of hysteresis control adopted in DTC, there is no difference in control action between a larger torque error and a small one, [24] suggests an improved approach by dividing the torque error into different intervals and give different control voltages for each of them. To deal with this issue an extra fuzzy controller has been introduced.

II. THE BASIC SYSTEM

Fig. 1 remembers the main elements of the DTC strategy. A simple vector model of the induction machine suggests the principle of the DTC strategy operation:

- it is possible to control the vector Φ_s by the vector V_s (RI_s almost null);
- Φ_r follows the variations of Φ_s with a time delay given by σT_r;
- controlling Φ_s in module and in phase by V_s, it is possible to control the amplitude and relative position of Φ_r, so the torque too.

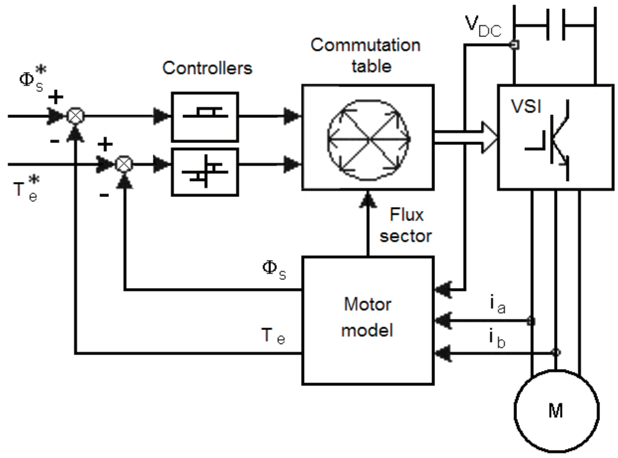


Fig. 1. The essential DTC structure.

$$\overline{V}s = R_s \cdot \overline{I}s + \frac{d\overline{\Phi}s}{dt}$$

$$\overline{V}r = 0 = R_r \cdot \overline{I}r + \frac{d\overline{\Phi}r}{dt} - j\omega\overline{\Phi}r$$

$$\frac{d\overline{\Phi}r}{dt} = \left(\frac{1}{\sigma \cdot T_r} - j\omega\right) \cdot \Phi_r = \frac{L_m}{L_s} \cdot \frac{1}{\sigma \cdot T_r} \cdot \overline{\Phi}s \quad (1)$$

$$t_e = \frac{3}{2} p \cdot \frac{L_m}{\sigma \cdot L_s \cdot L_r} \cdot \left|\overline{\Phi_s}\right| \cdot \left|\overline{\Phi_r}\right| \cdot \sin\gamma_\Phi$$

A functional system with induction motor and inverter must extend the basic architecture from fig. 1 with several elements (external and internal) - fig. 2. A compact image of a Matlab / Simulink model, with the associated In – Out variables is given by fig. 3.

Several motors, in a wide range of power (parameters) were considered for standard FOC and DTC models, insipired by [2]. The data for these machines are given by the next table.

TABLE I. MOTOR DATA

Param.	M1	M2	M3	M4	Units
PN	2.2	7.5	37.3	149.2	kW
UN	380	380	460	460	V
fN	50	50	60	60	Hz
n0	1500	1500	1800	1800	RPM
TN	15	50	200	820	Nm
Rs	0.435	0.63	0.087	14.8×10^{-3}	Ω
R'r	0.816	0.4	0.228	9.3×10^{-3}	Ω
Lm	69.3×10^{-3}	9.1×10^{-3}	34.7×10^{-3}	10.4×10^{-3}	H
Ls	2×10^{-3}	9.7×10^{-3}	0.8×10^{-3}	0.3×10^{-3}	H
Lr	2×10^{-3}	9.1×10^{-3}	0.8×10^{-3}	0.3×10^{-3}	H
J	0.089	0.22	1.662	3.1	Kgm^2
F	0.005	0.001	0.1	0.08	Nms
p	2	2	2	2	

The PI speed controller is pre and post-accompanied by several processing blocks (samplers, saturation, comparison) like in fig. 4. The input and output data is stored during the simulation by means of the blocks inpi080512 and outpi080512.

A good basic model of the system is confirmed by many simulations, in different operating conditions (load, speed profile and parameters variation

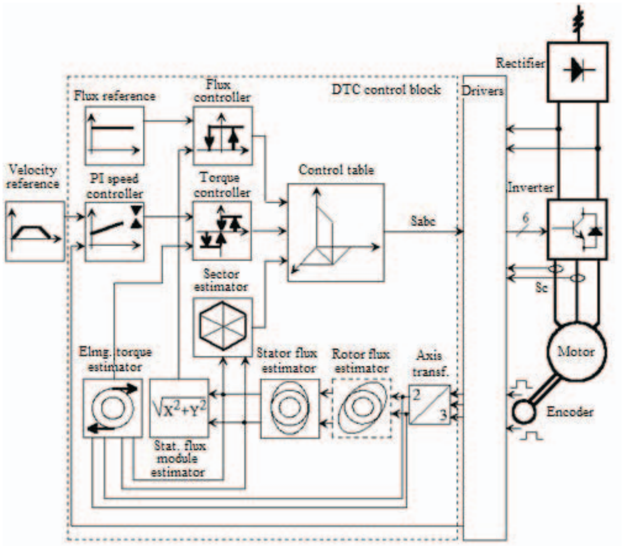


Fig. 2. The additional elements for a functional DTC based system with induction motor.

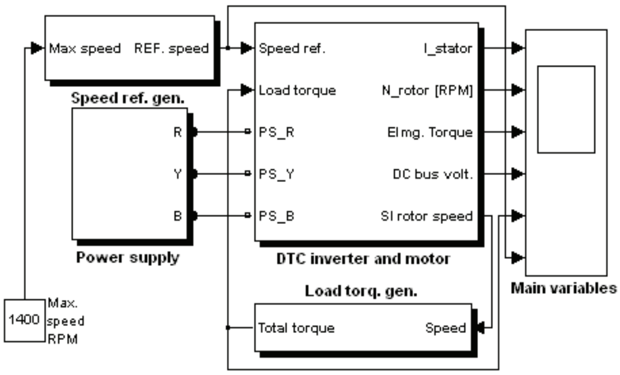


Fig. 3. A black box image of the system, revealing the main variables.

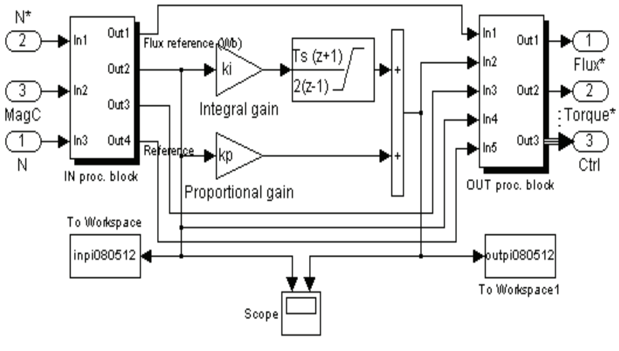
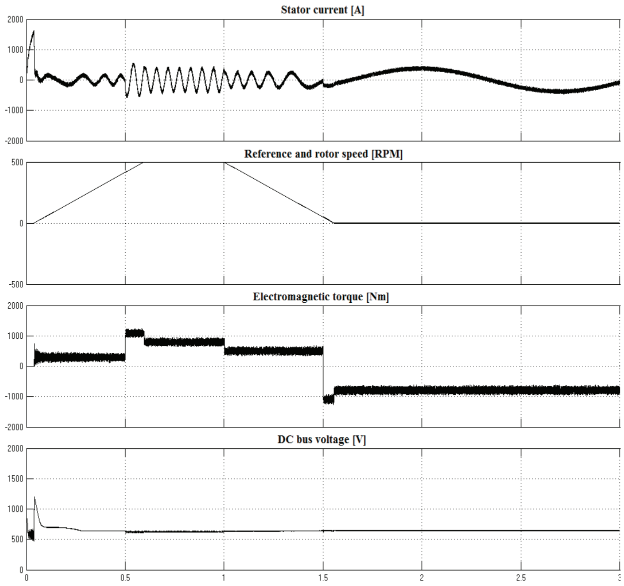
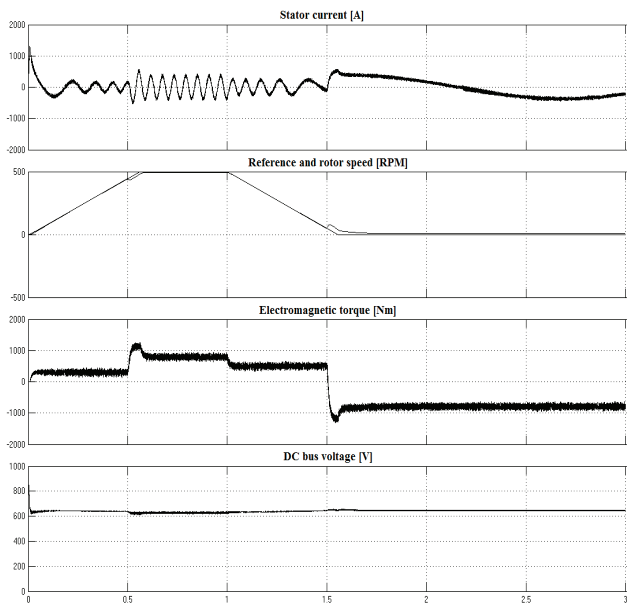


Fig. 4. The initial standard PI controller for the speed loop.

In this respect, a comparative study FOC vs. DTC was made in order to anticipate the sensitivity or the robustess of the target system to different conditions analyzed already for the FOC variant – [12], [13]. Fig. 5 and 6 reveal a good basic behavior of the DTC strategy, both for the standard / initial conditions (for which the loops were tuned). In fig. 5, the initial electromagnetic stress is diminished for the main variables of the system with DTC (current, DC voltage), the torque ripple is quite similar and the dynamic response is much faster for the FOC strategy. The load torque is piecewise constant. Fig. 6 presents the effect of the parameters modification (resistance bigger with 25 %, inertia increased by 35 %), with a load torque having an extra component depending on the speed and, finally, with a sampling period increased from 20 μs to 200 μs.



FOC - initial



DTC - initial

Fig. 5. The behavior of the system with FOC and DTC control – initial operating conditions.

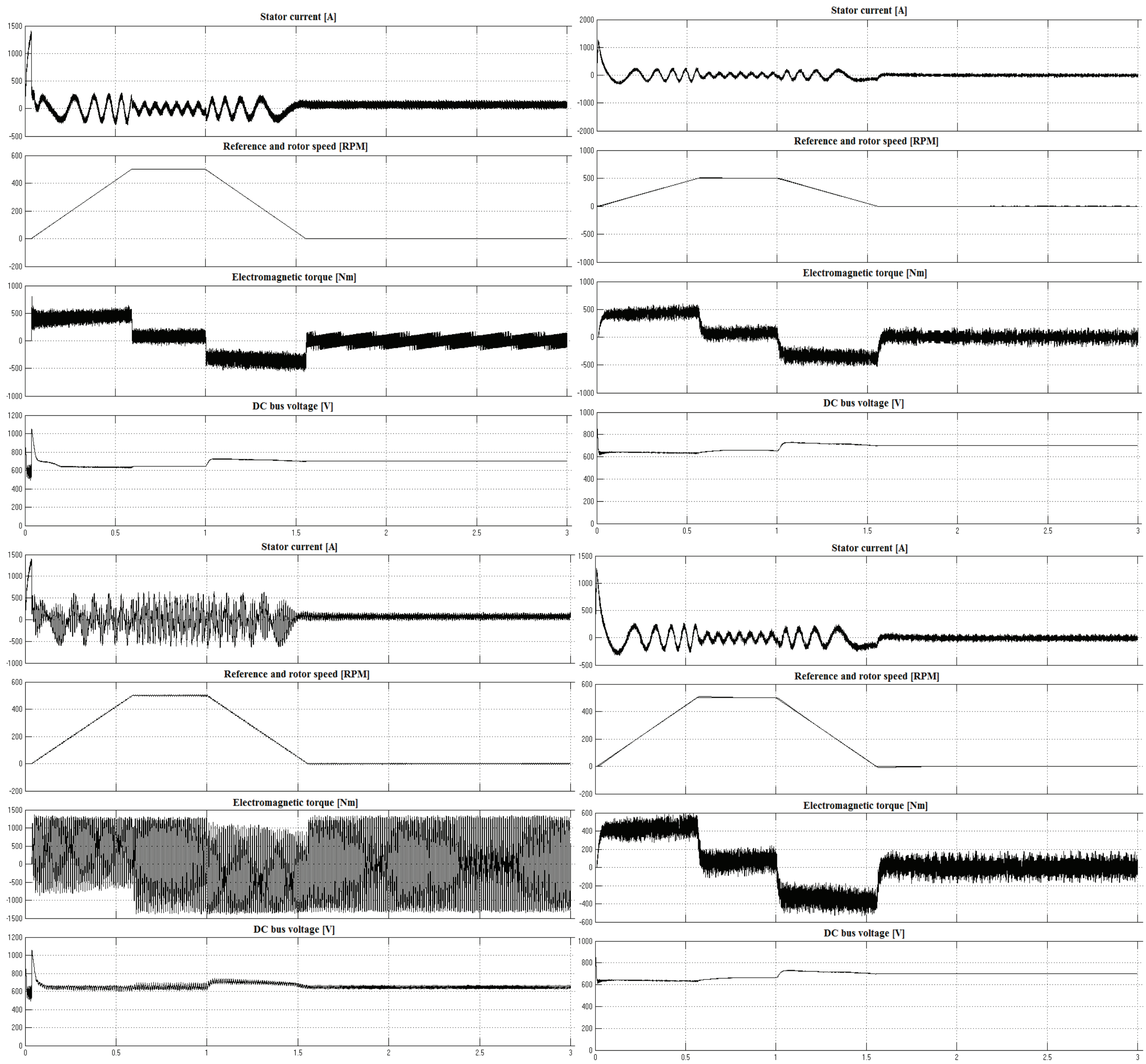


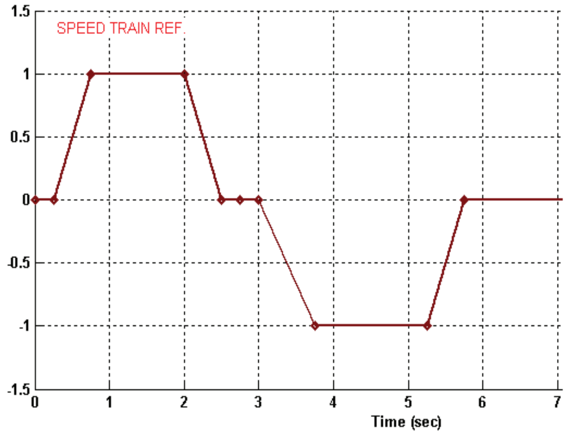
Fig. 6 FOC - left vs. DTC – right: the system having several modifies parameters – up; with a greater sampling period – down.

Now, it is more obvious a better bahavior of the system with a DTC solution, especially in terms of a very good robustness for the sampling period. This quality is essential for the real-time implementation, when the on-line processing conditions are quite far from those simulated on a model. More, the author proved that this remarqable property is specific for the fuzzy control. For the classic algorithms, even a slight modification of the sampling period could worse the systems' performance, even taking it to instability. This part of the study proves the ability of the DTC stategy to drive the system in similar conditions like FOC strategy. More, if inside a FOC structure, a neuro-fuzzy controller brought clear benefits and if a system with DTC has an initial robustness against the sampling period (a wonderful feature of the fuzzy control), some certain assumptions can be foreseen for combining these two control strategies : DTC and fuzzy logic.

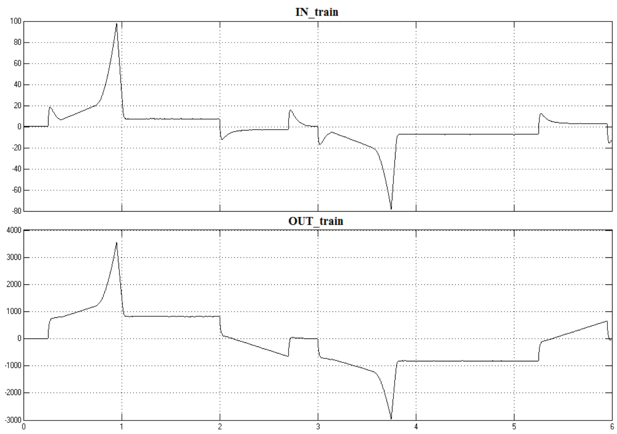
III. Fuzzy Controller Design

The best data provider for the synthesis of a fuzzy controller by means of ANFIS method was found to be a system operating symmetrically, in term of the reference speed diagram and of the load torque – [12]. Fig. 7 presents the speed reference (a), the IN – OUT data acquired from the initial PI controller (b) and (c) – these last diagrams intend to prove the absence of an apparent angular point in the diagram – a sudden change of a variable or of its derivate could lead to bad properties of the trainer network. Many training scenarios have been put into operations, with several different conditions:

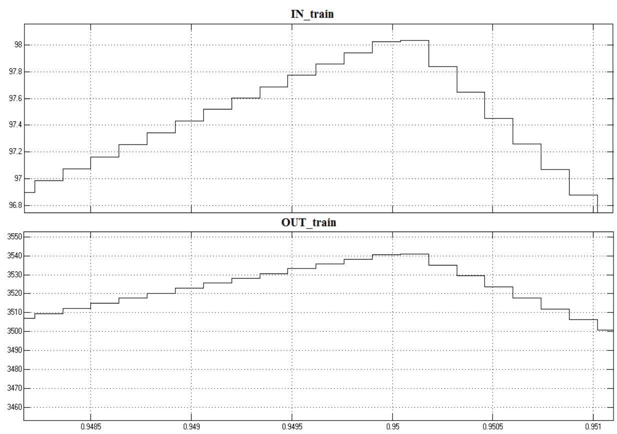
- the reference cycle and the motor load type (very important);
- the number of pair training data (quite impor
- the number of the fuzzy sets and their variation type (not very important);
- the number of the training epochs (less important);
- the fuzzy operator type (less important).



a.



b.



c.

Fig. 7. The speed reference and the IN – OUT data for the FIS

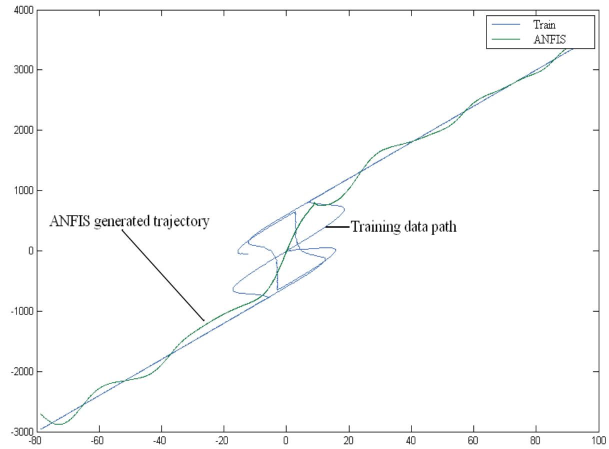
It can be seen that the number of the freedom degrees is enormous, so the design experience is important but does not suppress the necessity of many tests. The description conditions for the ANFIS method are:

- 7 fuzzy sets, Gauss bell type;
- 100 training epochs;
- Sugeno inference;
- 42858 training data pairs;
- AND, OR operators

ANFIS info:

Number of nodes: 32
Number of linear parameters: 14
Number of nonlinear parameters: 21
Total number of parameters: 35
Number of training data pairs: 42858
Number of checking data pairs: 0
Number of fuzzy rules: 7

Some presumptions of data quality and of a good training process are provided by partial results like from fig. 8. It can be seen a right tracking of the system trajectory in the steady state regime and a good averaging for the dynamic zones. The generated IN – OUT data are very closed for the same operating conditions like the original system (see fig. 7b) and keep the essential character for different conditions (the last diagram)



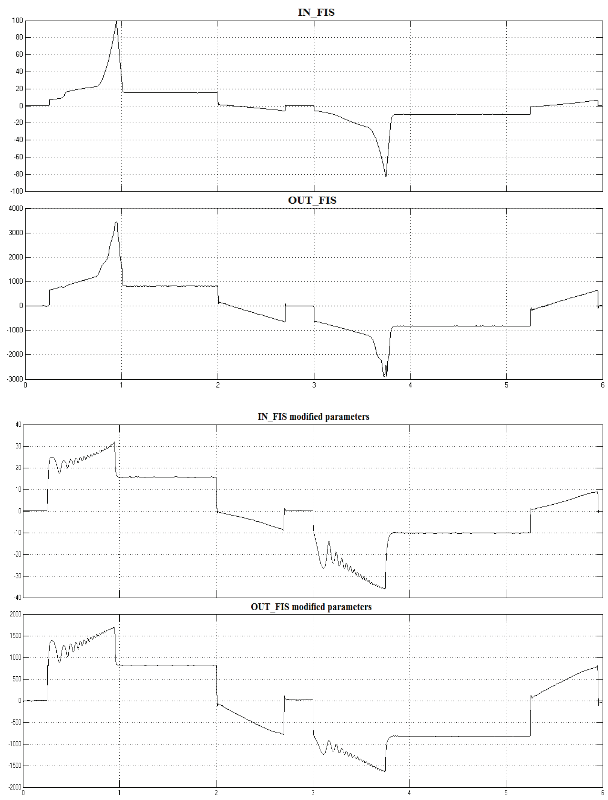


Fig. 8. The IN – OUT evaluation of the training artificial neural network.

The whole description of the fuzzy inference system (FIS) that generates the fuzzy controller is depicted in fig. 9. A post synthesis tuning is possible but the author experienced it only for good reasons and with a lot of care – [12], [13]. The critical conditions concerns the beginning of the regime, the commutation / angular point and the false features due to strong local variation (especially for the variation error where applicable). The big difficulty in sustaining a solution based on fuzzy control is, always, the lack of an analytical tool. Only many tests could prove the desired qualities.

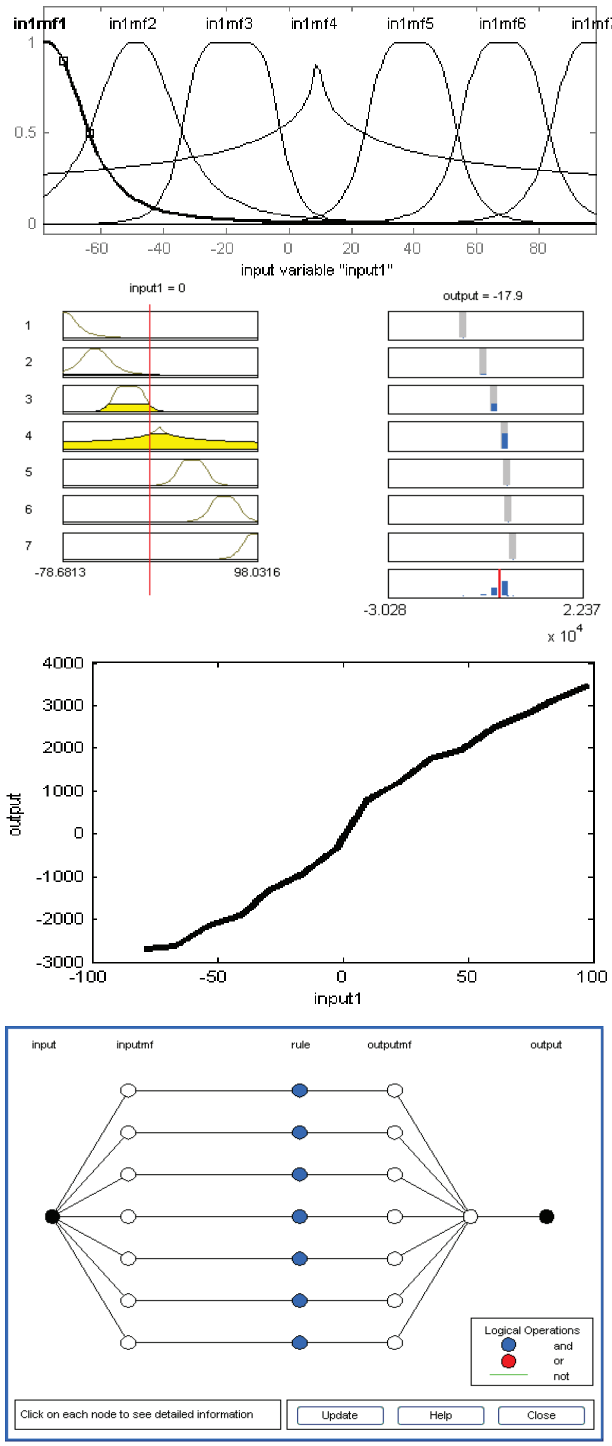


Fig. 9. The main graphical characteristics of the FIS.

IV. THE SYSTEM WITH NEURO-FUZZY SPEED CONTROLLER

For a load torque with the components illustrated by fig. 10, the fuzzy logic controller designed previously was inserted into the control structure – fig. 11. Functioning of the system was first tested in initial conditions (training). It can be seen in fig. 12a and b a very similar behavior for the basic DTC system and the neuro-fuzzy DTC variant; only a slight change in the DC bus voltage diagram makes the difference. That proves the quality of the training process. When the parameters changes (fig. 12c. and d. – the values mentioned in II section), both variants exhibit good results; however, the neuro-fuzzy controller is able to follow more closely the reference speed. Only a zoomed image of the results allows the assessment of performance indicators (steady state speed error under 1.33 %, a response delay of the speed diagram of 0.1 s).

Fig. 13 illustrates the evolution of the main variables for a different speed reference and the application of a step variation to the load torque during the steady state regime. The neuro-fuzzy speed controller is able to drive the loop but the output speed diagram feels, normally, the inertial effects, integrating set-point steps. Other scenarios proved also the validity of a SISO solution for the neuro-fuzzy speed controller. The tests for a more complex variant, considering also the speed error variation were less successful. A possible explanation is that two discrete / derivative aspects are combined: the first concern the error variation (with many design consequences on the ANFIS algorithm – [12], [13]) and the second comes from the principle of the discrete selection of the binary control sequence of the DTC strategy.

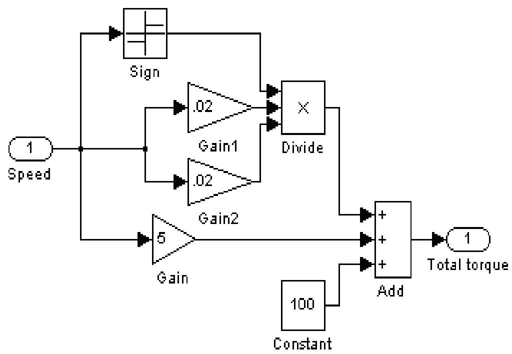


Fig. 10. The load torque generator.

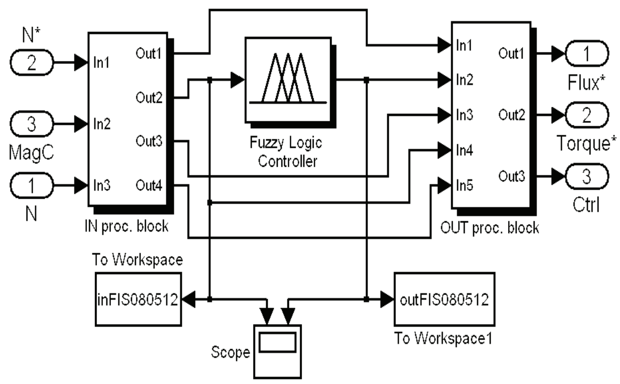


Fig. 11. The neuro-fuzzy speed controller.

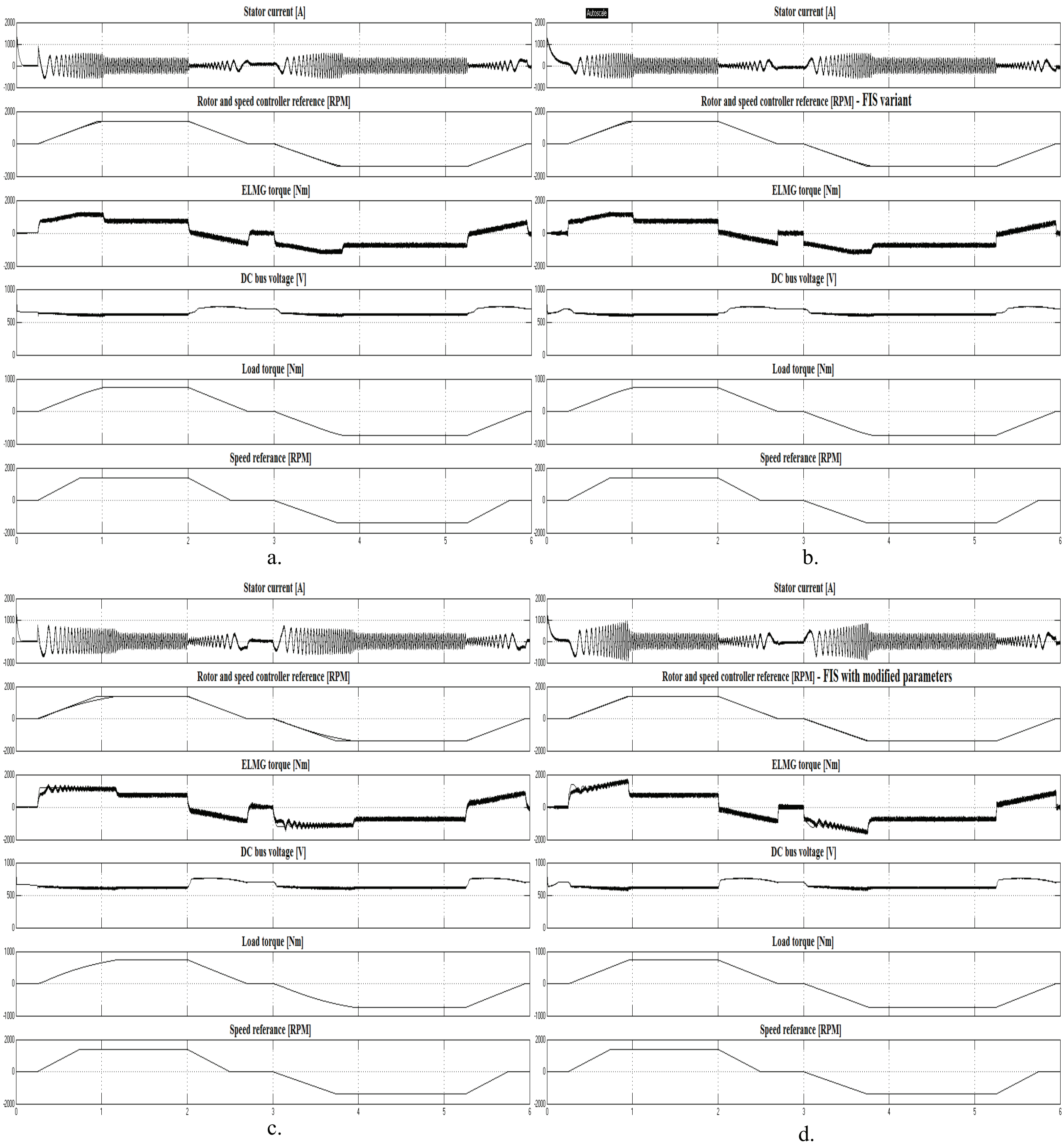


Fig.12. The main variables of the system for DTC (left) and neuro-fuzzy DTC (right): initial training condition (up) and several modified parameters (down).

V. Conclusions

The DTC strategy could be assumed being inappropriate for embedding a continuous (fuzzy) logic because its principle of changing suddenly from time to time the binary configuration of the state for the power devices. The study proves that artificial neural networks generalization and ability is able to generate valuable fuzzy controllers for the speed even in a SISO configuration. Compared with FOC strategy, for which the author has obtained very good results in a wide variety of conditions, it seems that this version only ensure a safe operation. Should be noted also that the improvement brought by the fuzzy controller to the DTC system is not as spectacular as for the FOC version, possibly due to a higher initial DTC robustness to parametric variations. However, different test conditions (motors, parameters, load and reference type and also large variations of the sampling period), are likely to encourage further studies and implementation in real-time. The IN-OUT data set it is very important the for the artificial neural network training.

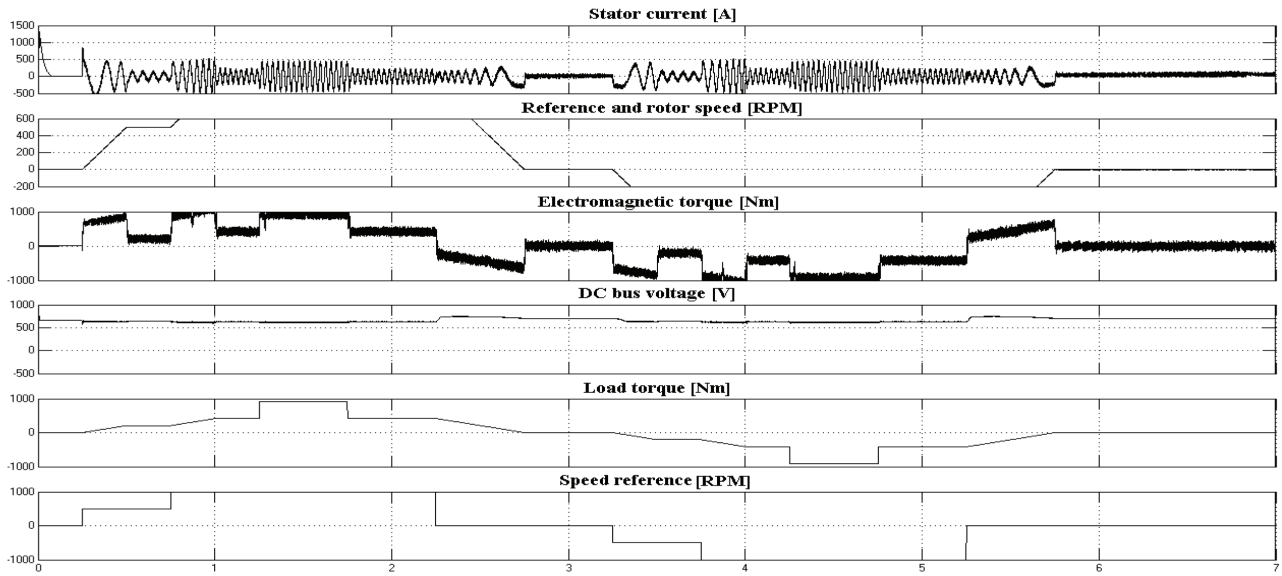


Fig. 13. The behavior of the system with neuro-fuzzy controller when the reference speed type changes.

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