On the Design of the DISO Controllers for a Neuro-Fuzzy Vector Control. The training data acquisition.

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ABSTRACT

The paper deals with the synthesis of some neuro-fuzzy speed and current controllers for a vector control based structure associated with an asynchronous motor and an inverter. Many operating conditions for the system are taken into account, like speed reference profile (including some special ones for a smooth motion in a transportation system), quadrants, load torque etc. The final goal is to substitute all the standard controllers with neuro-fuzzy variants, able to ensure a high robustness so that the influences of the motor parameters, load torque, sampling period and operating conditions could be minimized and good global performance could be achieved. The paper intends to reveal some details not directly visible applying an automatic neural network training procedure for the generating the fuzzy controllers. However, these details could improve the solutions. The results are compared with those from the initial / reference system.

INTRODUCTION

The fuzzy logic controllers (FLC) and the artificial neural networks (ANN) represent new tools in the analyze and the design of the electrical drives. Many papers deal with the applications of one or more of the artificial intelligence tools in the field of electrical drives with induction motor (IM) and the associated power electronics (Bose et al. 1997, Minth 1997). Some books and papers are oriented especially on applications (Bose et al.1997), (Godjevac 1997) – the last one being dedicated to the robotics, drives / motion control. It seems that using FLC for the control of asynchronous motors is not a very new idea. But the variety of approaches is very big. (Abad et al. 2005) 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 (VC) including FLC. However, some books and papers give more or less detailed guidelines for the IM and VC: (Caron and Hautier 1995, Roye 1997, Canudas 2000, Huy 2002). Although stated as a high quality strategy for the IM control (one of the best, anyway – (Leonhard 1997)), there are some important drawbacks related to the parameters sensitivity. The effort paid to overcome this problem is very important. In that meaning, (Rehman 2005) is a proof for how complex is any method trying to suppress the stator resistance sensitivity.

Tuning for an optimized VC by on-line procedures is a very challenging task, involving several difficulties and complex methods – (Lin and Yang 2003). (Lin and Hsu 2002) gives an ANN - based solution for the adaptive control for an induction servodrive. An early paper (Buhl and Lorenz 1991) proposes an ANN solution for the digital current regulation of inverter drives. (Hautier et al. 2004) makes a study for a fuzzy supervisor for an optimal VC in term of the best flux estimation. In (Shewy et al. 2005), 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 (Vas 1999).

The author proved by several previous results – (Mihai and Constantinescu 1999), (Mihai and Vasile 2007) 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 VC strategy. In some applications, an off-line pre-processing 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 VC structure for the IM, the aim of the paper is to analyze now the abilities of the VC - 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 over current. 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. (Koczowski et al. 2005) concerns a PID control robustness and shows some recent efforts, ideas and methods, revealing how difficult such a task is. Obtaining a large amount of training data in various

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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, the first step is to make a good tuning of the initial VC system.

Several induction motors, in the power range 2–37 kW, were considered for designing the fuzzy logic controller for the velocity loop and the current loops of a vector control structure using the IN-OUT training data acquired from a well-tuned standard VC system.

By the ANFIS method (Jang 1993), the appropriate speed and current neuro-fuzzy controllers (NFC) are generated. Then, a tuning for such controllers is performed for the local and global performance criterions improvement. In the next sections, are considered only the standard notations, SI units, time in seconds and the most of the results concern a 7.5 kW and 1456 rev/min motor.

THE INITIAL MODEL FOR TRAINING THE NEURAL NETWORKS.

The fig. 1 gives the image of the vector controlled system) with a PI speed controller and 3 hysteresis current controller, the evolution of the main variables and of some samples of the In-Out training data for the speed and current NFCs. For the tuning of the initial FOC structure, the velocity loop is simplified in an equivalent form as in the fig. 2. From the motion equation, with a PI controller ($k_{p\omega}$ and $T_{i\omega}$ as tuning parameters), the next relations are derived:

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

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

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

$$G(s)=\frac{1}{1+\frac{2\xi}{\omega_n}s+\frac{s^2}{\omega_n^2}}\qquad \begin{cases} J\times T_{i\omega} = \frac{1}{\omega_n^2} \\ \frac{2\xi}{\omega_n^2} = \left(k_{p\omega}+f\right)\times T_{i\omega} \end{cases} \tag{3}$$

From $\xi \leftrightarrow \omega_n t_{resp}$ (t_{resp} is the response speed time of the system) – (Buche 2001) is considered an unit damping factor, so $\omega_n t_{resp\ 5\%} \approx 4.75$ gives the tuning parameters:

$$\begin{cases} k_{p\omega}=J\times\frac{9.5}{t_{resp}}-f \\ T_{i\omega}=\frac{1}{J}\times\left(\frac{t_{resp}}{4.75}\right)^2 \end{cases} \tag{4}$$

As for the tuning of the hysteresis current controller, the only parameter (Δ) has influence mainly on the current (and electromagnetic torque) ripple; so, at this point the tuning is simple, according to a limit for this ripple and the upper commutation frequency supported by the devices inside the inverter.

For this initial model, the next possible scenarios and elements must be considered in order to deliver more or less better training data and for the NFC synthesis:

a. The strategy for the NFC synthesis:
- first, the inner (current) controller, with the classical PI controller for the speed loop;
- first, the external (speed) controller, keeping the hysteresis current controller;
- with an unique training data set taken from the initial model, the synthesis of the NFCs being made for both of the loops;
- SISO or DISO NFCs.
- unique or adapted to each phase current NFC;

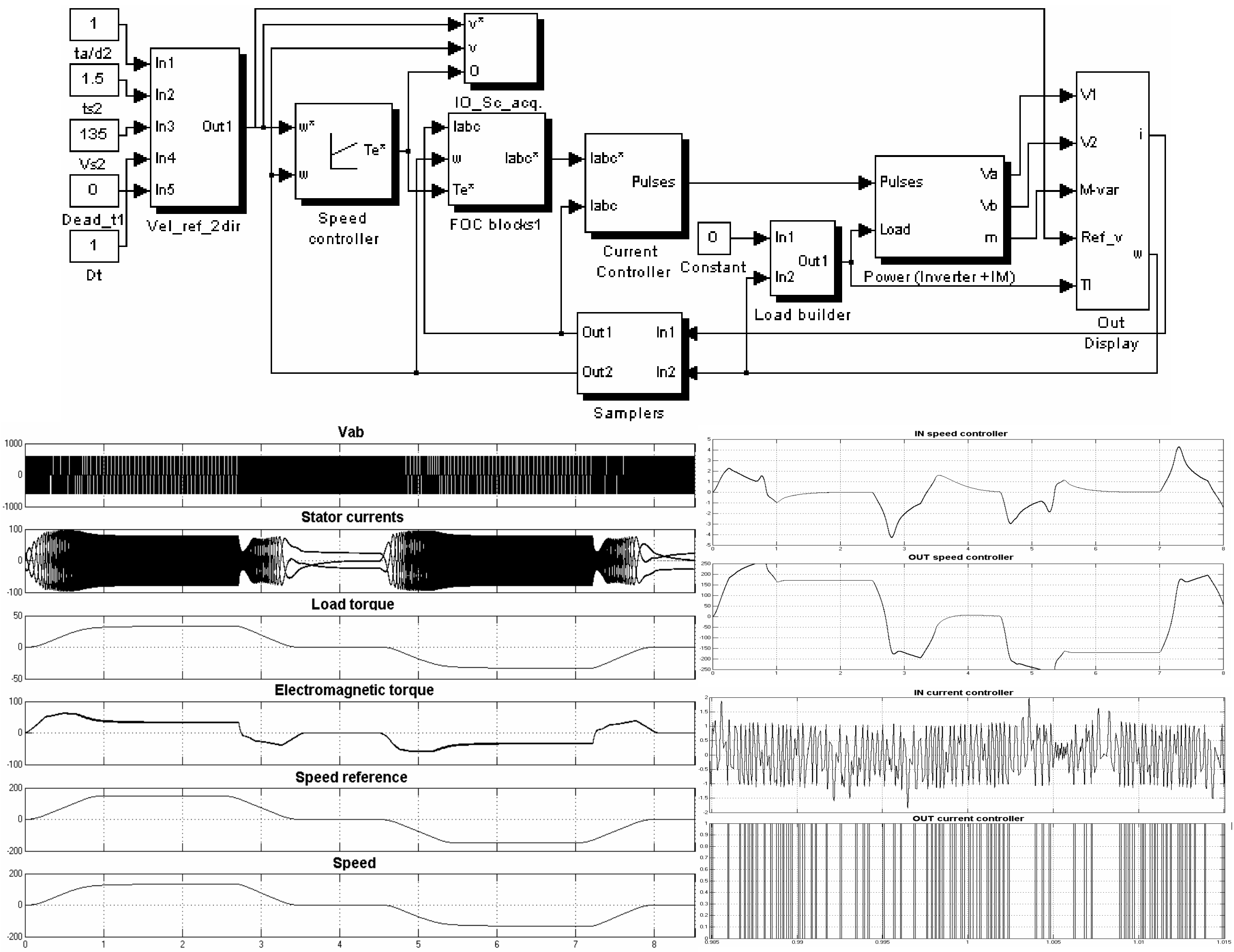
b. Optimization of the training data set, by:
- the sampling rate for the training data (test have been made from 10 us, that meaning n x 100,000 data pairs);
- the most relevant conditions for the operating regime (with a single operating quadrant or with a reversible speed profile, maximum reference speed, load torque as type and values);

c. The training program:
- the number of the fuzzy sets for each variable;
- the epoch number (from 20 to 30000);
- different kind of inference methods, fuzzy operators etc.

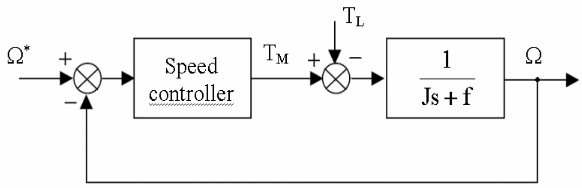
d. Post training tuning of the neuro-fuzzy controllers. By the author experience, the most suitable actions concern the redistribution of the fuzzy set so that:
- the too big surface control slopes must be avoided (the same big slopes in the input n-f controller bring bad values in their output correspondences – see the lack of a SISO training instead the consideration of the error variation as a second entry for the FLC).
- the angular points must be avoided;
- the IN/OUT variables scale of the NFCs must be inner in relation with the training scale of the same variables - some saturation blocks could be added if necessary;
- the steady-state regime from the training data must be found as input-output values in the surface control of the NFCs;

A DIRECT AND SIMPLE APPROACH

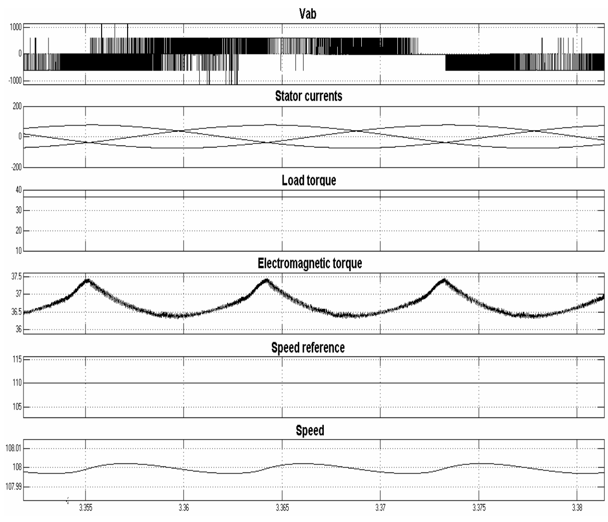
Joining the best (tuned) SISO NFCs - for the speed loop and for the current loops, the results were far from the expectations, although the training conditions for the system were the same for both synthesis. The fig. 3 presents the results for a control structure with NFCs (one for the speed, three identical for the current). Although the general behavior is acceptable (fig. 3a), some drawbacks related with the steady-state regime (speed error) and the local dynamic (fig. 3b), as well as a certain sensitivity to the speed reference values field, pushed the study toward some new ways. Some efforts paid to improve the behavior (concerning several from the above mentioned aspects) gave results (somehow better) not very encouraging. The fig. 4 could preview such a disappointment and makes difference between the training conditions. This kind of image is helpful



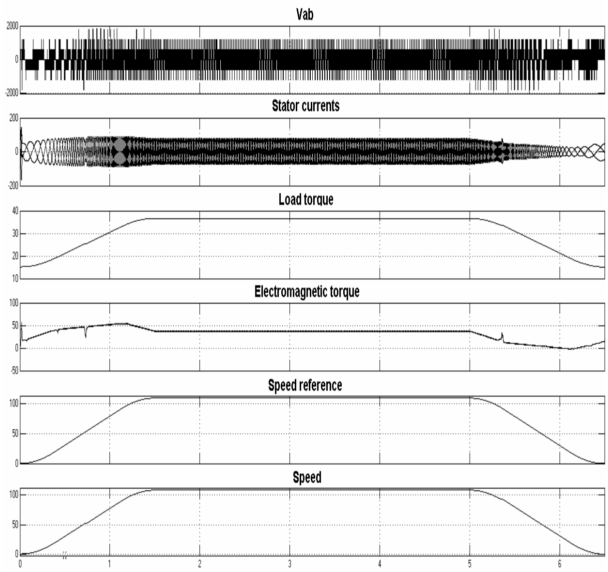
Figures 1: The initial system, its variables and the training IN-OUT data for the speed and current controllers.



Figures 2: For the speed controller tuning.



Figures 3b: Details for the integral neuro-fuzzy control by SISO units for speed and current.



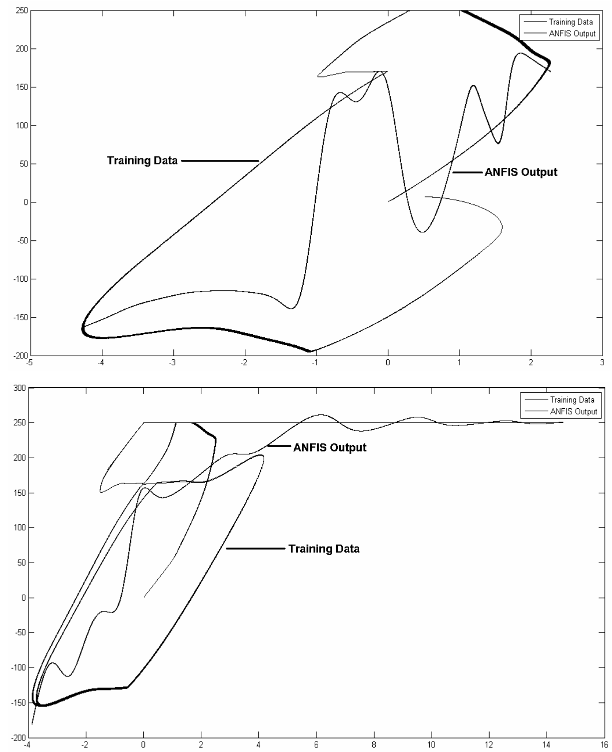
Figures 3a: The macroscopic variables for an integral neuro-fuzzy control by SISO speed and current units.

only for the speed loop. The training of a current NFC able to deliver firing pulses for the inverter has no more this benefit because the high rate commutations - fig. 5. The merit of such approach is that it proves the possibility to operate with all loops controlled by NF units.

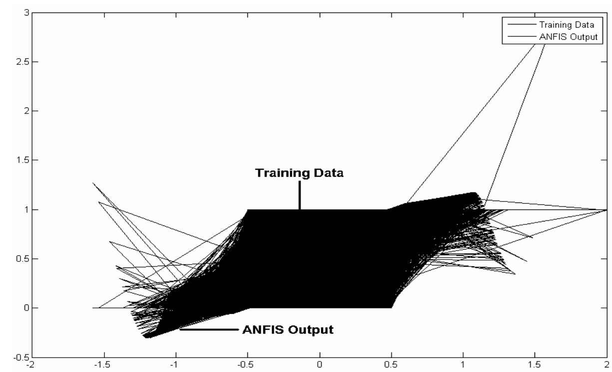
THE DISO APPROACH

The consideration of the error variation $\Delta\varepsilon_\omega$ for the speed loop allows a better control of the system, the derivative of the speed being the acceleration – an essential variable for the dynamic. The monitoring of the acceleration has benefits also in control of the kinematics for the applications with reduced mechanical shocks. The data amount increases, being involved 3 training vector for each controller. The training trajectory of the neural network (NN) improves a lot, as it can be seen in fig. 6. Although this kind of result (a) could certify the quality of the training data, the direct macroscopic results are not at all good (b-d) The next actions were tested in order to improve the behavior of the system with the same NFC:

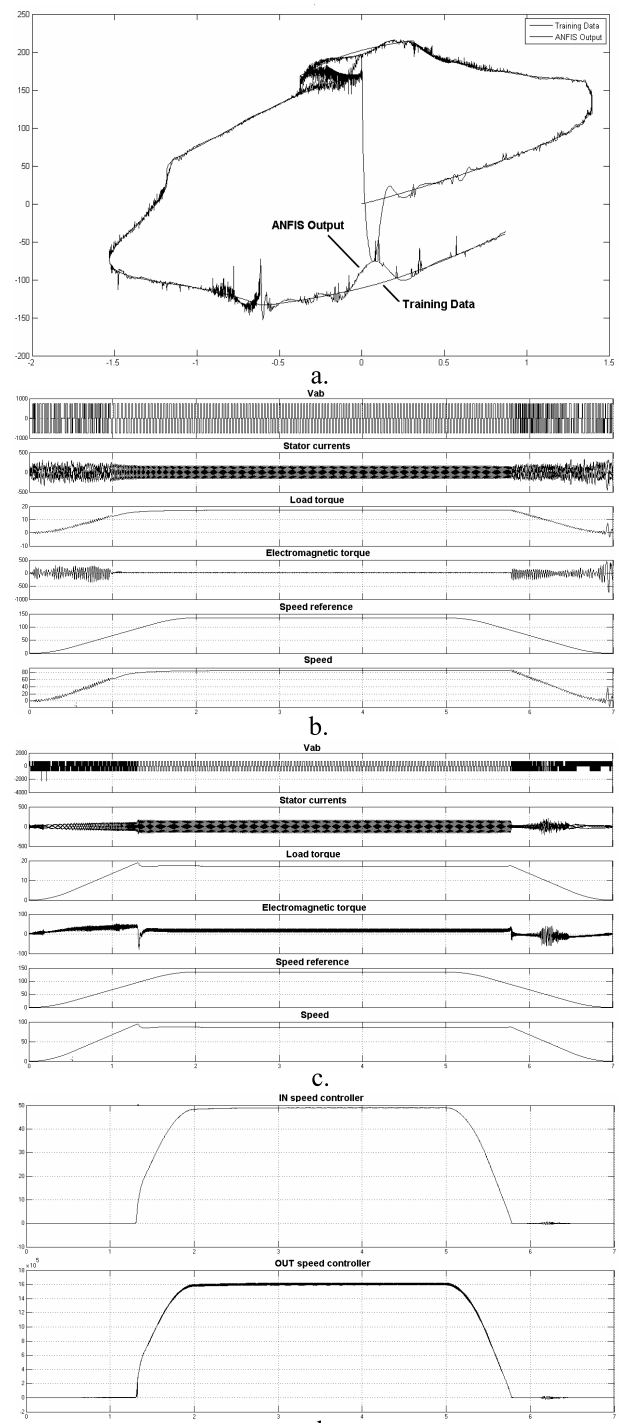
- the discrete filters (z^{-1}) are suppressed for both channels : ε_ω and $\Delta\,\varepsilon_\omega$. The speed ripple decreases a lot, however, the steady - state error is unacceptable (fig. 6.c) and the output of the NFC is beyond of the training range (fig. 6d) - the output of the controller reaches 18 x 10^5 !.
- the output of the speed NFC is saturated in the range of the initial training data. The results are much better. Some important oscillations of the electromagnetic torque still persist, because of the commutations of the fuzzy rules and the operation in the neighbor of the saturation levels.
- $\Delta\,\varepsilon_\omega$ is computed with $T_{s\ model} << T_{acq\ training\ data}$ (by 3 orders of magnitude) ; the results have the same aspect.



Figures. 4: The trajectories for training and NN output of a SISO speed NFC for different conditions:
1 direction / 13334 data pair and
2 directions / 250001 data pairs.



Figures 5: The trajectory for training and NN output of a SISO current NFC.



Figures 6: A good training data set and, however, some bad generated results with the speed NFC.

In order to obtain better results, the acquisition procedures for the training data could be still improved (analyzing the training state-space trajectories), as follows:

- a faster sampling (a sample period of 100μs, that meaning 130,000 n-tuples data: 2 for Input and 1 for Output), with the same rate for the discrete filters in the model;
- better operating conditions (longer cycle, other load);
- a limitation of the upper values for the first values of $\Delta\,\varepsilon_\omega$ - the speed error variation, according to:

$$\Delta\varepsilon_{\omega\ max} \approx \frac{\left.\frac{d\omega}{dt}\right|_{average}}{t_{start}/T_{sampl}} \qquad (5)$$

The figure 7 reveals by different 2D projections the accuracy of the training process in these conditions, as well as the 3D picture of the states-space trajectory.

According to a "fuzzy vision" for the behavior of the system, the variables In-Out of the speed NFC should have smooth variations, as affect of the fuzzy sets overlap, of several fired fuzzy rules aggregation and the action of the defuzzification. A comparison between the fig. 8 and 9 (for the standard system used in the training process and the system with a speed NFC) does not confirm this expectation. More, it seems that the "well temperate" behavior still existing for the SISO speed NFC is lost - see also the fig. 1. In fact, the high rate commutations of both In-Out variables of the speed NFC are normal for the DISO variant, as the direct effect of the derivative of the first input: $\Delta\,\varepsilon_\omega$. This second entry involves a supplementary sampling and its rate is related with the magnitude of the training data collection. A smaller sampling period for $\Delta\,\varepsilon_\omega$ leads to a bigger data set, hence consequences in the computation time. There are 2 main factors that influence this constraint : the training epoch number and the magnitude of the training data. In order to avoid the over-oscillations in the future In-Out variables for the speed NFC, different sampling rates were used :

- a small T_{s1} for generate $\Delta\,\varepsilon_\omega$, close to the integration step of the model:

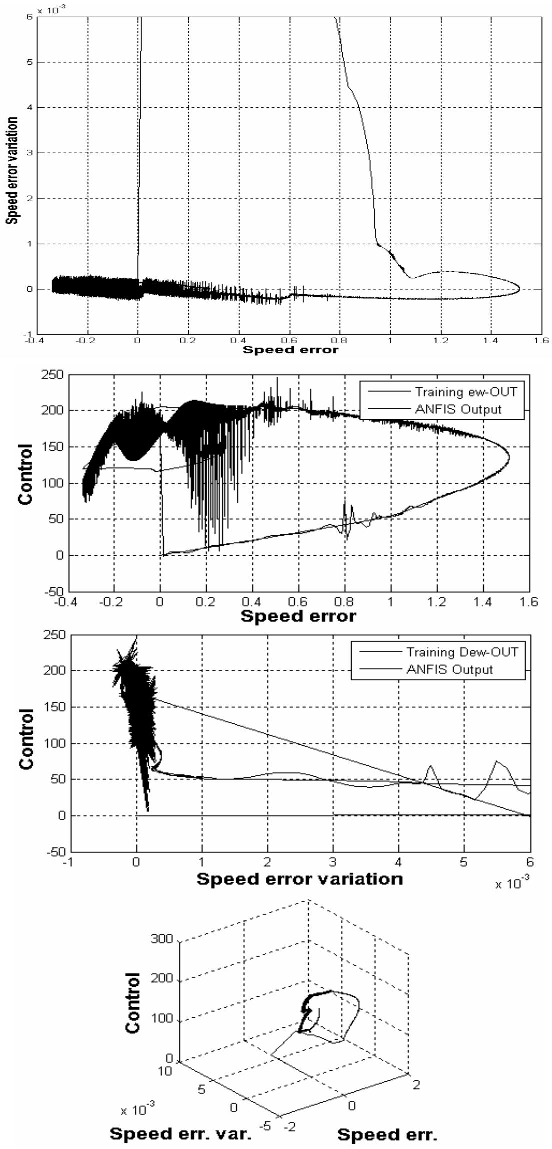
$$\Delta\,\varepsilon_{\omega\,k} = \varepsilon_\omega(k \cdot T_{s1}) - \varepsilon_\omega((k-1) \cdot T_{s1})\,) \qquad (6)$$

- a convenient T_{s2} for a resonable training data amount :

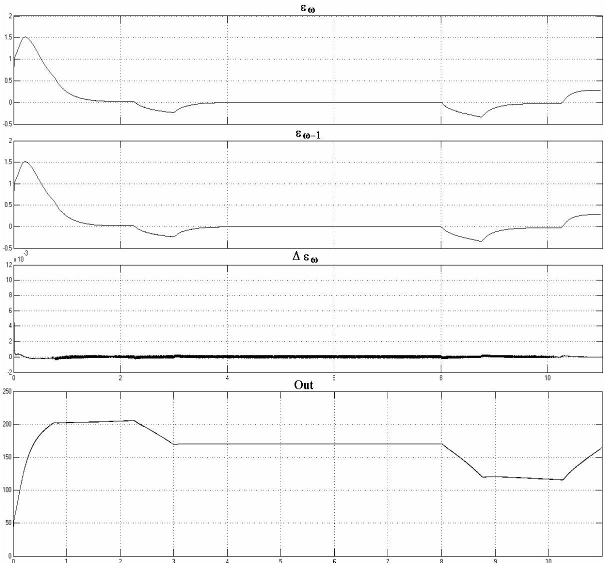
$$T_{s2} \geq t_{regime} \big/ N_{max\ adm\ DATA\ -1\ variable} \qquad (7)$$

CONCLUSIONS

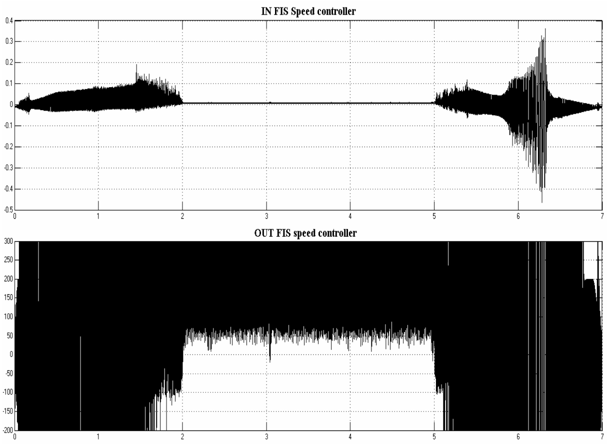
The fuzzy control brings several well-known advantages for the control of electrical drives systems. The attempt to combine a successful control strategy like the vector control with the benefit of one or more tools from the intelligence control field (fuzzy logic, neural networks) is entirely justified. The first and simple approach with a SISO structure for the controllers (speed and current loops) have proved the ability of a single neuro-fuzzzy controller at a time to obtain good performance and robustness. In order to improve this initial results, the author raised several ideas and made many test by modeling and simulation for extending the qualities of the neuro-fuzzy technique to a system having only such kind of controllers. It was proved that an important benefit is an extended robustness for very different operating cycle. The only way for obtaining good solutions is to design DISO NFCs. It could seem only another quantitative approach, but the design changes dramatically. Several aspects drive to many design details, although there is a powerful and easy to use method (and program) for generating the fuzzy controller by training the associated neural networks. The main concern outlined in the paper is the training data preparing. The results confirm that the suggested solution exists but every little improvement of the results implies a lot of subtle details and a lot of work. The fuzzy control solutions are simple and easy to obtain only for medium-to-good results.



Figures: 7 Images for the training (state-)space trajectories - as criterions for improving the training.



Figures 8: The data training set: the speed error, its variation and the saturated output for the initial speed controller.



Figures 9: The In-Out variables for the speed NFC.

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