ON THE DESIGN OF A NEURO-FUZZY CONTROLLER FOR THE VECTOR CONTROL STRATEGY. TUNING AND RESULTS.

Dan MIHAI

University of Craiova, email: dmihai@em.ucv.ro

Abstract – **The paper is continuing a work for a velocity controller synthesis by neuro-fuzzy techniques in a vector control with an asynchronous motor structure. The input – output data prepared in the previous paper are applied to a program in order to train a neural network able to generate a file for the speed fuzzy controller. The fuzzy solution is analyzed comparatively with the standard structure that generated it. Different training conditions, independent and combined influence of the motor parameters, load torque, sampling period and operating conditions are taking into account .**

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

1. INTRODUCTION

Neural networks and fuzzy systems are different approaches to introducing humanlike reasoning to knowledge-based intelligent systems. The integration of fuzzy logic and neural networks seems natural and full of benefits – [7]. Artificial Neural Network (ANN) learns from scratch by adjusting the interconnections between layers. Fuzzy Inference System (FIS) is a computing framework based on the concept of fuzzy set theory, fuzzy if-then rules, and fuzzy reasoning. Integrating ANN and FIS have attracted the growing interest of researchers due to the growing need of adaptive intelligent systems to meet the real world requirements. [10] proposes a taxonomy to describe different combinations of neural networks and fuzzy systems by Fuzzy Neural Networks, Concurrent Neuro - Fuzzy Models, Cooperative Neuro - Fuzzy Models, Hybrid Neuro - Fuzzy Models. An example for the last architecture is ANFIS (Adaptive-Network-Based Fuzzy Inference System) - [5], [6]. The first applications of fuzzy neural networks to consumer products appeared on the (Japanese and Korean) market in 1991. Some examples include [4]: air conditioners, electric carpets, electric fans, electric thermo-pots, desk-type electric heaters, forced-flue kerosene fan heaters, kerosene fan heaters, microwave ovens, refrigerators, rice cookers, vacuum cleaner, washing machines, clothes dryers, photocopying machines, and word processors. [11] provides a comparison of artificial neural networks and neuro-fuzzy systems applied for modeling and controlling a real system.

2. THE SINTHESYS OF THE NEURO-FUZZY CONTROLLER AND ITS TUNNING.

Several induction motors (IM), in the power range 2–37 kW, were considered for designing an appropriate fuzzy logic controller (FLC) for the velocity loop of a vector control structure - [8]. The same paper gives the IN–OUT data for training the ANN necessary to the neuro-fuzzy (N-F) controller. Its synthesis was made in different variants: M1, M2 and M3 motors; step input, reversal velocity profile and for restricted shock; a wide range of the training number epochs; different defuzzification methods. The ANFIS method / program – [5], [9] used the training data for the fuzzy controller synthesis. The Table 1 and the fig. 1 reveal the main characteristics of several training conditions. The fuzzy sets type was generalized bell curve membership function. Their distribution, uniform or not, has a visible influence on the surface control. The tuning of the N-F controllers consist, in fact, in the choice of the fuzzy sets number, their distribution and the selected defuzzification method: wtaver (WTA - weighted average) or wtsum (WTS - weighted sum). The fuzzy inference method is a Sugeno type. Some tests with several values for the epochs number proved a minor or no visible influence on the results in term of the training method error (combination between backpropagation and least squares procedures). Their number, however, could influence directly the surface control surface and, by that, some accuracy details of the system behavior. The influence of the AND/OR operators was not detectable in the shape of the surface control. The most important difference in the results validity comes from the IN-OUT training data that have a major influence on the distribution of the fuzzy sets; very seldom they have an uniform distribution. Also, different motor parameter sets generate N-F controller having very distinctive characteristics. Although the operating conditions for the gathering of the training data are very important, it is possible to have a very good behavior of the system when the operating conditions change from the training scenarios. The quality of the results is mainly appreciated by the evolution of the macroscopic variables of the system, like speed, torque, currents.

3. THE FUNCTIONALITY OF THE SYSTEM WTH A NEURO-FUZZY VELOCITY LOOP.

The image of the system having a neuro-fuzzy speed controller is given by the fig. 2. It is able, by some specific blocks (like the reference builder, the load torque generator) to ensure a wide variety for the operating conditions. The fig. 3 presents a comparison between the standard FOC control and the N-F speed controller, in various conditions - different from those in use for the training stage. The response of the N-F velocity loop is better when considering a rotor resistance increased with 20 % (fig. 3a and b). So, a major drawback of the vector control solution, their sensitivity to the resistance variation is diminished by the N-F loop. For a speed step input (set point) for M3, the fuzzy controller brings some important advantages: lower starting period and current, no speed overshoot and no saturation effect in torque. Another regime (ramp reference speed input after a low initial step) is revealed in fig. 3c-d. The main differences give a higher merit to the neuro-fuzzy solution: the maximum motor current is lower, an important reduction of the electromagnetic torque ripple is obvious, the absence of a saturation effect in torque response proves a good sensitivity of the controller to the energetic needs of the electromechanical part. The shorter time interval with higher acceleration torque for the fuzzy solution has consequences on the speed tracking, the speed rate having, because of that, two different values instead an equivalent unique ramp as for the standard control solution. But this consequence is not necessarily a bad one. The next results – fig. 3e-f show what is happening when an important load perturbation occurs – a short impulse during the steady-state regime, after a direct starting. It is visible a better dynamic response during the

Training by 20 epochs:
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: 6501
Number of checking data pairs: 0
Number of fuzzy rules: 7
Start training ANFIS ...
1 16.9038
...
20 15.8692
Designated epoch number reached --> ANFIS training completed at epoch 20.

30 epochs:
Start training ANFIS ...
1 17.1752
...
30 15.61
Designated epoch number reached --> ANFIS training completed at epoch 30.

300 epochs:
...
300 14.9323
Designated epoch number reached --> ANFIS training completed at epoch 300.

1000 epochs:
Start training ANFIS ...
1 17.1752
...
1000 13.8577
Designated epoch number reached --> ANFIS training completed at epoch 1000.

3000 epochs:
Start training ANFIS ...
1 16.9038
...
3000 14.826
Designated epoch number reached --> ANFIS training completed at epoch 3000.

Table 1. Some considered variants for the ANFIS program.

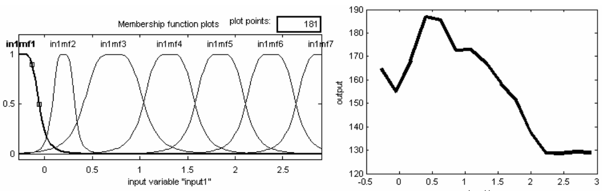


Fig. 1a N-F contr.: M2, no shock, 20 epochs.

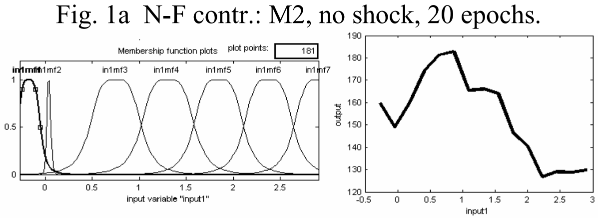


Fig. 1b N-F contr.: M2, no shock, 300 epochs, WTA.

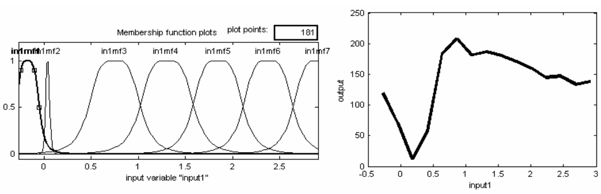


Fig. 1c N/F contr.: M2, no shock, 300epochs, WTS.

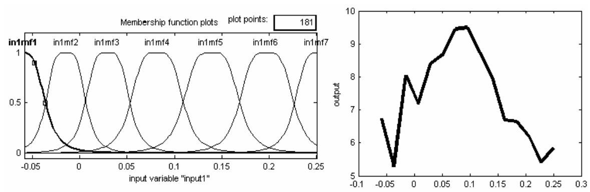


Fig. 1d N-F contr.: M1, no shock, 30 epochs.

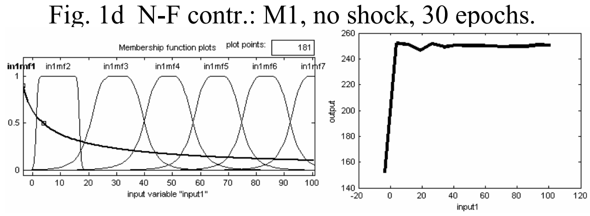


Fig. 1e N-F contr.: M2, step, 300 epochs.

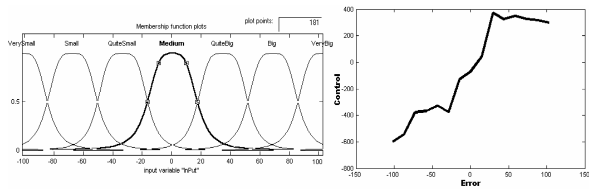


Fig. 1f N-F contr.: M3, reversal velocity, 30. epochs

starting of the system for the fuzzy variant (faster, lower overshoot and current, better energy distribution). Although the effect in the couple reaction is similar for both structures, the speed response gives an obvious advantage for the fuzzy speed controller. This is a proof of the robustness of such a solution. Same advantages are also visible for a 2-quadrant operation regime. The reversal speed profile is better followed by the fuzzy controller – fig. 3g-h. The author proved also – [9] that a very good behavior of the system is obtained with a fuzzy controller considering a wide variation of the sampling frequency (for which the standard algorithms are very sensitive) with implications in real-time experiments. In fact, for all the results, the response quality is related with the controller tuning. But the tuning of a fuzzy controller for complex plant models (or lack of all data of such models) is much easier than for standard PID control algorithms. However, in all tested conditions the fuzzy loop has the same benefits. All results show a better energy distribution during the dynamic regime and a non-saturated operation of the fuzzy controller. The fig. 4 reveals the ability of the N-F controller to diminish also the ringing (ripple) of the control signal and the very good tracking of the dependency input (error) – output (control). A much more complex situation is then considered - the load torque has a constant part, another proportional with the speed and a step variation during the deceleration period. The results are depicted by the fig. 5. Simultaneously, several changes were added to the initial training conditions: the value of the resistance is higher, the mechanical inertia is double, the sampling period is 10 times bigger and the reference has a different profile. The general aspect of the results seems quite similar, that meaning that both structure are able to manage the system in these conditions. However, a detailed analyze shows some benefits of the fuzzy variant. Indeed, the tracking speed reference is slightly better, especially during the acceleration interval, the standard solution having a longer delay for the steady-state entry. The current envelope reveals a better energy management. The interesting aspects concerning the first moments of the starting, explained in [17] for the pure vector control strategy, are found for the N-F results. The negatives initial values for the motor couple could be the effect of some week capabilities of the fuzzy logic to manage the extreme points of a bilocal problem. The fuzzy approach supposes a continuity / graduality of any variable and evolution; or, the initial time segment is highly related with a discontinuity. A tuning of the fuzzy sets could reduce the effect. The easiest way is to make a non-uniform distribution of these sets, with less large areas in the extreme sides. In the speed profile, it is detectable o small reversal time just after the starting. The interpretation could be done by the negative machine torque and an initial negative derivative for the velocity – [8]. Another detail from a zoomed result proves a right commutation for the power inverter. The torque ripple (with a vibrating aspect) is the same as for the standard structure, slightly reduced. The fig. 6 makes a comparison between the standard system and the N-F one, in terms of the harmonic behavior for the motor current. Again, the fuzzy controller for the speed loop seems more appropriate. The fig. 7 contains the results for the main variables when the FOC structure has a N-F controler and the reference profile ensures a low mechanical shock. It can be seen the good quality of the speed profile, which follows closely the reference signal. It is important to mention the ability of the controller to manage also the steady-state regime – a quite long one. Fig. 8 gives the system's evolution when the neuro-fuzzy controller was trained for a step speed input and the real reference velocity input is a reduced shock type one. The behavior is an unexpected good one, being directly visible a forced control during the first acceleration time – an useful property in certain operating conditions: big torque load, important initial frictions or stiffness torque. The torque produced by the motor has a strong initial shock and the system deceleration happens in good conditions – "naturally", although in the training stage this regime is not considered.

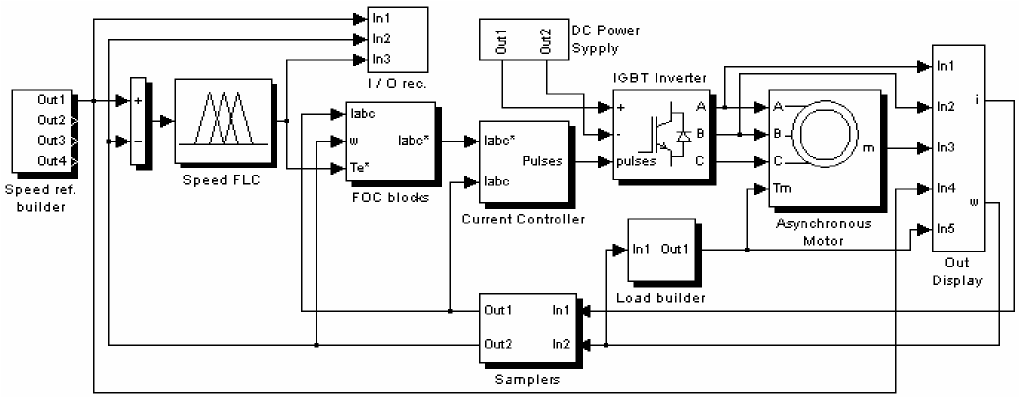


Fig. 2 The model with speed fuzzy controller.

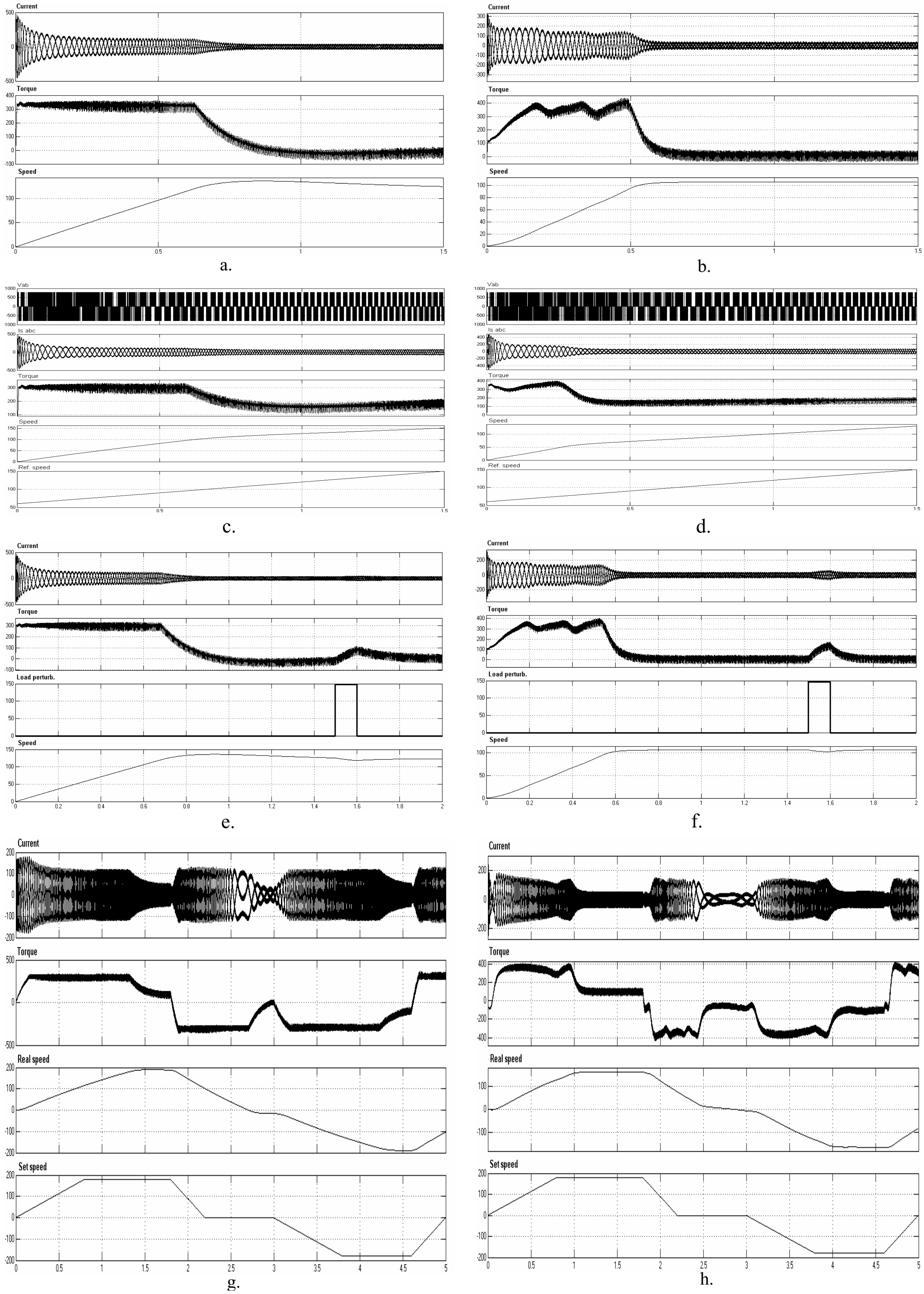
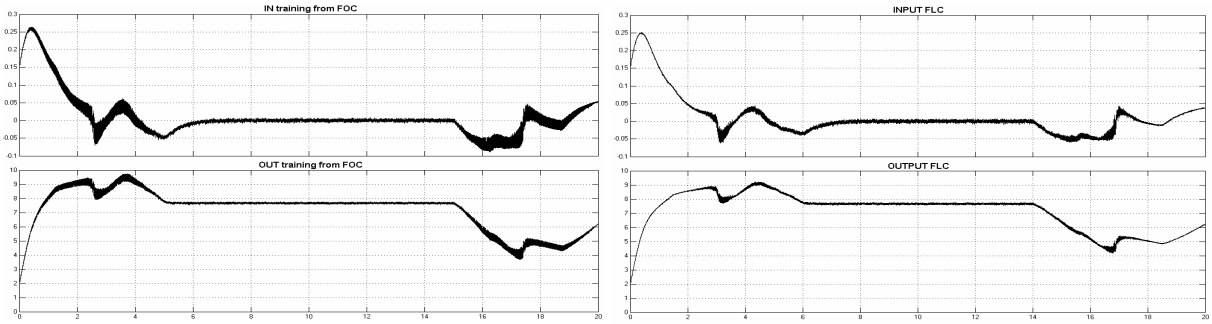


Fig. 3. The system equiped with M3 with the standard FOC structure (left side) and the N-F velocity controller (right side) in different operating conditions.

The results reveal also the ability of the N-F controller to make a good job when the operating conditions (the steady state speed value, the duration of the cycle) are largely different from the training. It is import to mention another quality of the N-F controller: a very low velocity error (0.1 %) during the final standstill regime. However, the real-time control algorithm must detect by a specific task the final rest condition and to deliver a simple OFF control signal to the drive (not using a computed N-F control), followed by a specific control value for keeping the system in rest when the load is energetically active. The velocity ripple during the steady-state regime (less then 0.01 %) has no mechanical meaning. The N-F controller can also manage the drive with a reduced mechanical shock and a longer or a shorter cycle as in the training stage.

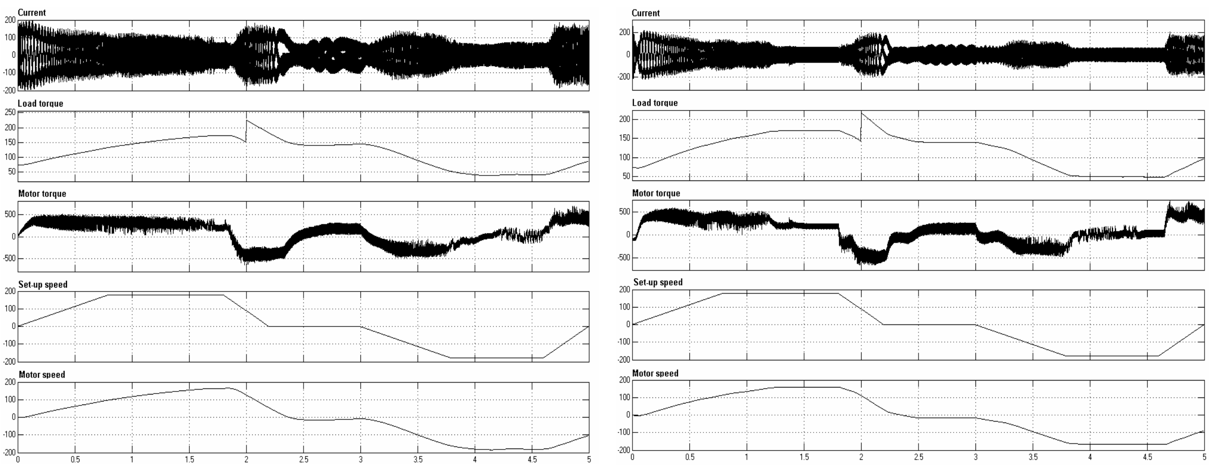
4. CONCLUSIONS

The synthesis of a velocity fuzzy controller for vector control is made by using a knowledge base and a computer aided tool for neural network - the ANFIS program. Although such a controller has an infinite parameters set, the tuning begins with the training set preparation. The main influence of this data is on the distribution of the fuzzy sets. Passing from two tuning parameters of a PI controller to multi-parameters tuning of a fuzzy controller (mainly by changing the



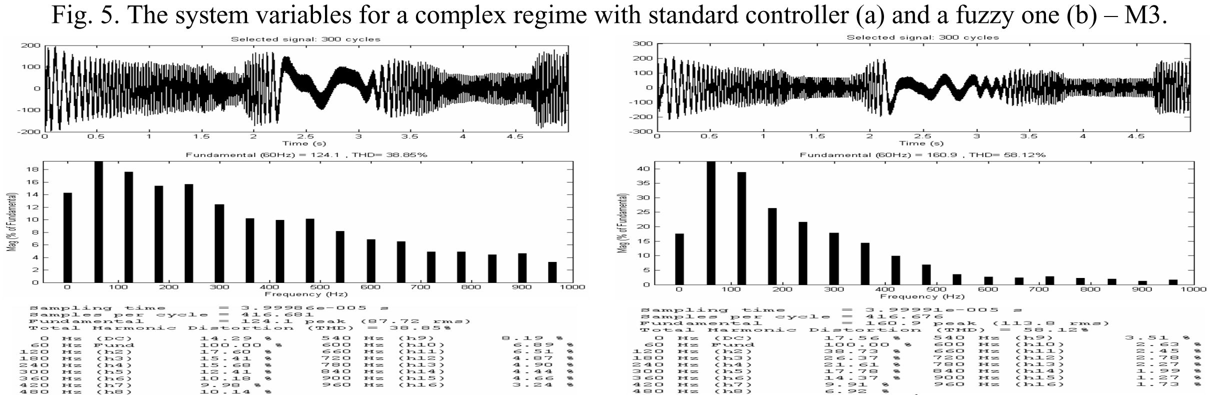
a. b.

Fig. 4. The In – OUT data for the speed controller for the FOC (a) and N-F (b) variants.



a. b.

Fig. 5. The system variables for a complex regime with standard controller (a) and a fuzzy one (b) – M3.



a. b.

Fig. 6. Standard (FOC) structure – a) and N-F control – b): current – harmonic analysis.

fuzzy sets into infinite possibilities) is an interesting and big challenge. Several training operating conditions were considered: for a step, ramp, reversal and having no mechanical shock input references. The file for synthesis of the controller obtained by a single training condition scenario (a reversal speed profile), is able to deliver very good results in many other conditions that those from the training stage, as: large variations of the system parameters, strong perturbations, other operating quadrants, input references and sampling values. The comparison between the initial (standard) structure and that based on a neuro-fuzzy speed controller, in different operation conditions, underlines obviously some advantages of this last one, in terms of the dynamic index, energetic criterions and robustness. 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. The solutions delivered could be sometimes, amazingly, smarter than those obtained in a classical manner, taking into account some hidden details. In this context, some unexpected results concerning functional details / moments of a simulated regime, prove that the neuro-fuzzy controller is, indeed, an intelligent one.

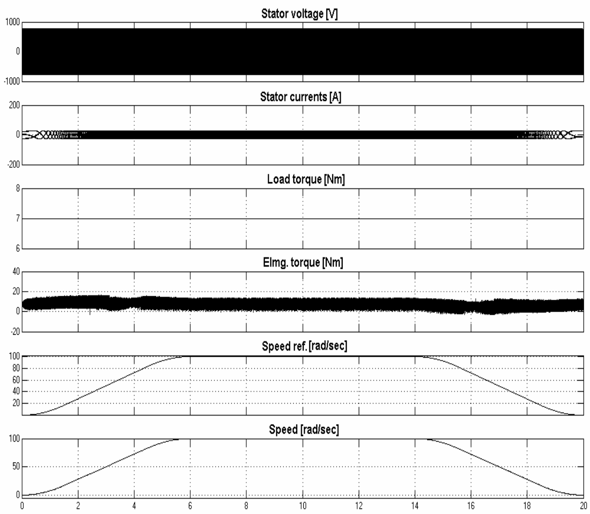


Fig. 7 The system behavior for: M1 – N-F controller – reduced shock - constant load 50 % - 30 epochs.

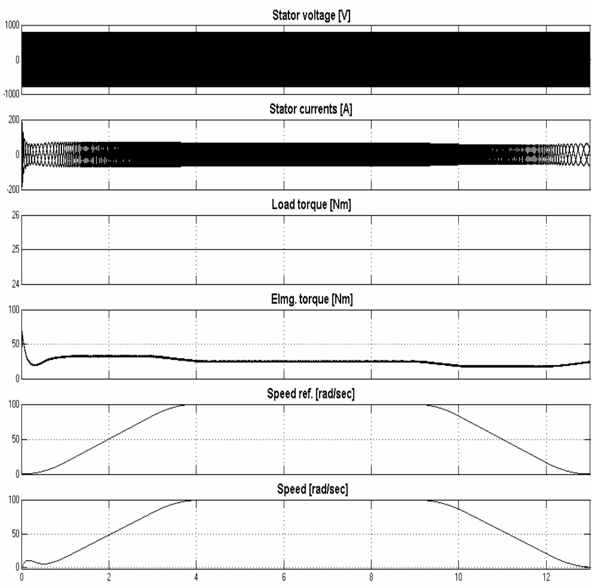


Fig. 8 The system behavior for: M 2 – N-F controller – reduced shock - constant load 50 % - training for step speed input.

References

[1] Abraham A., It is time to Fuzzify Neural Networks!, Tutorial, ICIMADE, 1-3 June 2001, Fargo, USA, pp 253 - 272.

[2] Altrock C. von, Fuzzy Logic and NeuroFuzzy Applications Explained, Prentice Hall PTR, 1995.

[3] Bose B.K., Fuzzy logic and neural networks in power electronics and drives, *IEEE Ind. Applic. Magazine*, pp.57 –63, Vol.6, May/Jun 2000.

[4] Fuller R., *Neural Fuzzy Systems*, Abo Akademi University, Abo 1995.

[5] Jang J.-S. R., ANFIS: Adaptive-network-based fuzzy inference system, *IEEE Trans. Syst., Man, Cybern.*, vol. 23, pp. 665–684, May/June 1993.

[6] Jantzen J., Neurofuzzy Modelling, Technical Univ. of Denmark, Depart. of Autom., Lyngby, DENMARK, Tech. report no 98-H-874, 1998.

[7] Kasabov N.K., *Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering*, A Bradford Book, The MIT Press, Cambridge, Massachusetts, 1998.

[8] Mihai D., On the Design of a Neur-Fuzzy Controller for the Vector Control Strategy. Data Preparing., ICATE'08, Craiova, Romania, 2008.

[9] Mihai D., Vasile C. Vector Control with Fuzzy Speed Loop for an Electrical Drive System with Asynchronous Motor, *Bull. Polytech. Inst. Iassy*, Romania, 2004, vol. L (LIV)/5, pp. 1037-1042.

[10] Nauck D., Beyond Neuro-Fuzzy: Perspectives and Directions, Third Europ. Congr. on Intell. Techn. and Soft Comput., (EUFIT'95), Aachen, 1995, pp. 1159 -1164.

[11] Vieiraa J., Diasb F. M., Mota A., Artificial neural networks and neuro-fuzzy systems for modelling and controlling real systems: a comparative study, *Eng. Appl. of Artif. Intell.* 17 (2004), pp 265–273.

[12] Wishart M. T., Harley R. G., Identification and control of an induction machine using artificial neural networks, *Conf. Rec. IEEE IAS Annu. Meeting,* Toronto, Ont., Canada, Oct. 1993, pp. 703–709.

[13] Woei Wan Tan, Hong Huo, A Generic Neurofuzzy Model-Based Approach for Detecting Faults in Induction Motors, *IEEE TRANS. ON IND. ELECTR.*, VOL. 52, NO. 5, OCT. 2005, pp. 1420-1427.