AN AGGREGATE MULTI-LOOP CONTROL FOR A DC SERVODRIVE. THE DESIGN OF THE NEURO-FUZZY CONTROLLER.

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Abstract **– The purpose of the study is the synthesis of a reliable and robust fuzzy controller for a 2nd order DC servodrive. A first step is to prepare the computations associated to the main control loops for the above mentioned servosystem. This approach aims to aggregate the relations for the position and the velocity loops as an unique computation formula expressed into the variables specific for the real-time processing, optimized and adapted to a microcontroller arithmetic. The systemic variables considered are the position error and its variation during a sampling period, this second input into the next neuro-fuzzy control having the physical meaning of the speed. Both variables are expressed as dependences of the number of encoder impulses delivered during the sampling time. A second step is the design of a neuro-fuzzy controller for both the control loops. The ANFIS method uses training data delivered by the well tuned conventional control structure for generating a DISO fuzzy controller. Some special blocks were added to the standard structure in order to improve the IN-OUT data quality. Appreciations are made for the quality of the training process and the characteristics of the fuzzy inference system are presented. A subsequent paper will analyze the system with the neuro-fuzzy controller and its real time-time implementation.**

Keywords: *DC drive, neuro-fuzzy control, design.*

1. INTRODUCTION

Several recent attempts combined the qualities of the fuzzy control with other different techniques included in the so called soft computing field. Some of these hybrid systems combined the fuzzy inference systems (FIS) with classical methods, like the sliding mode control. An electrical servodrive with the proposed position-control system possesses the advantages of a simple control framework, reduced chattering, stable performance and robustness to uncertainties – [11]. [16] proved by experiment that such systems have highly useable features with respect to the sensitivity to parameter variations, greatly reduced. The fusion between the artificial neural networks (ANN) and FIS was one of the first successful attempt to design new intelligent control technique – [1] for many fields, including the electrical drives systems with the associated power electronics – [4], [20]. Not a few studies have been carried on the application of the neuro-fuzzy control (NFC) on DC drives not only because these systems are more accessible but there is a very large application area that involves this motion control. A PID control combined with fuzzy logic was an idea to design a smart fuzzy rule-base – [19]. Therea are some fuzzy logic based control strategies for energy converters – [7], [17]. Another approach is to keep some standard controllers and to add a fuzzy one for one of the loop; such hybrid approach is to have an inner current loop monitored by a fuzzy controller while the main speed loop is monitored by a classical PI controller – [15]. Most of researches and applications, however, use a simple fuzzy controller structure. [6] operate with a structure that does not require information on the derivation of the controlled system output variable because obtaining of information on derivation is often difficult or too costly. Some adaptive fuzzy controllers are based on the load estimation – [5]. Newer papers proclaim the superiority of the adaptive neuro-fuzzy design in comparison other procedure – [3], combine the FIS with other components from soft computing, like genetic algorithms – [10]. The author experienced good results in using fuzzy logic controller (FLC) for the DC drives in a SISO variant – [12] and made a DISO approach for the AC drives – [14]. The considerations about the preparation of a multicriterial analytical support – [13] is now organized for designing a robust DISO N-F controller for a low inertia DC drive.

2. AN IMPROVED CONVENTIONAL CONTROL STRUCTURE FOR THE TRAINING OF THE NEURAL NETWORK

For a conventional control structure of the servodrive, with a P position controller and a PI inner velocity loop, the systemic variables will be prepared into a real-time computational style, adapted to the arithmetic of a standard target microcontroller. The main variables use the next notations: N_α* and $N_{\alpha k}$: position set-point and actual position, in encoder pulses number; $\varepsilon_{\alpha k}$, $\Delta\varepsilon_{\alpha k}$: position error, its variation referred to a sampling period T; $\Delta N_{\alpha k}$: pulse encoder number delivered by encoder during T; c_k: the computed control; k_{div}: division or multiplication factor for pulses from encoder, by additional hardware (increasing the time reserve or the position resolution). The encoder has $N_{p/r}$ pulses per revolution. The author suggests the next processing of the relations associated with the control loops:

- the position error $\varepsilon_{\alpha k}$:

$$\varepsilon_{\alpha k} = N_\alpha * - N_{\alpha k} \qquad (1)$$

- the position error variation during T, $\Delta\varepsilon_{\alpha k}$:

$$\Delta\varepsilon_{\alpha k} = \varepsilon_{\alpha k} - \varepsilon_{\alpha k-1} = \Delta N_{\alpha k} \qquad (2)$$

ω_k, the "software" speed, is computed by:

$$\omega_{ks} \approx \frac{\alpha_k - \alpha_{k-1}}{T} = \frac{2\pi \cdot k_{div} \cdot \Delta N_k}{N_{p/r} \cdot T} = c_{sp} \cdot \Delta N_k \qquad (3)$$

(2) and (3) reveal a physical meaning of $\Delta\varepsilon_{\alpha k}$, useful for an easy identification inside a fuzzy rules or look-up table. For standard controllers of the position loop (P) and of the speed loop (PI):

$$G_{R\alpha}(s) = k_{p\alpha} = \frac{\Omega^*(s)}{E_\alpha(s)} \qquad (4)$$

$$G_{R\omega}(s) = k_{p\omega} \cdot \left(1 + \frac{1}{s \cdot T_\omega}\right) = \frac{C(s)}{E_\omega(s)} \qquad (5)$$

the digital forms are derived:

$$\omega^*_k = k_{p\alpha} \cdot \varepsilon_{\alpha k} = k_{p\alpha} \cdot (N^*_\alpha - N_{\alpha k}) \qquad (6)$$

$$c_k = c_{k-1} + k_{p\omega} \cdot (\varepsilon_{\omega k} - \varepsilon_{\omega k-1}) + \frac{k_{p\omega} \cdot T}{T_i} \cdot \varepsilon_{\omega k} \qquad (7)$$

According to the real-time control strategy, this relations are transformed in terms of a single formula with the on-line images of the variables:

$$c_k = c_{k-1} + A \cdot \Delta N_{k-1} + B \cdot \Delta N_k + C \cdot \varepsilon_{\alpha k} \qquad (8)$$

With: $A = k_{p\omega} \cdot c_{sp}$; $C = \dfrac{k_{p\omega} \cdot k_{p\alpha} \cdot T}{T_i}$

$$B = -k_{p\omega} \cdot \left(k_{p\alpha} \cdot c_{sp} + \frac{c_{sp} \cdot T}{T_i}\right)$$

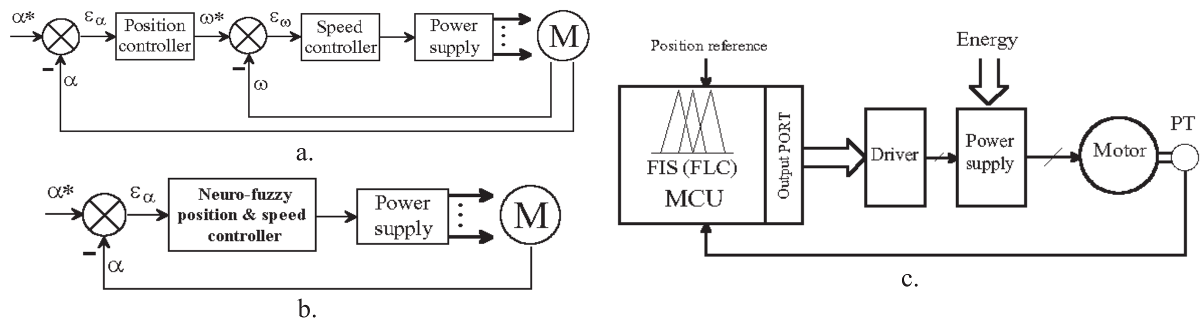

Figure 1: Basic control structures for the servodrive.

Many simulations and real-time experiments have been made and confirmed by their results the quality of this approach. That is why, such kind of structure will be put into operation for the acquisition of IN / OUT training data for a neuro-fuzzy controller. The model from fig. 1a is a source for the design of the controller of the configuration 1b and the on-line target structure is suggested by the fig. 1c. The authors' experience proved that when the variation error is considered into a digital form, some high rate variations could alter the natural data evolution, especially in the terminal and the angular points, as in the first moments of the movement and when the reference suddenly changes into a step style. That is why the Matlab / Simulink model – fig. 2 exhibits some improvements in this meaning by adding two extra blocks for filtering the reference channels of both loops. For the DC servomotor, a 2[nd] order model has been taken into account. The section for the acquisition of the training data is depicted by the fig. 3. After a right tuning, the macro results of the simulation – fig. 4, confirmed the quality of such model, especially in term of the time response and of a

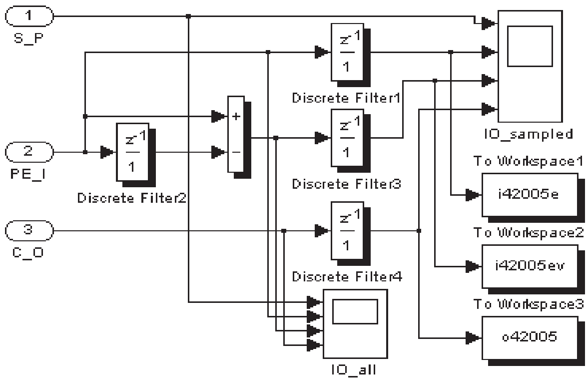

Figure 3: The acquisition section for the training.

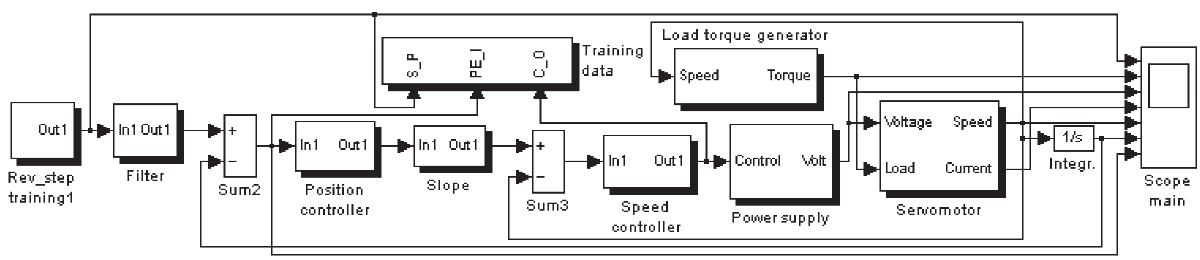

Figure 2: The model of a conventional control structure for extracting the training data.

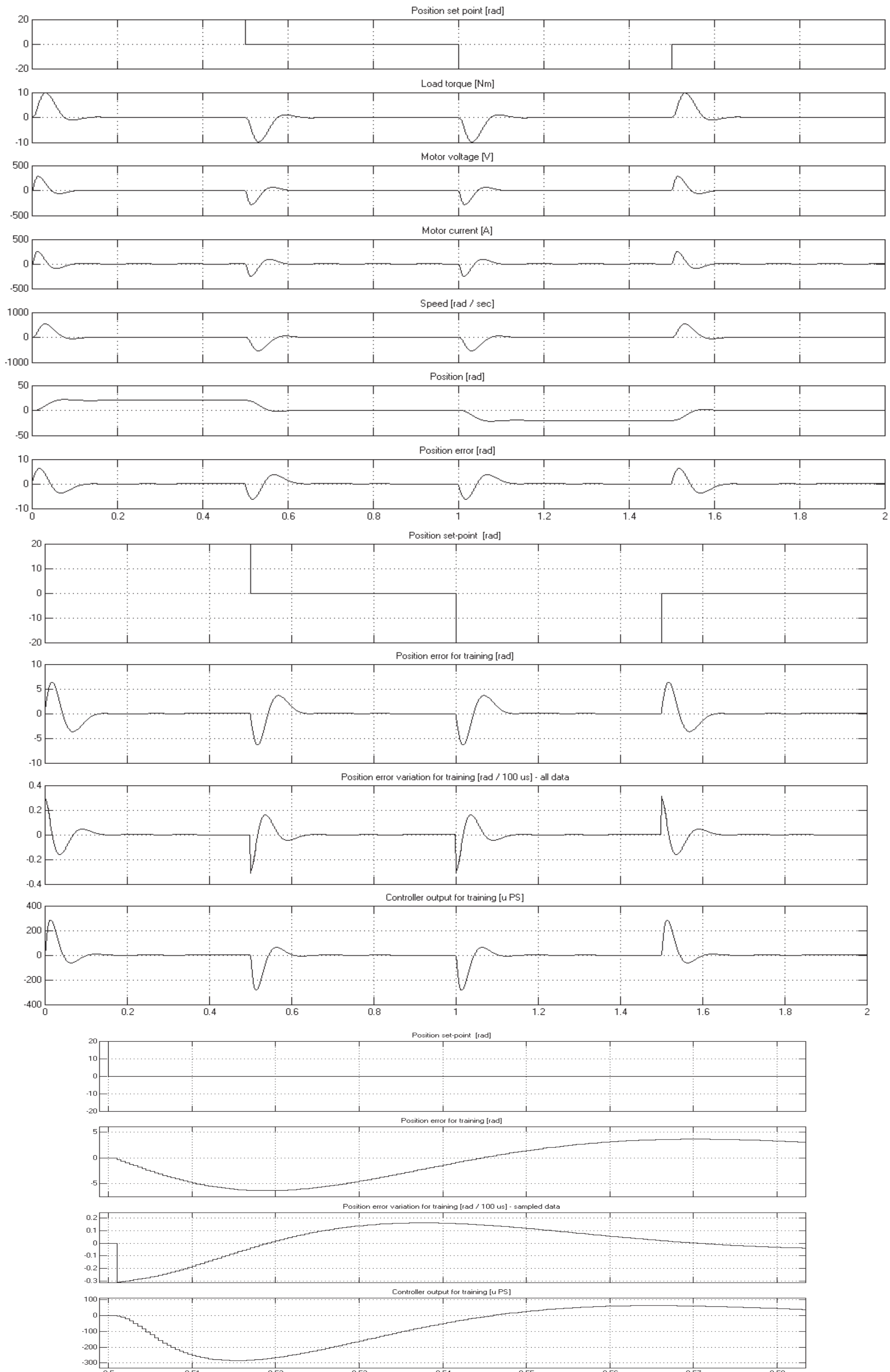

Figure 4: The results of the conventional structure and the obtained training data.

null position error. In this point it is important to make an essential remark about the initial model for the training data. Which is the best way to acquire valuable data:

a. using an ideal behavior and theoretical variables ranges?

b. considering many constraints in connection with the future target system and its associated operation conditions?

Although b. could seem to be the right answer, the author prefers to suggest a nuanced answer. It depends on the target application and on the training method of the artificial neural network (ANN). Using ANFIS, the author found that the specific computations for the whole state-space, beyond the rated variables ranges, could generate artificial and wrong values if many real constraints are taken into account. Fig. 4 presents also the content of acquisition section. The regime submitted considers a reversible control cycle and do not limit the control variable. The same figure has the diagrams for the IN / OUT variables stored (for the training) by sampling with a certain rate (hundreds of microseconds, so that the number of the training triplets (ε_α, $\Delta\varepsilon_\alpha$, ck) could be in the range of several thousands. The difference between the sampled and the initial variables is visible only in a zoomed view. The same fig. 4 offers such image, being visible also the above mentioned strong variation of the $\Delta\varepsilon_\alpha$ in the region of an angular point of the reference.

3. THE DESIGN OF THE N-F CONTROLLER

Many training scenarios have been put into operations, with several different conditions:

- the reference cycle and the motor load type (very important);
- the power supply regime – with / without saturation (important);
- the number of sets for the training data triplets (quite important);
- the number of the fuzzy sets and their variation type (not very important);
- the number of the training epochs (less important);

It can be seen that the number of the freedom degrees is huge. The design experience is important but does not suppress the necessity of many tests. Finally, the training conditions illustrated by the fig. 4 gave the best results.

The next lines give the essential about the ANFIS program and the final error obtained after 1000 training epochs.

ANFIS info:

Number of nodes: 131
Number of linear parameters: 147
Number of nonlinear parameters: 42
Total number of parameters: 189
Number of training data pairs: 4001
Number of checking data pairs: 0
Number of fuzzy rules: 49

...

Step size increases to 0.000010 after epoch 999.
1000 0.71842
Designated epoch number reached --> ANFIS training completed at epoch 1000.

The characteristics of the neuro-fuzzy controller (FIS- Fuzzy inference system) delivered by ANFIS is presented by fig. 5 and a first evaluation of its quality is given by the fig. 6 with the image of the training data as a trajectory in the space Input 1 - Input2 - Control, in comparison with the same dependence generated by FIS in the 3D as well as using 2D projections. There are no visible differences between the training set and that of the FIS result.

4. CONCLUSIONS

The design of DISO neuro-fuzzy controller for the servosystems give the possibility to control both the position and the speed. The acquisition procedure for the training data is more complex because the variation error consideration; the data amount is bigger and the images of the graphical characteristics associated to the training process as well as to the generated fuzzy inference controllers are less intuitive. The author suggests several relations for aggregate the computations of the position and the velocity loops into a single form adapted to the real-time computations. This approach is considered both for conventional algorithms and for the fuzzy control. The neuro-fuzzy controller was generated by an ANFIS program and in a next stage (subsequent paper) it will be tested on the model of the servodrive and it will be implemented as a real-time controller.

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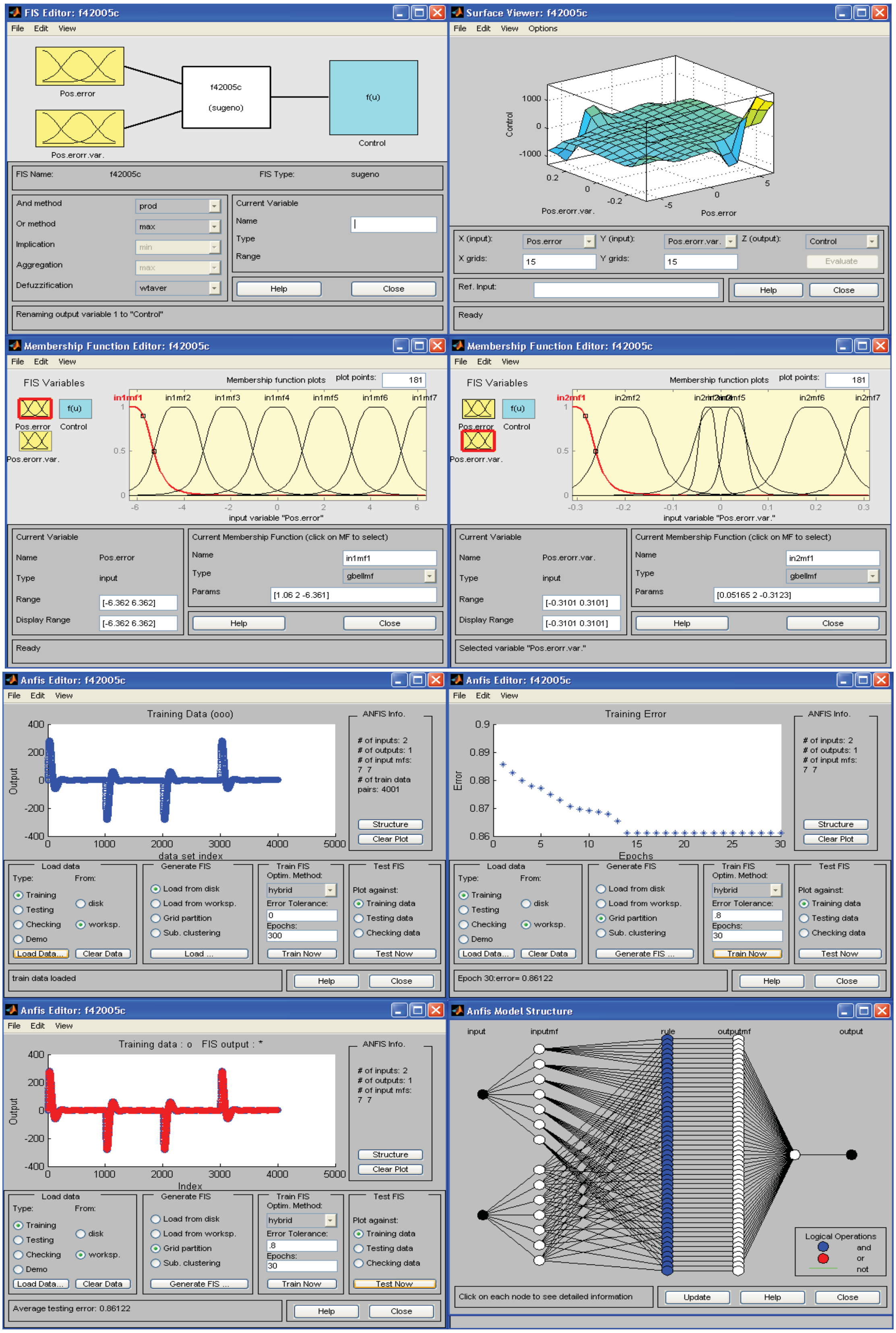

Fig. 5 The elements for the design of the neuro-fuzzy controller.

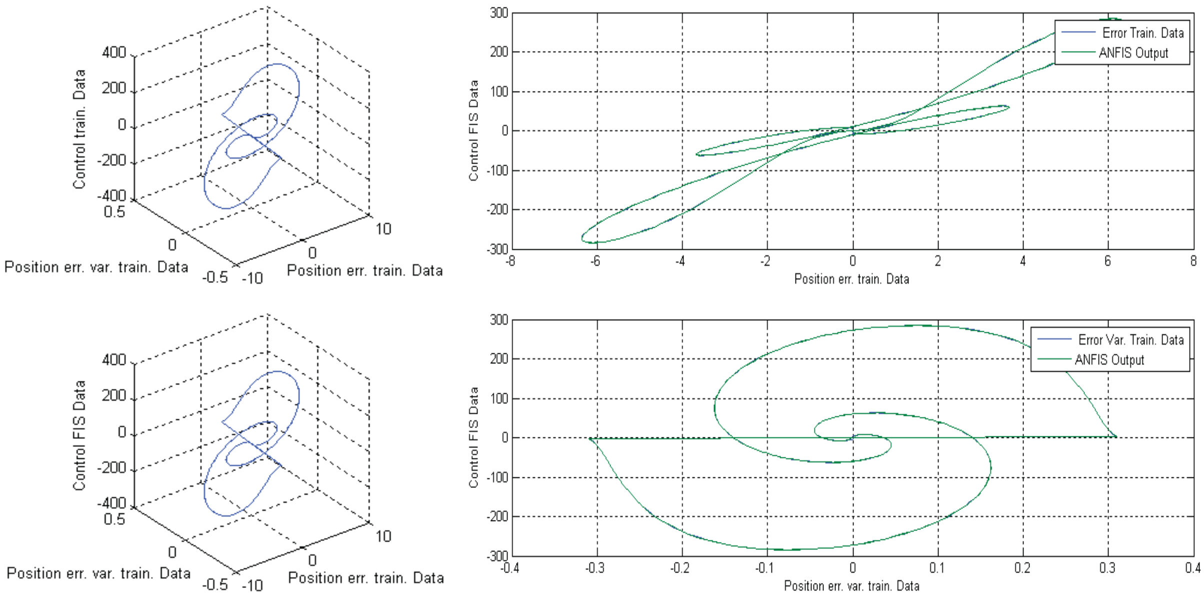

Fig. 6 The state-space trajectories of the training data, of the FIS controller and their projections.

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