Using a Hidden Mathematical Model Generated by Input-Output Data. The Reliability of a Neuro-Fuzzy Controller for a Servodrive.

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Abstract: - The paper deals with the synthesis of a neuro-fuzzy controller for a servodrive. Both position and speed loops are monitored by a single Sugeno fuzzy controller. The fuzzy solution is analyzed comparatively with the standard structure that generated it by training the neural network. Different training conditions are taken into account. The influence of the motor parameters, load characteristics, reference value and tuning parameters are considered. The proposed solution is simple and ensures a good and robust behavior.

Key-Words: - Neuro-Fuzzy Controller, Servodrive

1 Introduction

The author proved – [10], [11] that a well tuned fuzzy loop is able to compete and outrun the standard digital algorithms for positioning systems. But sometimes an off-line pre-processing associated with a fuzzy logic controller (FLC), justified, indeed, by a high quality of the results, diminishes the main advantage of the fuzzy logic: its simplicity. The aim of the paper is to bring back this quality by using a neuro-fuzzy approach with minimum design effort. The aim of the paper is to check if an invisible neuro-fuzzy model, found by automatic design from input-output data, is able to control a high demanding system in various conditions.

2 The initial structure and the generated data for training the neuro-fuzzy controller

Fig. 1 presents the initial model of the servodrive. having an external position loop and an inner speed one, the speed being computed from the position data. This structure is used in order to generate the training data for the neuro-fuzzy (N-F) controller. The behavior of this system (after a tuning of the controllers) is given by the fig. 2. The position error, as the input variable into the control chain and the final control variable are stored during the simulation for the training of the N-F Sugeno type controller by the ANFIS method – [7]. These data are shown by the fig. 3a comparatively with those variable obtained using a N-F controller based on a 20 epoch training (fig. 3b) and one for a 30 epoch training (fig. 3c). Of course, the training conditions are very important for obtaining a good N-F controller in term of its robustness. Fig 4 reveals the main elements for the N-F controller.

Several training conditions were experimented, concerning the fuzzy set choice / distribution and the number of epochs.

3 The neuro-fuzzy control structure and the simulation results

The new model, having a single neuro-fuzzy control unit, is presented by the fig. 5. It seems, really, much more simple. In fact, it is not quite so simple.

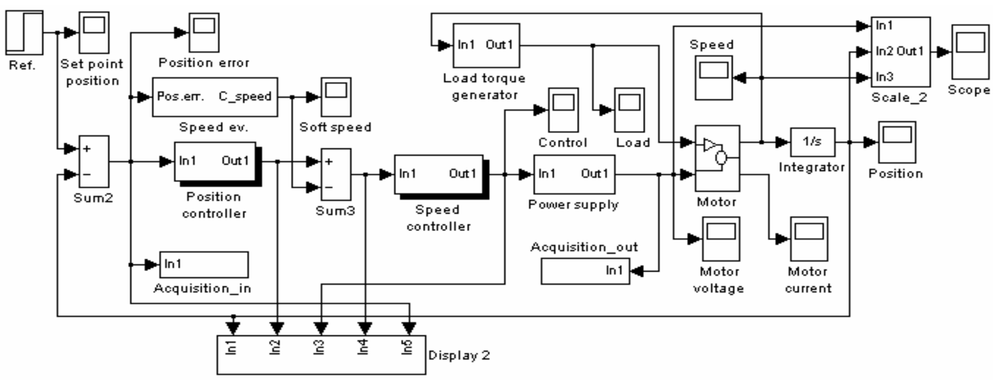


Fig. 4 The positioning system with standard controllers

Instead 2 controllers having together 3 tuning parameters (and o lot of tools / experience for handling their performance), this new model has a huge degree of freedom in tuning the N-F controller. It is about a infinite-parameters tuning (mainly by changing the fuzzy sets). Fortunately, this fact does

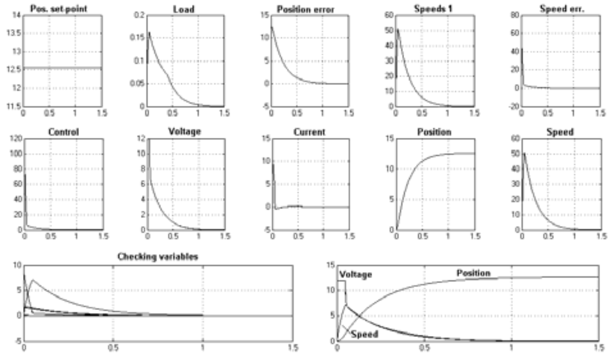
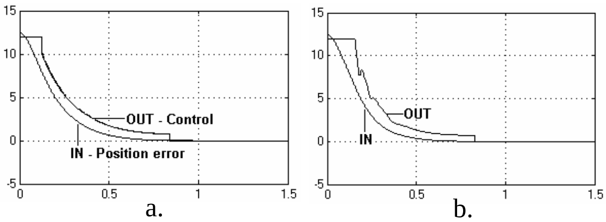
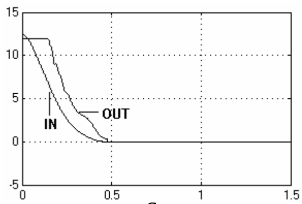


Fig. 2 The system with standard controllers: the main characteristic variables



a. b.

Fig. 3 The input–output variables for the N-N training and the results.



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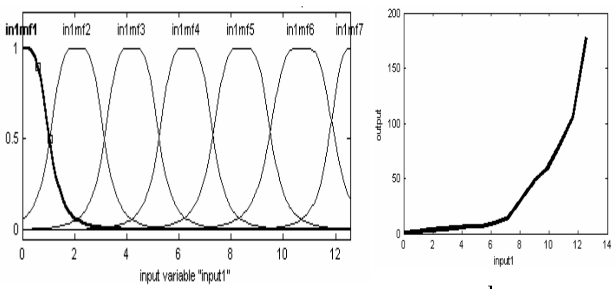


a. b.

Fig. 4 The implicit fuzzy sets and the image of the surface control for the Sugeno type fuzzy controller

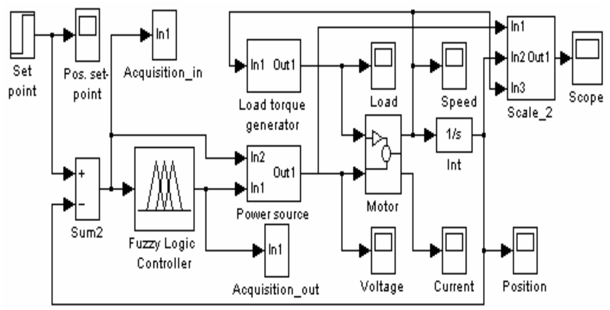


Fig. 5 The servosystem model with N-F unique controller

not lead to chaos, because a natural robustness quality of the fuzzy controllers – [1], [12].

The first results – fig. 6, concern the same initial conditions like for the standard structure, so they must be analyzed comparatively with those from fig. 2. The main variables evolution is very closed, hence the confirmation of a good training for the neural-network that is behind the fuzzy controller. One important performance criterion is related with the position error, that must be null finally. Another aspects are the length of the dynamic regimes and the overshoot. An obvious difference, however, comes from a more "vibrating" control delivered by the N-F controller. This is a good mark, denoting a useful sensitiveness of this one. It comes from the changing / balancing the fuzzy sets and the fuzzy rules. Only the current is affected, the mechanical inertia making smooth the position and the speed.

The next results try to establish the influence of different factors and conditions on the behavior of the standard and respectively the N-F structures. Fig 7 outlines a drawback of the standard controllers, their tuning parameters having a powerful influence on the system behavior. Fig 8 presents the influence of the mechanical inertia. The good tuning of the P / PI controllers makes the standard structure quite insensitive to the mechanical inertia – fig. 8.a. The N-F variant (fig. 8.b) leads to similar results, even better if the length of the dynamic regime. In both situations, the steady-state position error is null. The next comparison is made for a different value for the internal motor resistance (as a consequence of heating). As it can be seen in fig. 9a, the classical solution is no more able to control properly the system. The N-F solution has still good results – fig. 9b.

Other results when using the N-F controller are presented by fig. 10, for a different load torque of the motor and by fig. 11 for a lower set point for the position than the value used in the training step. It is

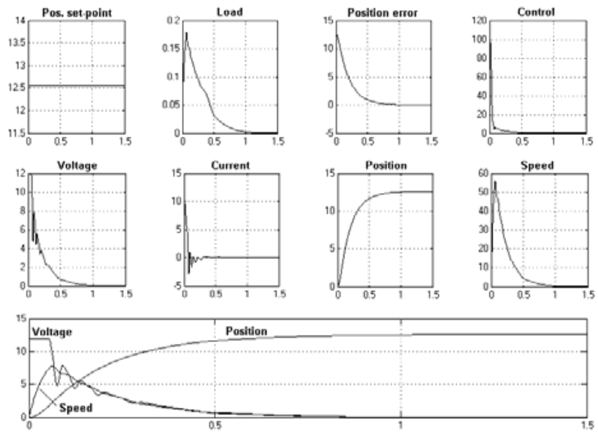


Fig. 6 Result set 1: the N_F controller operating in the training conditions

remarkable that even having a load close to the rated value for the motor (very different than for the training situation), the fuzzy structure makes an accurate control of the system. Also when the position reference differs. The motor voltage saturation interval is smaller and the time for accomplishing the task is lower, keeping a good quality of the characteristic variables evolution. The controller is smart enough for exploiting a lower value range for the speed, adapting efficiently the kinematics.

The next comparison concern the two solution considering a combination of several factors with different values than during the training step: internal resistance and inductivity, reference speed, load torque (including the friction term, a constant and a speed proportional term). A careful look of the results from fig. 12a shows that the standard controllers are no more able to ensure a null position steady-state error. The motor voltage has a variation not specific for such controller, being more similar to the fuzzy controllers. The N-F structure still works very well, with reach of the final position, almost the same short length of the dynamic regime and a nice, smooth variations (even for the motor current). Indeed, this situation and these results give

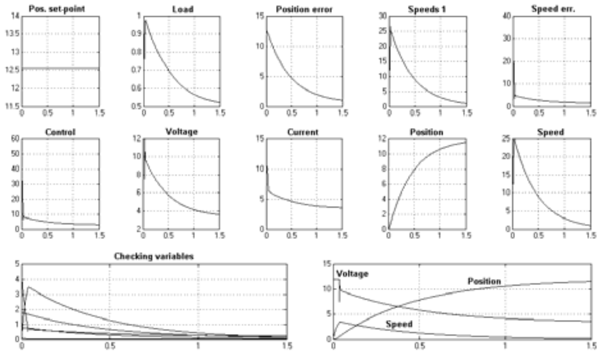
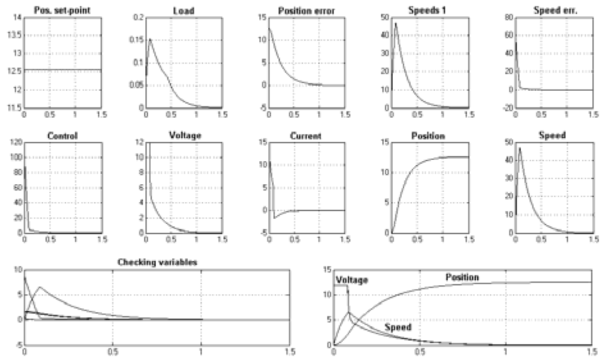


Fig. 7 Standard controllers having a slight deviation from optimal tuning



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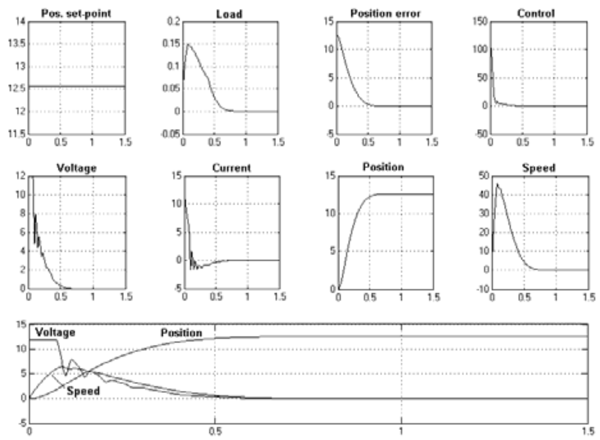
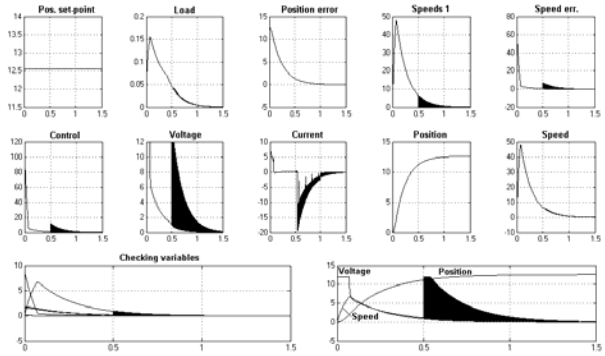


b.

Fig. 8 The behavior of the drive for a bigger mechanical inertia with standard controllers (a) and a N-F one (b)



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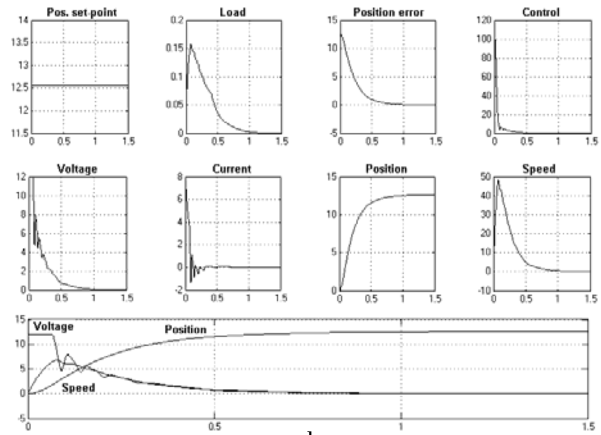


b.

Fig. 9. The influence of the motor resistance

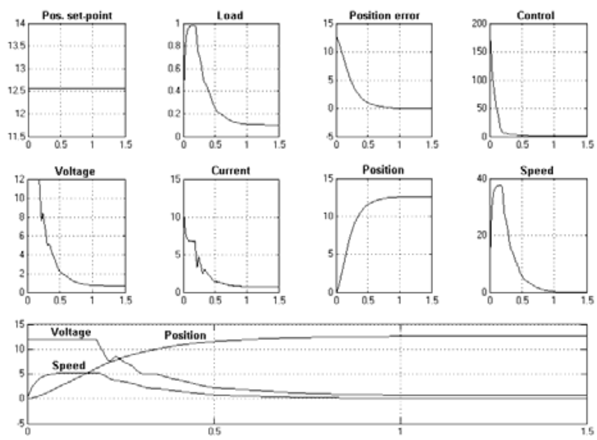


Fig. 10 A N-F control with a different load torque

confidence that the N-F solution has a high quality.

The next results try to consider the effect of different training conditions for the neural network used to generate the Sugeno controller. A first possibility concerns the imposed number of the training epochs. All the previous results were done for 20 epochs. The fig. 13 gives a kind of answer for 30 epochs. The surface control is much higher,

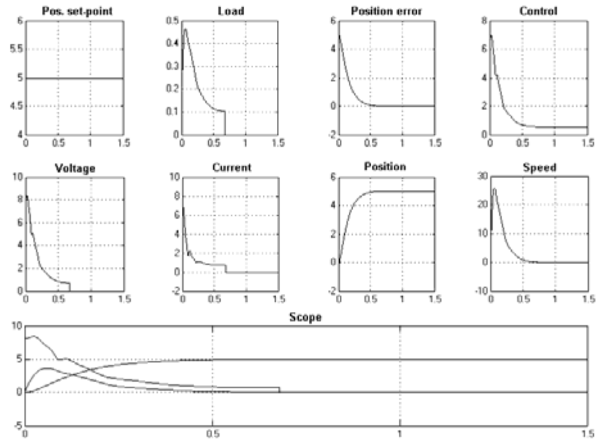
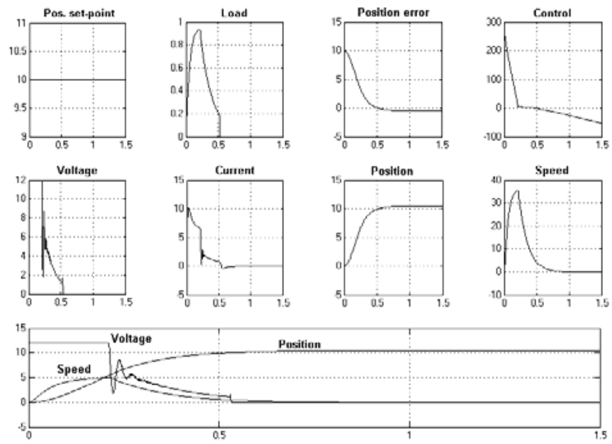


Fig. 11 The N-F control for a different position reference



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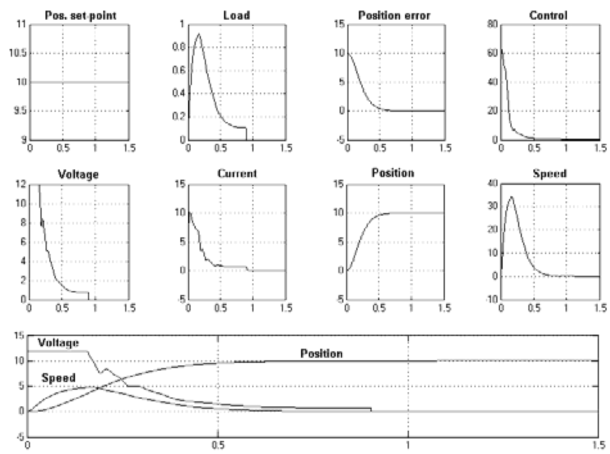


b.

Fig. 12 The behavior of the servodrive when a combination of different conditions is applied

pushing more energy to the drive. Indeed, although the main variables have a similar behavior, the positioning time is much shorter. It seems that it is worth training by more epochs. Another idea is to distribute non-uniformly the fuzzy sets. A more dense distribution in the small values region for the position error (the controller input) and for the control, could suggest a more accurate control in the final region of the trajectory, where the system must be closely controlled. The corresponding situation and results are depicted by the fig, 14. But, amazingly, some unexpected aspects deny this hypothesis. The controller computations lead to a negative zone in the control surface – unuseful for a proper control for one quadrant operation. And the macroscopic variables have evolutions from acceptable (but not very good) to bad. An opposite (strange) idea is to proceed to a non-uniform distribution of the fuzzy sets but in the opposite sense: the narrow sets in the initial region of the positioning regime – fig. 15. The surface control becomes normal and the main variables (position, speed, voltage for a lower and for a higher load torque) have good variations. The explanation is not at all simple, taking into account the initial saturation zone for the motor voltage (always). It seems that this new distribution, by the computation involved for the control, is able to ensure a longer saturation interval, with positive consequences. Despite some studies concerning the robustness of the fuzzy controllers – [12], stating the small influence of the membership functions, this results proves that for the Sugeno fuzzy controllers obtained by the ANFIS method, the choice of the fuzzy sets is an important tuning factor.

But the N-F is very robust for disturbances (noises) affecting the motor load. In the fig. 16a, a positive impulse was added to the load torque during the starting system and in the fig. 16b, a negative same impulse was considered. The behavior of the system is still very good. The next results – fig. 17, concern a similar temporary perturbation affecting a motor parameter: like for a brushed servomotor where it is possible to have strong variations of the internal resistance because of an imperfect slide contact. As it can be seen, the neuro-fuzzy controller is able to solve very well this situation.

The same controller, obtained by training the neural network with data from a step input, is put to drive the system when a different input type signal is applied – fig. 18. A ramp is followed by a constant set point speed. The FLC adapts very well its action to the new input signal. The systems makes a good job in a very reasonable time.

The results from the fig. 19 concern a bigger reference speed than the value used by the training program. For a set-point above the training value with 27 % and the controller performs a good positioning job, although a too low initial value is not very promising. When the input range is more far away from the training value, the things worsens, in term of a strange extension of this initial area with a sub-control. Finally, the system succeeds in making the final position error null, but after a long initial delay, during of a control lack. The explanations come from the computations beyond the values available from the training step; it seems that these computations obtain an adequate control after o long iteration chain.

4 Conclusions

By training a neural network it is possible to obtain a single high quality fuzzy controller for several control loops of a servodrive.

The identification of the best training conditions is an essential factor for the robustness of the system. A key role for the choice of these conditions comes from a deep understanding of the physical operation conditions and the involved elements: type and range inputs, parameters of the motor, parameters of the mechanical part (inertia, load torque as variation type and range values), disturbances that could affect the system. Theoretically, the neuro-fuzzy controller will be able to ensure the expected performance only in very similar operation conditions as in the training step. Various simulations performed by the author proved the ability of the obtained fuzzy controller (Sugeno type) to obtain good and very good results even when the operation conditions differ more or less from the training conditions.

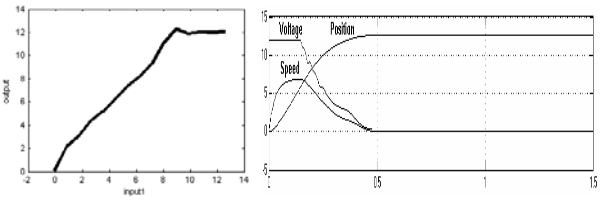


Fig. 13 Considering more training epochs

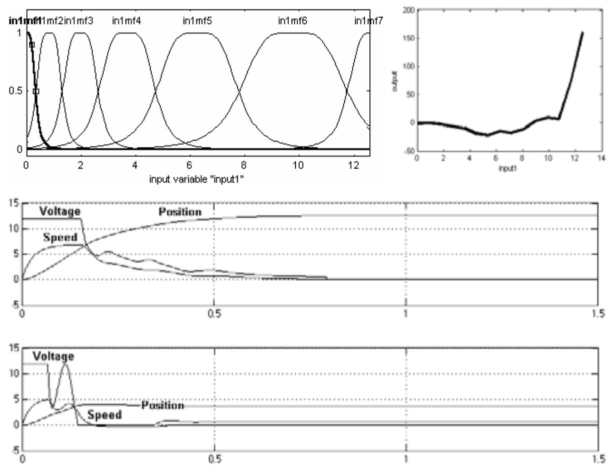


Fig. 14 A second fuzzy set distribution

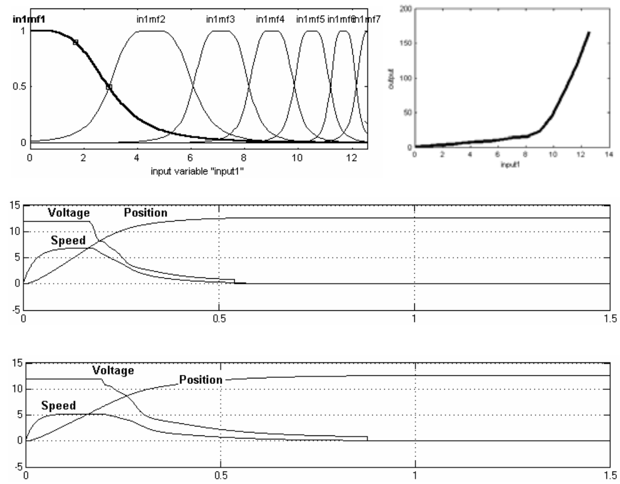
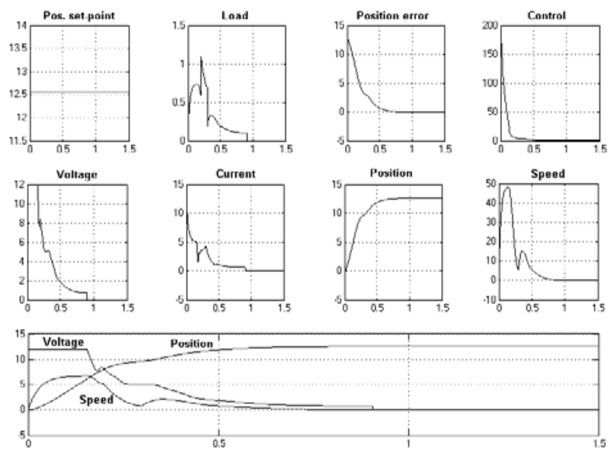


Fig. 15 A third fuzzy set distribution



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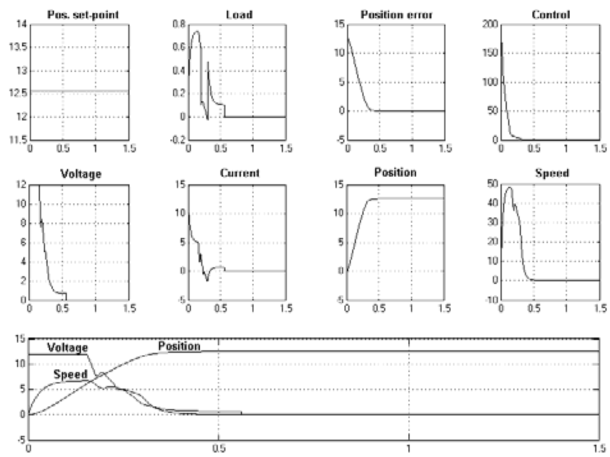

b.

Fig. 16 The influence of a perturbation (impulse affecting the load)

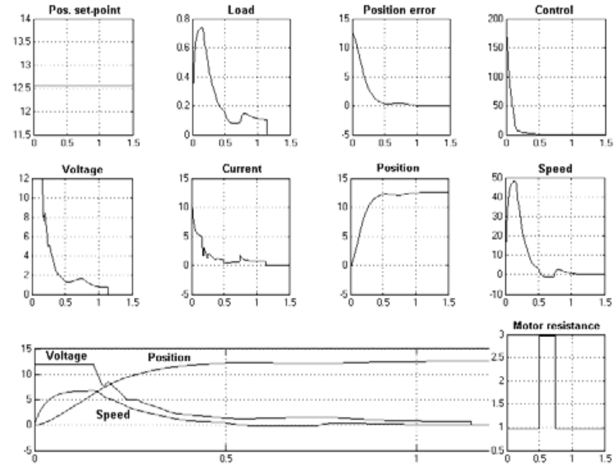

Fig. 17 The N-F results for a simulated bad contact of the brush

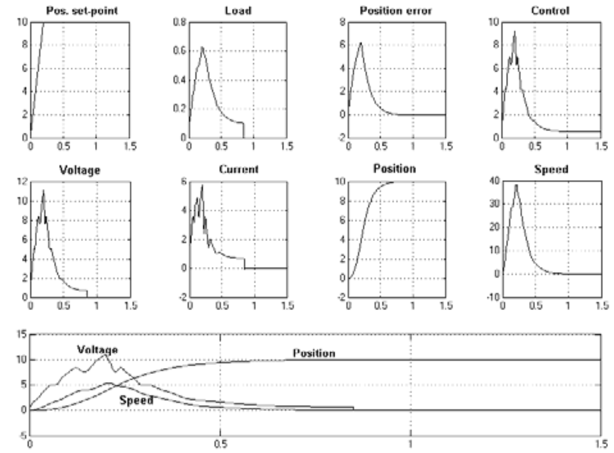

Fig. 18 How the N-F controller solves a different reference type signal

The implicit choice (uniform distribution) of the fuzzy sets by the ANFIS program seems to be the most appropriate. It is important to verify the image and the values of the surface control. The most important variable remains the error position, as the steady state value and the dynamic variation and the final region is essential for analyze the quality of the control. Different simulations proved, however, the great importance and influence of the first moments, even as the length of the saturation interval.

Although the neuro-fuzzy controller is able to make a good job for a slight outrunning of the input range - declared in the training step, it is highly recommended to avoid such a situation, especially with an important value.

Not all the motor parameters have the same influence on the robustness of the controller. The inertia is much lesse important than the internal resistance; this sensitivity for this parameter is found for other control algorithms too (like the vector control methods).

A comparison between the standard and the

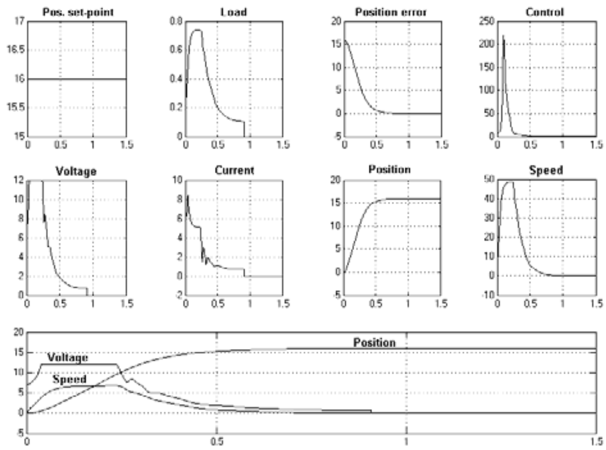

Fig. 19 The effect of a bigger reference

neuro-fuzzy controllers for a servodrive is favorable to this last ones.

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