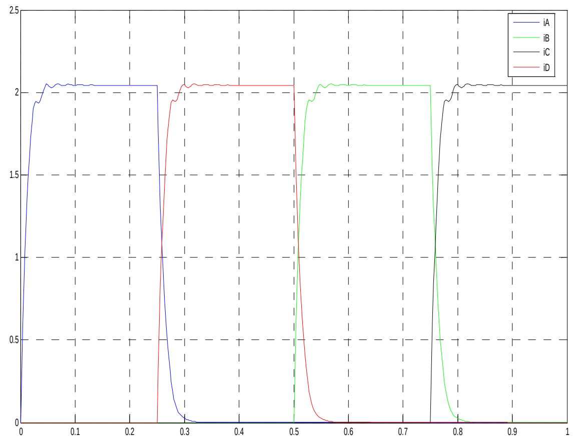

Figure 5 Currents in different phases

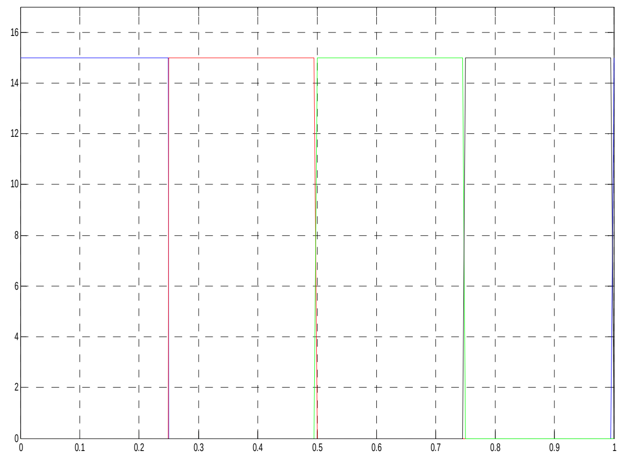

Figure 6 Voltages in different phases

Single phase is energized for 0.25s as shown in figure 6. When Phase A is powered, motor makes a step of 2.54mm, then the next phase, phase B, for another step of 2.54mm to reach the position of 5.08mm, and phase C and then phase D to arrive at the end to make a complete dental step 10.16mm.

In the case, in theory, of a problem while choosing the parametric identification method of testing motor, we try in this work to adopt a neural network approach, for the quality of their contributions in learning ability to better estimate the dynamic behavior of the considered motor. The work is limited to the neural network detection phase for their better approximation capabilities of nonlinear functions.

3 Neuronal Approaches

The neuron-fuzzy diagnosis ensures generation of residues by neural networks and their subsequent analysis by fuzzy logic.

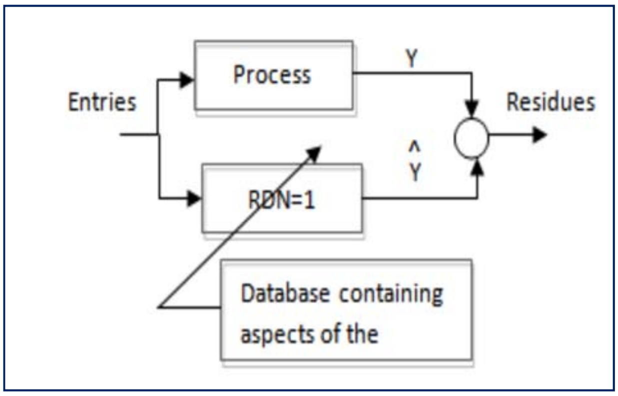

Figure 7 Neuro-fuzzy patterns for diagnosis

The steps for creating a neural network can be thus summarized:

Creating the database

- ✓ Expert knowledge,
- ✓ Key features of the process

Choice of neural network structure

- ✓ Layers number
- ✓ Neurons number
- ✓ The activation functions

Learning

- ✓ Network Initialization
- ✓ Back propagation of error
- ✓ Levenberg-Marquardt algorithm

Neural network validation

- ✓ Network evaluation
- ✓ Network tests

if unsatisfactory network:

- Change in the network structure
- Increasing the number of iterations of the learning phase
- Changing the initial values of the weights and biases

The desired algorithm followed this approach is well illustrated in the following diagram:

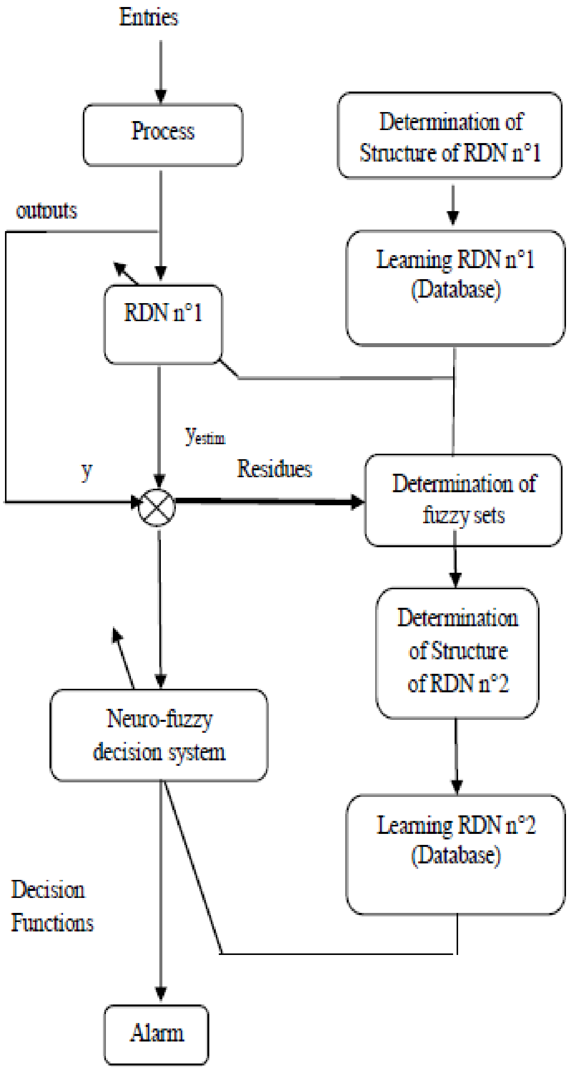

Figure 8 Neuro- fuzzy patterns for diagnosis

Our work was focused mainly on the step of neuronal estimation.

4 Validation based on an experimental response of the developed neural estimator

A method for the characterization of the achieved model which has been proposed in [3], which intends the development of a technique for estimating motor parameters studied based on the approximate feedback of speed, ($\dot{x}$), and the acceleration ($\ddot{x}$), and using the least squares method to determine the best parameters characterizing the motor.

The implementation of this technique for a pitch of 3.2 ms discretization and a position vector (X) : X = [0 0 0 1.5 2.5 4 6.5 11.5 17.5 26.5 38.5 46.5 47 46.5 41.5 36.5 29.5 25 25 27 31.5 35.5 37 35.5 35 32.5 30 30 30.5 32 32.5 32.5]^T leads to the response of the new model in Figure 7.

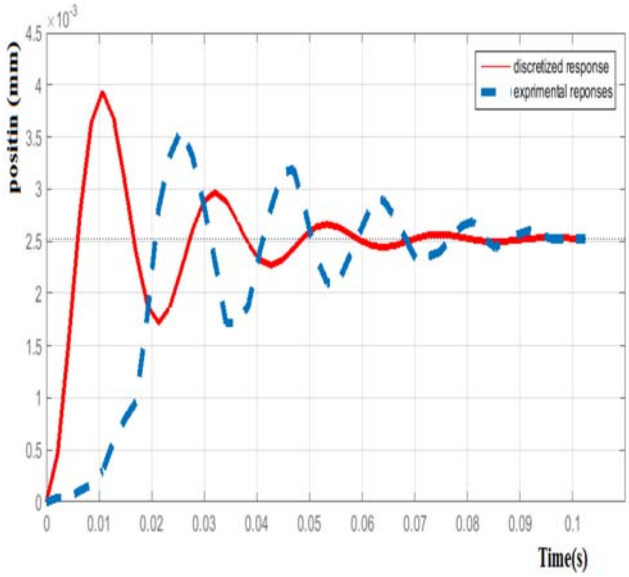

Figure 9 Unit-step responses for the new model

This experimental study of simulation allowed us to characterize a nonlinear dynamic model of reduced order. We note that during the preparation of this study, only the evolution of the variable of position was taken into account whereby generating the difference between the result of the model and that of experience. A model, which coincides exactly with the practical one, will be very effective for identifying the parameters of model that take into account any non-linearity of the studied system.
Using "Neural Network Toolbox" of Matlab, a neural network, having as activation function for the hidden layers, the "tangent sigmoid" and the "linear" functions for the output layer, is prepared.
We came up with an estimate, using a neural network, the response which coincides much better with the discrete response than the simulated one performed in [3].

Initially we worked on the phase A of the studied motor later we developed an own neural estimator for each phases B, C and D.

The results for phase A are illustrated in Figures 10 and 11.

- **number of Iterations =500**

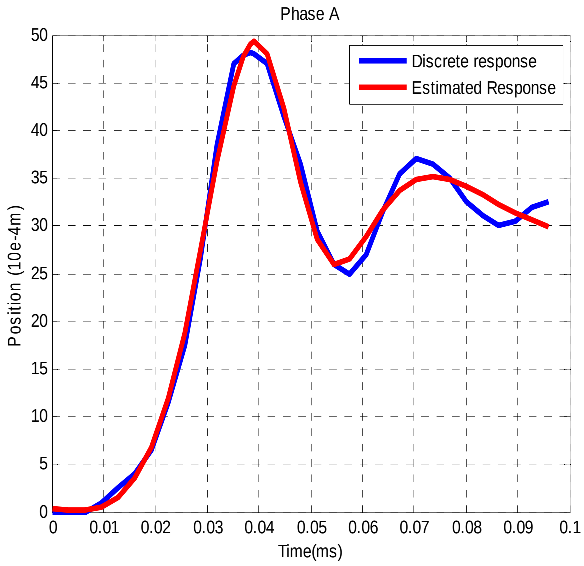

Figure 10 The estimated response for a number of iterations = 500

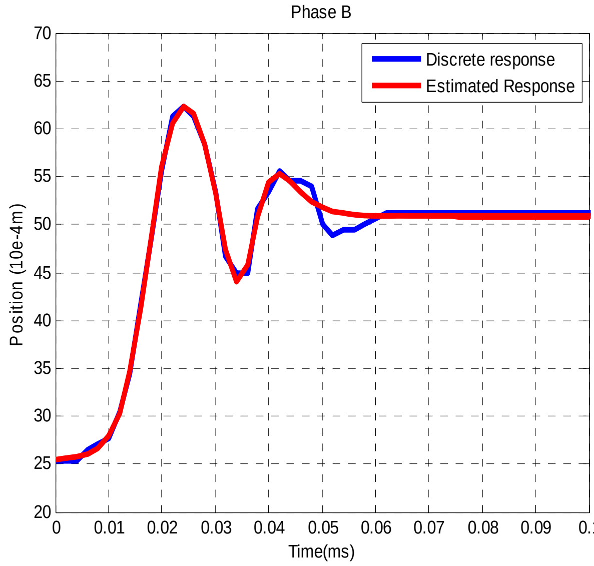

Figure 12 The estimated response for a number of iterations = 500 (Phase B)

- **number of Iterations =1000**

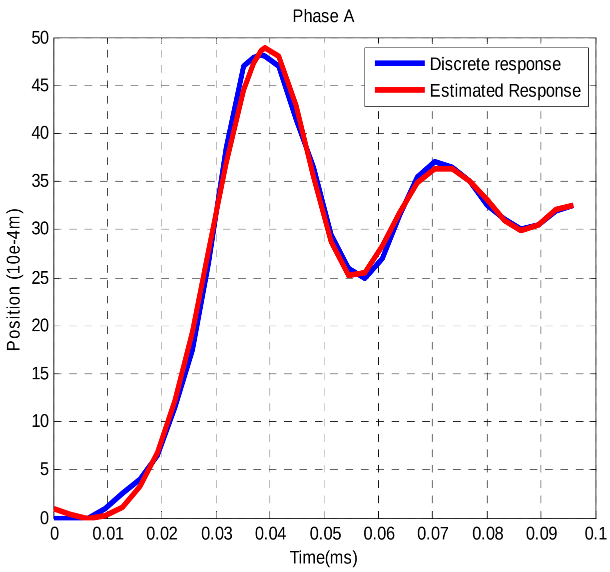

Figure 11 The estimated response for a number of iterations = 1000

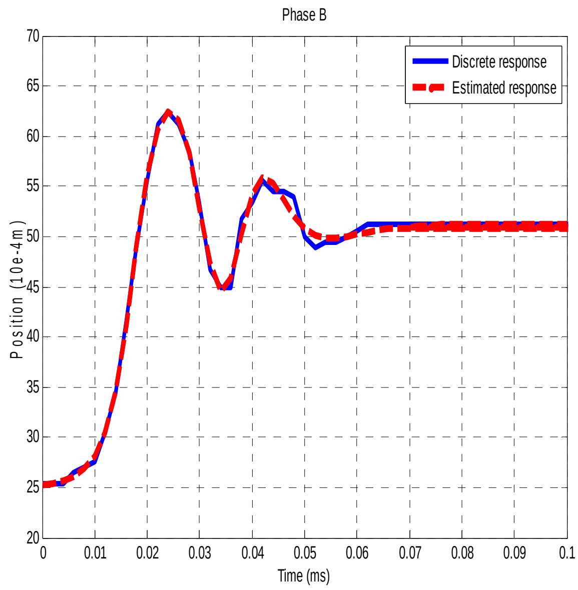

Figure 13 The estimated response for a number of iterations = 1000 (Phase B)

The results obtained (of the simulation model and of the neural estimator) for phase A satisfy well the aimed objectives.

The results for phase B are illustrated in Figures 12 and 13.

The results for phase C are illustrated in Figures 14 and 15.

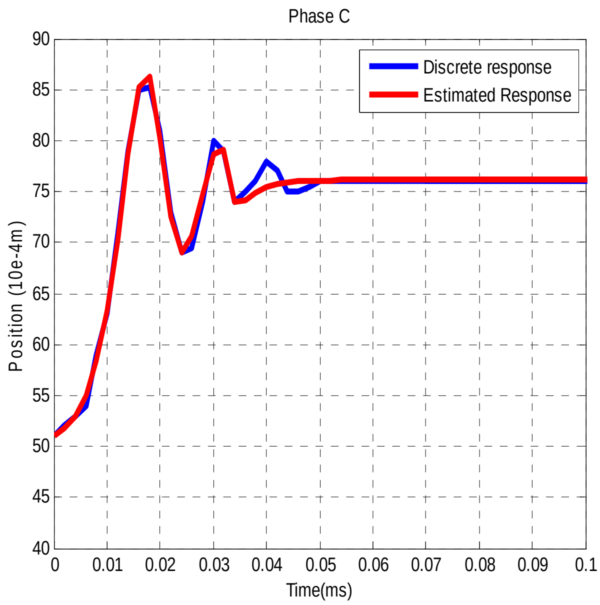

Figure 14 The estimated response for a number of iterations = 500 (Phase C)

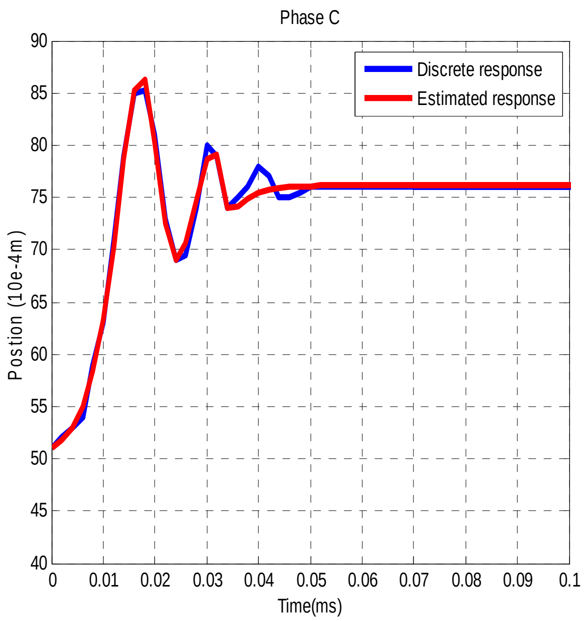

Figure 15 The estimated response for a number of iterations = 1000 (Phase C)

The results for phase D are illustrated in Figures 16 and 17.

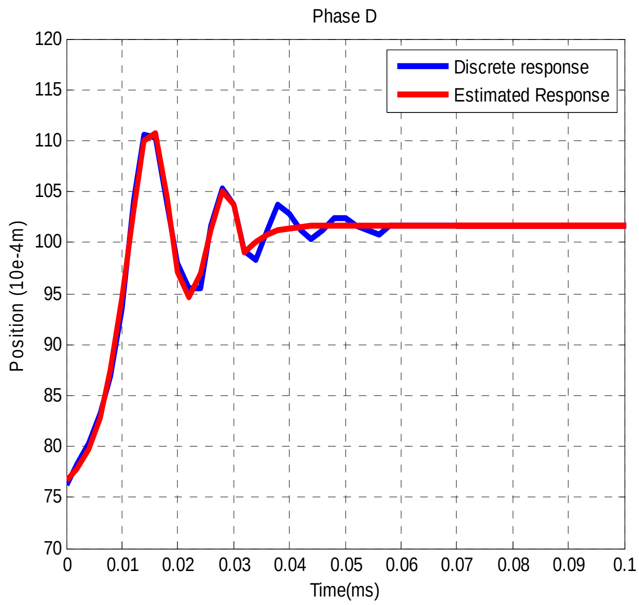

Figure 16 The estimated response for a number of iterations = 500 (Phase D)

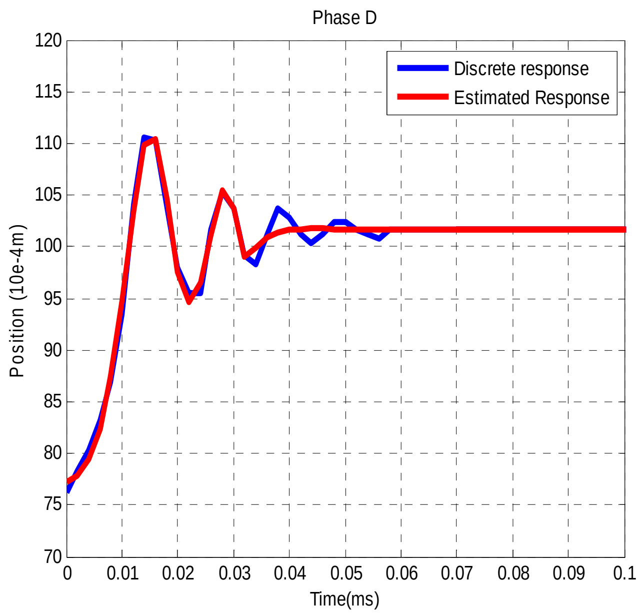

Figure 17 The estimated response for a number of iterations = 1000 (Phase D)

Initially, during the model simulation based on the four electrical equations and the mechanical one, we obtained the expected responses verifying that the generalized model of the test motor, developed in the work of the document [3], show this limitations and that the method adopted for the identification of the machine parameters do not result in adequate values for the simulation of the actual operation of the designed motor. Then, using a neural network, an estimate based on an experimental unit-step response of the machine is developed. The simulation showed that for a large number of iterations of the implementation of the network we reach a response that perfectly follows the experimental response.

The number of iterations of the implementation of the developed neural network affects the results of the simulation. Thus, for a higher number of iterations to thousand, the results were conclusive.

5 Conclusion

Our study presents a modeling more appropriate to the dynamic behavior of such a stepping motor.

In fact, since the first approach is not reliable; we have proceeded by a neural networks-developed estimator proceeding. The adoption of the selected neural network tool is argued by its learning capacity. Due to the non-linear nature of the model to be studied, such adopted tool seems, well adequate in respect of its excellent approximation of nonlinear functions.

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