## MODELING USING NEURAL NETWORKS: APPLICATION TO A LINEAR INCREMENTAL MACHINE

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*Abstract:* - Modeling a testing stepping linear and variable reluctance motor is achieved by applying techniques based on specific new tools for estimating the simulation responses of such studied machine. The target goal is to identify a mathematical model defining the finest possible motor behavior to study. In this work, we try to establish a comprehensive modeling, by the neural networks, of a linear stepping motor prototype, taking into consideration the electrical and mechanical characteristics and using the measurement results of the practical tests.

Key-Words: -Neural Networks, incremental linear machine, Modeling.

### **1** Introduction

Modeling an electromechanical system represents the objective of this work, usually expressed in two different ways;

-Electromagnetic modeling based on the use of the operating equations of the machine to model electromagnetic effects,

-Electromechanical modeling that considers a mathematical model with simplifying assumptions,

-The ferromagnetic materials are ideal ( $\mu r = \infty$ ).

-The notch effect is neglected.

-The effect of the induced currents is neglected.

-The Effect of mutual inductance is neglected.

Inspecting the defects in electromechanical devices is generally limited to the analysis of voltage, temperature current, speed, and vibration magnitudes. The growing demand in terms of robustness of the diagnostic tools required the development of new solutions based on the analysis new magnitudes and exploring of new complementary approaches to existing ones.

In this regard, we consider the results of identification and modeling obtained on a laboratory test prototype of a linear stepping reluctance motor to four supply phases.

# 2 Modeling tubular 4-phase stepping motor

The test prototype is a variable reluctance linear motor shown in Figure 1. [1]

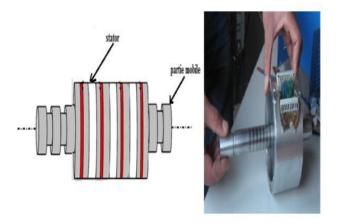


Figure 1 Schematic prototype of the SLRM

This relates to a linear motor provided with a tubular structure, with a smooth moving portion, formed of an alternation of identical dimension rings with materials of different magnetic behavior, guided in translation by linear bearings.

The toothed stator comprises four statoric modules, where house the windings of phases A, B, C and D in their magnetic circuit. Spacers of non-magnetic materials, of thickness  $\lambda p$ , are interposed between

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the phase modules to ensure magnetic separation and the regular operation of the machine.

The exploitation of results obtained by practical tests performed on the prototype test, were

permitted to identify and then to model the behavior of the machine.

The theoretical model of the machine concerned by this study is given by the equations of electrical and mechanical system (1), (2), (3), (4) and (5) [2].

$$\frac{d\nu}{dt} = -\frac{\pi L_1}{m\lambda} [i_A^2 \sin(\frac{2\pi}{\lambda}x) + i_B^2 \sin(\frac{2\pi}{\lambda}x - \frac{\pi}{2}) + i_C^2 \sin(\frac{2\pi}{\lambda}x - \pi) - \frac{2}{B} \sin(\frac{2\pi}{\lambda}x - \frac{3\pi}{2})$$
(1)  
$$-F_0 sign(\nu) - \zeta \nu - F_c]$$

With:

Fm: Developed electromagnetic force.

- F0: Dry friction force.
- Fc: Resisting force.

V=dx/dt: Linear speed of the movable part.

- x: Armature position.
- m: Armature mass.
- $\zeta$ : Dynamic viscosity coefficient.
- R: Statoric resistant.

$$U_{A} = Ri_{A} + L_{0}\frac{di_{A}}{dt} + L_{1}\cos(\frac{2\pi}{\lambda}x)\frac{di_{A}}{dt} + \frac{2\pi}{\lambda}L_{1}\sin(\frac{2\pi}{\lambda}x)vi_{A}$$
(1)

$$U_{B} = Ri_{B} + L_{0}\frac{di_{B}}{dt} + L_{1}\cos(\frac{2\pi}{\lambda}x - \frac{\pi}{2})\frac{di_{B}}{dt}$$

$$(2)$$

$$+\frac{-\alpha}{\lambda}L_{1}\sin(\frac{-\alpha}{\lambda}x-\frac{-\alpha}{2})vi_{B}$$

$$U_{C} = Ri_{C} + L_{0}\frac{di_{C}}{dt} + L_{1}\cos(\frac{2\pi}{\lambda}x-\pi)\frac{di_{C}}{dt}$$
(3)

$$+\frac{2\pi}{\lambda}L_{1}\sin(\frac{2\pi}{\lambda}x-\pi)vi_{c}$$
(3)

$$U_{D} = Ri_{d} + L_{0}\frac{di_{d}}{dt} + L_{1}\cos(\frac{2\pi}{\lambda}x - \frac{3\pi}{2})\frac{di_{d}}{dt} + \frac{2\pi}{\lambda}\sin(\frac{2\pi}{\lambda}x - \frac{3\pi}{2})vi_{d}$$
(4)

Uk, ik: Voltage and current in one phase (k=A, B,C, and D).

 $\lambda$  : rotor and stator tooth pitch.

The studied motor is characterized by the following parameters;

m=0.47Kg ;  $\zeta$ =21Nm/s ; R=7.34 $\Omega$  ; Uk=15V ; F0= 0.1N; F0= 0N.

With regards to a simulation a few simplifying assumptions have been adopted:

- Excluding the saturation
- Excluding the magnetic relaxation (insignificant hysteresis effect)
- Infinite permeability and resistivity of iron,
- Insignifiant leakage flux,
- Insignificant fringe and ends effects.

On the other hand, the system is considered to two time scales. It includes fast variables related to electrical parameters and other slow variables, those related to mechanical parameters of the system. Thus in [3] only equation (1), relative to the mechanical equation, was chosen for the model simulation.

The simulation is made by taking into account all the electrical and mechanical equations. The physical model of the machine is established by means of "Matlab" and "Matlab/simulink". [2] Was carried out by only the equation (1), the mechanical equation, for the model simulation. Indeed, it has neglected the electrical parameters (the fastest), the delay is neglected and the simulation is made by taking into consideration of all the electrical and mechanical equations. The physical model of the machine is established by means of "Matlab" and "Matlab/simulink".

Concerning the motor control, we excite a phase at a time as shown in the following table 1:

 Table 1 Motor drive's table.

Excitation	2.54mm	5.08mm	7.62mm	10.16mm
Phase A				
Phase B				
Phase C				
Phase D				

The results obtained are illustrated in the following figures:

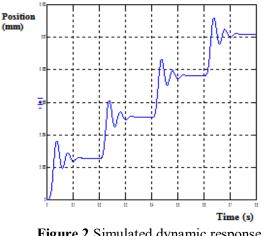


Figure 2 Simulated dynamic response of the motor

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.

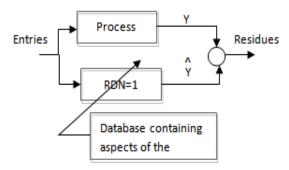


Figure 3 Neuro-fuzzy patterns for diagnosis

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
- $\checkmark$  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:

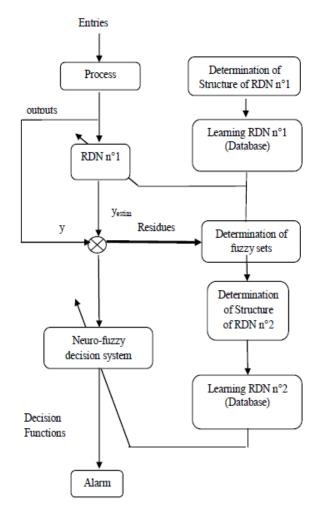


Figure 4 Neuro- fuzzy patterns for diagnosis

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.

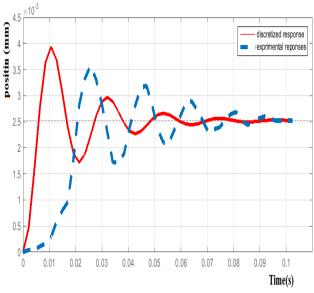


Figure 5 Unit-step responses for the new model

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]. The result of our work is illustrated in Figures 6 and 7.

• number of Iterations =500

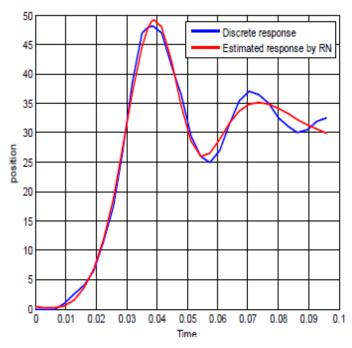


Figure 6 The estimated response for a number of iterations = 500

• number of Iterations =1000

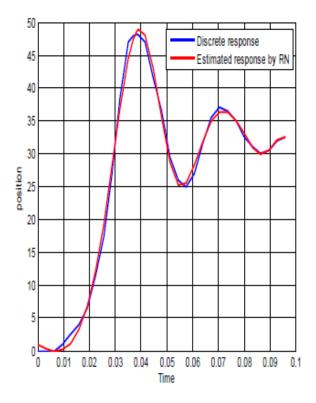


Figure 7 The estimated response for a number of iterations = 1000

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

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, a priori, well adequate in respect of its excellent approximation of nonlinear functions.

#### References:

[1] W. AMRI, M. Salhi, A. BEN AMOR, 2014."Une nouvelle stratégie de régulation intelligente d'un moteur à réluctance variable", International Journal of Innovation and Applied Studies Vol. 9 No. 4 .pp 1450-1458

[2] BEN SAAD, K., BEN SALAH, B., BENREJEB, M., BROCHET, P., Fuzzy logic controller for switched reluctance linear stepping motor Transactions on Systems, Signals and Devices, 2006,Vol. 1, No. 1, pp. 69-85

[3] A. Ben Amor, "Experimental Identification of a Linear Tubular Four Phase Stepping Motor," 2002 IEEE International Conference on Systems, Man and Cybernetics, Vol. 5, 2002.