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Using ANFIS System for Speed Regulation in "Linear Inductive Actuators"

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Abstract: In this study we have considered the muzzle exit velocity as our main objective performance. An adaptive neuro-fuzzy inference system is developed to predict the exit muzzle velocity. To assess simulation results, a small-scale prototype experiment is designed and constructed where, the simulation results of theoretical model are in good agreement with results obtained from prototype experiment. We used the approximation property of ANFIS to develop a regulator for muzzle velocity. It has been shown that ANFIS is a powerful method to model nonlinear and highly varying functions utilizing mathematical property of ANN in tuning rule-based fuzzy systems. For the case of this regulator, ANFIS has three inputs: desired velocity of the muzzle, initial temperature of the drive coils and capacitors and the mass of the projectile and initial voltage of the capacitors is the output. Simulation results showed that the desired muzzle velocity can be reached using ANFIS to determine the initial voltage of the capacitors.

Key word: ANFIS · Linear induction · ANN · Speed regulation

INTRODUCTION

The analysis of traveling wave tubular linear induction motors shows that induction is a feasible method of producing armature current and that efficient accelerators can be built without sliding contacts or arcs and offered the potential for extremely high efficiency, flexible, hypervelocity electromagnetic accelerators. [1]

Electromagnetic coil actuators or accelerators consists of a barrel formed by an array of coils and of a conductive projectile. (usually aluminum)[2]. An accelerating force is provided by the interaction between the magnetic wave produced by the barrel currents and the currents induced in the projectile sleeve. The resulting motion of the projectile is slower than that of the magnetic wave; the difference is termed the slip speed, as in an induction motor. To achieve high efficiency, the swing of the slip speed is limited by subdividing the barrel into several sections. In each section, the frequency of the currents is kept constant but increases from one section to the next, in steps, down the barrel, from the breech to the muzzle.[3]

This paper deals mainly with performance analysis of the capacitor driven electromagnetic coil-launchers using computer simulation. The Mesh-Matrix model and system equations used for simulation. [4-6]. Temperature effects on the conductivity of the sleeve and drive coil resistances and capacitors value are considered in simulation.

Regulation of Exit Velocity: The exit velocity of projectile mainly depends on initial stored energy in capacitors or initial voltage level of capacitors. To reach a given velocity, required initial capacitor voltage V_0 changes with initial temperature of drive coils and the mass of projectile. In consecutive firing, the temperature of drive coils and capacitor banks rises and initial stored voltage should be increased to reach the desired velocity. Also, may be it is needed to fill the projectile with some materials such as highly explosive materials which effects the amount of initial stored voltage. In Figure 1 the variation of versus given exit velocity m_p in different initial temperature of drive coils T_0 is shown. In this simulation the projectile hasn't been filled with any material and has its own weight. As can be seen from this figure, V_0 increases with increasing the desired exit velocity and it increases tremendously in higher initial temperature.

The variation of V_0 versus given exit velocity v_p in different mass of the projectile m_p when T_0= 30°C is shown in Figure 2. It can be concluded from this figure that needed initial voltage V_0 to reach a given velocity increases with increasing the mass of projectile.

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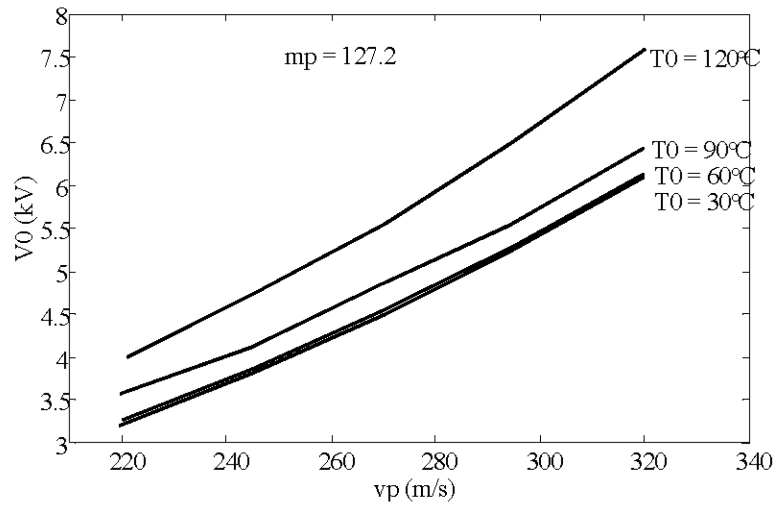

Fig. 1: V_0 versus T_0 in different m_p where m_p = 127gr.

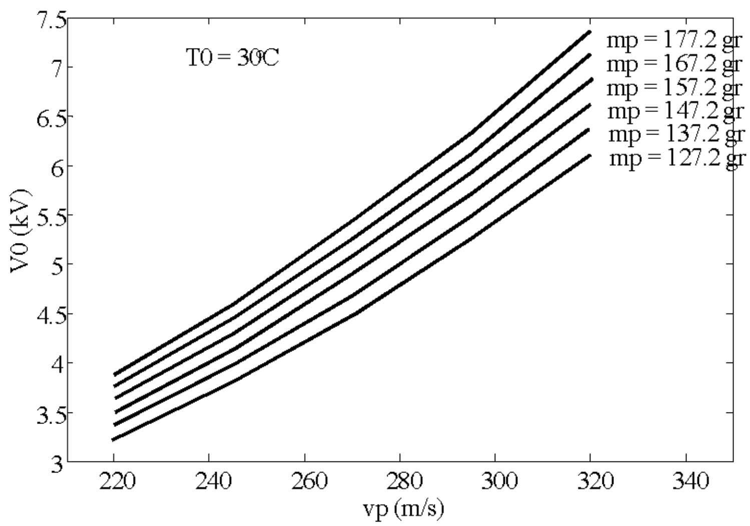

Fig. 2: V_0 Versus v_p in different m_p where T_0 = 30°C

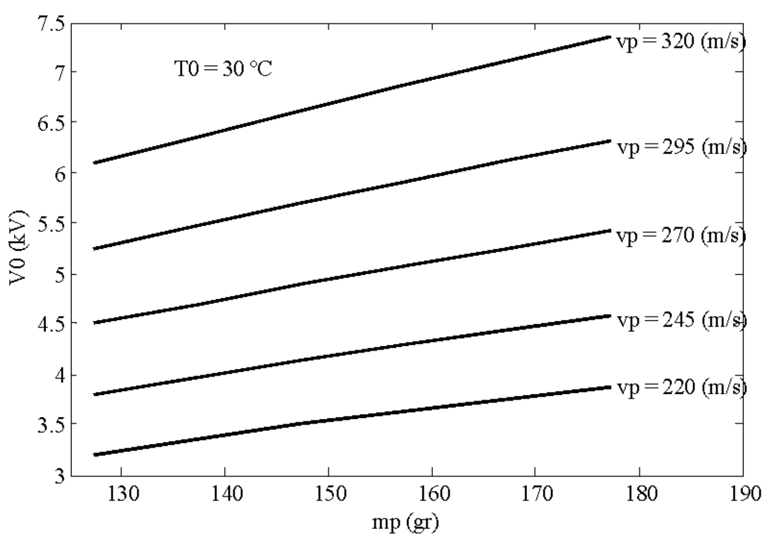

Fig. 3: V_0 Versus m_p in different where T_0 = 30°C

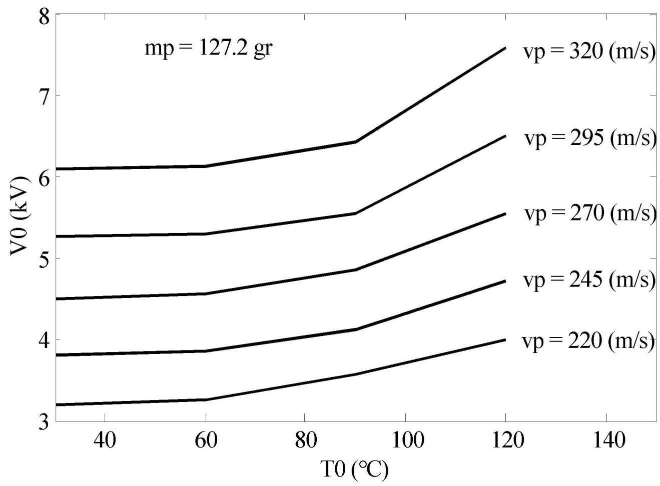

Fig. 4: V_0 Versus T_0 in different v_p where = 127gr.

This is shown in other form in Figure 3 where the variation of V_0 versus m_p in different exit velocities is depicted. Also, the variation of V_0 versusmpT_0 in different exit velocities is shown in Figure 4.

Therefore, what is important is determining accurate amount of initial stored energy in capacitors for a desired exit velocity in different initial temperature and mass of projectile. Because the launcher system is a nonlinear and time varying system, determining a routine regulator such as classic regulators is difficult and it doesn't work. To solve this problem we use two methods to determine accurate V_0 for a desired exit velocity. In the first method we used a three dimensional data interpolation (table look up) to set the value of V_0. To collect the data for interpolation, we have simulate the launcher system in different v_P, T_0 and m_P and determine the exact V_0 to reach the desired velocity. A data set of 240 simulations has been produced and has been used for interpolation.

Adaptive Neuro-fuzzy Inference System for Regulation of Exit Velocity: The method which we used to regulate the value of V_0, is training an adaptive neuro-fuzzy Inference system (ANFIS). Neuro-fuzzy systems are fuzzy systems, which use artificial neural networks (ANNs) theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way humans' process information. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling nonlinear functions. In ANFIS, the membership function parameters are extracted from a data set that describes the system behavior. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion [9-10].

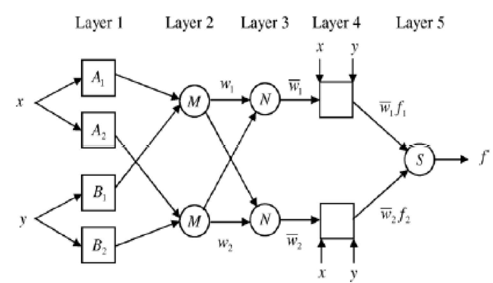

Fig. 5: ANFIS architecture

Architecture of ANFIS: The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation [9-11]. Such framework makes the ANFIS modeling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if-then rules based on a first order Sugeno model are considered:

Rule 1: if (x is A_1) and (y is B_1) then ($f_1=p_1x+q_1y+r_1$)
Rule 2: if (x is A_2) and (y is B_2) then ($f_2=p_2x+q_2y+r_2$)

Where x and y are the inputs, A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Figure 5, in which a circle indicates a fixed node, whereas a square indicates an adaptive node.

In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by

$$O_i^1 = \mu_{A_i}(x); i = 1, 2 \quad (1)$$

$$O_i^1 = \mu_{B_{i-z}}(y); i = 3,4 \quad (2)$$

Where μ_{Ai} and μ_{Bi-z} can adopt any fuzzy membership function. For example, if the bell shaped membership function is employed, μ_{Ai} is given by

$$\mu_{Ai}(x) = \frac{1}{1+\left\{\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}} \quad (3)$$

Where a_i, b_i and c_i are the parameters of the membership function, governing the bell shaped functions accordingly. In the second layer, the nodes are fixed nodes. They are labeled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as:

$$O_i^2 = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y);\ i = 1, 2 \quad (4)$$

Which Are the So-called Firing Strengths of the Rules: In the third layer, the nodes are also fixed nodes. They are labeled with N, indicating that they play a normalization role to the firing strengths from the previous layer. The outputs of this layer can be represented as

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2};\quad i = 1, 2 \quad (5)$$

Which Are the So-Called Normalized Firing Strengths: In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i);\ i = 1, 2 \quad (6)$$

In the fifth layer, there is only one single fixed node labeled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} \overline{w_i} f_i}{w_1 + w_2} \quad (7)$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters [10-11].

Learning Algorithm of ANFIS: The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$and$\{p_i, q_i, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as

$$f = \frac{w_i}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \quad (8)$$

Substituting equation 5 into equation 8 yields

$$f = \overline{w}_i f_1 + \overline{w}_2 f_2 \quad (9)$$

Substituting the fuzzy if-then rules into equation 9, it becomes

$$f = \overline{w}_1\ (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2) \quad (10)$$

After rearrangement, the output can be expressed as

$$f = (\overline{w}_1 x)p_1 + (\overline{w}_1 y)q_1 + (\overline{w}_1)r_1 + (\overline{w}2x)p_2 + (\overline{w}2y)q2 + (\overline{w}2)r2 \quad (11)$$

Which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed.

Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back-propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [10-11].

In this study, the MATLAB function of fuzzy toolbox *anfis* is used that using a given input/output data set, constructs a Sugeno-type fuzzy inference system (FIS) whose membership function parameters are tuned using either a back propagation algorithm for nonlinear parameters in combination with a least squares type of method for linear parameters. This allows fuzzy systems to learn from the data they are modeling. An initial FIS is used by *anfis* that provides an initial membership function for training. This initial FIS is necessary for constructing valid FIS structure before starting the training process and is produced by MATLAB function of fuzzy toolbox *genfis2*. Given separate sets of input and output data, *genfis2* generates an FIS using fuzzy subtractive clustering. It accomplishes this by extracting a set of rules that models the data behavior. The rule extraction method consists of determining the number of rules and antecedent membership functions and then uses linear least squares estimation to determine each rule's consequent equations. Consequently, it is returned an FIS structure that contains a set of fuzzy rules to cover the feature space. To train the *anfis*, input features are v_p, T_0 and m_p and the output is V_0. Propounded ANFIS was trained using 120 pairs of inputs and outputs and then was checked by another 120 pairs. Trained ANFIS has 62 nodes, 28 linear parameters and 42 nonlinear parameters and 7 fuzzy rules are used. In Figure 6 the output of the *anfis* is compared with V_0 checking data.

In Table 1, the performance of two mentioned regulating methods is evaluated via three different simulations. It can be concluded from this table that the exit velocity in ANFIS method is closer to the predetermined value than in cubic spline interpolation method.

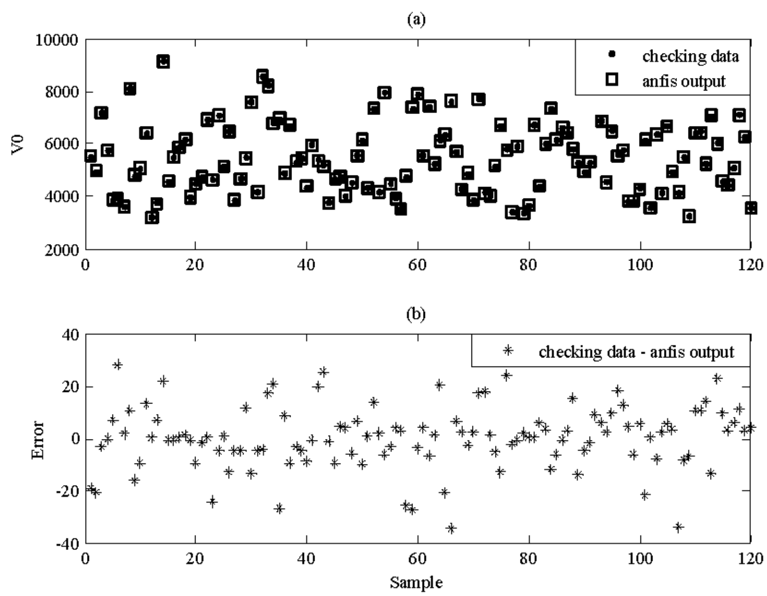

Fig. 6: Performance of the *anfis*. (a) V_0 of checking data and output of the *anfis* (b) error of the inference system

Table 1: Performance evaluation of ANFIS method and comparison with cubic spline method

				V_0 (kV)		Exit velocity v_p (m/s)	
	Desired $_{vp}$ (m/s)	m_p (gr)	T_0°C	*anfis*	interpolation	*anfis*	Interpolation
1	230	152	45	3.89	3.56	230.62	228.27
2	280	132	70	5.06	4.78	280.19	277.51
3	310	172	95	7.72	7.17	309.79	307.83

DISCUSSION AND CONCLUSION

An adaptive neuro-fuzzy inference system is developed to regulate the exit muzzle velocity. To assess simulation results, a small-scale prototype experiment is designed and constructed where, the simulation results of theoretical model are in good agreement with rest results obtained from prototype experiment.

Equivalent electrical circuit model of the coil-launcher provides us a very useful and simple approach to study and analyze them. Mesh matrix model based on the transient circuit analysis gives the insight of coil-gun performance. Furthermore, it is easily possible to consider temperature and frequency effects in this model. So, a very detailed simulation and analysis is achievable.

Our simulations for one and multi-section coil launchers showed that variable parameters and temperature increasing in drive coils have considerable effects on the performance of the coil-launcher. Power loss in drive coils is due to the high value of current required to travelling electromagnetic waveforms to be created in the barrel. But it increases the temperature of the drive coils and as a result the resistance of the drive coils increases and causes more power loss. Hence, the performance of the coil-launcher degrades and muzzle exit velocity decreases. Power loss in the phase capacitors and their changes due to the frequency variation, is also an important factor in degrading the performance. It should be considered that in a coil-launcher the performance could be considered energy transfer ratio (ETR), muzzle exit velocity, kinetic energy of the muzzle or other factors. In this study we have considered the muzzle exit velocity as our main objective performance.

We used the approximation property of ANFIS to develop a regulator for exit muzzle velocity. It has been shown that ANFIS is a powerful method to model nonlinear and highly varying functions utilizing mathematical property of ANN in tuning rule-based fuzzy systems. For the case of this regulator, ANFIS has three inputs: desired exit velocity of the muzzle, initial temperature of the drive coils and the mass of the projectile and initial voltage of the capacitors is the output. Simulation results showed that the desired muzzle exit velocity can be reached using ANFIS to determine the initial voltage of the capacitors.

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