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A New Application of an ANFIS for the Shape Optimal Design of Electromagnetic Devices

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***Abstract*—**This paper presents a new model based on simulated annealing algorithm (ASA) and adaptive neuro-fuzzy inference system (ANFIS) for shape optimization and its applications to electromagnetic devices. The proposed model uses ANFIS system to evaluate the electromagnetic performance of the device. Both the ANFIS and ASA method are applied to the design/optimization of the electromagnetic actuator. The results of the proposed approach are compared with other techniques such as: method of moving asymptotes, penalty method, augmented lagrangian genetic algorithm and simulated annealing method (SA). Among the algorithms, the proposed ANFIS-ASA approach significantly outperforms the other methods.

***Index Terms*—**Adaptive Neuro-Fuzzy Inference System, Simulated Annealing, Genetic Algorithm, Shape Optimization, Electromagnetic Actuator

I. INTRODUCTION

Electromagnetic actuators (EA) have been widely used in industrial applications because of their efficiency and power density [1-2-3-4]. Today, the change in its configurations with low prices has been stimulating the design/optimization for industrial applications [1-2]. In these devices, the main task is increasing of the magnetic force in electromagnetic actuator by geometrical shape optimization. Various optimization algorithms for shape optimization of an actuator have been proposed [1-3].

In [3], Aiello has developed several algorithms for optimization problem and is observed that shape optimization is one of the most complex problems which need robust numerical methods such as finite elements method (FEM),…, etc. Saldanha and Biedinger optimized geometry of cylindrical actuator so as to maximize their energy while limits on a certain value [4-5]. Based on numerical analysis, the responses of linear actuator were determined and the genetic algorithm has been applied.

In the classical optimization, the objective function calculation requires the use of a FEM code that solves the equations of Maxwell's. This calculation is usually very computer intensive, with one flow solution taking from several minutes to several hours or days in the most complex problems [1-2-3-4-5]. For these problems, it is required to make use several methods for replace the expensive FEM program for shape optimization problems.

Among different methods, neuro-fuzzy systems are mostly suitable for the representing objective functions that incorporate several design variables [6]. The neuro-fuzzy system works similarly to that of multi-layer neural network. This hybrid system uses the adaptive neural networks (ANNs) theory to characterize the input-output relationship and build the fuzzy rules by determining the input structure [7]. Neuro-fuzzy systems exploit the capacity of the two concepts, fuzzy logic theory and ANNs, by utilizing the values of parameters in the adaptive nodes of adaptive neural networks in tuning rule based system that approximate the functional relations between responses and input variables of the process under study.

In [7], we presented a new model for parameters identification using the FEM coupled with ANFIS system. The objective of this paper is to propose the new fast optimization method for solving inverse electromagnetic problem in electrical engineering such as the geometrical shape optimization problem. In this case, the ASA-ANFIS model has been implemented on a linear electromagnetic actuator for its optimum design to maximize force magnetic. Our approach is radically different from those developed elsewhere. In effect, in our new approach, the scheme is separated in two steps: training the ANFIS with a data set and geometrical shape optimization with the ASA method.

This paper is organized as follows. Section II defines the geometry of the electromagnetic actuator. In sections III and IV, we demonstrate the electromagnetic field computation and magnetic force calculations for modeling this device. Sections V and VI, we describe the design parameters, cost function and practical constraints of the actuator. Also, sections VII and VIII represent the proposed model and the process optimization using ASA and ANFIS. Section IX represents the detailed results and discussion. Finally, the section X concludes this work and recommends future directions.

II. ACTUATOR DISCRIPTION

The electromechanical structure is presented in Fig. 1. The actuator has an axisymetrical configuration. It is composed of two coils, fed separately. This actuator has been the subject of an internal study in electrical engineering laboratory in grenoble, conducted by Saldanha [4] in the context of industrial collaboration.

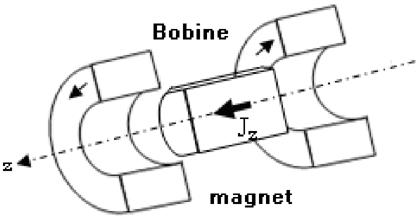

Fig. 1. Axisymmetric linear actuator

The cross section of the fixed part adopts an O shape, which is symmetrical with the horizontal median plane and a cylindrical coordinate system (r, θ, z) is used. The mobile part is a magnet ring with a cylindrical cross section. It is free to move linearly and horizontally.

III. Electromagnetic Field Computation

For magneto-static fields, the field intensity and flux density must obey:

$$R\vec{o}t(\vec{H}) = \vec{J}_s \tag{1}$$

$$Div(\vec{B}) = 0 \tag{2}$$

Where H is the magnetic field intensity, B is magnetic flux density and J is electrical current density. For isotropic material, the constitutive equations to Maxwell's equations are:

$$B = \mu_a \, H + B_r \tag{3}$$

$$J = \sigma \cdot E \tag{4}$$

Where μ is magnetic permeability, σ is electric conductivity, B_r is residual magnetic flux density of the permanent magnet. The B_r is related to the coercive field intensity H_c by - μ H_c.

The magnetic vector potential A is the obvious choice in most instances. The divergence condition on B implies the existence of a vector potential defined by:

$$R\vec{o}t(\vec{A}) = \vec{B} \tag{5}$$

The magnetic field can be considered as a magneto-static problem. Substituting (5) to (1) we obtain:

$$R\vec{o}t(\nu \, R\vec{o}t\,(\vec{A})) = \vec{J}_s + R\vec{o}t(\nu\vec{B}_r) \tag{6}$$

The FEM is one of the most numerical methods used to solve differential equations. The FEM is widely used by scientists and engineers [9]. After assembling all the elementary equations, a differential system of equations is obtained which may be written as:

$$[M]\,[A] = [F] \tag{7}$$

Where [M] is the global coefficient matrix, [A] is the matrix of nodal magnetic vector potentials and [F] is nodal term sources. The Gaussian elimination algorithm is then used to solve the above banded matrix equation. More details about the finite element theory can be found in reference [8].

IV. Forces Magnetic Calculation

The force in a direction is given by the derivation of the magneto-static energy w in relation to a virtual displacement q [9]:

$$F = -\frac{\partial W}{\partial q} \tag{8}$$

The energy of the systemis given by:

$$W = \int_{\Omega} \left(\int_{0}^{B} H \, dB \right) d\Omega \tag{9}$$

The magnetic field on the z axis is going to generate an axial force on the magnet. In a cylindrical configuration the symmetry allows us to consider only the axial component of the magnetic field. The force is given by [4]:

$$F_z = \frac{1}{\mu_0} \int_{z_2}^{z_1} \int_{0}^{R} \frac{\partial B_z}{\partial z} \, Jz \, 2\pi r \, dr \, dz \tag{10}$$

This magnet is supposed to have a constant polarization J and permeability equal to μ_0. The magnetic force (Fig.2) can be directly calculated with the values of the magnetic vector potential A generated by the coils at the ends of the magnet volume [4]:

$$F_z = J_z \frac{2\pi R}{\mu_0} \left[A(R_1, z_1) - A(R_1, z_2) \right] \tag{11}$$

Where R is the exterior radius of the magnet.

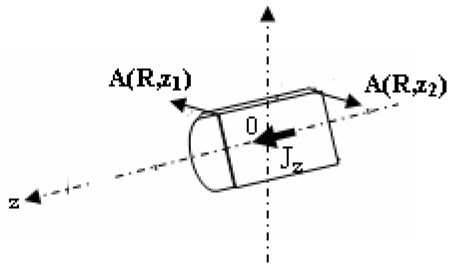

Fig. 2. Potential vector "A" due to the Coils [4]

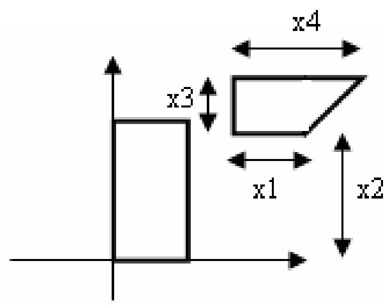

Fig. 3. Design variable of the actuator

V. Design Parameters

The geometry of the actuator is illustrated by four design parameters x_i (i =1…4) selected to change the shape of the actuator (Fig. 3). The optimization problem is to define the parameters x_i in order to insure a given constant force F_0 along the z-axis at the N points (Fig. 2).

VI. Cost Function and Practical Constraints

The aim of shape optimization is to maximize the magnetic force with a global constant volume. This optimization consists of minimizing an objective function, which is the error between the target magnetic force (5N) and a magnetic force F_z. Generally, the optimization is considered as a nonlinear problem to locate a solution that minimizes the following cost function:

$$\begin{aligned} & minimize\ f(x)=\sqrt{\frac{1}{np}\sum_{i=1}^{np}\left[1-\frac{F_z(L_i,x)}{F_0}\right]^2} \\ & g(x_i, i=1,..,4)\le 0 \end{aligned} \tag{12}$$

Where F_z is the magnetic force exerted on the magnet core by considering the displacement L_i (0mm to 18 mm) and N is the N positions of the magnet defined by z_i (Fig.2). The actuator design also needs to satisfy the following constraints [4]:

1. The excitation coil current density is $J=2.68A.mm^{-2}$.
2. The inequality constraints:

$$\begin{aligned} & g(x_i, i=1,..,4); \\ & x_i^2-(x_i^{\max}+x_i^{\min})x_i+x_i^{\max}x_i^{\min}\le 0 \end{aligned} \tag{13}$$

The lower and upper bounds of the parameter of the problem are defined in Table 1. Each solution must respect an equality constraint on the magnetic force whose value is set by the user (F_0), and four inequality constraints are considered.

Table 1. The Lower and Upper Bounds of the Design Parameters

Parameter (mm)	Lower bounds	Upper bounds
x1	2.5	25
x2	5	25
x3	2.5	50
x4	2.5	25

VII. Design/Optimization Method

A. Adaptive Neuro-Fuzzy Inference System

Neuro-fuzzy methods are usually applied when is required to solve a function approximation problem or where the manual design process should be supported or replaced by an automatic learning process. Many neuro-fuzzy systems for function approximation are inspired on the Takagi-Sugeno fuzzy systems, because it is best suited for learning purposes through gradient based methods if differentiable membership function are used. Adaptive network-based fuzzy inference system is one of the first and still one of the popular neuro-fuzzy systems [7].

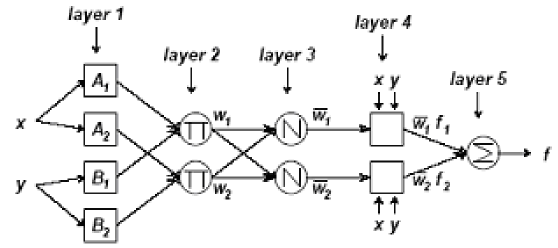

Fig. 5. The general architecture of ANFIS [7-6]

ANFIS is a neuro-fuzzy method to determine the parameters of a Sugeno-type fuzzy model which is represented as a special feed-forward network. Fig.5 show the structure of a two input ANFIS. This hybrid system is generally based on the Takagi-Sugeno's fuzzy If-Then rules as shown in Fig.4. In general, neuro-fuzzy system has input and output layers, and three hidden layers that represent membership functions and fuzzy rules. Each node in a layer receives input signals from a previous layer and transmits its output signals to nodes in the next layer [7].

In the adaptive network, we use both circle (fixed nodes) and square nodes (adaptive nodes). By varying these parameters, we are really changing the node function (adaptive nodes) and the behavior of adaptive network [7]. For the first-order Sugeno inference system, typical two rules can be expressed as [7-6-11]:

Rule 1: if x is A_1 and y is B_1 then $f_1= p_1*x+q_1*y+r_1$
Rule 2: if x is A_2 and y is B_2 then $f_2= p_2*x+q_2*y+r_2$

Where x and y the inputs variables to the node I, A_i and B_i are fuzzy sets (or the linguistic table), which are characterized by convenient membership functions and finally, p_i , q_i and r_i are the consequence parameters [6-7-10]. The structure of this inference system is shown in Fig.5.

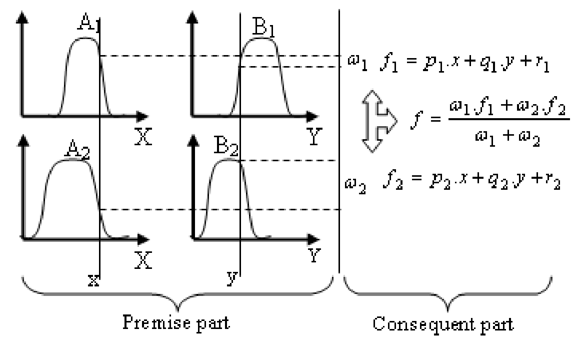

Fig. 4. Sugeno fuzzy if-then rule and fuzzy reasoning mechanism

Layer 1: Each node in this first layer is adjustable node. The output signals are the fuzzy membership functions of the input signals, which are given by the node function as [7]:

$$
\begin{aligned}
O_i^1 &= \xi_{A_i}(x), i = 1,2 \\
O_i^1 &= \xi_{B_{i-2}}(y), i = 3,4
\end{aligned} \tag{14}
$$

Where A_i and B_{i-2} is the linguistic variable. The fuzzy membership function generally chooses a generalized bell-shape with upper limit and lower limit equal to 1and 0. The generalized bell-shape function depends on three parameter sets a, b, and c as given by [7]:

$$\xi(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}} \tag{15}$$

Where the parameter b is usually positive. The parameter c locates the centre of the curve. The parameter sets in this first layer are named as premise parameters.

Layer 2: all nodes in this layer are not adaptive (fixed node, labelled as π). Each node calculates the firing strength of a rule w_i or the output signal through multiplication [6-7-10]:

$$
\begin{aligned}
O_i^2 &= t\left(\xi_{A_1}(x), \xi_{B_{i-2}}(y)\right) \\
&= \xi_{A_i}(x) . \xi_{B_{i-2}}(y) = \omega_i
\end{aligned} \tag{16}
$$

Layer 3: In this layer, every node isn't also adaptive. Nodes in the third layer (Labelled as N) compute the normalized firing strength w_i by dividing each rule firing strength by the summation of all of them. The output signals can be represented as [6-7-10]:

$$O_i^3 = \overline{\omega}_i = \frac{\omega_i}{\omega_1 + \omega_2} \tag{17}$$

Layer 4: Nodes (adjustable node) in this layer compute the weighted output of the rules by evaluating the Takagi-Sugeno type linear approximator fi multiplied by the normalized firing strength [6-7-10]:

$$O_i^4 = \overline{\omega}_i . f_i = \overline{\omega}_i \left(p_i . x + q_i . y + r_i\right) \tag{18}$$

Layer 5: this layer has only one node labelled S that is a fixed node. The output of the system is computed by the node in the last layer as a summation of all incoming signals. Hence, the global output signal of the node is given by [7]:

$$O_i^5 = \sum_i \overline{\omega}_i f_i = \frac{\sum_i \omega_i . f_i}{\sum_i \omega_i} \tag{19}$$

Though the gradient method can be applied to identify the parameters in an adaptive network, the method is generally slow and likely to become trapped in local minima. Instead, the hybrid learning rule which combines the gradient method and the least squares estimate (LSE) to identify parameters results in a more efficient way to train the network. The output of the ANFIS can be expressed as [10]:

$$output = F(I, S) \tag{20}$$

Where I is the set of input variables.

For this overall output, we can divide the parameter set S into two sets S_1 (premise parameters) and S_2 (consequent parameters). For the backward pass, the error signals propagate backward and by descent method [6-7-10] we can calculate (or update) the premise parameters with respect the overall error measure:

$$E = \sum_{p=1}^{p} \sum_{m=1}^{N(L)} \left(T_{m,p} - O_{m,p}^L\right)^2 \tag{21}$$

Where $T_{m,p}$ is the m^{th} component of the p^{th} target output vector, and $O_{m,p}$ is the m^{th} component of the actual output vector produced by the p^{th} input vector. The partial derivative depends on the type of membership function (MF) used. In this case, the gradient is used to update the MF parameters α, then [7-10]:

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{p} \frac{\partial E_p}{\partial \alpha} \sum_{m=1}^{N(L)} \left(T_{m,p} - O_{m,p}^L\right)^2 \tag{22}$$

And the gradient vector is:

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{23}$$

The learning rate can be written:

$$\eta = \frac{k}{\sqrt{\sum_{\alpha} \left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{24}$$

Where k is the step size, which can be changed to vary the speed of convergence. A hybrid learning algorithm (gradient method and least square estimate) is proposed to fine tune the values of these parameters.

Given the ANFIS architecture shown at Fig. 4, it is observed that given the values of premise parameters, the overall output can be expressed as linear combinations of the consequent parameters. More precisely, the output f in Fig. 4 can be rewritten as [10]:

$$
\begin{aligned}
f &= \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_1}{\omega_1 + \omega_2} f_2 \\
&= (\overline{\omega}_1 . x) p_1 + (\overline{\omega}_1 y) q_1 + (\overline{\omega}_1) r_1 \\
&+ (\overline{\omega}_2 x) p_2 + (\overline{\omega}_2 y) q_2 + (\overline{\omega}_2) r_2
\end{aligned} \tag{25}
$$

This is a linear combination of the modifiable parameters $p_1, q_1, r_1, p_2, q_2, r_2$.

B. *Adaptive Simulated Annealing*

The optimization process by simulated annealing was first described by Kirkpatrick et al [12], and is based on work by Metropolis et al [13] in the area of statistical mechanics. SA algorithm contains two steps: the first, perform search while the temperature is decreasing. The second determine the acceptance. The acceptance of the novel result is according to the Metropolis's condition based on the Boltzman's probability [12]. The acceptance probability of solution point i is defined by [16]:

$$P = exp\left(Ej^{'} - Ej \;\; /KT \;\right) \tag{26}$$

Where K is the Boltzman's constant and T is the temperature of the heat bath, $Ej^{'}$ is the current energy state for the system and E_j is a subsequent energy state.

The first simulated annealing employed Gaussian distribution as a generator and was proposed by Kirkpatrick. Szu [13] proposed a fast simulated annealing by using Cauchy/Lorentzian distribution. Another modification of the SA, the so-called adaptive simulated annealing was proposed by Ingber [14-15-16] and was designed for optimization problem in a constrained search space. For x^k a parameter in dimension i at annealing time k with rang $x \in [x^{min}, x^{max}]$ the new value is generated by [16]:

$$x_i^{k+1} = x_i^k + \lambda(x_i^{max} - x_i^{min}) \tag{27}$$

Where x^{min} and x^{max} are the maximum and minimum of the i^{th} domain. This is repeated until a legal x_i between x^{min} and x^{max} is generated. λ_i ($\in$ [-1,1]) the random variable generated by the following generating function [14-15-16]:

$$g(\lambda_i) = \prod_{i=1}^{n} \frac{1}{2\left(\left|\lambda_i + T_i\right|\right)\; ln\left(1 + \frac{1}{T_i}\right)} \tag{28}$$

The i values and T_i are identifies the parameter index and temperature. The parameter λ_i is calculated by the cumulative probability distribution, which can be defined as [14-15-16]:

$$g(\lambda_i) = \frac{1}{2} + \frac{sign(\lambda_i)}{2} \frac{ln\left(1 + \frac{|\lambda_i|}{T_i}\right)}{ln\left(1 + \frac{1}{T_i}\right)} \tag{29}$$

In this case, by the idea of Ingber it can be seen to choose $g(\lambda_i)=u_i$, we can apply this formulation:

$$\lambda_i = sign(u_i - 0.5) T_i \left[(1 + \frac{1}{T_i})^{|2u_i - 1|} - 1 \right] \tag{30}$$

The new generation distribution function in ASA has much fatter trails than Gaussian and Cauchy generation function. The solution can be obtained statistically if the annealing schedule is [15-16]:

$$T_i(k) = T_i(0) exp(-c_i k^{1/n}) \tag{31}$$

Where ci is a user-defined parameter whose value should be selected according to the guidelines in reference [13-14-15], but n is the dimension of the space under exploration. The same type of annealing schedule should be used for both the generating function and the acceptance function1/(1+p).

Reannealing in ASA algorithm periodically rescales the generating temperature in terms of the sensitivities s_i calculated at the most current minimum values of the cost function. After every acceptance points, reannealing takes place by the first calculating the sensitivities [14-15-16]:

$$s_i = \partial E / \partial x_i \tag{32}$$

The annealing time is adjusted according to s_i, based on the heuristic concept that the generating distribution used in the relatively insensitive dimension should be wider than that of the distribution produced in a dimension more sensitive to change [14-15-16].

VIII. PROCESS OPTIMIZATION USING ASA AND ANFIS

In this paper, we present a new model or technique in the geometrical shape optimisation. The new approach can be summarized as follows:

a) Preparation of data for training and testing of ANFIS.
b) Load training/ testing data Generate initial FIS model.
c) ANFIS training and testing. The trained ANFIS network is then tested with testing data which not belong to the original data set.
d) Obtain ANFIS to predict objective function
e) Create initial solutions.
f) Predict responces via ANFIS objective model (y).
g) Optimization process: ASA algorithm is utilized to obtain the optimal objective value.
h) the ANFIS package must be able to accept parameters generated by ASA, to perform the ANFIS computation automatically, and to return the value of the objective function to the ASA algorithm

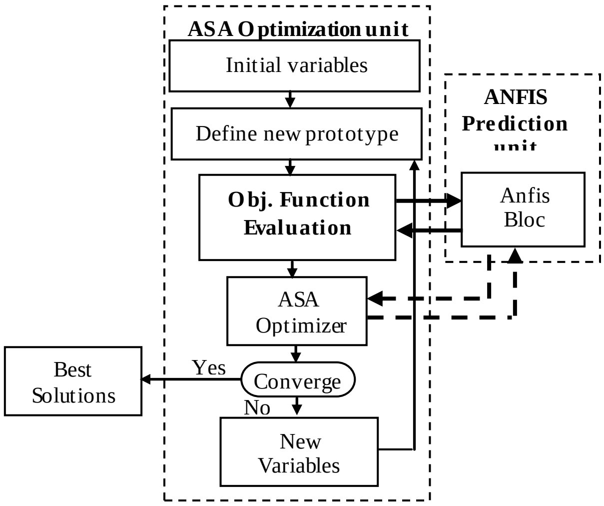

Fig. 6. Optimization process with ANFIS approach

The strategy selected is based on two components as illustrated in Fig. 6. The first one is a neuro-fuzzy network which is used to approximate the strength magnetic performance, the second one, is used to solve the optimization problem via ASA algorithm. To calculate the objective function of design parameters, the ANFIS package must be able to accept parameters generated by ASA, to perform the ANFIS computation automatically, and to return the value of the objective function to the ASA algorithm.

IX. Results and Discussion

A. FEM Modelling

Our axsiymmetrical model is based on the 2D-element finite method (2D-FEM) which permits to calculate the global magnetic force. Fig.7 shows the equipotential lines of magnetic vector potential and Fig. 8 shows the change of the maximum magnetic force results by the FEM simulation.

The mesh is automatically generated by dividing the geometry into discrete elements. Standard triangular elements are applied here. The open boundary was set at a radius of 4.R (exterior radius) using the Dirichlet condition. The generated mesh had approximately 705 nodes. It is important to select an adequate mesh to represent correctly the electromagnetic phenomena and then, to reduce the numerical errors that can influence the convergence of the optimization process. The problem was solved on a PC with P4 2.4G® CPU under Matlab 7 workspace using the Partial Differential Equation Toolbox for the finite element meshes generation.

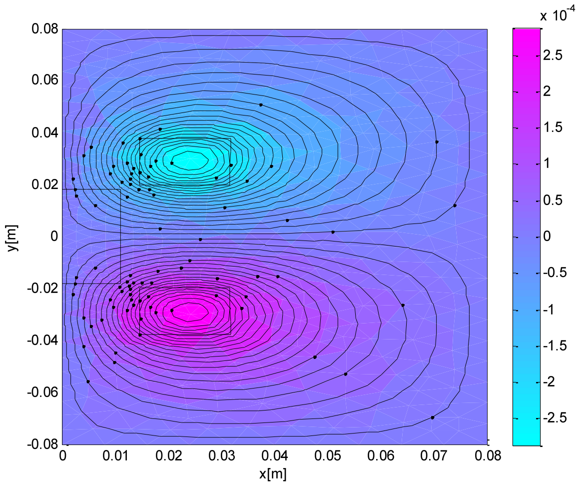

Fig. 7. Equipotential lines of magnetic vector potential

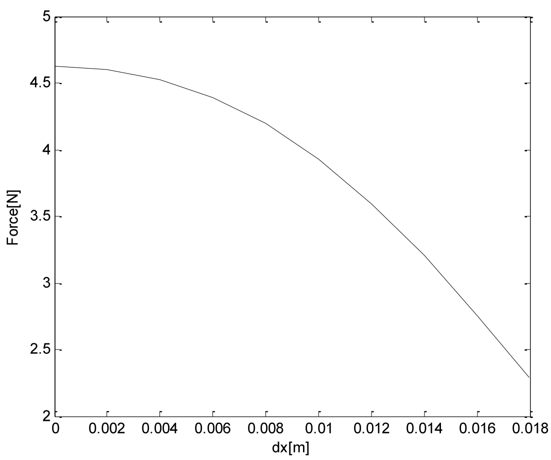

Fig. 8. Force actuator versus magnet displacement

B. Predicted Force Magnetic using ANFIS System

The data set was divided into two data sets: the training data set and the testing data set. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the computation of magnetic force. Fig.9 shows the fuzzy-rule architecture of the ANFIS using a generalized bell-shaped membership function defined in equation (15). The initial input MFs have been generated spanning uniformly over the range of each input. The number of MFs for the input variables is three. The ANFIS model is formed by several fuzzy rules with linear sequences.

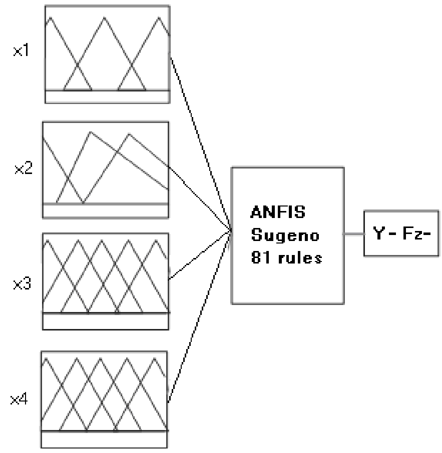

Fig. 9. Fuzzy-rule architecture of the ANFIS model.
System ANFIS: 4 inputs, 1 output, 81 rules

First step uses an adaptive neuro fuzzy inference system (ANFIS) to approximate the response y (magnetic force, Fz). The input variables of this problem are x1, x2, x3 and x4 and the output is a magnetic force (F_z). The algorithm uses training examples as input and constructs the fuzzy if–then rules and the membership functions of the fuzzy sets involved in these rules as output. The ANFIS shown in Fig. 9 was implemented by using a MATLAB software package (MATLAB version 6.0 with fuzzy logic toolbox).

The ANFIS shown in Fig. 9 used 209 training data in 1500 training periods and the step size for parameter adaptation had an initial value of 0.2. There is a total of 81 fuzzy rules in the architecture. ANFIS has proved to be an excellent universal approximator of non-linear functions. It is capable to represent the magnetic force. Using a given input/output data set, the ANFIS method constructs a fuzzy inference system (FIS) whose membership function parameters are tuned using a hybrid learning algorithm that combines least square method (forward pass) with gradient descent method (backward pass) is used to adjust the parameter of membership function. Fuzzy inference system, which maps inputs through input membership functions and associated parameters, and then through output membership functions and associated parameters of outputs, can be used to interpret the input/output map. The ANFIS system is started with inputs data set. Next, the steps of our approach are [7]:

1. The paired data with the form of ([x1,x2,x3,x4]) are given to the trained ANFIS network.
2. The trained ANFIS network completes the forward pass which the overall output f is the electric conductivity.
3. After training phase the trained ANFIS system is tested with another independent data.
4. The error is calculated for every one epoch by computing the root mean square errors (RMSE).
5. Training of the ANFIS is performed using both least squares method and back-propagation. In the forward pass the consequent parameters (pi, qi and ri) are updated using least squares and in the backward pass the premise parameters (ai, bi and ci) are identified using back-propagation. This is offline learning, because the trained ANFIS network accepts all data sets. Also, all parameters are updated [7].
6. After these steps calculation, if the number of ANFIS training epochs is achieved then the system terminates.

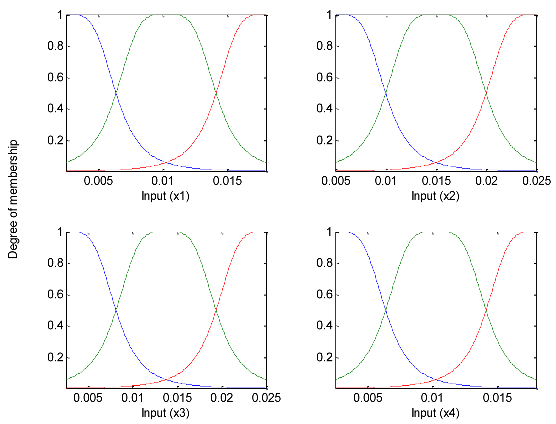

Fig. 10. Final bell-shaped membership functions

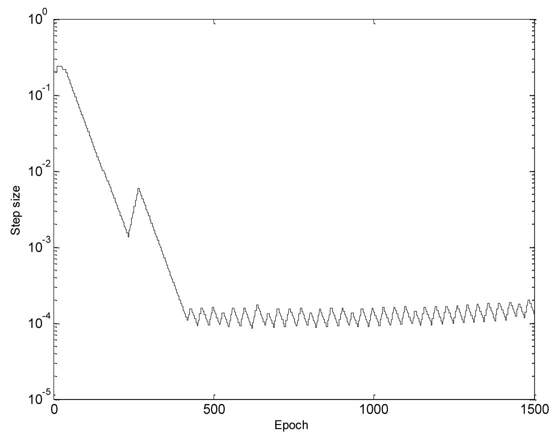

Fig. 11. Parameter step adaptation

Three types of fuzzy sets are used for indicating “small-S”, “medium-M”, “large-L” respectively. Also, each fuzzy value such as “large-L” is denoted by the control parameters p, q and r. These parameters are used in computing the output of the ANFIS system separately. Fig. 10 illustrates the final membership functions for each input variable. The steps of parameter adaptation of the ANFIS are shown in Fig. 11.

Table 2 : RMSE and Average Percent RMSE of Training and Testing Data

RMSE of training data	RMSE of testing data	Average percent RMSE of training data	Average percent RMSE of testing data
0.021	0.0742	0.8894	3.7167

Table 2 shows the results of training and test results of ANFIS with generalized bell curve type MFs. The best test performance is with 3 MFs. Average percentage error in training is 0.8894 %. The training time increases with the number of MFs.

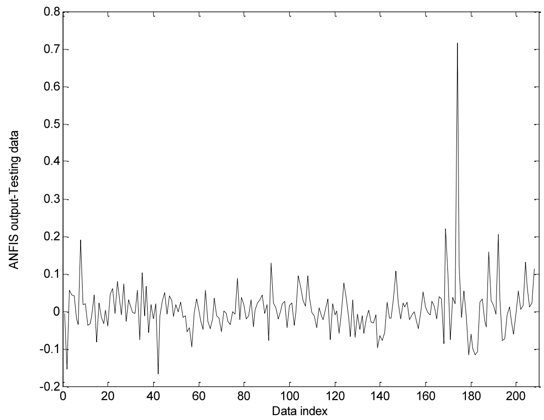

Fig. 12. Errors between the ANFIS output and testing data

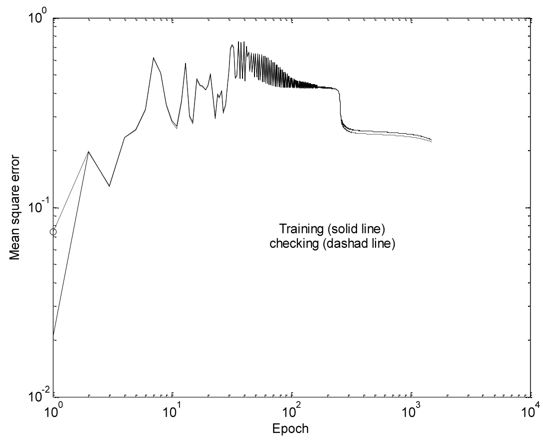

Fig. 13. ANFIS training and checking errors

Fig. 12 illustrate the errors between ANFIS output and the independent data set (testing data) for evaluating trained ANFIS network. Good agreement between the two data sets proves that ANFIS has learned well the behavior of the prediction process. At 1500 training periods for ANFIS, the network error convergence curve was derived as shown in Fig. 13. From this curve, the final convergence value is 0.0742 (ANFIS). The minimal checking error occurs at initial epoch for ANFIS, which is indicated by a circle. Notice that the checking error curve goes up after this initial epoch, indicating that further training overfits the data and produces worse generalization (See Fig. 12).

Once a value function is assessed and validated the ANFIS is used to approximate the magnetic force and the objective optimization problem will be reduced to a problem as follows:

$$\max_{x1,x2,x3,x4} y(Fz(x1, x2, x3, x4)) \tag{34}$$

C. ANFIS-ASA Shape Optimization

The ASA method combined with ANFIS prediction system was tested on the shape optimization. The task is to find new optimum conditions for electromagnetic actuator. The results obtained from five techniques are given below in Table 3. The ANFIS presented in this study has high accuracy and requires no complicated mathematical functions. The proposed ASA approach was compared with three non-traditional techniques (GA-ALM, MMA, PE, ASA and BEM-GA). All the parameters are the same in all cases. Fig. 15 shows the behavior of the objective function values through the various iterations of the different methods.

Table 3. Comparison of Results for Five Methods

Algorithms	Optimal solutions (mm)				Average Optimiz. Time [s]
	x1	x2	x3	x4	
GA-ALM	17.3	23.1	24.0	16.0	45893.1
ANFIS-ASA	**17.2**	**23.9**	**25.0**	**17.8**	**27.246**
ASA	17.5	24.4	24.8	17.2	1943.67
MMA [4]	16.7	24.6	23.4	16.1	3548.12
BEM-GA [5]	17.7	24.1	23.9	15.8	1578.56

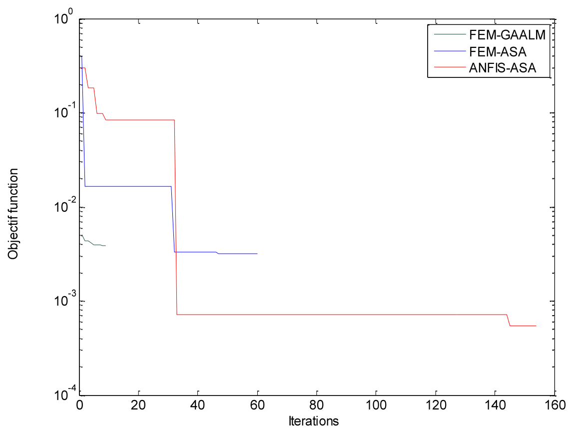

Fig. 15. Objective function versus iterations

The Fig. 14 shows the change of the magnetic force by the different methods. The results indicated that the new method "ANFIS-ASA" significantly outperforms the GA-ALM, MMA, PE and ASA methods. With the new model (ANFIS-ASA), the convergence to an optimal solution can be assured after a number of iterations. The ANFIS has advantage of being a quick method compared to the classical iterative optimization methods. Clearly, from the results, the new approach provides a sufficiently approximation to the true optimal solution.

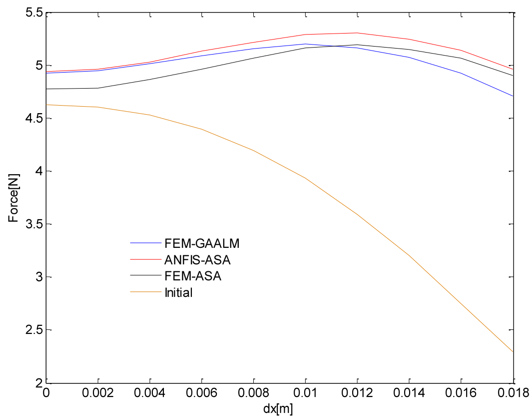

Fig. 14. General forces results

X. Conclusion

In this work, non-conventional optimization techniques have been studied for the shape optimization. The hybrid ANFIS-ASA integrates neural network, fuzzy logic and simulated annealing optimization to approximate the magnetic force and to optimize this quantity. The results of the proposed approach are compared with results of five non-traditional techniques (FEM-GA-ALM, FEM-MMA, FEM-PE, FEM-GA and FEM-ASA). Among the algorithms, ANFIS-ASA outperforms all other algorithms.

The ANFIS results were in very good agreement with the results available in the literature obtained by using the FEM. Since the ANFIS presented in this study has high accuracy and requires no complicated mathematical functions, it can be very useful for the development of fast CAD models.

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