Design Optimization of electromagnetic actuator using genetic algorithms approach

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Abstract: In this paper is concerned with the application and implementation of a new genetic algorithm approach in designing optimal geometries of an axisymmetric electromagnetic actuator where the objective is to maximize the force-displacement. The magnetic force evaluated using the virtual work approach.

Keywords: finite element method, magnetic force, genetic algorithm, electromagnetic actuator.

1. Introduction

Performance improvement is an important condition in the design or in the optimization of electromagnetic frameworks. A physical function optimization needs a robust process to reveal its unique global solution when several local ones exist. Nowadays, the computer power allows the use of genetic algorithms for practical realizations. Even if they are not presented as classic methods, they offer a very robust computation with little information on the goal function to start the search [1]. In this paper, we propose a new approach to optimize linear actuator. This new method is based in the performance of genetic algorithm. In order to validate the GA proposed for the optimization of electromagnetic actuator, one problem already solved by the authors in [5], was reconsider. This problem is a highly efficient linear electromagnetic actuator with an axisymmetry (Fig. 1). The main constitutive parts are yoke (static magnetic circuit), the circular coil, and the mobile magnetic piece.

The objective of the design is to determine the optimum shape of the electromagnetic actuator in order to maximise the magnetic force F acting on the mobile part all along the displacement.

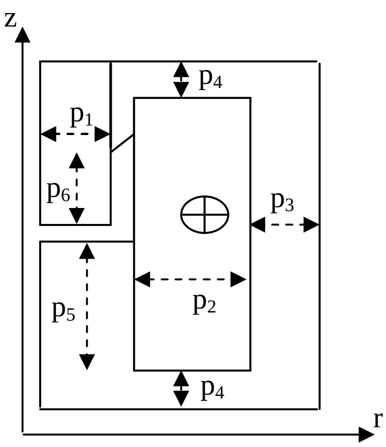

Fig.1 Structure of the magnetic actuator

We can notice that F obviously depends on the six chosen geometrical parameters. To this profile, which is the global solution of the optimization, corresponds a certain value of the mobile part geometry ($p_1, p_2, p_3, p_4, p_5, p_6$). The computation is done with a classic 2D axisymmetric finite element method. It takes into account the magnetic saturation and allows the force determination with the virtual works approach.

2. Applied Genetic Algorithms

In this paper, we tested one stochastic method on optimizing the electromagnetic actuator geometry to eventually draw conclusions on their suitability for this problem. The selected method included well-known widely used in optimization: Genetic algorithm.

2.1. Genetic Algorithm

Genetic algorithm (GA) is a population-based mechanism in the traditional procedure of which every two parent solutions give birth to two child (successor) solutions, transferring a new combination of genes in the form of new chromosomes to them. Each chromosome is identified by genes (decisions) accepting some values such as 1 (acceptance of a character), and 0 (rejection of that character), carrying a value which shows its fitness or effectiveness (in solving the problem). The population size is kept fixed, always made up of the best valued individuals (chromosomes). Like the natural phenomena in genetics, genes are mutated; and to make sure that new generations never fall behind their predecessors the chromosomes of the elites of the population are always kept in the new generation. To have a workable genetic algorithm, one needs to have (a) a mating procedure, (b) a chromosome value estimation procedure, and (c) supple mental procedures, such as mutation, and elite preservence. A general version of this algorithm is as follows [1]:

Step 0. Initialize.

Step 1. Create a population of individuals.

Step 2. Compute the values of the individuals.

Step 3. If convergence criteria are satisfied, go to 7

Step 4. Identify parent individuals randomly based on a probability proportional to their fitness values.

Step 5. Create the children of a pair of parent individuals by their crossovers.

Step 6. Choose chromosomes for mutation, and go to step 2.

Step 7. Stop.

There are several proposed procedures for implementing each of the above steps. The readers are referred to Goldberg [4] for further readings in this area.

3. Magnetic Field and Force Computation

The design analysis will be displayed on axisymmetrical nonlinear magnetostatic field problems. The governing equations can be formed in terms of θ the components A of the magnetic vector potential and J_s of the excitation current density of the windings as:

$$\frac{\partial}{\partial z}\left(\nu\left(B^2\right).\frac{\partial A}{\partial z}\right)+\frac{\partial}{\partial r}\left(\nu\left(B^2\right).\frac{1}{r}.\frac{\partial(r.A)}{dr}\right) + \frac{\partial}{\partial r}\left(\nu\left(B^2.\frac{A}{r}\right)\right)=-J_s \qquad (1)$$

Where B is the magnetic flux density, $\nu\left(B^2\right)$ is the magnetic reluctivity which expresses the magnetic nonlinear characteristics, while r, z and θ are cylindrical coordinates. In order to prevent numerical problems related to the A/r term (singularities mainly in the stiffness matrix but also in the tangent matrix during treatment of the nonlinear problem), an auxiliary potential is introduced as follows:

$$A(r,z)=r.A^*(r,z) \qquad (2)$$

Finite element discretization leads to the algebraic nonlinear system [8]:

$$\sum_{l=1}^{n} K_{kl}\left(\nu\left(B^2\right)\right).A^* - F_k = 0 \qquad (3)$$

$$\text{for} \quad k=1,2,...,n$$

Where n is the number of nodes.

The solution of this nonlinear equation can be obtained iteratively using the point fixed algorithm.

3.1. Magnetic Forces

Here magnetic force expressions derived from the virtual work method are given in the context of the axisymmetrical nonlinear magnetostatic field.

3.1.1 Virtual Work Approach

The interface between two different media such as air and iron is shown for a 2D system in Fig. 2, together with the FE discretisation. Consider the portion of the interface defined by nodes MND. To determine the local force F_{kq} associated with node N, the node is virtually displaced in the q-direction by an increment δq, as illustrated in Fig. 2, while the neighbouring nodes remain fixed. When the magnetic vector potential formulation is used, the force F_{kq} associated with node N can be calculated as the derivative of the stored magnetic energy with respect to the virtual displacement at constant flux linkage, or the derivative of the magnetic co-energy with respect to the virtual displacement, and the local force F_{kq} is derived by differentiating the magnetic stored energy with respect to the direction q, with flux linkage held constant [3]:

$$F_{Kq} = -\frac{\partial W}{\partial q} \tag{4}$$

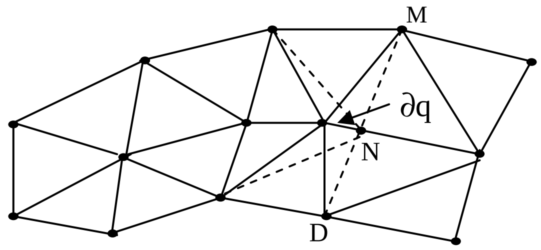

Fig.2 Displacement node at an air-iron interface

The stored magnetic energy W is given by:

$$W = \int_S \left[\int_0^B H.dB \right] .dS \tag{5}$$

Where S is the surface of the field region, B is the flux density and H is the magnetic field intensity. In the FE formulation the domain S is divided into a set of finite elements and the total energy W is obtained by adding the energy contribution of each element. Therefore the total energy W becomes:

$$W = \sum_{e=1}^{M} \int_{V_e} \left[\int_0^B H_e.dB_e \right] .dS_e \tag{6}$$

Where M is the total number of finite elements in the field region and S_e is the volume of element e. When using first order element, equation 7 simplifies to:

$$W = \sum_{e=1} \nu_e \left(B^2\right) . \frac{B^2}{2} .S_e \tag{7}$$

When ν_e the reluctivity of element e is expressed in terms of the flux density squared:

$$\nu_e = \nu_e \left(B^2\right) \tag{8}$$

Substituting equ. 4 into equ. 1 and differentiating with respect to the virtual displacements yields the expression for the local force F_{kq} associated with node K:

$$F_{hq} = \sum_{e=1}^{n} \left[\begin{array}{l} \frac{S_e}{2} . \frac{\partial B^2}{\partial q} .\nu_e + \frac{S_e}{2} .B^2 . \frac{\partial B^2}{\partial q} . \frac{\partial \nu_e}{\partial B^2} \\ + \frac{\partial S_e}{\partial q} .\nu_e . \frac{B^2}{2} \end{array} \right] \tag{9}$$

It should be that in this equation the summation is only over the n element directly connected to node h since the energy associated with the remaining element is unaffected by the displacement.

The term $\partial \nu_e / \partial B^2$ is easily obtainable for each nonlinear finite element, and is already available when the fixed point algorithm is used to solve the nonlinear system of equations resulting from the FE formulation. The derivatives $\partial/\partial q$ require the Knowledge of the coordinate derivatives of the nodes of elements attached to the displaced node.

4. Numerical Example

The test problem considers the simple magnetic actuator shown in Fig. 3 with the related data and analysis variables. This example is taken from [5]. The solenoid winding is composed of 50 coil turns with a current of 10 A. The magnetic steady state is analysed by FEM taking into account magnetic saturation, where the reluctivity is calculated at each iteration step, from an analytical function of $B^2 = |B|^2$.

$$\nu_f = \left(\nu_i + \nu_f .\exp\left(\tau.B^2\right)\right) \quad (10)$$

The nonlinear problem is solved with a relative error $\|\Delta A^*\| / \|A^*\|$ less than 0.001.

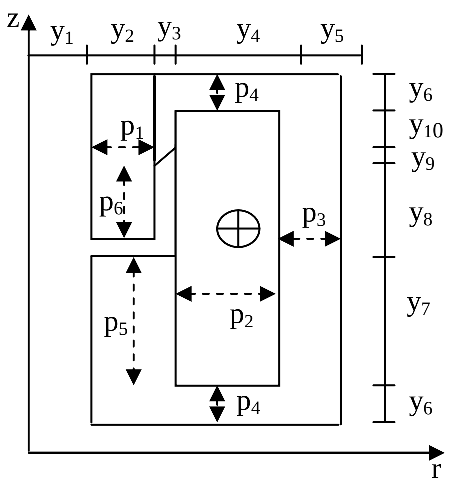

Fig.3 Description of the problem

As an application example, the shape analysis of magnetic forces has been used to design the magnetic actuator described above. The initial geometric values are defined as the solenoid excitation is set at 500 A. The other parameters remain unchanged.

The design objective is to maximize the force-displacement characteristic taking into account the geometrical constraints. If $F_z(z_i, p)$ is the force exerted on the plunger at position z_i ($z_i = y_{11}$ in Fig. 3) and F_0 a reference force (here $F_0 = 100\,\text{N}$), the problem can be mathematically stated as:

$$\text{min imiser } f(x) = \sqrt{\frac{1}{np}\sum_{i=1}^{np}\left[1 - \frac{F_z(z_i, p)}{F_0}\right]^2} \quad (11)$$

Subject to equality constraints:

$$g_1(p):\ p_4 + p_5 - 0.433.L_c(p) = 0 \quad (12)$$

$$g_1(p):\ \pi.R_c(p)^2.L_c(p) - 7.363.10^{-6} = 0 \quad (13)$$

$$g_3(p):\ 2.\pi.(y_1 + y_2 + y_3).y_6 - \pi\left((y_1 + y_2 + y_3)^2 - y_1^2\right) = 0 \quad (14)$$

$$g_4(p):\ \pi.\left(R_c(p)^2 - (R_c(p) - y_3)^2\right) - \pi.\left((y_1 + y_2 + y_3)^2 - y_1^2\right) = 0 \quad (15)$$

And to inequality constraints:

$$g_5(p):\ -L_c(p) + 18.10^{-3} \geq 0 \quad (16)$$

$$g_6(p):\ L_c(p) - 12.10^{-3} \geq 0 \quad (17)$$

Where the parameters L_c and R_c define the height and exterior radius of the actuator. In order to keep variations of the shape variables inside acceptable limits, additional constraints have to be specified:

$$pl_i \leq p_i \leq pu_i \quad \text{for } i = 1,\ldots,6 \quad (18)$$

Where the lower and upper values, pl_i and pu_i, respectively, are given in Tab. 1. In (11) the np specific points of z_i are distributed from 0.1 to 0.35 mm at regular intervals of 0.05 mm, giving $np = 6$ The constraint function (12) is a linear geometrical constraint, while the function (13) which defines the volume of the actuator is a nonlinear constraint, as are the constraints (14) and (15) which prescribe identical sections along the flux path. The equality constraints (16) and (17) define the margin within which the height of the actuator is allowed to vary. As with the optimization algorithms, a GA method is used to solve the nonlinear programming problem (11)–(17).

Main variables to determine general behavior of genetic algorithm are the number of population 30, probability of crossover, 0.6 and probability of mutaion, 0.001.

Recall that with this type of algorithms, during each iteration step, nonlinear constrained optimisation problems have been solved by the penalty function method. In that case, the fitness function is given as [1]:

$$f = \begin{cases} f & \text{if } \; P_i \text{ is feasible} \\ f \pm c \times g_{max} & \text{otherwise} \end{cases} \quad (19)$$

Where F is the value of objective function, symbol $\pm$ is used to keep penalty, g_{max} is given as:

$$g_{max} = \max\{0, g_i(p), |h_j|\} \quad (20)$$

Where $g_i(p)$ are the inequality constraints, $h_j(p)$ the equality constraints i and j are the number of the inequality constraints and the equality constraints, respectively.

The convergence criteria used in the present work is when the percentage difference between the average value of all the designs and the best parent in a population (non-penalized values) reaches a very small specified value ε. Thus

$$\left| \frac{\bar{f} - f_j(\text{best})}{\bar{f}} \right| \leq \varepsilon \quad (21)$$

Where $\bar{f}$ the average fitness value is in a generation, $f_j(\text{best})$ is the fittest design and ε is the convergence rate.

5. Validation

The results of this application using the GA approach are presented in Tab. 1 and Fig. 4, 5, 6 and 7. Fig. 4 and 5 below represents the initial magnetic force and the evolution of optimized magnetic force versus the parts-displacement of the electromagnetic actuator obtained by GA approach.

Tab. 1 Optimal solution of the magnetic actuator

P (mm)	Lowers bounds	Uppers bounds	Optimal values
P1	1.37	3.13	**3.02**
P2	3.00	15.0	**7.86**
P3	0.03	1.20	**0.88**
P4	1.00	3.50	**2.41**
P5	1.00	8.00	**2.79**
P6	1.00	8.00	**1.90**

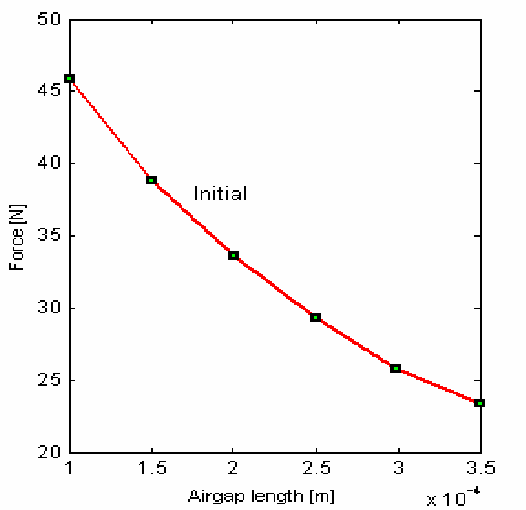

Fig. 4 Evolution of magnetic force versus the displacement

Fig. 7 shows the behavior of a lower minimum and good final average values. The GA convergence history for the force magnetic and the better solution are show in Fig. 6 and Tab 1. Fig. 8

presents the initial and final structure of the electromagnetic actuator.

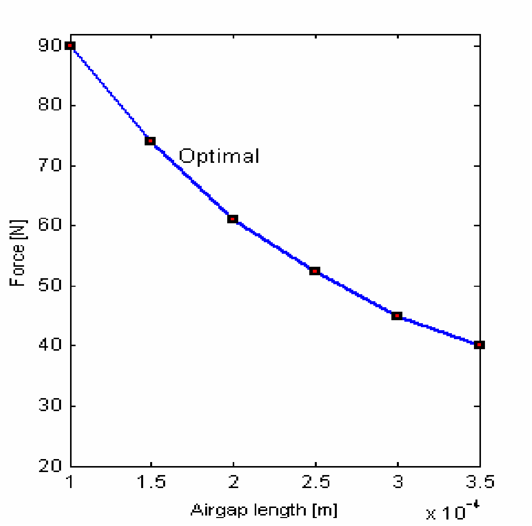

Fig.5 Evolution of optimized magnetic force versus the displacement

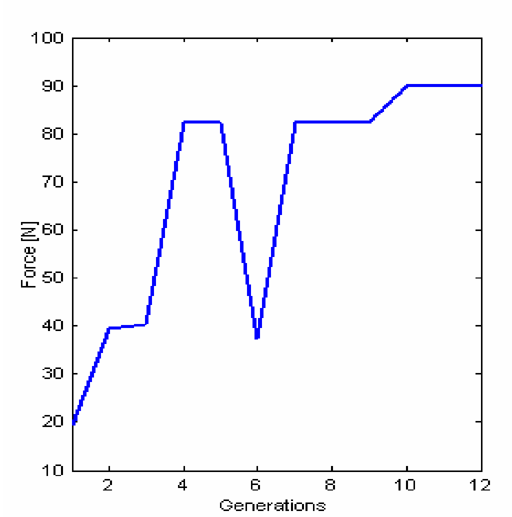

Fig.6 Maximisation of magnetic force versus generation count

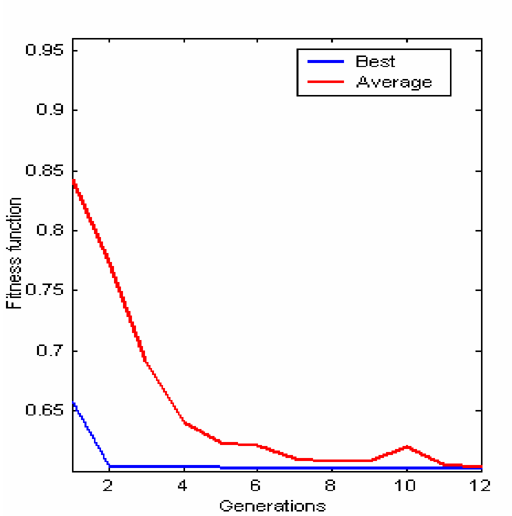

Fig. 7 Reduction of fitness function versus generation count

The electromagnetic model and the core of GA optimization with constraints are implemented in Matlab language.

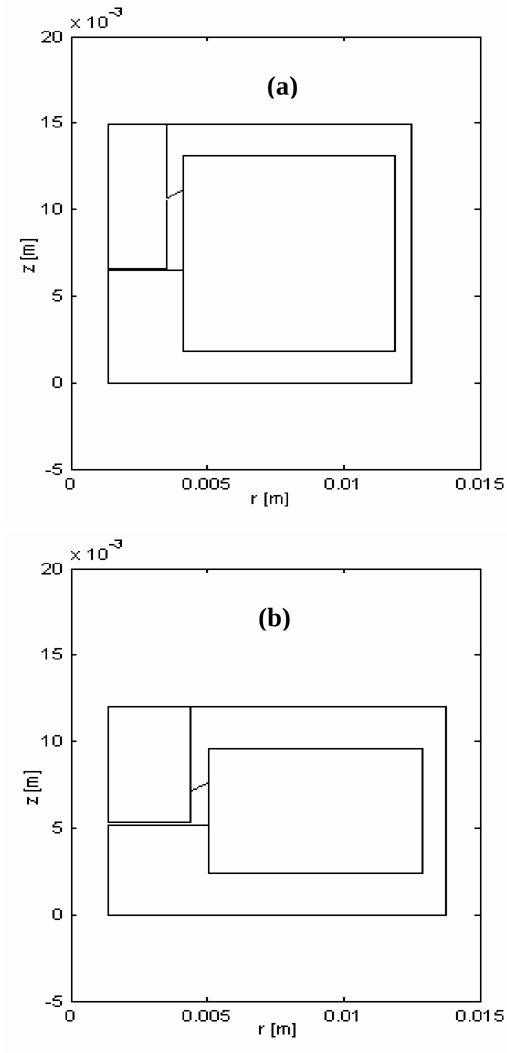

Fig. 9 Structures of the electromagnetic actuator. (a) Initial. (b) Optimal

6. Conclusion

The design optimization of an electromagnetic actuator with a new genetic algorithm approach is presented. GA approach minimization is used to solve the problem for design optimization coupled with an electromagnetic finite element modelling by minimizing a specific goal function. The solutions found are robust but the computation time remains important. According to the optimization processes diversity, the association of the genetic algorithm approach with another method is proposed to be a very efficient tool in the search of any global solution.

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