Electromagnetic Device Optimization Based on Electromagnetism-Like Mechanism

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Abstract **—** The algorithm based on the Electromagnetism-Like mechanism results from the Coulomb's law of electromagnetics. In this paper, a novel stochastic approach based on the Electromagnetism-Like mechanism is applied to the optimization of electromagnetic devices. In order to show the effectiveness of the proposed method, it has been demonstrated on a magnetizer by optimizing its pole face to obtain the desired sinusoidal magnetic flux density distribution.

Index Terms **—** Electromagnetic devices, Electromagnetism-Like mechanism, finite element method, and optimization.

I. INTRODUCTION

In all areas of engineering the efficient and effective design of products is crucial. Therefore, designers are faced with the challenge of optimizing ever more complex components, devices and systems this is more specifically so in the field of electromagnetic devices (EMD) where the optimization is of paramount importance [1-3]. In the area of EMD, building physical prototypes is a time consuming and prohibitively high cost approach and can represent a large percentage of the total costs involved in bringing a product to market [1, 4]. Reducing this time and cost burden has been, and still is, a key issue. Therefore, designing engineers have spent considerable time and effort on the creation of algebraic models to simulate the physical EMD and eventually to predict its performance [1]. Nowadays, real laboratories are replaced by computer environments for this purpose. In these virtual laboratories the physical EMD is replaced by a virtual prototype, which can be tested with the same level of accuracy as the physical EMD but with significant reductions in time and cost [4]. Moreover, with the development of more accurate and complex models in addition to the development of cheap and powerful computing systems, we are able now to simulate the physics involved in the operation of an EMD at a high level, which is as good as, or sometimes better than, what can be achieved from a physical prototype in a real laboratory [1].

Prototype evaluation is a critical component of the design process. In general, such a system explores the design space in order to find a set of parameters, which most nearly meet the specifications without violating a set of imposed constraints [5]. Such a search has two basic steps. In order to improve the performance of an existing prototype device, this last one is modified which represents the first step. The second step consists of measuring that performance to determine if any improvements have been done. This is generally described as an optimization process [1]. Thus, the purpose of optimization within a design activity is to find an improved solution for given requirements [1].

In general, searching techniques can be divided into two distinctive groups: deterministic and stochastic techniques [6]. The deterministic searching techniques are usually based on the calculation of the gradient of the objective function. On the other hand, for stochastic methods, computation of gradients is not necessary [6].

In the field of EMD design, optimization problems are very complex and involve many difficulties [7, 8]. Therefore, in many cases, deterministic methods are inappropriate for EMD

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optimization and stochastic techniques become a necessity [2]. Therefore, recently stochastic methods have been widely applied for multivariable inverse shape optimization, mainly due to their ability to avoid being trapped in a local optimum of the objective function [6]. Consequently, many researchers have devoted themselves in finding some reliable stochastic optimization methods, such as Electromagnetism-Like mechanism (EM) method.

The EM algorithm, which is proposed by Birbil and Fang [9] is one of the newest meta-heuristic. It is based on the attraction-repulsion mechanism of electromagnetism theory to move the sample points towards the optimality [10]. This method is applicable on nonlinear problems with bounded variables. This method considers each point as a charged particle. Each particle is impressed by other particles and consequently transmitted to better solution space [10]. The ease implementation and flexibility of the EM gains more attention from a lot of researchers, and it has been extended and applied in different researches, most of which have reported its promising performance [10].

In this work our main objective is to apply the EM for the optimization of EMD. First, we present the EM method, its advantages and how it works. Next, we illustrate the performance of our proposed method on the optimization of the pole face shape of a magnetizer problem. Finally, we conclude our paper with some final remarks and points.

II. ELECTROMAGNETISM-LIKE MECHANISM

As mentioned earlier, the EM is a flexible, effective, and a population based heuristic method, which is used to search for the optimal solution of global optimization problems proposed by Bïrbïl and Fang in 2003 [9]. It originates from the attraction–repulsion mechanism of the electromagnetism theory of physics by considering potential solutions as electrically charged particles spread around the solution space.

This heuristic EM consists of four stages. These are initialization of the algorithm, calculation of the total force exerted on each particle, movement along the direction of the force, and application of neighbourhood search to exploit the local minima [9]. Each of these four stages is discussed in more detail below. The general EM algorithm proposed in Birbil and Fang's paper is described in Algorithm 1.

Algorithm 1: EM (m, MAXITER, LSIT ER, δ)
m: number of sample points,
MAXITER: maximum number of iterations,
LSITER: maximum number of local search iterations,
δ: local search parameter, δ ∈ [0, 1].

1: Initialize()
2: iteration ←1
3: **while** iteration <*MAXITER***do**
4: Local(*LSITER*, δ)
5: **F** ←CalcF()
6: Move(**F**)
7: iteration ←iteration + 1
8: **end while**

As mentioned earlier, the first stage is the initialization of the algorithm. In this procedure, *m* particles are randomly generated inside the feasible domain, which is an *n* dimensional hyper-solid. Each coordinate of a point is assumed to be uniformly distributed among the corresponding upper and lower bounds. After a point is sampled from the space, the objective function value for the point is calculated using the function pointer *f(x)*. At the end of the initialization procedure, *m* points are identified and the point that has the best function value is stored in x^{best} [9, 11].

After determination of the initial solutions, the second step is to conduct a local search for the local optimum. Local search can be divided into three kinds, i.e., no local search, local search only on current better particle and local search on all particles [12]. Any local method of optimization such as hill-climbing [13, 14] or gradient-based methods [15] could be introduced in this phase. Random selection near the original solution is proposed in the primary algorithm [11].

The third step is to calculate the total force exerted on each particle. Here the superposition principle of the electromagnetism theory is used. The proportion of the charges of the points and the inverse proportion of the distance between the points are utilized to calculate the force exerted on the particle through other points [11]. In each iteration we compute the charges of the particles according to their objective function values. The virtual charge q^i of the i-th particle determines point i's power of attraction or repulsion. It is determined by the cost function value, and is calculated by,

$$q^i = \exp\left(-n\frac{f(x^i) - f(x^{best})}{\sum_{k=1}^{m}\left(f(x^k) - f(x^{best})\right)}\right) \forall i \quad (1)$$

where *f(.)* denotes the cost function and m denotes the population size. The $f(x^{best})$ denotes the best cost function value. The particle with largest charge (i.e., best cost function value) is called the "optimum particle". A particle will have stronger attraction, as it appears near the optimum particle. The particle attracts other particles with better cost function values, and repels other particles with worse cost function values [12].

In order to improve efficiency and solution accuracy by exploring the attraction-repulsion mechanism of the EM algorithm, [16] studied the effect of charges associated with each point in the population. The total force exerted on the i-th particle is determined from the Coulomb's law and superposition principle, and is given as,

$$F^i = \sum_{\substack{j=1 \\ j\neq i}}^{m} \left\{ \begin{array}{c} (x^j - x^i)\dfrac{q^i q^j}{\|x^j - x^i\|^2} \\ if f(x^j) < f(x^i) \\ (x^i - x^j)\dfrac{q^i q^j}{\|x^j - x^i\|^2} \\ if f(x^j) \geq f(x^i) \end{array} \right\} \forall i \quad (2)$$

where $f(x^j) < f(x^i)$ represents attraction and $f(x^j) \geq f(x^i)$ represents repulsion. From equation (2), we conclude that the resultant force between particles is proportional to the product of the charges and is in inverse proportion to the distance between the particles. Of course, a particle will not produce the force to affect itself. In general, the force in equation (2) is normalized as,

$$F^i = \frac{F^i}{\|F^i\|} \ \forall i\,. \quad (3)$$

The final stage involves moving along the orientation of the force. After calculating the total force of one point, this point moves by a random step length in the path of the force to cause the particles to move into any unvisited zones along this path. The update of each particle depends on the resultant force, and is given by,

$$x^i = \begin{cases} x^i + \alpha F^i(b_{upper} - x^i) \\ \quad if F^i > 0 \\ x^i + \alpha F^i(x^i - b_{lower})' \\ \quad if F^i \leq 0 \end{cases} \quad (4)$$
$$\forall i;\quad i \neq best\,,$$

where b_{upper} is the upper bound, b_{lower} is the lower bound, and α is a random value uniformly distributed between zero and one. The particle moves toward the upper bound by a random step length α as the resultant force is positive, whereas it moves toward the lower bound as the resultant force is negative. In the mechanism, the optimum particle of the population does not move, because it has the best cost function value and then attracts all other particles [12].

The second through the fourth stages are repeated until a termination criterion is reached. The termination criterion could be the maximum number of iterations given by the user or the amount of iterations performed without replacing the current optimal solution. In other words, if the current best point is not changed for certain number of iterations, the algorithm may be stopped. However, this decision has to be studied carefully since algorithm may be stopped before converging to the global optimum. On the other hand, un-necessary function evaluations may be avoided by stopping earlier [9]. In the initial algorithm, the maximum number of iterations was used [11]. EM has been successfully applied to various cases [11]. As the EM algorithm has not yet been utilized for EMD optimization, this study attempts to apply EM for this purpose.

III. APPLICATION EXAMPLE

In shape optimization tasks, each set of particles or charges of the total number of sample points represents the geometry of a specific design. This design is translated into a model to be solved using the Finite Element Method (FEM). Then a fitness value is obtained after solving this model. Thus, it is a paramount task to identify the optimal set of parameters by comparing the obtained fitness. These parameters are used to form the outlines of different regions of the modeled EMD, in our case the magnetizer.

The initial version of the magnetizer problem was the pole face shape of a motor. Then, it has been developed and has become an independent benchmark for the optimization of EMD called the magnetizer problem. The most important constraint of the design is to have a smooth pole face shape with no zigzags. This is achieved by not allowing individual nodes on the pole face to move independently but by determining their position from the 3rd order polynomial used to define the pole face geometry as it is detailed in the following section. The advantage of this problem is its ability to consider more design variables by adding more nodes to the pole face shape.

A. Magnetizer problem description

The application of EM for electromagnetic device optimization is illustrated on a magnetizer problem modeled as a 2D magneto static field analysis using FEM. The geometry of the modeled part of the magnetizer example is shown in Fig. 1. It has four main parts, which are the pole face, the coil or windings, the outer shell, and the material to be magnetized. In the FEM model, a low permeability (close to that of the air) is assigned to the object to be magnetized (non-magnetic material). However, the pole face and the outer shell are treated as magnetic materials and a permeability of 1000 is assigned to them. A high current is applied to the coil region. The non-linearity is not taken into account when solving the governing equations of the model. The goal is to optimize the magnetizer's pole shape in order to obtain a sinusoidal increasing magnetic flux density along chord AB positioned halfway through the width of the magnetized piece.

The pole shape is modeled using Uniform Non-rational Cubic B-splines (UNBS) with n control points. UNBS interpolation provides local control of the curve i.e., when a control point is moved, this affects only a small part of the curve. A B-spline is constructed from a string of curve segments whose geometry is determined by the control points. These curves are known as piecewise polynomials. A curve segment does not have to pass through a control point, unless this control point is repeated at least three times, which is desirable at the two end-points [17, 18].

Once the locations of the n control points are set, the shape of the pole face is constructed from a series of curve segments $S_1, S_2, S_3, \ldots, S_{n-3}$. As the curve is cubic, curve segment S_i is influenced by the control points P_i, P_{i+1}, P_{i+2}, P_{i+3}, and curve segment S_{i+1} is influenced by P_{i+1}, P_{i+2}, P_{i+3}, P_{i+4}. There are n control points, so there are n-3 curve segments. A single segment $S_i(t)$ of a B-spline curve is defined by [19],

$$S_i(t) = \frac{(1-t)^3}{6} P_i(t) + \frac{3t^3 - 6t^2 + 4}{6} P_{i+1}(t) + \frac{-3t^3 + 3t^2 + 3t + 1}{6} P_{i+2}(t) + \frac{t^3}{6} P_{i+3}(t)\,. \quad (5)$$

In equation (5), the coefficients are called the B-spline blending functions and $0 \leq t \leq 1$.

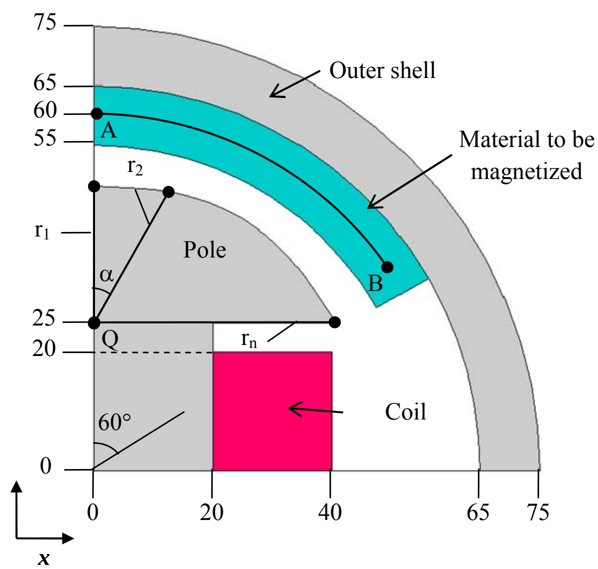

Fig. 1. Geometry of the magnetizer to be optimized.

In this work, we have chosen to apply the EM on two cases called CASE 1 and CASE 2. In CASE 1 the pole shape is modeled using eight control points, P_1, P_2, P_3, and P_4, where P_1 and P_2 are repeated three times each to force the curve to pass at these two ending points. For the eight control points of the pole face shape, five curve segments are generated. The nodes on the pole face are then placed on this B-spline approximation.

In CASE 2 we have added two more control points. Similarly to CASE 1, once the locations of the control points are set, the curve that shapes the pole face is constructed with B-splines. In this case the pole face curve touches the control points P_1 and P_6, each of which is represented with three coinciding B-spline control points.

1. Design variables

There are n (n = 4 for CASE 1 and n = 6 for CASE 2) points that control the pole face's shape, which are noticed as P_1 through P_n. The control points are mapped onto a polar coordinate system with its origin at Q as shown in Fig. 1. The radial coordinates, r_1 through r_n (separated from each other by 30° and 18° for CASE 1 and CASE 2, respectively), constitute the n design variables with mapping ranges given in Table 1 for CASE 1 and in Table 2 for CASE 2. These ranges are calculated for each design parameter based on the geometry of the device and the number of control points. Once determined, the radial and angular coordinates of a control point are mapped back to the x and y coordinates and UNBS are used to approximate the shape of the pole face from the n control points.

Table 1: Design variables and their ranges used in the magnetizer problem for CASE 1.

Design variable	Lower bound [mm]	Upper bound[mm]
r_1	22.0	29.5
r_2	22.0	31.3
r_3	22.0	38.7
r_4	22.0	48.5

Table 2: Design variables and their ranges used in the magnetizer problem for CASE 2.

Design variable	Lower bound [mm]	Upper bound[mm]
r_1	22.0	29.5
r_2	22.0	30.2
r_3	22.0	32.3
r_4	22.0	36.0
r_5	22.0	41.4
r_6	22.0	48.5

2. Objective function

The difference which has to be minimized between the desired and calculated magnetic flux densities along the chord AB (as shown in Fig. 1) is,

$$F = \sum_{1}^{N} \frac{|B_{desired} - B_{calculated}|}{B_{desired}} \qquad (6)$$

where N is the number of test points. $B_{desired}$ and $B_{calculated}$ represent the desired and calculated magnetic flux densities, respectively. The desired flux density distribution $B_{desired}$, is calculated using the following formula,

$$B_{desired} = B_0 \sin(\theta) \quad 35° \leq \theta \leq 89° \qquad (7)$$

where B_0 is the maximum value (magnitude) of the desired magnetic flux density distribution to be specified by the designer. In this paper B_0 is chosen to be 0.27 T.

3. EM optimization parameters

The proposed EM based method has been implemented using Matlab Software. Initially, several runs have been done with different values of the EM key parameters (such us the number of sample points and the local search parameters) in order to identify the best combination. In our implementation the EM runs for each case with the key parameters given in Table 3.

B. Results

The results obtained when the EM described above runs for CASE 1 and CASE 2 are given in Table 4 and 5 and Fig. 2 through Fig. 7. In Table 4 and Table 5 the values of the optimized control points are given for CASE 1 and CASE 2, respectively. Figures 2 and 5 show the optimized magnetizer pole face and the isopotential lines for CASE 1 and CASE 2, respectively. In Fig. 3 the desired magnetic flux density distribution along chord AB is compared against the distribution of the optimal solution calculated using EM for CASE 1. Figure 6 gives the same comparison for CASE 2. We can notice that there is a clear improvement, which is due to the higher number of control points. Finally, Figs. 4 and 6 sketch the changes in the best fitness of each iteration over the 50 iterations for CASE 1 and CASE 2, respectively. We can notice here that the fitness for CASE 1converges quickly and to a best value than CASE 2. This is due to the same reason mentioned earlier.

Table 3: EM optimization parameters for CASE 1 and CASE 2.

Name	Description	Value
n	Dimension of the problem (number of design variables)	CASE 1: 4 CASE 2: 6
m	Number of sample points	10
MAXITER	Maximum number of iterations	50
LSITER	Maximum number of local search iterations	5
δ	Local search parameter, δ∈[0,1]	1×10^{-4}

Table 4: Coordinates of the optimized control points for the magnetizer of CASE 1.

Design variable	Optimal solution [mm]
r_1	25.458
r_2	27.576
r_3	33.349
r_4	37.626

Table 5: Coordinates of the optimized control points for the magnetizer of CASE 2.

Design variable	Optimal solution [mm]
r_1	25.239
r_2	26.338
r_3	27.583
r_4	30.544
r_5	34.318
r_6	37.405

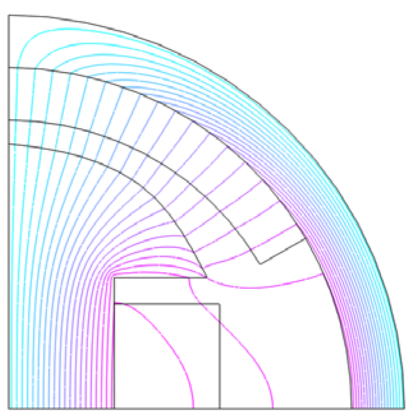

Fig. 2. Optimized magnetizer pole face and iso-potential lines for CASE 1.

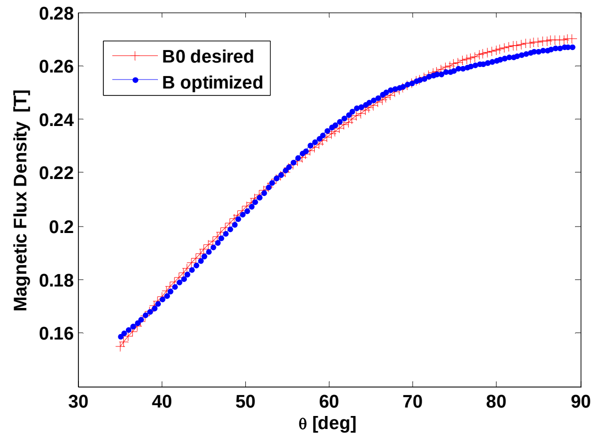

Fig. 3. Comparison between the desired and optimal magnetic flux density for CASE 1.

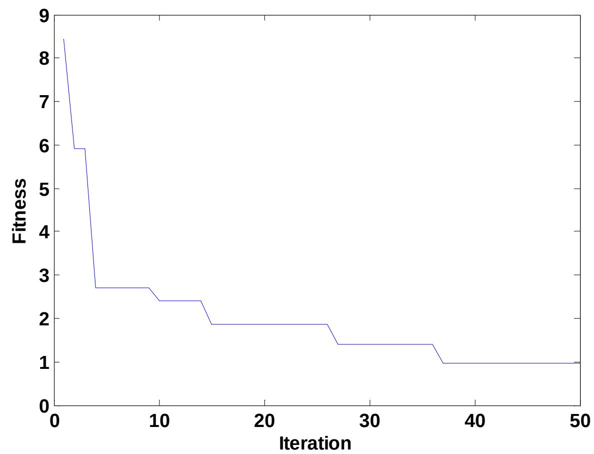

Fig. 4. Change of the best fitness over iterations for CASE 1.

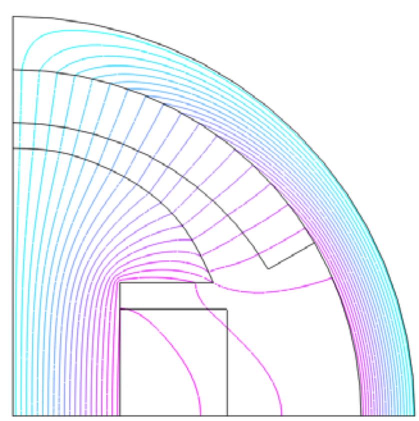

Fig. 5. Optimized magnetizer pole face and isopotential lines for CASE 2.

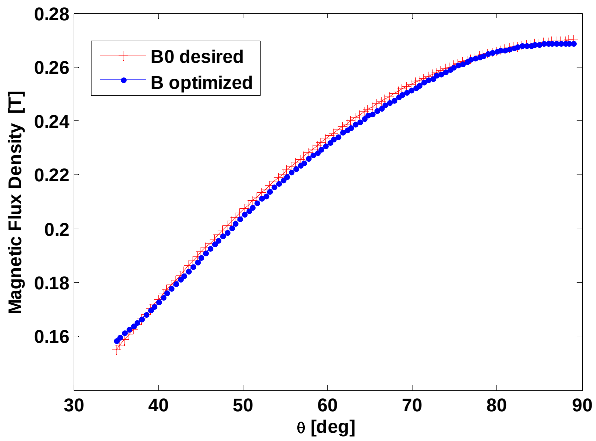

Fig. 6. Comparison between the desired and optimal magnetic flux density for CASE 2.

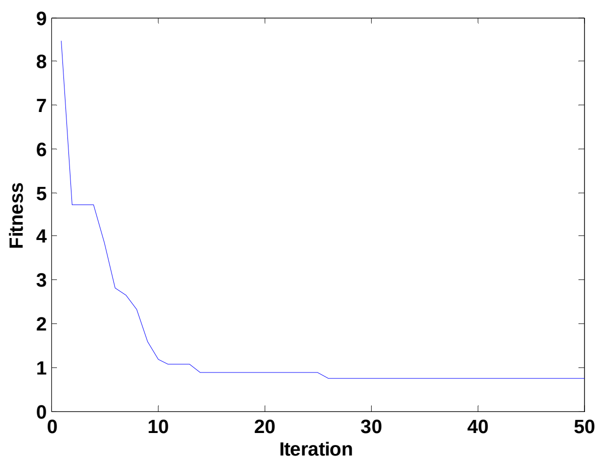

Fig. 7. Change of the best fitness over iterations for CASE 2.

IV. CONCLUSION

This paper describes an electromagnetism based algorithm, which is a powerful yet easy algorithm for EMD design and optimization. The results obtained in this paper show that the EM constitutes a potential and efficient tool for the design and optimization of EMD. The proposed method is successfully applied on a magnetizer shape optimization problem. Two cases with different number of control points are studied. In both cases the EM converges rapidly to optimum (in less than 50 iterations). However, the comparison of the results between these two cases indicates that the efficiency is increased in CASE 2. These improvements are primarily attributed to the higher number of control points used.

EM algorithm is a free derivative method it uses only the fitness value. These characteristics render it robust as it can adapt to the environment. EM can be used as a stand-alone approach or as an accompanying algorithm for other methods. The strength of the algorithm lies in the idea of directing the sample points toward local optimizers by utilizing an attraction-repulsion mechanism. Finally, EM is fully parallelizable. The evaluation of each set of points is independent from other sets. This trait makes the use of Connection Machine type computers or work stations farms where CPUs are shared very profitable for EM applications.

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