Optimal Design of Electromagnetic Devices Using the League Championship Algorithm

Houssem R. E. H. Bouchekara [1], Mouaaz Nahas [2], and Hamza M. Kaouach [3,4]

[1] Laboratory of Electrical Engineering of Constantine, LGEC, Department of Electrical Engineering
University of Freres Mentouri Constantine, 25000 Constantine, Algeria
bouchekara.houssem@gmail.com

[2] Department of Electrical Engineering, College of Engineering and Islamic Architecture
Umm Al-Qura University, P.O. Box: 5555, Makkah, 21955 Saudi Arabia
mmnahas@uqu.edu.sa

[3] ECE Department, Umm Al-Qura University, 21493 Al-Lith, Saudi Arabia
hkaouach@uqu.edu.sa

[4] HF APW Communications, University Campus, 29238 Brest, France
hamza.kaouach@gmail.com

Abstract ─ Nowadays, there is an increasing attention on novel metaheuristics and their applications in different problems of science and engineering. A new efficient optimization method, called the League Championship Algorithm (LCA) is applied in this paper for the optimal design of electromagnetic devices. This method is inspired by the competition of sport teams in an artificial sport league for several weeks and over a number of seasons. The performance of the proposed algorithm is tested against two benchmark problems: the magnetizer and the outrunner-type brushless DC motor. The obtained results show that the LCA is an efficient and competitive algorithm for constructing optimal design of electromagnetic devices.

Index Terms ─ Electromagnetic devices, league championship algorithm, metaheuristics, optimal design, optimization.

I. INTRODUCTION

Optimal design of devices is one of the major problems in electrical engineering. It involves choosing – from many possible variants – the best or the optimum variant based on one or several criteria [1].

The optimal design of Electromagnetic Devices (EMD) using metaheuristics has been successfully implemented and applied since the development of such algorithms in the early 1980s. Some relatively recent examples of the application of metaheuristics for the optimal design of EMD include, among others, Genetic Algorithms [2], Evolution Strategies [3], Tabu Search [4], Artificial Immune Systems [5], Particle Swarm Optimization [6], Electromagnetism-Like Mechanism [7], Imperialist Competitive Algorithm [8], Bacterial Chemotaxis [9], Black-Hole-Based Optimization [10] and Teaching Learning Based Optimization [11].

Furthermore, recently, great deals of efforts have been devoted to the development and application of new optimization metaheuristics inspired from real life phenomena. In this context, a new developed metaheuristic which has not yet received adequate attention in the electromagnetic optimization community is the League Championship Algorithm (LCA). The LCA is a novel algorithm inspired from the concept of sport league championships. In LCA, the league (population) is composed of teams (individuals) that compete in an artificial league over several weeks for a number of seasons [12], [13].

The main objective of this paper is, first, to review the basic algorithmic features of the LCA optimizer and, second, to apply LCA for achieving optimal design of EMD. The LCA algorithm proposed is then tested on a magnetizer benchmark problem and an Outrunner-type Brushless DC (OBLDC) motor benchmark problem.

The remainder of this paper is organized as follows. Section 2 provides a detailed description of the LCA. In Section 3, the proposed algorithm is applied to the two benchmark problems mentioned above. Finally, summary and conclusions are drawn in Section 4.

II. LEAGUE CHAMPIONSHIP ALGORITHM (LCA)

A. Overview

The LCA introduced by Husseinzadeh [12] is a new

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metaheuristic algorithm developed to solve continuous optimization problems [14]. Like some other known optimization algorithms, LCA uses a population of solutions to obtain the optimal one. Each team (i.e., individual) in the league (i.e., population) represents a feasible solution to the problem that is being solved. These teams compete in an artificial league for several weeks (iterations). Based on the league schedule for each week, teams play in pairs (say, for example, team i plays against team j) and the outcome is determined in terms of win or loss based on the playing strength of the teams. The team strength (which is basically corresponding to the fitness value) results from a particular team formation (solution). Keeping track of the previous week events, each team can make the required changes in the recovery period in order to set up a new formation for the next week competition (this simply means that a new solution is generated). In the same way, the championship continues for a number of seasons (stopping criterion) [14].

B. The algorithm

Algorithm 1 provides the basic steps of the LCA in a greater detail. As in the other optimization algorithms, the LCA works with a population of individuals. Therefore, in the initialization process, a league of L teams is generated and the teams' playing strengths are evaluated. Here, the league, teams, and playing strengths represent the population, solutions and fitness values (respectively). Also, L is an even number which represents the league size. Considering a function of n variables, each team comprises n players, where each one corresponds to a different variable. In the first step, the teams' best formations take the initialization values. In the second step – which is the competition phase – the teams compete in pairs based on the league scheduler for $S \times (L - 1)$ weeks; where S is the number of seasons and a week (iteration) is represented by t. After each competition (or game) between team i and team j (for example), the outcome is produced in terms of win or loss based on the playing strength of each team; here, we assume no tie games can occur. In the recovery step (which is the third step), each team devises a new formation based on the team's current best formation and the previous week events, too. Selection in LCA is greedy in the sense that the current best formation is replaced by a more productive team formation that has a better playing strength. In other words, If the new formation is the fittest one (i.e., the new solution is considered the best solution obtained so far for the ith member of the population), then the new formation is considered as the team's current best formation. The algorithm stops after a certain number of seasons [12], [13].

In our description of the LCA algorithm, we have used some concepts like: generating the league schedule, determining the winning or losing team and finally setting up a new team formation. More details on the mechanism of these concepts are given in [12] and [13].

Algorithm 1: The League championship algorithm [12]

1. Initialize the league size (L) and the number of seasons (S); t=1;
2. Generate a league schedule;
3. Initialize team formations (generate a population of L solutions) and determine the playing strengths (function or fitness value) along with them. Let the initialization be also the teams' current best formation;
4. While $t \leq S.(L-1)$:
5.   Based on the league schedule at week t, determine the winner/loser among every pair of teams using a playing strength based criterion;
6.   t=t+1;
7.   For i=1 to L:
8.   Devise a new formation for team i for the forthcoming match, while taking into account the team's current best formation and previous week events. Evaluate the playing strength of the resulting arrangement;
9.   If the new formation is the fittest one (that is, the new solution is the best solution achieved so far for the ith member of the population), hereafter consider the new formation as the team's current best formation;
10.   End for
11.   If mod(t,L-1)=0
12.   Generate a league schedule;
13.   End if
14. End while.

C. Implementation of the LCA for the optimal design of EMD

The implementation of the LCA for the optimal design of EMD is illustrated in Fig. 1. It can be seen that the process begins by selecting the device to be optimized. This step is followed by: defining the objective function, providing the design variables with their mapping ranges, and imposing some constraints if needed. Then, the Decision Maker (DM) has to choose the more appropriate model for the selected EMD; i.e., it can be based on an analytical model or numerical models such as the Finite Element Method (FEM), the Finite Difference Method (FDM), or any others. Once the model is selected, the DM has to select the software among many (commercial or open source) software which are available for the designers. After that, and in order to apply the LCA, parameters like the league size, the number of seasons, the type of formation and the probability of success have to be defined. The LCA is then run for the optimization. Once the results are obtained, the DM has to decide – using his/her experience – whether the design is satisfactory or not. If it is so, the process must be stopped, otherwise the LCA parameters should be modified and the LCA run until the designer is satisfied with the obtained results.

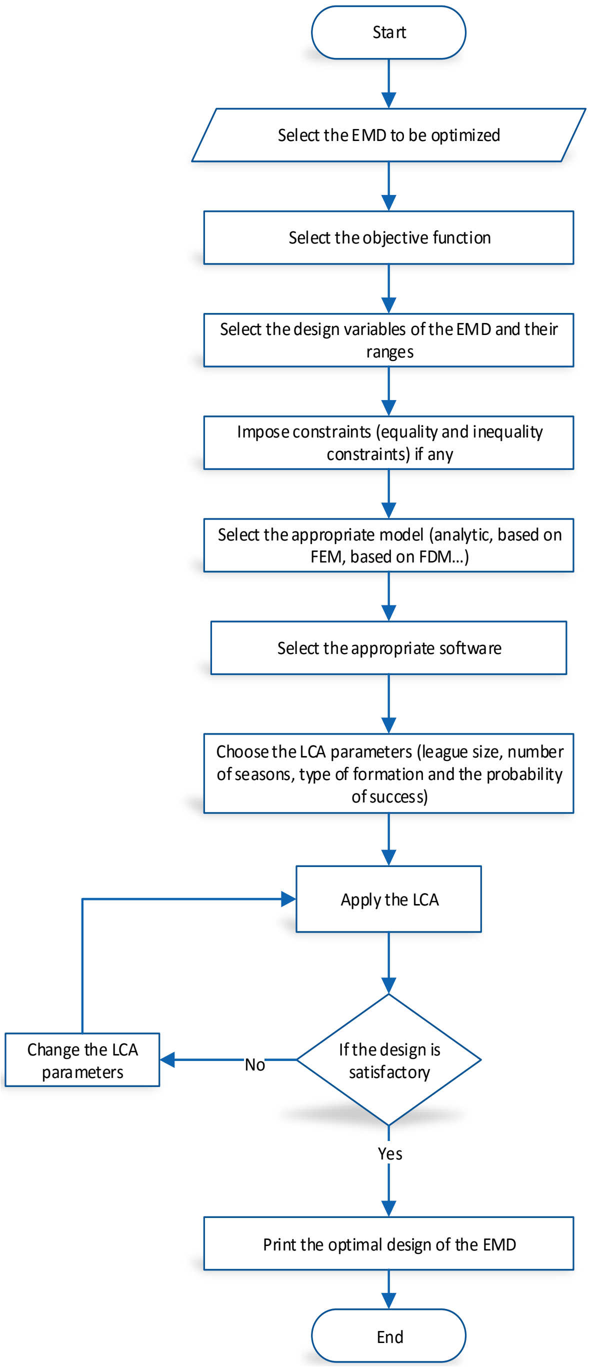


Fig. 1. Flowchart of the implementation of LCA for the optimal design of EMD.

III. APPLICATIONS

As mentioned earlier, the LCA has been applied to the following two benchmarks: the magnetizer benchmark problem and the OBLDC motor benchmark problem. Here is the detailed description of the two benchmarks.

A. The magnetizer problem

1) Description

The magnetizer problem is modeled as a linear 2D magnetostatic field analysis using the Finite Element Method (FEM). The geometry of the modeled part of the magnetizer is shown in Fig. 2. The key objective here is to optimize the pole shape of the magnetizer in order to get a predefined profile of the magnetic flux density along chord AB positioned halfway through the width of the magnetized piece [10].

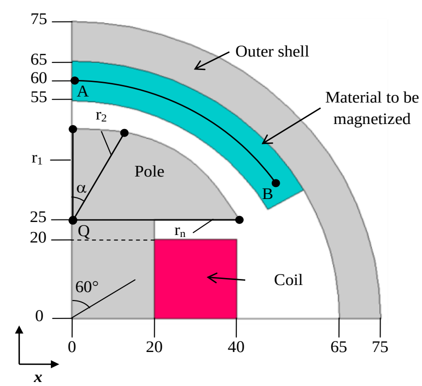


Fig. 2. Geometry of the magnetizer [15], [16].

The pole shape is modeled using Uniform Nonrational Cubic B-Splines (UNBS) with n control points P_1, P_2…P_n corresponding to the radial distances r_1, r_2… r_n and separated by α as shown in Fig. 2. 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 curve is confined to the convex hull formed by the control points, and unless a control point is repeated at least three times, it does not touch the control points [15], [16].

In the FEM model, a low permeability (close to that of the air) is assigned to the object that is to be magnetized (nonmagnetic material), a permeability of 1000 is assigned to the pole face and the outer shell and a high current is applied to the coil region (5 A/mm^2).

2) Design variables

As mentioned above, the pole shape is modeled using n control points. In this work, we have chosen two values for n: n=4 and n=6. The n control points can move radially from the fixed point Q. Therefore, there are n design variables which are the radial distances from Q, i.e., r_1 through r_n with mapping ranges given in Table 1. Once the locations of the control points are found, the curve that shapes the pole face is constructed with B-splines. This curve touches the control points P_1 and P_n, each of which is represented with three coinciding B-spline control points.

Table 1: Design variables and their ranges used in the magnetizer problem for n=4 and n=6

	n=4		n=6	
Design Variable	Lower Bound [mm]	Upper Bound [mm]	Lower Bound [mm]	Upper Bound [mm]
r_1	22.0	29.5	22.0	29.5
r_2	22.0	31.3	22.0	30.2
r_3	22.0	38.7	22.0	32.3
r_4	22.0	48.5	22.0	36.0
r_5	-	-	22.0	41.4
r_6	-	-	22.0	48.5

3) Objective function

The distribution of the magnetic flux density is evaluated at N sample points along the chord AB. Based on the desired profile of the magnetic flux density distribution in the chord AB, two cases are proposed and investigated in this paper:

CASE 1: the objective is to get a sinusoidal increasing distribution of B.

CASE 2: the objective is to get a uniform distribution of B.

In both cases the objective is to minimize the summed square of the difference between the desired and calculated magnetic flux densities (along the chord AB) which is identified as the error. Thus, the objective function can be written as follows:

$$f_{obj} = \sum_1^N \left(B_{desired_i} - B_{calculated_i}\right)^2, \qquad (1)$$

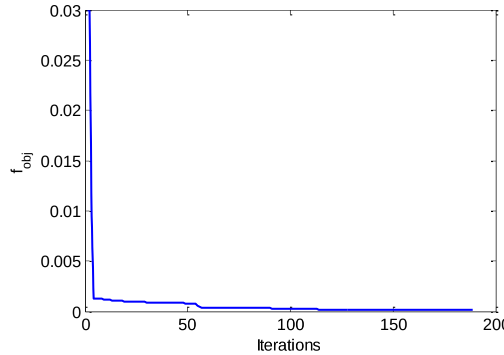
where: $B_{desiredi}$ and $B_{calculatedi}$ represent the desired and calculated magnetic flux densities at i, respectively. The desired flux density distribution $B_{desired}$ is calculated using the following formula:

$$B_{desired} = \begin{cases} B_0 \sin(\theta_i) & \text{CASE 1} \\ B_0 & \text{CASE 2'} \end{cases} \qquad (2)$$

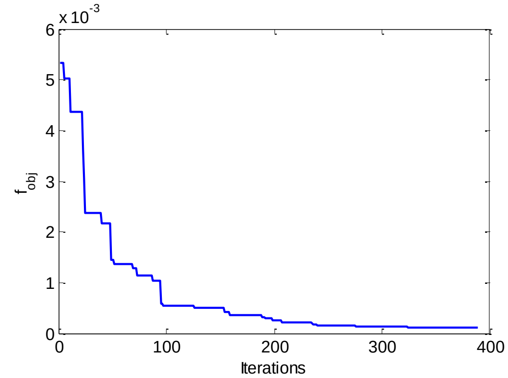
where: $35° \leq \theta_i \leq 89°$, $i = 1, \dots, N$, B_0 is chosen to be equal to 0.27 T and N = 50.

4) Results

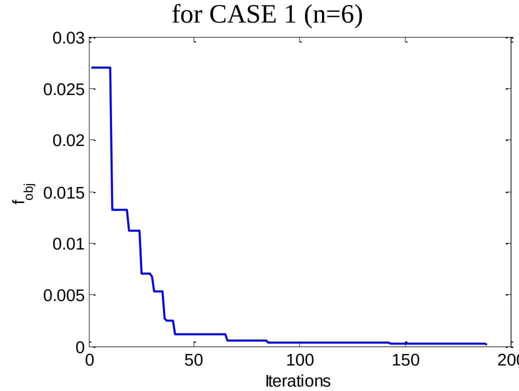
The proposed algorithm has been applied to the magnetizer problem for CASE 1 and CASE 2. The optimal solutions found are tabulated in Table 2. Moreover, Fig. 3 shows a set of results for both cases; i.e., evolutions of the objective function over iterations, isopotential lines, comparison between the desired and optimal magnetic flux densities, and comparison between optimal profiles.



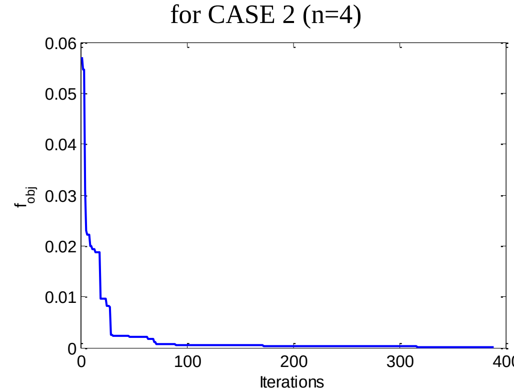
(a) Evolution of the objective function over iterations for CASE 1 (n=4)



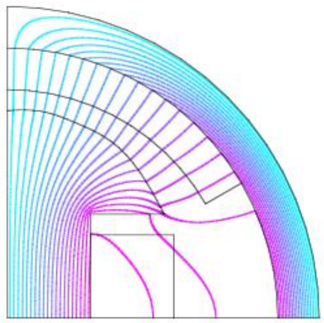
(b) Evolution of the objective function over iterations for CASE 1 (n=6)



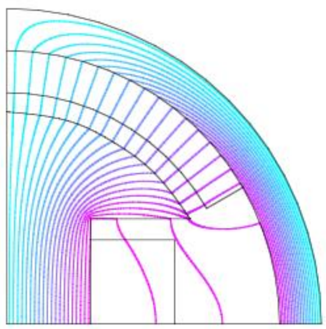
(c) Evolution of the objective function over iterations for CASE 2 (n=4)



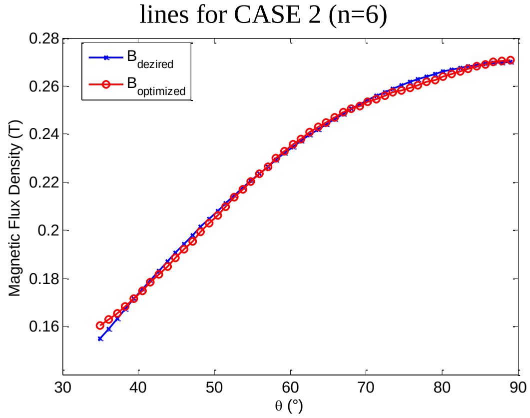
(d) Evolution of the objective function over iterations for CASE 2 (n=6)



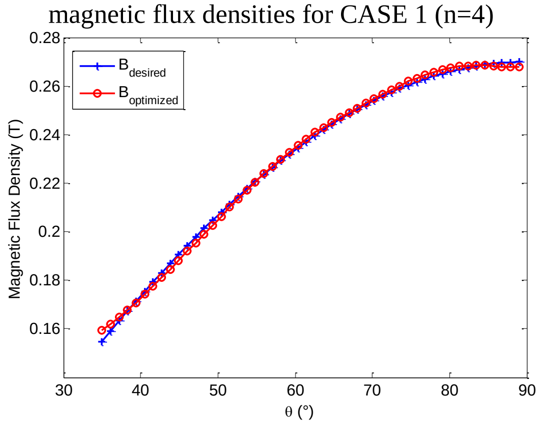
(e) Optimized magnetizer pole face and isopotential lines for CASE 1 (n=6)



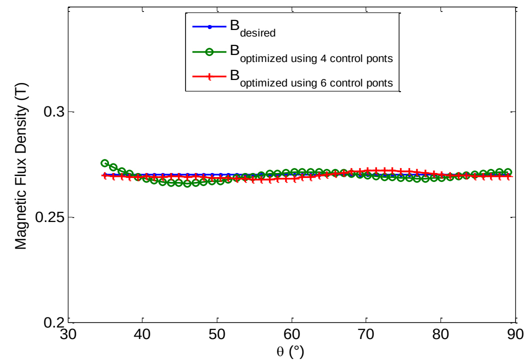
(f) Optimized magnetizer pole face and isopotential lines for CASE 2 (n=6)



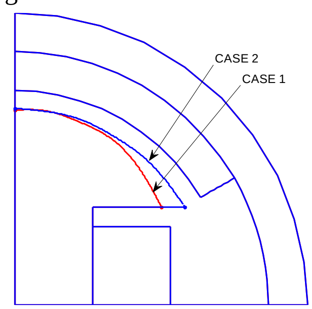
(g) Comparison between the desired and optimal magnetic flux densities for CASE 1 (n=4)



(h) Comparison between the desired and optimal magnetic flux densities for CASE 1 (n=6)



(i) Comparison between the desired and optimal magnetic flux densities for CASE 2



(g) Comparison between the optimal profiles found in CASE 1 and in CASE 2

Fig. 3. Obtained results for the magnetizer problem.

It can be clearly noticed that there is an improvement in the results when a higher number of control points is used. Furthermore, it is worth highlighting that the difference in the profiles depends on the objective function, i.e., whether the desired magnetic flux density is constant or sinusoidal. The optimized pole face has a constant air gap in CASE 1, however, this air gap gradually increases in CASE 2.

The proposed LCA is compared with some well-known optimization methods which are: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Black Hall Based Optimization (BHBO) and Electromagnetics Like-Mechanism (EM). The results of such a comparison are summarized in Table 3.

Table 2: Optimal solutions found for the magnetizer problem

	Optimal Values [mm]			
	n=4		n=6	
Design Variable	CASE 1	CASE 2	CASE 1	CASE 2
r_1	25.64	25.60	24.96	25.44
r_2	27.51	27.78	26.66	26.03
r_3	33.25	34.68	27.39	28.55
r_4	37.79	44.26	31.07	31.38
r_5	-	-	33.82	37.50
r_6	-	-	37.67	43.68

Table 3: Coordinates of the optimized control points for the magnetizer problem for CASE 1 compared with those obtained using some well-known optimization methods

	Optimal Values [mm]				
Design Variable	LCA	GA	PSO	EM [7]	BHBO [10]
r_1	24.96	25.882	25.639	25.239	25.444
r_2	26.66	25.537	25.779	26.338	25.941
r_3	27.39	28.140	28.149	27.583	28.232
r_4	31.07	30.565	30.161	30.544	29.715
r_5	33.82	34.401	35.058	34.318	35.691
r_6	37.67	37.380	36.764	37.405	36.351

B. OBLDC motor problem

1) Description

In this second example, we aim to optimize a 12 stator tooth 14-magnet outrunner-type (a motor with exterior rotor) brushless DC motor of the type commonly used to propel small Unmanned Aerial Vehicles (UAVs) (Fig. 4). The objective here is to minimize the size of the motor, given a specified bulk current density in the windings and a desired torque that should be produced at the specified current density [17].

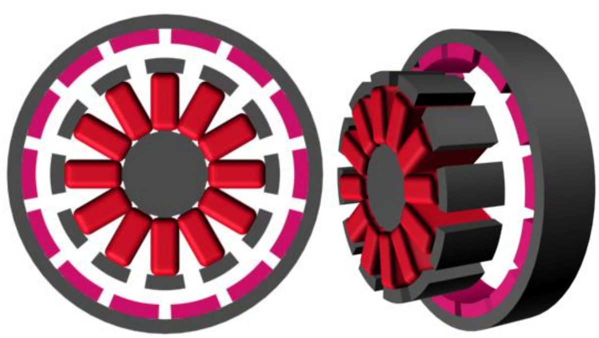


Fig. 4. Geometry of the OBLDC motor.

2) Design variables

In this example, we have 10 design variables that represent the geometry of the motor. These variables with their mapping ranges are detailed in Table 4.

3) Objective function

As mentioned before, the objective for this example is to minimize the size of the motor. In this work the desired torque is selected as 1 N.m. Therefore, the objective function can be expressed as follows [17]:

$$f_{obj} = \frac{1}{1000}\left(\pi \times \frac{\mathrm{hh} + \mathrm{rso}}{2} \times (\mathrm{rro}^2 - \mathrm{rsi}^2)\right), \quad (3)$$

where: rro is the rotor outer radius and the factor $\frac{1}{1000}$ is to scale the objective function to units of cm^3.

Table 4: Design variables and their ranges used in the OBLDC motor problem

Design Variable	Lower Bound [mm]	Lower Bound [mm]	Upper Bound [mm]
rso	Stator outer radius	8.0	20.0
rsi	Stator inner radius	2.0	5.0
dm	Magnet thickness	0.1	2.0
ds	Depth of slot opening	0.1	2.0
dc	Can thickness	0.1	2.0
fm	Pole fraction spanned by the magnet	0.2	1.0
fp	Pole fraction spanned by the iron	0.2	1.0
ft	Width of tooth as a fraction of pole pitch at stator ID	0.2	1.0
fb	Back iron thickness as a fraction of tooth thickness	0.2	1.0
hh	Length	15.0	50.0

4) Results

The proposed algorithm has been applied to the OBLDC motor problem. The optimal results found are tabulated in Table 5. Moreover, Fig. 5 shows the isopotential lines of the optimal motor obtained. The objective function using LCA gives the value of 43.0644 cm^3 which is better than the one obtained using Random Optimization (RO) that is 45.002 cm^3 [17].

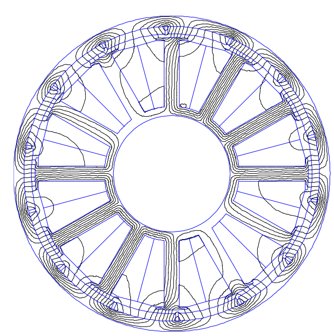


Fig. 5. Optimized 14 magnet OBLDC motor and isopotential lines.

Table 5: Optimal design of the OBLDC motor problem

Design Variable	Optimal Values [mm]
rso	18.736
rsi	8.000
dm	1.033
ds	1.446
dc	0.322
fm	0.959
fp	0.450
ft	0.507
fb	0.588
hh	24.267

IV. CONCLUSION

In this paper, the recently-developed LCA optimization algorithm has been used to find the optimal design of EMD. In order to assess its effectiveness in the selected problem domain, the proposed LCA algorithm has specifically been applied to the magnetizer problem and to the OBLDC motor problem. In the first problem, two cases with different number of control points were studied. In both cases, it was found that the LCA converged rapidly to optimum. In the second problem, the size of the motor was minimized as a result of applying the LCA algorithm. Also, a comparison with other optimization algorithms for this particular benchmark was performed and our results show that LCA is a competitive optimization algorithm.

The results obtained in this paper clearly show that the LCA constitutes a potential (as well as efficient) tool to be used for the optimal design of EMD. Detailed comparison with alternative optimization algorithms for the two benchmark problems (and many others in the same domain) can be a good base for future research work.

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