Optimization Design of Electromagnetic Devices Using an Enhanced Salp Swarm Algorithm

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Abstract **─** An Enhanced version of the Salp Swarm Algorithm (SSA) referred to as (ESSA) is proposed in this paper for the optimization design of electromagnetic devices. The ESSA has the same structure as of the SSA with some modifications in order to enhance its performance for the optimization design of EMDs. In the ESSA, the leader salp does not move around the best position with a fraction of the distance between the lower and upper bounds as in the SAA; rather, a modified mechanism is used. The performance of the proposed algorithm is tested on the widely used Loney's solenoid and TEAM Workshop Problem 22 design problems. The obtained results show that the proposed algorithm is much better than the initial one. Furthermore, a comparison with other well-known algorithms revealed that the proposed algorithm is very competitive for the optimization design of electromagnetic devices.

Index Terms **─** Design optimization, electromagnetic devices, salp swarm algorithm.

I. INTRODUCTION

Optimization of devices is an important task in different fields of engineering. It consists of determining some design variables or parameters in order to get the best performance of a device. Usually, this process is highly constrained that limit the final solution.

The process of optimization design is generally performed in the following three main steps:

1. Create an optimization design model or problem formulation.
2. Solve the optimization problem.
3. Analyze and interpret the obtained results.

In the first step, a mathematical model is created, or in other words, the problem is mathematically formulated. Here the framework of optimization is determined by defining the objective function to be minimized (or maximized), identifying the design variables to be optimized, and the constraints to be respected. Since the usefulness of the outcome primarily depends on this step, it is of utmost significance in the optimization design process.

The second step consists of solving the mathematical problem defined in the first step. Here three approaches can be usually used, including analytical approaches, graphical approaches, and numerical approaches.

The third and last step of the optimization design process is the posterior analysis. In this step, designers perform some analyses on the obtained design to verify its performance superiority by asking simple questions – is it optimal or can it be further improved or is it feasible and/or realizable.

The optimal design of Electromagnetic Devices (EMDs) follows the same steps described in this section. Furthermore, with the increase in the complexity of EMDs, more and more designers are using modern metaheuristic methods as optimization methods in the second step of the optimization design process.

In the literature, many metaheuristics have been implemented and applied to EMD optimization. Some examples of algorithms among others are: Genetic Algorithms (GA) [1], [2], Tabu Search (TS) [3], Simulated Annealing (SA) [4], evolution strategies (ES) [5], Electromagnetic-like Mechanism (EM) [6], Black Hole (BH) [7], Gravitational Search Algorithm (GSA) [8], Teaching Learning Based Optimization (TLBO) [9], Artificial Bee Colony (ABC) [10], Firefly Algorithm (FA) [11], League Championship Algorithm (LCA) [12], Social spider optimization (SSO) [13].

However, most of the modern metaheuristics are developed and tested on some well-known mathematical set of benchmarks, and then compared with each other to assess their performance. Therefore, using a metaheuristic, as it is developed and tested on mathematical benchmarks, without any modification or

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adaptation to design EMDs can lead to non-optimal solutions. Consequently, the objective of this paper is to develop an enhanced version of a new metaheuristic method developed in [14] which is called the Salp Swarm Algorithm (SSA) for the optimization design of EMDs.

The remainder of this paper is organized as follows. In section II, the SSA algorithm is presented. In section III, the developed ESSA is detailed. Section IV contains the discussion of the obtained result. Lastly, conclusions have been drawn in the final section of this paper.

II. SALP SWARM ALGORITHM

The SSA is inspired by the behavior of salps while navigating and foraging in oceans [14]. Salps leave in an environment hard to access, which makes research on these creatures not abundant. In the ocean usually, salps form a swarm called salp chain. In [14], a mathematical model is proposed to model the salp chain behavior. The pseudocode of the SSA is given in

Fig. 1 [14]. Like other population-based metaheuristics, the SSA initializes with a population of salps generated at random positions inside the searching space. Next, the population is categorized into two main groups called leaders (the salps in the front of the chain) and followers (the remaining salps of the chain). Then, the fitness of each salp is evaluated, and the best salp (that has the minimum fitness) is considered as the source of food to be chased by the salp chain.

The positions of the best and the follower salps are updated using the following equation [14]:

$$x_j^1 = \begin{cases} F_j + c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left(\left(ub_j - lb_j\right)c_2 + lb_j\right) & c3 < 0 \end{cases}, \quad (1)$$

where j indicates the jth dimension, x_j^1 is the position of the first salp (leader), F_j is the position of the food source, ub_j and lb_j indicates the upper and lower bounds, respectively, $c_1 = 2e^{-\left(\frac{4\text{ Current Iteration}}{\text{Maximum Number of Iterations}}\right)^2}$ is a balancing factor between exploration and exploitation, c_2 and c_3 are random numbers.

In the other side, the position of followers is updated using the following expression:

$$x_j^i = \frac{1}{2}\left(x_j^i + x_j^{i-1}\right). \quad (2)$$

Then if a salp crosses the border of the search space, it is brought back inside the search space. The process described here iterates until a predefined termination criterion is satisfied:

```
Inputs    The objective function, problem dimension, population size, Maximum number of iterations
Output    Best Salp
Initialization: initialize the salp population
while the termination condition is not satisfied
Calculate the fitness of each salp
The best salp is set as F
Update c1
    for each salp (x_i)
        if i == 1
            Update the leading salp position
        Else
            Update the follower salp position
        end if
    Check if there are salps outside the search space
    end for
end while
```

Fig. 1. Pseudo code of the SSA algorithm.

III. ENHANCED SALP SWARM ALGORITHM

In this paper, an enhanced version of the SSA noted as ESSA is developed. The ESSA has the same general structure as the SSA with some modifications in order to enhance its performance for the optimization design of EMDs. For the ESSA, instead of moving the leader salp around the best position with a fraction of the distance between the lower and upper bounds as in eq. (1), another mechanism is used. In this mechanism, three different salps are randomly selected from the leader salps (x^1, x^2 and x^3). Then a random number (c_2) is generated. Based on this number, the position of the salp is updated as follows:

$$x_j^i = \begin{cases} x_j^1 + c_1\left(x_j^2 - x_j^3\right) & c_2 < \frac{1}{3} \\ x_j^2 + c_1\left(x_j^3 - x_j^1\right) & \frac{1}{3} < c_2 \leq \frac{2}{3} \\ x_j^3 + c_1\left(x_j^1 - x_j^2\right) & \frac{2}{3} < c_2 \leq 1 \end{cases}. \quad (3)$$

It is worth to mention that, In the SSA, the factor c_1 is a balancing factor between exploration and exploitation that varies in each iteration. However, in the ESSA, a random number generated using a normal distribution with mean parameter μ and standard deviation parameter σ. After several tests, μ and σ are selected as 0.4 and 0.1, respectively. These two parameters can be modified or tuned in order to solve or optimize more devices.

Another modification incorporated on the ESSA compared with the SSA is that the positions of salps before their update is saved and compared to the positions after the update step. A salp moves to a new position only if this one is better than its old position.

IV. APPLICATION

Both SSA and ESSA are applied to the widely used Loney's solenoid and TEAM Workshop Problem 22 design problems. The following two subsections present the tested design problems and analyze the obtained results.

A. Loney's solenoid problem

One of the well renowned benchmarks in the optimal design of EMDs is Loney's solenoid. It is characterized by its geometry [15], having a relatively small number of degrees of freedom. Figure 2 shows the solenoid's axial cross section which consists of three coils; one acts as the main coil and the remaining two coils act as the correcting coils. The inner and outer radii of the main coil are represented by r_1 and r_2, having a length of h. Both correcting coils are of same dimensions, whereby r_3 and r_4 represent the inner and outer radii, each having the length L. Both correcting coils are separated by a distance S, symmetric about the z-axis.

The length L and the position S of the two correcting coils must be determined to generate a uniform magnetic flux density **B** in a certain interval along the main solenoid axis [16]. The determination of [16] (Coelho and Alotto, 2009) (Coelho and Alotto, 2009) both length and position can be treated as a design problem.

Mathematically, the problem can be stated as follows:

$$\min OF(S, L), \tag{4}$$

where the objective function F is given by:

$$OF = \frac{(B_{max} - B_{min})}{B_0}, \tag{5}$$

where: B_{min} and B_{max} denote the minimum and maximum inductions, respectively, inside the interval $(-z_0, z_0)$. At $z = 0$, the flux density is represented by B_0.

The developed ESSA is applied to Loney's benchmark and the outcome is compared to the initial version of SSA and other well-known optimization algorithms like: Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Artificial Bee Colony (ABC), Differential Evolution (DE), and Biogeography-Based Optimization (BBO). Since all the tested algorithms are stochastic by nature due to the use of random numbers, all algorithms have been tested 30 times (to allow a fair statistical analysis) while evaluating objective function up to 2000 times in every run. The population size for all algorithms is 50.

Table 1 tabulates all the obtained results using different algorithms. In this table the statistical values of the objective function are displayed that include best, worst, mean and standard deviation (SD).

It can be noticed from this table that, while the SSA obtained the worst results in all statistical parameters across 30 runs, the ESSA obtained the best results in every sense demonstrating the tremendous enhancement incorporated on the initial version of the SSA.

It can also be noticed that both PSO and DE have achieved correct results since they are ranked second and third, respectively, when comparing the best values while ABC is second best when comparing mean values.

The best design obtained by the ESSA is specified by S = 12.6935 cm and L = 2.4328 cm with $OF(S, L) = 2.4536 \times 10^{-8}$.

Figure 3 shows the plot of objective function versus iterations for this case.

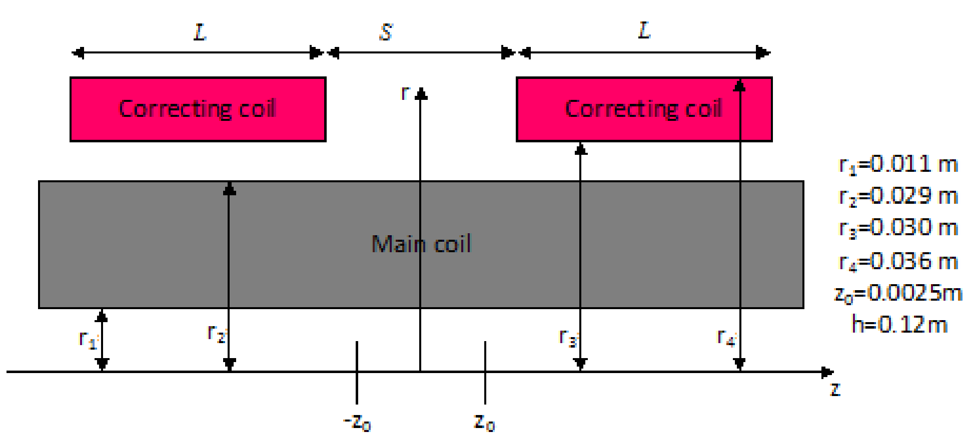


Fig. 2. Cross-section of Loney's solenoid.

Table 1: Simulation results of $OF \times 10^8$ for evaluating up to 2000 objective function evaluations in 30 runs

Algorithm	Best	Worst	Mean	SD
ESSA	2.4536	3.9663	3.7456	0.2651
PSO	2.6897	32.6602	4.7527	5.2770
DE	2.9335	26.3693	5.3043	5.7152
ABC	3.3661	5.3839	3.9539	0.4257
GA	3.4698	10.8799	4.5536	1.3575
BBO	3.8280	87.6055	9.6934	14.9701
SSA	5.3586	239.21	44.551	57.885

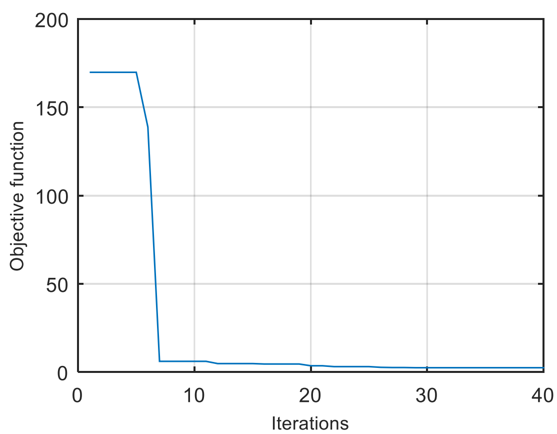


Fig. 3. Objective function $OF \times 10^8$ vs iterations for 2000 maximum objective function evaluations in the best run.

B. TEAM22 Benchmark

The TEAM Workshop Problem 22 or TEAM22 concerns the optimal design of a superconducting magnetic energy storage (SMES) device (Fig. 4). This problem consists of determining the optimal configuration of the SMES device that can store a certain amount of energy. At the same time the value of the stray field, is reduced as maximum with respect to a reference value [9]. This problem has eight design variables and its objective function is given by:

$$\mathrm{OF} = \frac{\mathrm{B}^2_{stray}}{\mathrm{B}^2_{norm}} + 100\frac{|E - E_{ref}|}{E_{ref}}, \quad (6)$$

where: E_{ref} =180MJ is the reference value of the desired energy, B_{norm} is the reference value of the stray field and it is equal to 200μT, B_{max} represent the maximum values of the magnetic induction, whereas the stray field B_{stray} (evaluated along a line a and line b on 22 equidistant points b sketched in
Fig. 4) is defined as:

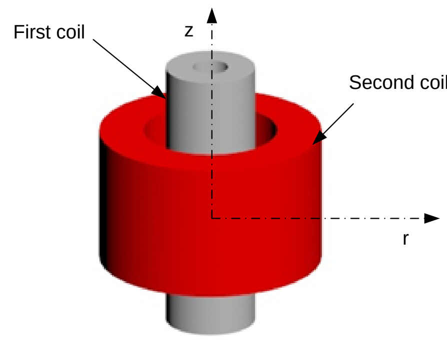
$$\mathrm{B}^2_{stray} = \frac{\sum_{i=1}^{22} |B_{stray,i}|^2}{22}. \quad (7)$$

The constraints imposed on the problem are:

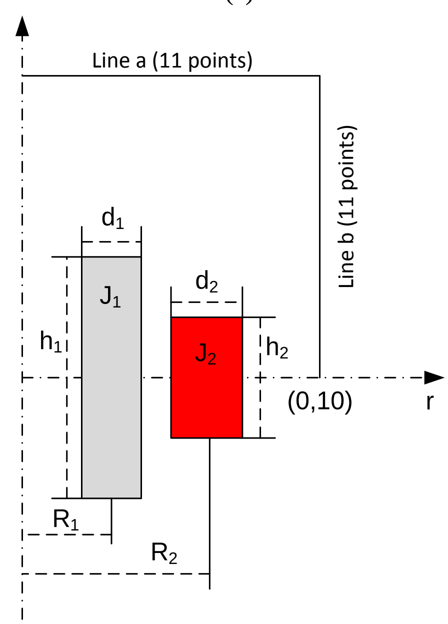
$$R_1 + \frac{d_1}{2} < R_2 - \frac{d_2}{2}, \quad (8)$$

$$|\mathbf{J}| = (-6.4|\mathrm{B}_{max}| + 54)\ A/\mathrm{mm}^2, \quad (9)$$

where: $\mathbf{J}$ is the current density.



(a)



(b)

Fig. 4. TEAM22 configuration: (a) 3D representation of the SMES device, and (b) representation of the right-half transverse cut over the SMES device.

The developed ESSA has been applied to TEAM Workshop Problem 22 and the results are compared with the initial version SSA and other well-known optimization algorithms over 10 runs with 5000 maximum objective function evaluations in each run. The population size for all algorithms is kept 50.

The results obtained using the tested algorithms for the second benchmark are tabulated in Table 2. It must be noted from this table that the proposed ESSA is ranked at the top while the initial version of SSA is ranked fourth when the comparison criterion is the best value obtained. Using the same criterion BBO and DE stand second and third, respectively. If the mean value is the ranking criterion, ESSA is ranked first while SSA is ranked 6 out of 7 algorithms or the penultimate one. Using the same criterion GA and BBO are ranked second and third, respectively. These results show one more time the improvement of the proposed ESSA compared to the initial SSA. They also show the superiority of the proposed algorithm compared with many other optimization algorithms.

The best design obtained by the ESSA is specified by R1 = 1.4809 m, R_2 = 2.4793 m, h_{12} = 1.2726 m, h_{22} = 1.2839 m, d_1 = 0.4845 m, d_2 = 0.1000 m, J_1 = 17.195 MA/m^2 and J_2 = -16.824 MA/m^2 with OF=0.5413.

Furthermore, the evolution of the objective function versus iterations for the second case is depicted in Fig. 5.

Table 2: Simulation results of OF for evaluating up to 5000 objective function evaluations in 10 runs

Algorithm	Best	Worst	Mean	SD
ESSA	0.5413	0.9057	0.7790	0.0971
BBO	0.6028	0.9656	0.8316	0.1303
DE	0.6396	0.9964	0.8593	0.1162
SSA	0.7146	1.0209	0.9489	0.1021
PSO	0.7197	1.0379	0.8994	0.1093
ABC	0.7279	1.4869	1.0388	0.2522
GA	0.7425	0.9037	0.8244	0.0498

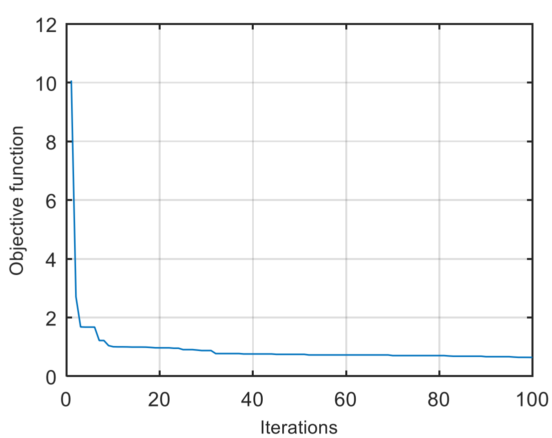


Fig. 5. Objective function OF vs iterations for 5000 maximum objective function evaluations in the best run.

V. CONCLUSIONS

In this paper, an enhanced version of the Salp Swarm Algorithm is developed and implemented for the design optimization of electromagnetic devices. The developed algorithm has better performance than the initial version. Furthermore, the ESSA has outperformed many other well-known optimization algorithms on the selected benchmark problem as it has been modified and adapted to the design of EMDs.

Future work can focus on developing a multi-objective salp swarm algorithm to be applied to more EMDs.

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