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Modified blind naked mole-rat algorithm applied to electromagnetic design problems

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Abstract: In this paper, we proposed a modified meta-heuristic algorithm based on the blind naked mole-rat (BNMR) algorithm to solve the multiple standard benchmark problems. We then apply the proposed algorithm to solve an engineering inverse problem in the electromagnetic field to validate the results. The main objective is to modify the BNMR algorithm by employing two different types of distribution processes to improve the search strategy. Furthermore, we proposed an improvement scheme for the objective function and we have changed some parameters in the implementation of the BNMR algorithm. The performance of the BNMR algorithm was improved by introducing several new parameters to find the better target resources in the implementation of a modified BNMR algorithm. The results demonstrate that the changed candidate solutions fall into the neighborhood of the real solution. The results show the superiority of the propose method over other methods in solving various mathematical and electromagnetic problems.

Key words: electromagnetic design problems, global optimization, meta-heuristic algorithm

1. Introduction

The meta-heuristic algorithms are fitting apparatuses for tackling complex engineering problems. Due to their applications in the field of engineering, numerous researches have been conducted to develop meta-heuristic algorithms. Meta-heuristic algorithms have a fast convergence rate and have been utilized to overcome the disadvantages of traditional techniques in the comprehensive pursuit of the best arrangement in an issue space for the dominant part of subjects. Having the option to escape effectively from local optima and dodge untimely intermingling by utilizing a heuristic system, they can accomplish ideal arrangements in a short time. Meta-heuristic algorithms are especially useful when managing enormous scope and obliged issues, and are considered as a compelling answer for an assortment of enhancement issues.

Recently, various researches studied meta-heuristic and haphazardly techniques in the electromagnetic field on the grounds that deterministic strategies neglect to locate the global optimal. Note that deterministic algorithms were well known before. In clear strategies, problems and vulnerabilities in the plan of an engineering issue are regularly unavoidable. Consequently, research has been led to create meta-heuristic strategies and to advance the speed of convergence rate by utilizing various parameters and administrators. Due to the type of issues in the field of electromagnetism, there is no global enhancer that can tackle all the problems. Hence, it is important to investigate and build up other global enhancements for electromagnetic design problems.

Optimization of Loney's solenoid benchmark is a complicated issue in electromagnetic in which meta-heuristic algorithms can be all around applied [1]. The modeling difficulties incorporate the suspicions utilized in the electromagnetic frameworks and their advancement by boosting or limiting the planned boundary. In this manner, the capacity to optimize the Loney's solenoid benchmark expands the demonstrating exactness of designing gadgets in the electromagnetic field.

Alotto and Coelho [2] utilized an optimization algorithm, Nelder-Mead simplex technique, with focusing on local search. The researchers focused on opt-aiNet and opt-aiNet-NM draws near, and tackled the electromagnetic optimization benchmark issue. As of lately, the gravitation search algorithm (GSA) is presented as a novel optimization method [3]. The GSA has a few impediments, for instance, the reliance of the fitness function on the mass of the active ingredients. To tackle this problem, the authors presented an adjusted procedure. The modified algorithm was contrasted with different strategies in solving of the electromagnetic backwards issue.

Duca *et al*. [4] introduced an altered ant colony optimization algorithm dependent on the abilities of ant-like factors. In another research, a new methodology focused on accomplishing a superior compromise among misuse and investigation periods of the inquiry is characterized. Despite the fact that GABC optimization technique provided good outcomes, the execution of the GABC advancement algorithm is complicated [5].

The quantum particle swarm optimization (QPSO) algorithm [6] is a meta-heuristic algorithm that is developed based on the original PSO algorithm and quantum hypothesis idea. Duca *et al*. [6] presented another mutation methodology and added to the principle best arrangement. The QPSO algorithm accomplished exact outcomes. Nonetheless, further examination indicated that the algorithm experiences a few drawbacks, for example, the probability of getting caught in a local optimum [6].

Using the PSO algorithm, Griuprina *et al*. [8] utilized a methodology with key parameters contrasted with the past techniques and revealed reasonable outcomes. Santos Coelho [7] utilized this mutation procedure and acquainted another heading factor to improve the global search instrument [7]. In this strategy, distinctive neighboring techniques, for example, random mean and the Gaussian attractor are utilized. Utilizing the GQPSO algorithm [7], the authors accomplished an arrangement contrasted with the other PSO-based algorithms. However, one of the downsides of the QPSO technique is the untimely combination. To upgrade the global search to locate a global ideal arrangement and forestall untimely convergence in the QPSO technique, Rehman *et al*. [9] proposed a mutation methodology for the mean best position and advancement of powerful factors. The creators demonstrated that the MQPSO strategy beats the QPSO algorithm. In the MQPSO method, Rehman *et al*. acquainted a few parameters with update of the recently presented mutation procedure. The goal was to find some kind of harmony in the compromise among investigation and abuse phases of the search process [9].

We consider the optimization of Loney's solenoid benchmark in the modified blind, naked mole-rat algorithm that we call the MBNMR algorithm. We modify the BNMR algorithm by employing two different types of distribution processes to improve the search strategy. Also, we added an improvement scheme for the objective function and we have changed some parameters in the implementation of the BNMR algorithm. The performance of the BNMR algorithm was improved by introducing several new parameters to find the better target resources in the implementation of the Modified BNMR algorithm. With these changed the candidate solutions will fall into the neighborhood of the real solution. The outcomes acquired were prevalent in examination with those of different techniques. The MBNMR algorithm was effectively utilized in the plan of an electromagnetic device, as upheld by the test results. The proposed strategy extensively diminishes the deviation in the ideal solutions.

2. Modified blind naked mole-rat algorithm

The blind naked mole-rat (BNMR) algorithm is a bio-inspired meta-heuristic algorithm that is built based on the social behavior of blind naked mole-rats in large colonies. In the BNMR algorithm [10–12], the search process starts from the center of the colony, where the queen and the offspring reside. In the modified version of the BNMR algorithm, the search process by the worker and the soldier moles are handled separately.

At the beginning, the initial population of the blind naked mole-rat colony is produced and starts the random search of the entire problem space. The size of the initial population is twice the number of food sources. Note that each food source is considered as a potential solution in the problem space.

In the modified version, in order to produce a candidate food position in the memory of each mole-rat, the following was defined:

$$\begin{gathered} x_i = x_i^{\text{Minimum}} + \beta \left(x_i^{\text{Maximum}} - x_i^{\text{Minimum}} \right) \\ i = 1, \ldots, S \end{gathered}, \tag{1}$$

where: x_i is the i-th food source, β is the random variable within the [0, 1] interval, and S is the total number of food sources. The function $(F(x_i))$ can be defined as follows:

$$\begin{gathered} F(x_i), \quad x_i \in R^D \\ i = 1, \ldots, S \end{gathered}, \tag{2}$$

where x_i is the D-dimensional vector. Therefore, the food sources, i.e. solutions, are the targets of the search process and must be found by the worker moles. This includes finding the location of the food sources and their neighbors, determining its richness, evacuating the food source, and storing it in the pantry. Thus, the random movement of worker moles from the center of the colony towards the food sources and their neighbors begins. At the same time, the worker moles are responsible for digging the tunnels while searching for the food sources. In every iteration, each worker mole tries to update its practicable food source location, i.e. a solution using a local search process.

The update process is used to simplify the process of finding the food source in a neighborhood and determine the unexplored regions as some regions might be overlooked due to the randomness of the search process within the problem space. The update process significantly increases the convergence speed of the algorithm. The following equations are used to update the regions and search for food sources in a neighborhood.

$$N_i = \begin{cases} x_i + \mu\,[x_i - x_k] & \text{if } \ Q < 0.5 \\ x_i & \text{Otherwise} \end{cases}, \qquad (3)$$
$$i = \{1, 2, \ldots, k, \ldots, S\} \quad i \neq k$$

where μ is the random integer in [–1, 1]. Herein, S is the number of food sources, and Q is the integer in [0, 1], which reflects the neighborhood's distance from the food sources. Q is usually between 0.5 to 1. Note that i and k are slightly different. The difference is problem-dependent and might change according to the optimization problem.

Once the food sources are found by the worker moles, their locations and access routes are shared with the other members of the colony and the queen. The queen then sorts the obtained food sources in a table by their fitness value in descending order. The fitness value of a food source is determined by both its original quality and the shortest path from the center of the colony to its location. Furthermore, the queen selects the food sources based on the probability P, which is computed using the following equation:

$$P_i = \frac{Fitness_i = FS_i \times R_i}{\sum\limits_{j=1}^{N} Fitness_j}. \qquad (4)$$

The *Fitness* is evaluated by the soldier moles. FS_i reflects the richness of the food source and, R_i is related to the shortest path to the food source. N is the total number of food sources. From Eq. (4), we can find better solutions. For more accuracy, we have to consider the velocity and position of agents in the D-dimensional problem space. In order to reach this target, we have controlled these two parameters by the following equations:

$$\begin{aligned} X_i^D(t+1) &= X_i^D + v_i^D(t+1), \\ V_i^D(t+1) &= R_i \cdot v_i^D(t) + q_i^D(t) \cdot \left(1 - \frac{t}{I}\right)^q, \\ i &= 1, \ldots, N, \end{aligned} \qquad (5)$$

where X is the position and V is the velocity of a mole. q is the constant and the best value of it is 0.07, D is the dimension of the problem space, and R_i is the random variable in [0, 1] with uniform distribution. I is the constant, and t indicates the iteration in each step of the process.

The first food source representing the highest probability, is selected by the queen. Thereafter, two worker moles carrying the information of the food source are selected to perform the recruitment process and move toward the food source. Once they reach the food source, one of these two workers randomly select some of the soldiers to collect the food. The other worker selects and leads another group of soldiers to search the neighborhood for more food sources. Collecting the food from the sources and searching the neighboring regions for new food sources at the same time would significantly reduce the required time for reaching an optimal solution, which consequently increases the convergence rate. This process would be repeated for all food sources and their neighborhoods until there is no food source left, i.e. the optimal solution is found.

The next part of the algorithm is concerned with defending the colony and stopping the invaders that are trying to enter the tunnels. In the proposed algorithm, in each iteration, the points with low fitness values are considered as invaders and are eliminated from the optimization process. In other words, they are no longer considered as members of the population involved in the optimization process. The number of eliminated points in each iteration is a factor of its counterpart in the previous iteration, and is determined by the following equation:

$$B_i^t = \zeta \times B_i^{t-1}, \tag{6}$$

where ζ is equal or larger than 1 and is the problem-dependent constant determined by the designer. B_i^t is the number of eliminated points for the i-th food source in iteration t. In each iteration, the eliminated points are replaced with new points that are randomly selected in the entire problem space.

Using this idea, we can inject mutation processes into the proposed algorithm. Therefore, the new members with their new information prevent the algorithm from being trapped in a local minimum.

We employed two types of population distribution to cover the entire problem space; a uniform distribution and a beta distribution which uses a fraction of the initial population. Thus, the entire problem space is searched and the chance of being trapped in a local maximum is reduced. Even in the case that the algorithm is trapped in a local maximum, the new members of the colony without prior knowledge about the problem space might change the course of optimization from diverging to a local maximum, or the search path might change at the regions of the beta distribution.

Furthermore, we developed the proposed algorithm in case of maximization problems, the best and worst solutions are given as follows:

$$\begin{aligned} X_{\text{best}} &= \text{Maximum}_j \left\{ Fitness_j(t) \right\} \\ X_{\text{worst}} &= \text{Minimum}_j \left\{ Fitness_j(t) \right\}, \\ j &= 1, \dots, N \end{aligned} \tag{7}$$

while in minimization problems, the best and worst solutions are given by Equation (8):

$$\begin{aligned} X_{\text{best}} &= \text{Minimum}_j \left\{ Fitness_j(t) \right\} \\ X_{\text{worst}} &= \text{Maximum}_j \left\{ Fitness_j(t) \right\}. \\ j &= 1, \dots, N \end{aligned} \tag{8}$$

3. Numerical validation

3.1. Mathematical test

In order to measure the potential and reliability of the MBNMR algorithm and assess the performance against other algorithms, solving different standard benchmark issues is the best methodology. Accordingly, to investigate the abilities of the MBNMR algorithm and compare it with the other optimization algorithms, the best option is to use the algorithms to solve benchmark functions with various degrees of complexity [16].

In order to evaluated the performance of the algorithm, the dimensionality of the benchmark functions should be suitably high, and various characteristics such as modality, separability, and differentiability must be considered. For example, modality characteristic refers to the number of ambiguous extremes of the functions, which has a negative impact on the search process of the meta-heuristic algorithms, and the modality of separability refers to the complexity of the benchmark functions. These characteristics are intensified as the dimensionality of the benchmark functions increases. Selecting and solving a set of benchmark functions is an appropriate approach to evaluate the performance of meta-heuristic algorithms.

We present the accompanying benchmark functions because of their intricacy to accomplish ideal focuses. The four standard benchmark functions are exhibited in Table 1 [13], and the control parameters of the apparent multitude of all the algorithms are summarized as follows:

GABC; the population size equals 100, the number of sites selected for neighborhood search equals 15, the number of bees recruited for best sites equals 10, $\rho = 0.3$, the number of iterations equals 2 000;

QPSO; the population size equals 100, $\alpha = 1.0$, $\phi_1 = 1.0$, $\phi_2 = 1.5$, $\omega_{\min} = 0.7$, $\omega_{\max} = 0.97$, the number of iterations equals 2 000;

GQPSO; the population size equals 100, $\alpha = 1.0$, $\phi_1 = 0.9$, $\phi_2 = 1.6$, $\omega_{\min} = 0.7$, $\omega_{\max} = 0.97$, the number of iterations equals 2 000;

MQPSO; the population size equals 100, $\alpha = 0.5$, $\beta = 0.5$, $\phi = 0.9$, $\omega_{\min} = 0.56$, $\omega_{\max} = 0.98$, the number of iterations equals 2 000;

ACOR; the population size equals 100, $\xi = 0.86$, $q = 1E - 4$, $\omega = 0.5$, the number of iterations equals 2 000;

IGSA; the population size equals 100, $\alpha = 0.5$, $\beta = 0.5$, the number of iterations equals 2 000,

MBNMR; the population size equals 100, $Q = 0.5$ and 0.9, $\alpha = 0.5$, $\beta = 0.5$, $\gamma = 0.5$, the number of iterations equals 2 000.

In experimental studies, each algorithm was run 30 times, i.e. 30 independent runs, to make sure the final solutions are reliable. A population size of 100 was considered with a dimension of 50. The number of iterations to reach the stop criterion was set to 2 000. It must be noted that the minimum value is zero for all objective functions. Table 1 presents the final results of the algorithms in terms of mean and variance after 30 runs of each algorithm. Figure 1 compares the convergence rate of the employed algorithms for each function. The initial population size was set to 30, 50, 80, and 100. The optimal solutions were obtained in a short period by testing and repeating the algorithm independently. Therefore, a population of 100 was used for all algorithms.

As evident from Table 2, the MBNMR algorithm offers better performance than the other methods listed in the table with the standard benchmark functions $f_1(x)$, $f_2(x)$, $f_3(x)$, and $f_4(x)$.

Table 1. The list of four standard benchmark functions

Formulation	**Global optimum**
$f_1(x) = -a \exp\left(-b\sqrt{\frac{1}{n}\sum_{m=1}^{n} x_m^2}\right) - \exp\left(\frac{1}{n}\sum_{m=1}^{n}\cos(c \cdot x_m)\right) + a + f_{\mathrm{bias}},$ $x \in [-32,\ 32]^n, \quad a = 20, \quad b = 0.2, \quad c = 2\pi, \quad f_{\mathrm{bias}} = 1,$	0
$f_2(x) = \sum_{m=1}^{n}\left(100 \cdot \left(S_{m+1} - S_m^2\right)^2 + (S_m - 1)^2\right) + f_{\mathrm{bias}},$ $S = x - o + 1, \quad f_{\mathrm{bias}} = -390, \quad x \in [-100,\ 100]^n,$	0
$f_3(x) = \frac{1}{4000}\sum_{m=1}^{n} S_m^2 - \prod_{m=1}^{n}\cos\left(\frac{S_m}{\sqrt{m}}\right) + 1 + f_{\mathrm{bias}},$ $S = x - o, \quad f_{\mathrm{bias}} = 450, \quad x \in [-100,\ 100]^n,$	0
$f_4(x) = \sum_{m=1}^{n}\left(\prod_{j=1}^{m} s_j\right)^2 + f_{\mathrm{bias}},$ $S = x - o, \quad f_{\mathrm{bias}} = -450, \quad x \in [-100,\ 100]^n.$	0

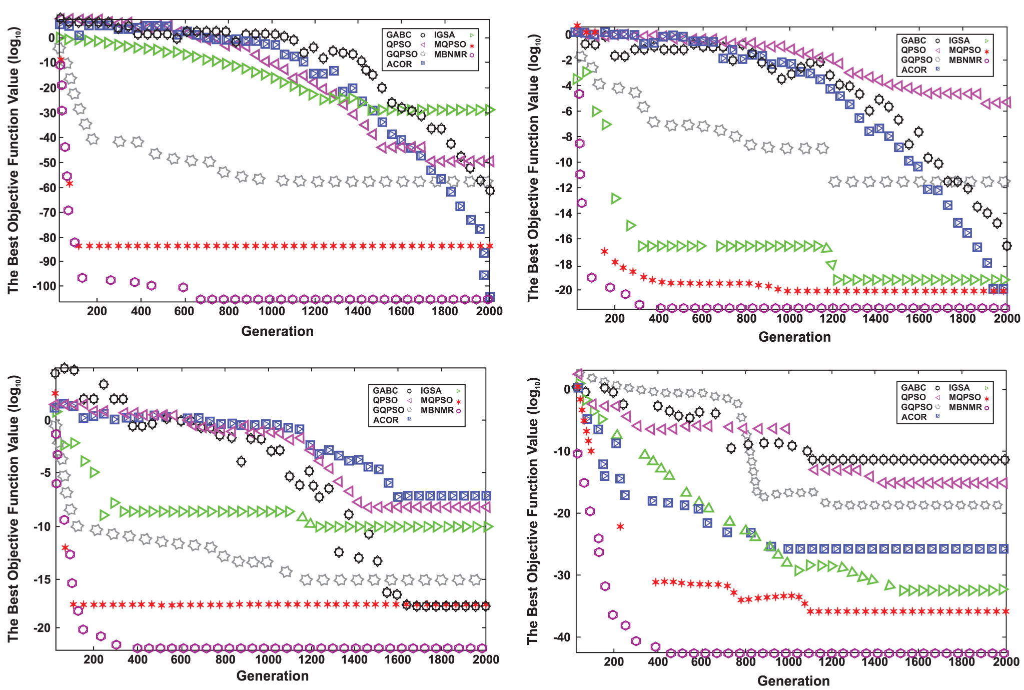

Fig. 1. Convergence rate comparison of different optimal algorithms for solving $f_1(x)$, $f_2(x)$, $f_3(x)$, and $f_4(x)$ functions

The MBNMR algorithm provides a reliable convergence rate to reach the optimum solution. According to Figure 1, the MBNMR algorithm shows a better performance compared to the other methods in terms of convergence rate to the best optimal solution.

Table 2. Mean and variance of different methods for 50 dimensional problems

Methods		$f_1(x)$	$f_2(x)$	$f_3(x)$	$f_4(x)$
GABC	Mean	3.77E – 15	4.77E + 3	1.79E + 2	1.35E – 1
	Variance	1.87E – 21	2.38E + 2	6.04E +1	1.99E – 2
QPSO	Mean	3.84E – 15	1.22E + 4	2.11E + 1	3.27E – 1
	Variance	2.67E – 21	0.77E + 2	7.55E – 1	2.78E – 2
GQPSO	Mean	9.32E – 14	6.34E + 1	5.17E – 1	5.66E – 4
	Variance	1.66E – 22	2.18E – 1	4.36E – 2	9.02E – 5
MQPSO	Mean	2.18E – 19	2.44E – 4	7.28E – 5	8.22E – 7
	Variance	5.72E – 31	7.16E – 6	1.22E – 6	4.67E – 10
ACOR	Mean	3.67E – 19	1.88E – 1	4.22E – 1	4.62E – 6
	Variance	2.16E – 23	5.62E – 2	3.66E – 2	2.88E – 8
IGSA	Mean	2.14E – 19	9.03E – 4	7.26E – 3	1.18E – 6
	Variance	0.55E – 25	3.06E – 5	0.79E – 4	2.94E – 9
MBNMR	Mean	1.89E – 22	2.77E – 6	6.44E – 8	3.08E – 11
	Variance	1.35E – 35	3.66E – 9	2.34E – 9	1.09E – 16

Using the considered benchmark functions, the proposed method was compared to the other methods, namely the modified quantum particle swarm optimization (MQPSO) [9], Gaussian-quantum particle swarm optimization (GQPSO) [7], quantum particle swarm optimization (QPSO), Gaussian artificial bee colony (GABC) algorithm [8], improved gravitational search algorithm (IGSA) [3], and ACOR [4] algorithms.

A population size of 100 and dimension 50 was used, and the stop criterion was set to 2 000 iterations in each algorithm. To confirm the final solutions, each algorithm was run 5 times for each selected function, and the result was approved once significant inconsistencies were observed.

We compared the outcomes of the MBNMR algorithm to the other employed algorithms by using the number of objective function calls. The comparison results are presented in Table 5.

3.2. Numerical application

We employed the MBNMR algorithm to solve the engineering inverse problems in electromagnetism in order to validate its results.

3.3. Loney's solenoid benchmark problem

Specifying the location and volume of two correcting coils is important in Loney's solenoid design. The coils create magnetic flux with uniform distribution in the solenoid. Figure 2 shows the top half-plane of the axial cross-section of Loney's solenoid [2, 5, 8, 9, 14, 15].

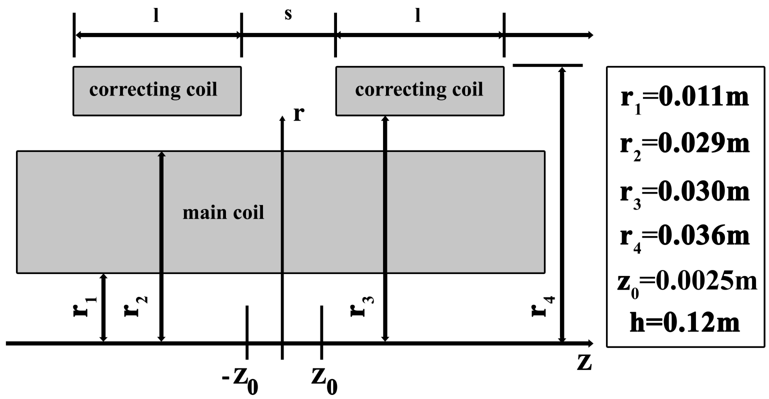

Fig. 2. Axial cross section of Loney's solenoid

In this study, the objective is to determine the distance between the two coils and their lengths with other parameters known. The magnetic flux density (B) must remain uniform in $[-z_0,\ z_0]$.

The two coils (s) and their lengths (l) are bounded to [0, 0.2] and are determined in all other dimensions (the location s and length l of the two correcting coils are unknown) [14].

The field can be calculated along the axis by analytical integration or finite-element methods. However, for comparison, each coil was presented in coaxial current sheets similar to other studies. Accordingly, the original problem can be solved through the following minimization problem:

$$\min F(s, l), \tag{9}$$

where F is the objective function and is defined as follows:

$$F = \frac{B_{\text{Maximum}} - B_{\text{Minimum}}}{B_0}. \tag{10}$$

There B_{Maximum} and B_{Minimum} denote the maximum and minimum values of magnetic flux densities and fall in a range of $[-z_0, z_0]$, and B_0 is the flux density at the center of the solenoid ($z = 0$). The function F is a non-analytic, ill-conditioned, function with a gorge behavior [12], because of B_{Maximum}, B_{Minimum}, B_0, and the positions of B_{Maximum} and B_{Minimum} belong in the $[-z_0,\ z_0]$ range and are functions of s and l.

The objective function is highly noisy, as the field is calculated by representing coils as four sheets (each coil is divided into four current sheets in the radial direction [12]), B_{Maximum} and B_{Minimum} are evaluated at ten points at regular intervals in $[-z_0, 0]$.

The local minima are determined in three areas in the domain of F, namely $F > 4 \times 10^{-8}$ (high-level area, HL), $3 \times 10^{-8} < F < 4 \times 10^{-8}$ (low-level area, LL), and $F < 3 \times 10^{-8}$ (very-low level area, VL). The very-low level region is an oval area in the thin low-level valley. In VL and LL regions, any minute variation in parameters can lead to variations several times the magnitude of the objective function.

It is noted that the tuning process is time-consuming if a meta-heuristic algorithm has a large number of parameters, and especially when these parameters are optimized one by one regardless of their interactions. In general, the effectiveness of a meta-heuristic algorithm heavily depends on parameters and interactions among them. Therefore, we conducted parameter tuning for finding the optimal values before running the proposed algorithm. For the problems in this study the selected parameter values of the MBNMR algorithm are not necessarily needed to be optimal as the parameter tuning is performed by a self-adaptive approach. The self-adaptive approach demonstrates the highest degree of reliance on our MBNMR algorithm itself in sitting the parameters. Therefore, it is concluded that the self-adaptive approach is the optimal approach for tuning parameters of the proposed algorithm. Herein, Q, α, β, and γ are used as the initial values at the beginning of the tuning process and updated dynamically.

4. Discussion

This study analyzes the performance of the proposed algorithm with several algorithms in the electromagnetic field for the inverse issue. The explanation behind choosing these algorithms are quickly referenced beneath.

The GABC algorithm has a superior performance compared with SOMA, TRIBES based on the PSO algorithm [5]. The QPSO algorithm has a superior performance compared with BPSO, IPSO, GPSO, and MPSO algorithms [7]. The MQPSO algorithm has indicated good outcomes compared to the LIQPSO, QPSO, GQPSO, PSO, DE2, ARDGDE2, and QPSO algorithms [9]. The IGSA algorithm has been compared against the GABC, TRIBES (PSO), QPSO, IPSO, ACOR, and SGSA algorithms and has gained incredible results [2].

The MBNMR algorithm is compared with different optimization algorithms such as, GABC, NSGA-II, QPSO, GQPSO, MQPSO, ACOR, and IGSA that have previously been applied to global optimization and the electromagnetic design problems. A population size of 100 and measurement of 50 was utilized. The stopping criteria was set to 2 000 iterations in every algorithm. To confirm the final solution, every algorithm was run five times for each chosen function and the outcomes were endorsed once, no huge irregularities were watched.

The convergence rate performance of MBNMR, GABC, QPSO, GQPSO, MQPSO, ACOR, and IGSA algorithms, as far as the mean best values of objective function assessment numbers, is shown in Figure 1. The outcomes show the better convergence performance of the MBNMR algorithm for every one of the four functions. The convergence speed of the MBNMR algorithm is sturdier when compared with different algorithms. The GABC algorithm has the lowest convergence rate when compared with the other applied strategies. The QPSO, GQPSO, ACOR, and IGSA algorithms are not reliable for the comprehending four standard benchmark functions and experience issues arriving at the local optimal focuses.

Every convergence chart is separated into four sections, based on the assessment axis, so as to additionally assess the advancement characteristics of the algorithms. For the first section, the convergence rate and enhancement for the mean best value for the each of the four benchmark functions are altogether better for the MBNMR algorithm. For the second, third, and fourth sections, mean best value of the objective function diminishes gradually comparing with first section.

As indicated by Figure 1, the acquired outcomes by the MBNMR algorithm are more reliable. The convergence rate is higher than the number of iterations in the MBNMR algorithm and it is a productive algorithm regarding less multifaceted complexity, a better convergence rate and arriving at the optimal point in a less ideal opportunity to illuminate standard benchmark functions than the MQPSO algorithm. The execution of the MQPSO is more intricate that the MBNMR algorithm, which makes the MQPSO algorithm less ideal for different applications with respect to complex engineering issues, more parameters should be characterized. The outcomes indicate that the MBNMR algorithm outperforms the wide range of various algorithms of all benchmark functions and give better performance. The GABC, QPSO, GQPSO, MQPSO, ACOR, and IGSA techniques need at any rate three or five times more function assessments than the proposed algorithm to arrive at nearly the comparable mean best qualities.

According to Table 2, the MBNMR algorithm has fewer mean and variance values than those from the GABC, QPSO, GQPSO, ACOR, and IGSA algorithms. The proposed algorithm has arrived at a satisfactory average and a superior variance compared to the MQPSO algorithm, indicating the quality of the MBNMR algorithm.

Table 3 shows the best optimal response to the Loney's solenoid problem in 30 separate implementations for every algorithm. The outcomes show the MBNMR algorithm has the best performance comparing to the other techniques.

Table 3. Best optimal solution for Loney's solenoid in 30 runs

Method	**Separation *s* (cm)**	**Length *l* (cm)**	**$F(s,l) \times 10^{-10}$**
GABC	14.35627	7.66728	0.8837
QPSO	14.88454	9.00373	0.4468
GQPSO	12.99673	9.76255	0.8842
MQPSO	12.00256	4.67726	0.3247
ACOR	14.11183	8.56278	0.9904
IGSA	11.05688	3.99772	0.1467
MBNMR	9.167277	3.02265	0.1007

The evolutionary algorithms are usually employed to minimize the objective functions during the search for the optimal solution. The optimization process becomes more complex by increasing the dimension of the problem. This is especially true for the optimization technique with a large number of input parameters. The MBNMR algorithm has less parameter than the other algorithms in this study.

Table 4 presents the maximum, the mean, and the minimum (best) values of $F(s,l) \times 10^{-8}$ for the all algorithms. The outcomes show that the MBNMR algorithm has the best performance when compared to the other techniques. The MBNMR algorithm accomplished the best standard deviation with the lowest number of iterations and the minimum number of objective function calls shown in Table 5 in comparison to all benchmark problems, as the algorithm has less unpredictability then the other utilized techniques.

Table 4. Comparing the maximum, mean, and minimum values of $F(s,l) \times 10^{-8}$, standard deviation, number of iterations and CPU time of all the employed optimization methods

Method	maximum (worst)	mean	minimum (best)	Standard Deviation	Number of iterations	CPU Time in seconds
GABC	4.26786	3.55748	2.67535	0.08667	1867	5.673
QPSO	3.98534	3.42773	2.60044	0.02574	1642	5.832
GQPSO	3.67525	3.22557	2.45627	0.06643	1702	4.672
MQPSO	1.58662	1.24566	0.90672	0.00198	1297	3.349
ACOR	1.78638	1.43779	1.25663	0.04552	1378	8.877
IGSA	1.96525	1.52837	1.10067	0.03743	1637	9.455
MBNMR	1.13388	0.89443	0.62765	0.00011	998	0.658

Table 5. Comparing the number of objective function calls of all the employed optimization methods with two dimensions ($D = 30, 50$)

Method		$f_1(x)$	$f_2(x)$	$f_3(x)$	$f_4(x)$
GABC	$D = 30$	247108	193672	207405	189637
	$D = 50$	388290	344728	329993	302891
QPSO	$D = 30$	217004	189722	211008	181002
	$D = 50$	349777	307839	344882	289017
GQPSO	$D = 30$	215884	179728	199564	159627
	$D = 50$	364557	298019	277543	245992
MQPSO	$D = 30$	103670	98473	127996	89637
	$D = 50$	214894	170728	192647	146827
ACOR	$D = 30$	178452	166029	182546	164827
	$D = 50$	288023	302763	266537	248628
IGSA	$D = 30$	188435	188792	189360	157526
	$D = 50$	279667	309828	270537	224627
MBNMR	$D = 30$	58910	76928	57910	51892
	$D = 50$	86784	101738	84927	81720

It is noted that parameter tuning is a complex process for all the optimization algorithms, but the MBNMR algorithm has fewer parameters to tuned. So, in the meta-heuristic algorithms a few objective function calls are needed, so that the proposed algorithm was satisfied. This is clearly seen in Table 5.

It is apparent in the structure of Figure 1, and Tables 2 to 4 that the adjustments looking like the objective assets and the kind of distribution that improved the performance of the MBNMR algorithm to accomplish adequate outcomes, are quicker than different techniques.

We aimed to eliminate unnecessary calls to the objective function to decrease the computational costs. The comparison results between the MBNMR algorithm and the other algorithm shown in Table 5, that indicate the superior performance of the proposed algorithm for solving four different benchmark functions, and electromagnetic inverse problems used in numerical experiments.

We conclude that the MBNMR algorithm has the best performance and the best characteristics of the last arrangements in solving mathematical and electromagnetic inverse problems, comparing to the different algorithms introduced in this study.

5. Conclusion

The modified blind, naked mole-rat algorithm is proposed for solving electromagnetic design issues. We focused on numerical optimization issues to confirm the performance and abilities of the MBNMR algorithm. We utilized the MBNMR algorithm to illuminate the progression of standard benchmark functions with different modality, separability, and differentiability properties to assess the nature of global search (in the numerical examination, the maxima and minima of a function), just as the performance at the local limits and local optima. Assessing the reproduction results and measurable examination, the MBNMR algorithm shows the unrivaled presentation with respect to the convergence rate and speed, just as, the capacity to accomplish the best global search process when compared to the other utilized algorithms. The proposed algorithm can possibly reach far higher convergence rates and speeds. In any case, the other algorithms miss the global optimum point.

The MBNM algorithm requires less computation time, which makes the method suitable for multi-objective optimization in industrial design problems. Future works may focus on applying distinctive distribution functions and administrators to improve the search cycle of the algorithm. Moreover, utilizing control parameters to further differentiate the population distribution is a relevant procedure that can be explored.

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