A Wind Driven Optimization Algorithm for Global Optimization of Electromagnetic Devices

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To prevent the premature convergence of existing wind driven optimization algorithms, a wealth of improvements are proposed. Specific measures are; to guarantee the balance between exploration and exploitation searches, the origin point of every parcel is dynamically and randomly selected using a tournament selection mechanism, and the so far searched best solution used to guide the movement of parcels is randomly initialized by introducing a new designed mechanism; to utilize fully the latest information accumulated from the searched history to guide the searches towards potential solutions to enhance convergences, the so far searched worst parcel is used to shift the new parcel away from the parcel in issue. Numerical results on two case studies are reported in order to showcase the feasibility and the merit of the proposed method in solving both practical engineering design problems and mathematical test functions.

***Index Terms*—Global optimization, inverse problem, natural-inspired algorithm, wind driven optimization.**

I. A Wind Driven Optimization Algorithm

In the study of design optimizations or inverse problems, a lot of efforts have been devoted to the development of stochastic and heuristic algorithms in the last couple of decades for finding the global optimal solutions of the problems, as both traditional deterministic and stochastic optimal methods have their deficiencies in finding such solutions. In this regard, simulated annealing, genetic, evolutionary, particle swarm optimization as well as ant colony algorithms have all been successfully developed and applied to solve specific types of inverse or optimal problems. So far no universal global optimizer is applicable to all inverse and optimization problems [1]. On the other hand, it is essential to retain and ensure there are diversity in the global optimizers in the study of inverse and optimal problems in computational electromagnetics. In this paper, an improved wind driven optimization algorithm is proposed.

To develop artificial intelligence, including the heuristic optimal algorithms, mother nature is a perfect example of inspiration. The proposed Wind Driven Optimization (WDO) algorithm is inspired from the modeling of the climate [2],[3]. In our living environment, wind blows from the high pressure zone to the low pressure zone at various speeds to equalize the air pressure imbalance. Based on Newton's second law of motion and some simplifications, the velocity vector, v, and the position vector, x, of the WDO algorithm are updated using

$$v(k+1)=(1-\alpha)v(k)-gx(k)+(RT\left|1-\frac{1}{i}\right|(x_{opt}-x(k))) + (\frac{cv^{\text{othr\_dim}}(k)}{i}) \quad (1)$$

$$x(k+1)=x(k)+\Delta t\times v(k+1) \quad (2)$$

where, α is a friction coefficient, g is the gravitational constant, R is the universal gas constant, T is the temperature, c is a constant, i is the ranking among all air parcels, x_{opt} is the best parcel so far searched, Δt is the step length.

Compared to other nature-inspired optimal algorithms, WDO is very simple and easy to implement numerically. However, as a new evolutionary method, WDO may be prone to premature convergences when solving complex global optimization problems [3], due to possible diversity loss of parcels and the corresponding imbalance between exploration and exploitation searches. To address the aforementioned shortcomings and to guarantee proper balance between exploration and exploitation searches, two different approaches are proposed below.

Physically, the second term, $-gx(k)$, in (1) presents the gravitational force, which is in fact an attractive force, that pulls the parcels towards the absolute origin of the coordinate system. Since every parcel is always attracted towards this common point under the influence of this gravitational force, the diversity of the parcels is reduced. To address this problem, the origin point of every parcel is dynamically and randomly selected by using a tournament selection mechanism. In the tournament selection procedures, two feasible solutions are first selected among all parcels of the current population, and the best one will then be used as the origin of the current population, and (1) and (2) are then modified to

$$v(k+1)=(1-\alpha)v(k)-g[x_{orig}(k)-x(k)] + (RT\left|1-\frac{1}{i}\right|(x_{opt}-x(k)))+(\frac{cv^{\text{othr\_dim}}(k)}{i}) \quad (3)$$

$$x(k+1)=w\times x(k)+(1-w)\times\Delta t\times v(k+1) \quad (4)$$

where, $x_{orig}(k)$ is the new origin determined using the proposed tournament selection method, w is a control parameter which decreases linearly from its maximum value to its minimal one in the iterative process of the algorithm.

To further balance the exploration and exploitation searches, x_{opt} in (3) will be randomly initialized if it does not change after a pre-defined number of consecutive search cycles. In other words, a new x_{opt} will be randomly selected from the history of the so far searched best solutions if, after a pre-defined number of consecutive iterations, there are no further improvements on the so far best solution. As given by the last term in (3), inappropriate choice of the intervals might give rise to extremely small or extremely large velocities as the intervals for different dimensions have significant impacts on engineering optimization or inverse problems. In order to ensure the interval size is proper, the intervals for all dimensions are normalized to [0 1] in the proposed algorithm.

To utilize fully the latest information accumulated from the searched history to guide the searches towards potential solutions to enhance the convergence speeds, the so far searched worst parcel is used in the proposed algorithm to shift the parcels away from the parcel in issue. Therefore, after updating position using (4), the d^{th} dimension of parcel j is shifted from the worst particles using

$$x_d^j(k+1) = \begin{cases} x_d^j(k+1) & (if\ |(x_{opt})_d^j - (x_w)_d| \le \varepsilon) \\ x_d^j(k+1) + Ln[x_d^j(k) - (x_w)_d]\ (otherwise) \end{cases} \quad (5)$$

where, $(x_w)_d$ is the d^{th} dimension of the so far searched worst position, Ln is a positive constant called the negative learning rate.

II. Numerical Validation and Conclusion

The proposed WDO method has been validated using different case studies and mathematical test functions. However, due to space limitations, only the numerical results on two case studies are reported to showcase its feasibility and merit in solving optimal and inverse problems.

To compare the performances of the proposed WDO algorithm with existing WDO based optimizers, a mathematical test function as given in [3] is first solved using the proposed algorithm as well as a hybrid combination of WDO and Differential Evolution algorithm (WDO-DE) [3]. The mathematical test function is defined as

$$\begin{aligned} &\min\ f(x) = -\sum_{i=1}^{4} \alpha_i \exp(-\sum_{j=1}^{3} A_{ij}(x_i - P_{ij})^2 \\ &\alpha = (1.01.23.03.2)^T \\ &A = \begin{bmatrix} 3.0 & 10 & 30 \\ 0.1 & 10 & 35 \\ 3.0 & 10 & 30 \\ 0.1 & 10 & 35 \end{bmatrix}, P = \begin{bmatrix} 0.3689 & 0.117 & 0.2673 \\ 0.4699 & 0.4387 & 0.747 \\ 0.1091 & 0.8732 & 0.5547 \\ 0.0381 & 0.5743 & 0.8828 \end{bmatrix} \end{aligned} \quad (6)$$

The global optimal solution of this mathematical test function is -3.86278. For a fair comparison, the algorithm parameters for the proposed WDO and WDO-DE algorithms are the same. The mean results, standard deviations (Std), the optimal fitness values, the worst fitness values of the two algorithms for 50 independent and random runs are compared in Table I. In this comparison, the results for WDO-DE algorithm are directly cited from the original publication of [3]. From these numerical results, it is observed that the proposed algorithm significantly outperforms the well developed WDO-DE algorithm in all performance aspects of stochastic parameters.

To validate the proposed algorithm on engineering inverse problems, it is then applied to solve the Team Workshop problem 22 of a superconducting magnetic energy storage configuration with 8 free parameters [4]. This problem can be expressed mathematically as

$$\begin{aligned} &\min \quad f = w_1 \frac{B_{stary}^2}{B_{norm}^2} + w_2 \frac{|Energy - E_{ref}|}{E_{ref}} \\ &\text{s.t} \quad J_i \le (-6.4\,|(B_{\max})_i| + 54)\ (A/mm^2)(i=1,2) \end{aligned} \quad (6)$$

where; *Energy* is the stored energy in the SMES device; $E_{ref} = 180MJ$; $B_{norm} = 2\times10^{-4}$ T; J_i and $(B_{\max})_i$ $(i=1,2)$ are, respectively, the current density and the maximum field in the i^{th} coil; B_{stary}^2 is a measure of the stray fields [4].

TABLE I
Performance Comparison of Different Algorithms for 50 Runs on the Test Mathematical Function

Algorithm	The mean	The Std	The Best	The worst
Proposed	−3.86274508	5.263458×10^{-15}	−3.86274508	−3.86274508
WDO-DE	−3.73158405	0.076497205	−3.85565215	−3.52239202

For this case study, the 8 parameter problem, the Continuous Case, is selected. The performance parameters in the objective functions are determined using a two-dimensional finite element analysis. In accordance to the conditions mentioned above, the proposed algorithm is then employed to find the global optimal solution of the SMES devices. The iterative (function calls) number for the proposed algorithm to converge to a solution in a typical run is about 1986. Table II tabulates the final solutions of a typical run of the proposed WDO method, as well as the best ones searched so far by fellow researchers from the Institut für Grundlagen und Theorie der Elektrotechnik (IGTE). From these numerical results, it is obvious that the optimal values of the decision parameters found by the proposed WDO algorithm are almost identical to the best ones so far searched by IGTE. This positively validates the robustness and effectiveness of the proposed algorithm in solving complex electromagnetic design problems. Nevertheless, the optimized objective function using the proposed algorithm is slightly worse than that of the best one searched so far by IGTE, although the differences in the decision parameters for the two approaches are almost the same.

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TABLE II
Performance Comparison of the Proposed Method and the IGTE Solution for the SMES Configuration

Results	R_1(m)	R_2(m)	$h_1/2$(m)	$h_2/2$(m)	d_1(m)	d_2(m)	J_1(MA/m^2)	J_2(MA/m^2)	f_{obj}	No. iterations
Proposed	1.5703	2.1001	0.7845	1.4188	0.6000	0.2563	17.3359	-12.5658	6.7125×10^{-3}	1986
By IGTE	1.5703	2.0999	0.7846	1.4184	0.5943	0.2562	17.3367	-12.5738	5.5203×10^{-3}	/