

Sea Turtle Optimization for Electrical Engineering Applications

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Computational optimization using stochastic methods, such as metaheuristics, can help optimize real engineering problems. This paper presents an new algorithm inspired by the sea turtle life cycle - STO (Sea Turtle Optimization). The algorithm has been used and applied successfully to optimize continuous problems. This strategy is naturally hybrid, alternating phases of intensification and diversification during the search process. This methodology is applied on high-dimensional benchmark problems, and the results are better or similar than ones obtained by other strategies.

Index Terms—Optimization, Electrical Engineering, Metaheuristics, Sea Turtle Optimization.

I. INTRODUCTION

THE survival of any species is directly related to diverse search processes, such as for food and water, or processes that require less effort and are more efficiency. Real optimization problems in general are difficult to solve because they have a complex objective function, many parameters to be optimized, and subject to many constraints. Additionally, solving real problems with deterministic algorithms can result in hard optimization problems, requiring long time to achieve the solution. The interest in solving real problems with reduced computational efforts has driven optimization research and the development of stochastic algorithms, particularly metaheuristics, in recent decades [1]. Evolutionary/Genetic Algorithms (EA) and Particle Swarm Optimization (PSO), among others, are examples of metaheuristics inspired by natural or social behavior, such as genetics or natural evolution.

Two concepts related to metaheuristics mechanisms are important: intensification (exploitation) and diversification (exploration) [2]. The first one refers to an intensive dig into a relatively small portion of the search space, while the other refers to a global search. The balance in the application of these two concepts, usually, is accomplished with the use of hybrid techniques [3]. This paper presents a new optimization approach, STO - Sea Turtle Optimization, that alternates phases of the exploitation and exploration during the optimization process. The STO has been successfully applied to solve benchmark high-dimensional problems. Moreover, STO has been used for solving real problems, such as the Shortest Path Problem on barrier maps and air-breathing hypersonic vehicles [4].

II. STO - SEA TURTLE OPTIMIZATION

The sea turtles life cycle is complex, but it can be divided into three stages: the first stage relates to the birth of the hatchlings, the next stage corresponds to the turtles growth period, and the last stage involves reproduction, when the sea turtle returns to the nesting areas.

The Sea Turtle Optimization (STO) algorithm includes cycles of intensification and diversification, where the switching between these phases occurs naturally, with no need for special restart mechanisms or hybridization techniques. Phase 01 of the STO is inspired by the first stage of the life cycle of turtles, which occurs when the hatchlings walk on the sand with small steps (intensification phase). Phase 02 of the STO is inspired by the second stage of the life cycle of turtles, which happen when the turtles explore the ocean in search of food (diversification phase). Phase 03 of the STO is inspired by the stage of the turtles life cycle related to the nesting areas, when turtles go to the sand to lay their eggs and restart phase 01.

The STO can be classified as a swarm intelligence, population-based, attraction-based, and equation-based algorithm [5]. The phase 01 - walking to the sea (exploitation), phase 02 - Sexual maturity (exploration), and phase 03 - Reproduction of the STO consists of:

- Phase 01 - Walking to the sea: For each nest $n_i, i \in \{1, \dots, R_T \cdot N_T\}$ (N_T : number of the turtles, R_T : rate of female turtles that defines the number of nests, and initial iteration, $R_T = 1$), with N_P random directions $v_j, j \in \{1, \dots, N_P\}$ (N_P : number of the hatchlings generated at each nest) are defined such that $\max(v_j) = R$, where R represents a small distance in the search space. Each direction corresponds to one hatchling. The position

$b_{ij}(t+1)$, t is the current iteration of the hatchling j of the nest i is given by:

$$b_{ij}(t+1) = b_{ij}(t) + Rand_1 * v_j, \quad (1)$$

where $Rand_1 \in [0, 1]$. In each step, the hatchlings of each nest i are evaluated and the best one is memorized in b_i^* . From the second step on ($t > 0$), a mortality rate R_p is applied after the evaluation of the hatchlings. The reduction k of the number of hatchlings in each step is given by $k = R_p \cdot N_P + 1$. The k worst hatchlings are eliminated. When $k = 1$ the news solutions obtained on the nests used in the cycle and the solutions the others nests not actualized, formed a new population of N_T turtles to phase 02.

– Phase 02 - Sexual maturity: In each iteration $t(t \in \{1, \dots, T_S\})$ (T_S : number of iterations of the sexual maturity) of this phase a turtle x_i interacts with another turtle x_j , selected randomly with $i \neq j$. This interaction can be of attraction or of repulsion. The position of the turtle is updated as follows:

$$x_i(t+1) = x_i(t) + Rand_2(x_i(t) - x_j(t)), \quad (2)$$

with $Rand_2 \in [-1, 1]$. When finalized the phase 02, a number of turtles $R_T \cdot N_T$ are randomly selected to start a phase 03.

– Phase 03 - Reproduction (New Nests): The best known position of each turtle $x_i^{Historic\ Best}$ is used to determine the most favorable nesting sites found passed by the turtle. A new nest $n_i, i \in \{1, \dots, R_T \cdot N_T\}$ whose position is given by the expression:

$$n_i = x_i + Rand_3(x_i^{Historic\ Best} - x_i), \quad (3)$$

with $Rand_3 \in [R_k, 1]$, where R_k is a percentage of the proximity of the nest. The N_T , R_N , and T_S parameters are associated with diversification. The third one corresponds to the time of migration of the turtles before the restart of the local search period. The N_P , R_K , and R , are associated with the intensification. The local search is privileged as the number of hatchlings increases and the maximum step size decreases. The R_P is associated with the balance between exploitation/exploration.

The flowchart of STO is presented in Fig. 1. In phase 01 (walking to the sea), within each nest and for a number of iterations, a local search algorithm is used to obtain a new solution that will form the population for phase 02, to be used in the next cycle. If no stopping criteria are met, phase 02 (sexual maturity) begins with the solutions obtained in phase 01 and applies a global population search algorithm. Phase 02 is executed for a number of iterations, and if no stopping criteria are met, phase 03 (reproduction) is initiated. A heuristic that relates the current solution to its best known historical position is applied to generate a new nest to restart phase 01. This cycle is repeated until the stopping criteria are met.

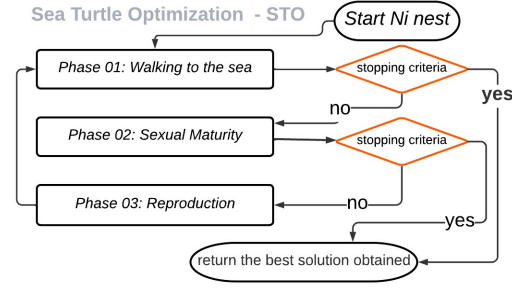


Fig. 1. The simple flowchart in which STO.

The results obtained by STO demonstrate that it is a competitive algorithm to the ones presented in the literature when applied to test functions. Table I presents some results obtained for four benchmark functions (AMGM, Deb No. 1, Rana, and Xin-She Yang No. 3) [6]. In each problem, 30 variables were considered, proving that STO obtained solutions are better or equivalent to than algorithms well-established in the literature, such as PSO and EA. We highlight that in the Xin She Yang No. 3 problem, only STO reached the global minimum.

TABLE I
RESULTS OBTAINED FOR TEST FUNCTIONS WITH 30 VARIABLES.

Function	AMGM		Deb N1		Rana		Xin-She Yang No. 3	
	Best	Median	Best	Median	Best	Median	Best	Median
EA	1.39e-07	2.25e-06	-8.5e-01	-8.1e-01	-1.2e+04	-1.1e+04	0.00e+00	0.00e+00
PSO	0.00e+00	0.00e+00	-1.0e+00	-1.0e+00	-9.5e+03	-6.7e+03	0.00e+00	0.00e+00
STO	0.00e+00	0.00e+00	-1.0e+00	-1.0e+00	-1.3e+04	-1.0e+04	-1.0e+01	-9.4e-01

The performance of the STO on benchmark functions suggests that this method could be effectively applied to real electromagnetic problems. So, in the full paper STO will be applied on geometric optimization of overhead transmission lines. The aim is to maximize the power transfer capacity and minimize the electromagnetic fields on the soil level.

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