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# Snake optimization algorithm based on non-dominated sorting

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***Abstract :*** *Snake optimization algorithm is a new swarm intelligence optimization algorithm proposed in 2022, but it can only perform single-objective optimization, so in this paper, non-dominated ordering is introduced to convert the single-objective snake optimization algorithm into multi-objective snake optimization algorithm (NS-SO). NS-SO is tested for performance comparison with NSGA2 and MOPSO. Two benchmark test functions from ZDT, the most widely used multi-objective optimization test set, are selected as comparison targets. The effectiveness of the improvement and the superiority of NS-SO are verified.*

***Keywords :*** *Snake optimization algorithm、Non-dominated sorting、Multi-objective optimization algorithm、Test function*

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## I. Introduction

In the case of single-objective optimization, there is only one objective, and any two solutions can be compared on the basis of the single objective, which can lead to an uncontroversial optimal solution. Multi-objectification is opposed to traditional single objective optimization. The concept of multi-objective optimization is that when more than one objective needs to be achieved in a given scenario, it is difficult to come up with a unique optimal solution due to the ease of intrinsic conflict between the objectives, where one objective is optimized at the cost of inferiority of the others, and instead, coordination and compromise is made amongst them, so that the overall objective is as optimal as possible [1-3].

The Snake Optimization Algorithm was proposed in 2022 and it simulates the behavior of snakes in nature such as foraging, fighting, mating and laying eggs. The algorithm divides the search process into two phases: global exploration and local exploitation. In the exploration phase, the algorithm takes into account environmental factors, such as cold regions and food availability, as the snake searches for food in its surroundings. The exploitation phase, on the other hand, consists of multiple transition phases to improve the algorithm's search efficiency. Snakes will mate if food is plentiful and temperatures are low, otherwise they will simply search for food or eat what is available. During mating, either a fighting mode or a mating mode may occur. In fighting mode, male snakes compete for the best female, while females choose the best male. In mating mode, the mating behavior of each pair of snakes depends on the availability of food. If mating occurs, the female snake lays eggs that hatch into new snakes. However, snake optimization algorithms have some limitations such as only single objective optimization can be performed [4].

Therefore, this paper introduces the non-dominated ordering to convert the single-objective snake optimization algorithm into a multi-objective snake optimization algorithm and tests the performance of NS-SO in comparison with NSGA2 and MOPSO. Two benchmark test functions from ZDT, the most widely used multi-objective optimization test set, are selected as comparison targets. The effectiveness of the improvement and the superiority of NS-SO are verified [5-7].

## II. Algorithm for Multi-Objective Optimization

2.1.Snake Optimization Algorithm

The optimization search procedure of the Snake Optimization Algorithm (SO) is bifurcated into two stages: investigation and utilization. Its mathematical depiction is as follows.

1) Population initialization.

$$S_i = S_{min} + r \times (S_{max} - S_{min}) \tag{1}$$

Where: $S_i$ is the position of the ith snake; r is a random number in the range [0,1]; $S_{max}$ and $S_{min}$ are the upper and lower bounds of the solution problem, respectively.

2) Divide the population into two groups, males and females. The population size is O. The number of male snakes is $O_m$; the number of female snakes is $O_f$. Divide the population using the following two equations.

$$O_m \approx O / 2 \tag{2}$$

$$O_f = O - O_m \tag{3}$$

Assess every group and specify the temperature and food quantity. Within every group, identify the most suitable male $f_{best,m}$, the top female $f_{best,f}$, along with the position of the food $f_{food}$. The equation(4) is used to determine the temperature.

$$Temp = \exp(\frac{-t}{T}) \tag{4}$$

Where: t is the current number of iterations; T is the maximum number of iterations.
The equation defining the quantity of food Q is equation (5).

$$Q = c_1 \times \exp(\frac{t-T}{T}) \tag{5}$$

Where: $c_1$ is a constant, taken as 0.5.
3) Exploration phase (no food)
When Q falls below the Threshold (Threshold=0.25), the snake initiates a search for food by randomly choosing a spot and altering its position. The investigative stage is represented by the following equation (6).

$$S_{i,m}(t+1) = S_{rand,m}(t) \pm c_2 \times A_m \times ((S_{max} - S_{min}) \times rand + S_{min}) \tag{6}$$

Where: $S_{i,m}$ is the male snake position; $S_{rand,m}$ is the randomly selected male snake position; rand is a random number in the range of [0,1]; $c_2$ is a constant taken as 0.05; and $A_m$ is the male snake's ability to search for food, which is calculated as equation (7).

$$A_m = \exp(\frac{-f_{rand,m}}{f_{i,m}}) \tag{7}$$

Where: $f_{rand,m}$ is the $S_{rand,m}$ fitness value of the randomly selected male snake location, and $f_{i,m}$ is the $S_{i,m}$ fitness value of the male snake location.
Identifying the position of the male snake allows for the determination of the female snake's location using the equation(8).

$$S_{i,f} = S_{rand,f}(t+1) \pm c_2 \times A_f \times ((S_{max} - S_{min}) \times rand + S_{min}) \tag{8}$$

Where: $S_{i,f}$ is the female snake location; $S_{rand,f}$ is the randomly selected female snake location; rand is a random number in the range of [0,1]; $c_2$ is a constant taken as 0.05; $A_f$ is the female snake's ability to search for food, which is calculated as equation (9).

$$A_f = \exp(\frac{-f_{rand,f}}{f_{i,f}}) \tag{9}$$

Where: $f_{rand,f}$ is the $S_{rand,f}$ fitness value for a randomly selected female snake location, and $f_{i,f}$ is the $S_{i,f}$ fitness value for a female snake location.
4) Development phase (with food)
When Q exceeds the Threshold, and Temperature surpasses the Threshold (0.6), it indicates that the temperature reaches a high state. The snake's sole activity is foraging, and the formula forupdating its position is as follows.

$$S_{i,j}(t+1) = S_{food} \pm c_3 \times Temp \times rand \times (S_{food} - S_{i,j}(t)) \tag{10}$$

Where: $S_{i,j}$ is the position of the individual snake (male or female); $S_{food}$ is the optimal position of the individual snake; rand is a random number in the range [0,1]; and $c_3$ is a constant, taken as 2.
When the Temperature falls below the Threshold (0.6) and Q exceeds the Threshold, it indicates a state of coldness. This snake species is either engaged in combat or engaged in breeding.
(a) Combat mode

$$\begin{cases} S_{i,m}(t+1) = S_{i,m}(t) + c_3 \times FM \times rand \times (Q \times S_{best,f} - S_{i,m}(t)) \\ S_{i,f}(t+1) = S_{i,f}(t) + c_3 \times FF \times rand \times (Q \times S_{best,m} - S_{i,f}(t)) \end{cases} \tag{11}$$

Where: $S_{i,m}$ is the position of the ith male snake; $S_{best,f}$ is the best position in the group of female snakes; $S_{i,f}$ is the position of the ith female snake; $S_{best,m}$ is the best position in the group of male snakes; rand is a random number in the range of [0,1]; FM represents the male snake's fighting ability and FF represents the female snake's fighting ability.FM and FF are calculated using equation (12).

$$\begin{cases} FM = \exp(\frac{-f_{best,f}}{f_{i,m}}) \\ FF = \exp(\frac{-f_{best,m}}{f_{i,f}}) \end{cases} \tag{12}$$

Where: $f_{best,f}$ is the fitness value of the best position $S_{best,f}$ in the group of female snakes; $f_{best,m}$ is the fitness value of the best position $S_{best,m}$ in the group of male snakes; $f_{i,m}$, and $f_{i,f}$ are the fitness values of the current individual in the group of male and female snakes, respectively.

(b) Breeding mode

$$\begin{cases} S_{i,m}(t+1) = S_{i,m}(t) + c_3 \times M_m \times rand \times (Q \times S_{i,f}(t) - S_{i,m}(t)) \\ S_{i,f}(t+1) = S_{i,f}(t) + c_3 \times M_f \times rand \times (Q \times S_{i,m}(t) - S_{i,f}(t)) \end{cases} \tag{13}$$

Where: $S_{i,m}$ is the position of the ith male snake; $S_{i,f}$ is the position of the ith female snake; rand is a random number in the range of [0,1]; $M_m$ and $M_f$ are the mating ability of the male and female snakes, respectively, as calculated by Equation (15).

$$\begin{cases} M_m = \exp(\frac{-f_{i,f}}{f_{i,m}}) \\ M_f = \exp(\frac{-f_{i,m}}{f_{i,f}}) \end{cases} \tag{14}$$

Where: $f_{i,m}$ is the fitness value of the ith male snake position and $f_{i,f}$ is the fitness value of the ith female snake position. If breeding is successful, the worst male and female snakes are selected and replaced them with the expression (15).

$$\begin{cases} S_{worst,f} = S_{min} + rand \times (S_{max} - S_{min}) \\ S_{worst,m} = S_{min} + rand \times (S_{max} - S_{min}) \end{cases} \tag{15}$$

where $S_{worst,m}$ is the worst position among male snakes; $S_{worst,f}$ is the worst position among female snakes.

### 2.2. Multi-Objective Snake Optimization Algorithm Based on Non-Dominated Ordering

In multi-objective optimization algorithms, non-dominated sorting stands out as a highly effective and favored method, primarily aimed at harmonizing the connections among the objective functions to identify the best solutions where each function attains a comparatively low (or high) value. Utilizing a non-dominated sorting approach, the NSSO algorithm preserves the population's diversity by effectively employing a fitness-sharing function, ensuring the retention of the population's top individuals. The outcomes are quite impressive. Figure 2 displays the flowchart for the NSSO algorithm.

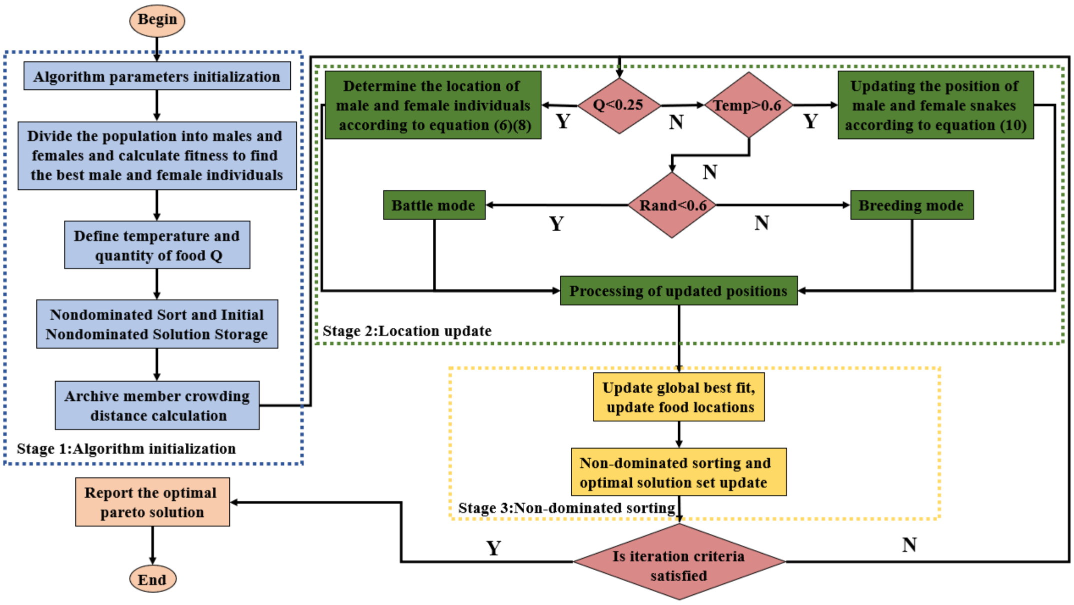



**Figure 1.** Diagram illustrating the multi-faceted snake optimization process.

The enhancement procedure for the NSSO algorithm is segmented into three primary phases as outlined below. Stage 1: Begin by setting up the snake population and the parameters of the algorithm. Segment the population into two categories of male and female snakes based on Equations (2) and (3), and assess the fitness to identify the most suitable male and female snakes. Establish the air temperature and the quantity of food Q as per Equations (4) and (5). Calculate the non-dominant solution in the initial population and save it in the Pareto file, then calculate the crowding distance of each Pareto file member.

Stage 2：Location Updates.

IF (Q<0.25){Update the position of male and female snakes according to equations (6) and (8)}。

ELSE

IF (Temp>0.6) {Updating the position of male and female snakes according to equation (10)}

ELSE

IF (rand>0.6) {Update the position of male and female snakes according to equation (11)}

ELSE {Update the position of male and female snakes according to equation (13) and the position of the worst male and female snakes in the population by equation (15) }。

END IF

END IF

END IF

Stage 3:Sorting without domination. Discover novel, non-prevalent solutions within the population and store them in the Pareto archive, while discarding any dominant solutions from the Pareto archive. Execute a sort that is not dominated and proceed to revise the Pareto optimal solution. Continue the procedure until the condition for iteration is met.

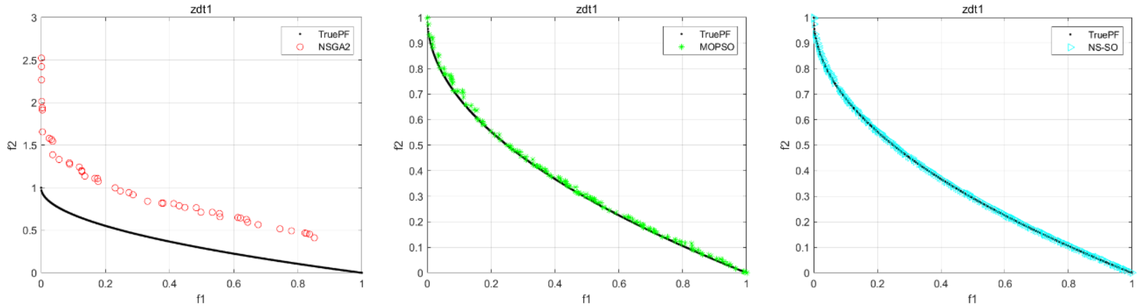
## III. Algorithm Performance Comparison

In order to verify the performance of the NS-SO algorithm in solving multi-objective optimization problems, the performance of the NS-SO algorithm is tested against NSGA2 and MOPSO in this section. Two benchmark test functions from ZDT, the most widely used multi-objective optimization test set, are selected as the objectives. All the test functions are bi-objective optimization with minimized objective functions f1 and f2. The 2 benchmark test functions are shown in Table 1.

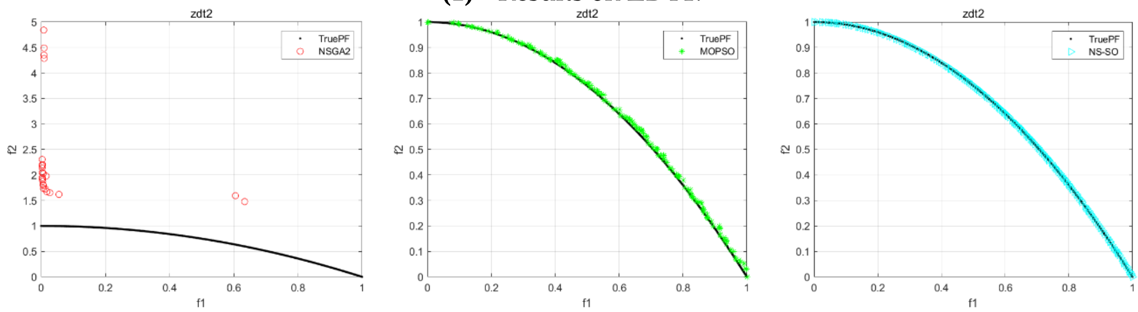
**Table 1:** Target test functions.

| Function name | Number of variables | Boundary | Objective function | Optimal solution |
|---|---|---|---|---|
| ZDT1 | 10 | [0,1] | $f_1(x) = x_1$ <br> $f_{2(}x) = g(x)\left[1 - \sqrt{x_1 / g(x)}\right]$ <br> $g(x) = 1 + \frac{9\left(\sum_{i=2}^{n} x_i\right)}{(n-1)}$ | $x_1 \in [0,1]$ <br> $x_i = 0$ <br> $i = 2, \cdots, n$ |
| ZDT2 | 10 | [0,1] | $f_1(x) = x_1$ <br> $f_{2(}x) = g(x)\left[1 - (x_1 / g(x))^2\right]$ <br> $g(x) = 1 + \frac{9\left(\sum_{i=2}^{n} x_i\right)}{(n-1)}$ | |

In the comparison test experiments, in order to weaken the perturbation of the random part of the algorithms on the optimization results, each test function was run independently for 30 times, the population size was set to 100, the size of the repository was set to 200, and the maximum number of iterations was set to 300. The parameters of each algorithm were selected from the corresponding references. Figure 2 shows the best Pareto optimal frontiers obtained by the 2 algorithms for the 2 bi-objective benchmark test functions.




**(1)** Results on ZDT1.




**(2)** Results on ZDT2.

**Figure 2.**Comparison of the Best Pareto Optimal Frontier Obtained by the Multi-Objective Algorithm on ZDT1 and ZDT2

The simulation results of the two bi-objective benchmark test functions show that both NS-SO can find the true Pareto frontiers of the test functions, and the convergence and coverage of NS-SO outperforms the comparison algorithms, NSGA2 and MOPSO, among the three bi-objective benchmark test functions, which verifies the excellence of the NS-SO algorithm.

## IV. Conclusion

In order to solve the shortcomings of the snake optimization algorithm which can only solve single objective, non-dominated ordering is introduced to transform the single objective snake optimization algorithm into a multi-objective snake optimization algorithm,and NS-SO is tested for performance comparison with NSGA2 and MOPSO. Two benchmark test functions from ZDT, the most widely used multi-objective optimization test set, are selected as comparison targets. The effectiveness of the improvement and the superiority of NS-SO are verified.

## Reference

[1]. Sharifi, M. R., Akbarifard, S., Qaderi, K., & Madadi, M. R. (2021). A new optimization algorithm to solve multi-objective problems. Scientific Reports, 11(1), 20326.

[2]. Abdollahzadeh, B., &Gharehchopogh, F. S. (2022). A multi-objective optimization algorithm for feature selection problems. Engineering with Computers, 38(Suppl 3), 1845-1863.

[3]. Deb, K. (2015). Multi-objective evolutionary algorithms. Springer handbook of computational intelligence, 995-1015.

[4]. Hashim, F. A., & Hussien, A. G. (2022). Snake Optimizer: A novel meta-heuristic optimization algorithm. Knowledge-Based Systems, 242, 108320.

[5]. Priya, R., Ramesh, D., &Udutalapally, V. (2021). NSGA-2 optimized fuzzy inference system for crop plantation correctness index identification. IEEE Transactions on Sustainable Computing, 7(1), 172-188.

[6]. Cheraghi, R., & Jahangir, M. H. (2023). Multi-objective optimization of a hybrid renewable energy system supplying a residential building using NSGA-II and MOPSO algorithms. Energy Conversion and Management, 294, 117515.

[7]. Wang, M., Wang, J. S., Song, H. M., Zhang, M., Zhang, X. Y., Zheng, Y., & Zhu, J. H. (2022). Hybrid multi-objective Harris Hawk optimization algorithm based on elite non-dominated sorting and grid index mechanism. Advances in Engineering Software, 172, 103218.