Kai MENG, Chen CHEN, Bin XIN, 2022. MSSSA: a multi-strategy enhanced sparrow search algorithm for global optimization. *Frontiers of Information Technology & Electronic Engineering*, 23(12):1828-1847.
https://doi.org/10.1631/FITEE.2200237

MSSSA: a multi-strategy enhanced sparrow search algorithm for global optimization

Front Inform Technol Electron Eng

Key words: Swarm intelligence; Sparrow search algorithm; Adaptive parameter control strategy; Hybrid disturbance mechanism; Optimization problems

Corresponding author: Chen CHEN
E-mail: xiaofan@bit.edu.cn
ORCID: https://orcid.org/0000-0001-9354-6974

Motivation

- The initial sparrow search algorithm (SSA) populations are initialized at random without rules, and the initial population cannot be appropriately assigned in the searching space of practical problems, which limits the accuracy of initial solutions.
- A fixed ratio of producers to scroungers does not accurately reflect the actual optimization searching process and strikes a limited balance between exploration and exploitation.
- Insufficient population diversity causes the SSA to fall into local optima.

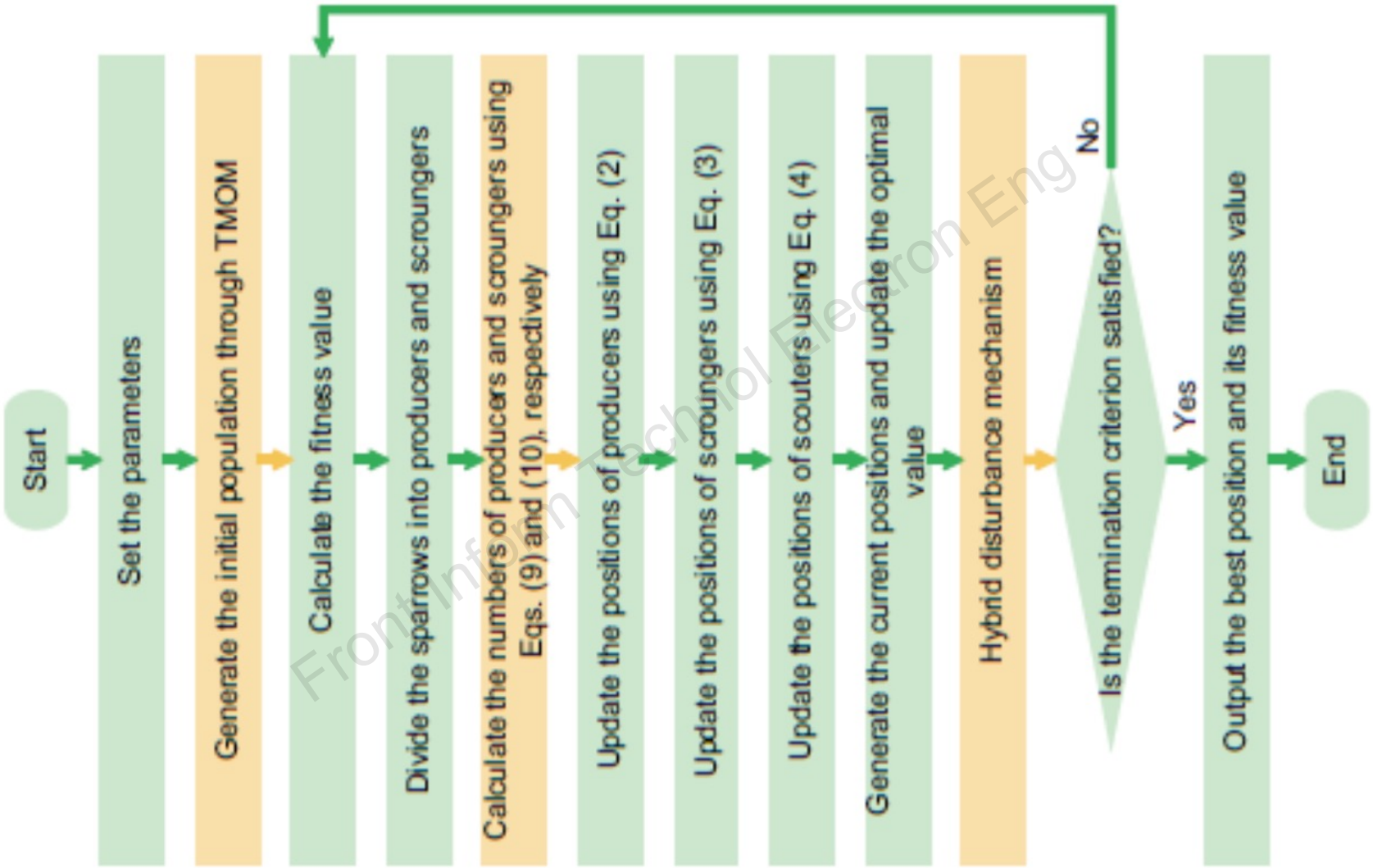
Front Inform Technol Electron Eng

Main idea

1. A modified sparrow generation mechanism based on a chaotic map and opposition-based learning (OBL) is developed to generate a high-quality population while increasing the population diversity.
2. An adaptive parameter control strategy, which can dynamically adjust the ratio of producers to scroungers, is adopted to achieve a better balance between intensification and diversification.
3. A hybrid disturbance mechanism is incorporated into the SSA to improve the ability to jump out of local optima and to improve the convergence speed.

Front Inform Technol Electron Eng

Method



Front Inform Technol Electron Eng

Fig. 1 Flowchart of the proposed multi-strategy enhanced sparrow search algorithm (MSSSA)

Method (Cont'd)

Algorithm 1 Pseudo-code of the TMOM

Initialize the parameters: population size n, the maximum iteration number of TM $s_{\max}$, and the lower ($x_{\mathrm{lb},j}$) and upper ($x_{\mathrm{ub},j}$) bounds of $x_{i,j}$
for $i \leq n$ **do**
  for $j \leq d$ **do**
    Set the initial variables $\mathrm{ch}_{i,j}(0) = 0.152$
    for $s \leq s_{\max}$ **do**
      Execute the tent map (TM) operation based on Eq. (5)
    end for
    Generate the initial value $x_{i,j}$ based on Eq. (6)
  end for
end for
for $i \leq n$ **do**
  for $j \leq d$ **do**
    Compute the value of $\mathrm{ox}_{i,j}$ based on Eq. (7)
  end for
end for
Merge TM population $x_{i,j}$ and OBL population $\mathrm{ox}_{i,j}$
Choose the best n sparrows from the produced population as the initial population

Algorithm 2 Pseudo-code of the proposed MSSSA

Input: the number of sparrows n, the maximum number of iterations $T_{\max}$, the number of producers N_{p}^{*}, the number of scouters n_2, and the alarm value q
Output: the global best position and its optimal fitness value

Generate a high-quality initialized population using Algorithm 1
Calculate the fitness value for each sparrow
Sort all the sparrows according to their fitness values and select the current best and worst individuals
while $t < T_{\max}$ **do**
  $q = \mathrm{rand}(1)$
  Calculate the numbers of producers and scroungers by Eqs. (9) and (10), respectively
  for $i = 1 : N_{\mathrm{p}}^{*}$ **do**
    Update the positions of producers by Eq. (2)
  end for
  for $i = N_{\mathrm{p}}^{*} + 1 : n$ **do**
    Update the positions of scroungers by Eq. (3)
  end for
  for $i = 1 : n_2$ **do**
    Update the positions of scouters by Eq. (4)
  end for
  for $i = 1 : n$ **do**
    Record the new position of the sparrow generated at this time as $x_{i,j}^{\mathrm{new}}$
    if $f\left(x_{i,j}^{\mathrm{new}}\right) \leq f\left(x_{i,j}^{t}\right)$ **then**
      Replace the position $x_{i,j}^{t}$ by $x_{i,j}^{\mathrm{new}}$
    else
      Calculate the new position Y_{new} through the hybrid disturbance mechanism by Eqs. (11)–(17)
      if $f(Y_{\mathrm{new}}) \leq f\left(x_{i,j}^{t}\right)$ **then**
        Replace the position $x_{i,j}^{t}$ by Y_{new}
      end if
    end if
  end for
  $t = t + 1$
end while
return the global best position and its fitness value

Front Inform Technol Electron Eng

Major results

MSSSAwt means MSSSA without TMOM, MSSSAwa denotes MSSSA without the adaptive parameter control strategy, and MSSSAwh is MSSSA without the hybrid disturbance mechanism.

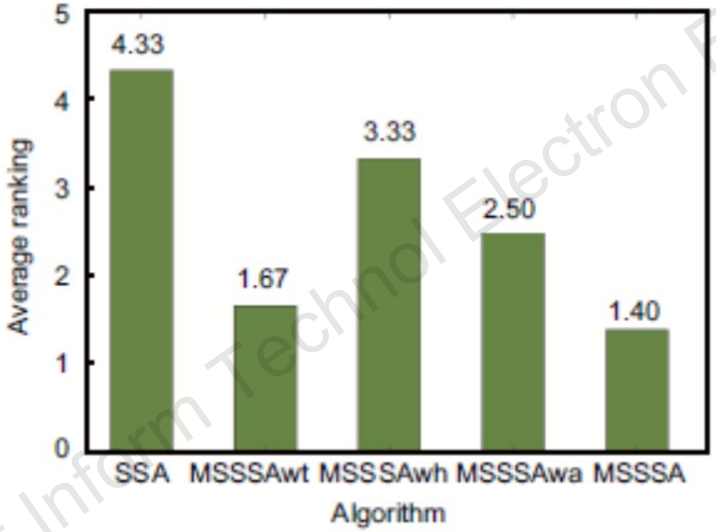
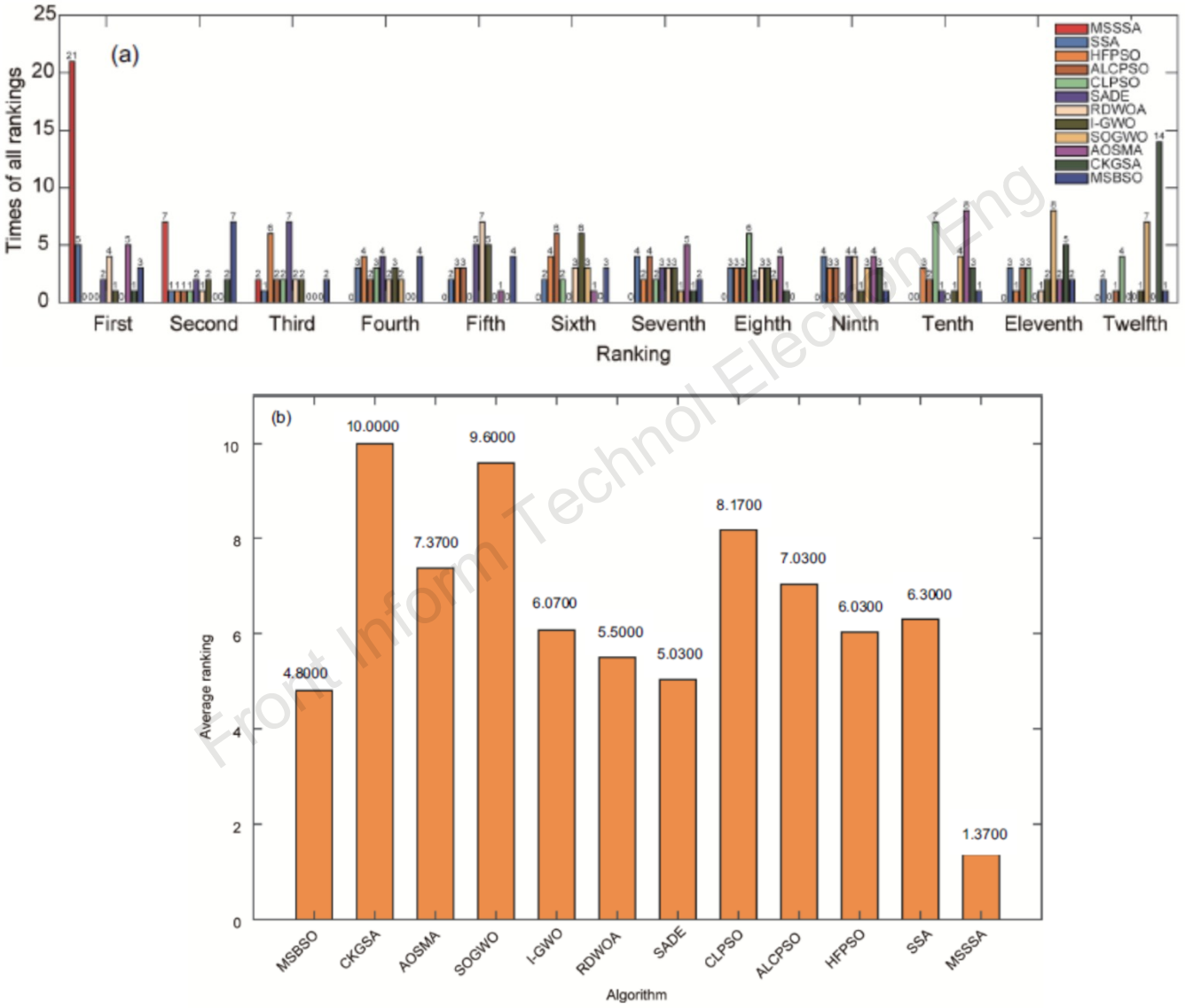


Fig. 5 Ranking statistical bar of MSSSA and its degradative variants

Front Inform Technol Electron Eng

From Fig. 5, the average ranking of the SSA is inferior to that of any of the MSSSA and its degradative variants, indicating that each enhancement strategy is effective and boosts the performance of the SSA to some degree. In addition, the rank from the best to the worst is MSSSA, MSSSAwt, MSSSAwa, MSSSAwh, and SSA, which implies that the MSSSA provides the best optimization performance.

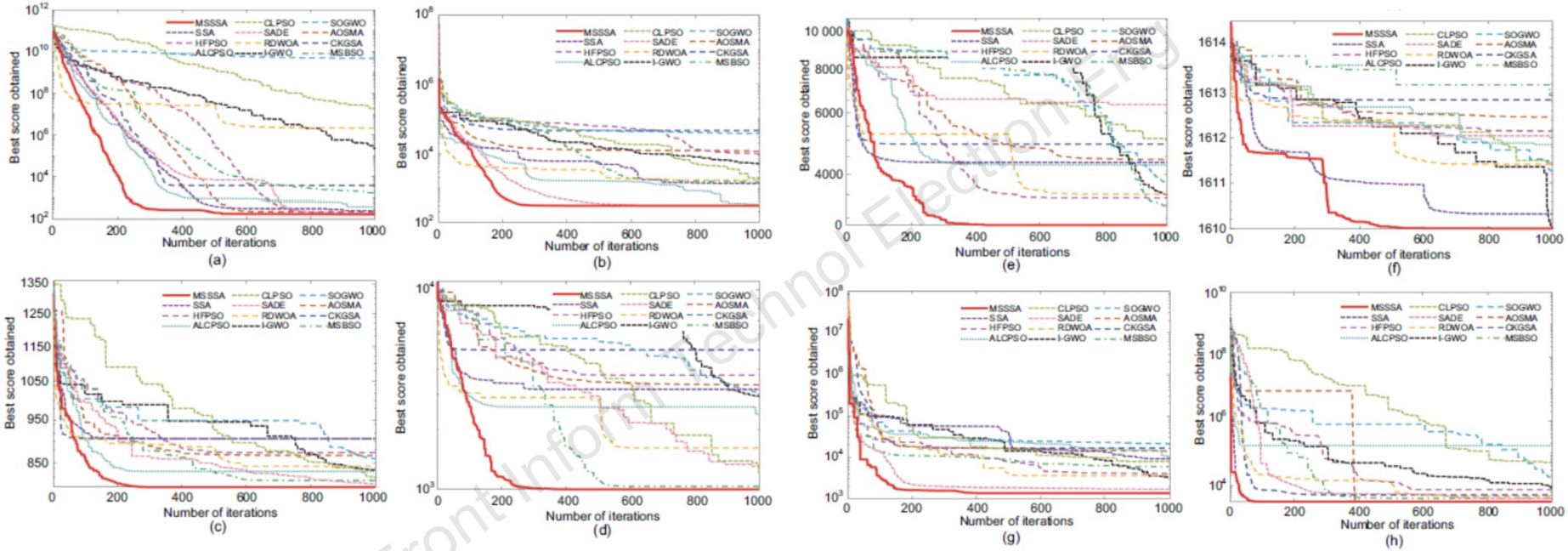
Major results (Cont'd)



Front Inform Technol Electron Eng

Fig. 6 Ranking statistics on the CEC2014 benchmark functions: (a) ranking statistical bars of 12 algorithms; (b) average ranking bar of 12 algorithms

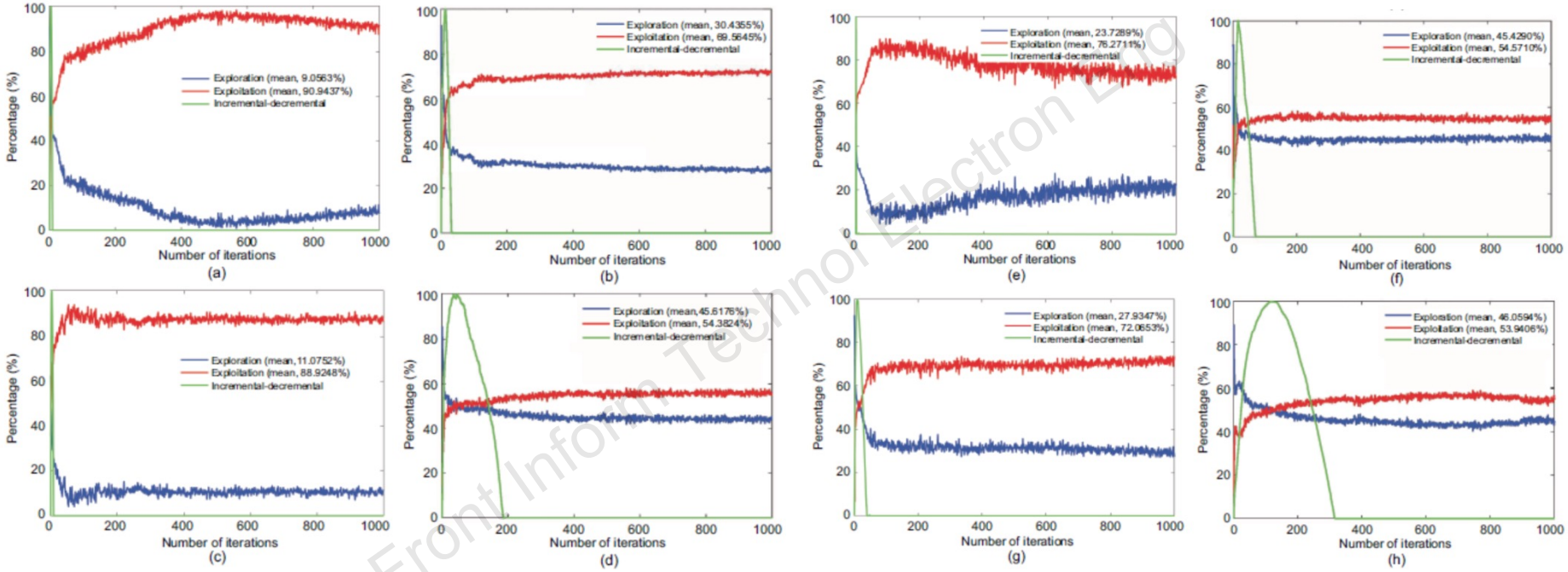
Major results (Cont'd)



Front Inform Technol Electron Eng

Fig. 7 Convergence curves of the MSSSA and the other algorithms on some selected CEC2014 functions: (a) F2; (b) F3; (c) F8; (d) F10; (e) F11; (f) F16; (g) F20; (h) F29

Major results (Cont'd)



Front Inform Technol Electron Eng

Fig. 8 Balance analysis of the MSSSA and SSA on F1, F12, F18, and F38: (a) MSSSA on F1; (b) SSA on F1; (c) MSSSA on F12; (d) SSA on F12; (e) MSSSA on F18; (f) SSA on F18; (g) MSSSA on F38; (h) SSA on F38

Major results (Cont'd)

Table 2 Best solutions of all the methods on the pressure vessel design problem

Algorithm	T_s	T_h	R	L	Best cost
MSSSA	0.7782	0.3846	40.3196	200.0000	**5885.3328**
SSA	0.7816	0.3864	40.4980	197.5312	5891.2446
HFPSO	0.7782	0.3847	40.3196	200.0000	5891.5859
ALCPSO	0.7782	0.3847	40.3196	200.0000	5891.5859
CLPSO	0.7824	0.3867	40.5352	197.2093	5903.5077
SADE	0.7782	0.3847	40.3196	200.0000	5891.5859
RDWOA	0.7782	0.3847	40.3198	199.9971	5891.5929
I-GWO	0.7788	0.3850	40.3516	199.5766	5893.5039
SOGWO	0.7793	0.3852	40.3588	199.5329	5897.7459
AOSMA	0.7782	0.3847	40.3531	199.9515	5891.7025
CKGSA	0.8808	0.4354	45.6354	137.2379	6093.9033
MSBSO	0.7782	0.3847	40.3196	200.0000	5891.5859

Best result is in bold. T_s, T_h, R, and L are the optimum variables

Table 3 Statistical results of all the methods on the pressure vessel design problem

Algorithm	Best	Mean	Worst	Std
MSSSA	**5885.3328**	**5890.6000**	5949.2423	15.3203
SSA	5891.2446	6432.1386	7318.9684	454.5260
HFPSO	5891.5859	6280.0335	7345.4732	375.5908
ALCPSO	5891.5859	6256.0094	7345.4732	415.7870
CLPSO	5903.5077	6069.2958	6325.9864	90.5242
SADE	5891.5859	5891.5859	**5891.5859**	**0.0000**
RDWOA	5891.5929	6694.9463	7345.4739	678.3317
I-GWO	5893.5039	5894.8587	5898.5681	1.0787
SOGWO	5897.7459	5999.9967	7026.6903	261.6701
AOSMA	5891.7025	6632.4350	7345.4056	635.9922
CKGSA	6093.9033	89 198.8909	227 939.4854	74 928.6694
MSBSO	5891.5859	5891.5859	**5891.5859**	**0.0000**

Best results are in bold

From Inform Technol Electron Eng

Major results (Cont'd)

Table 4 Best solutions of all the methods on the speed reducer design problem

Algorithm	Optimal values for variables							Best cost
	b	m	z	l_1	l_2	d_1	d_2	
MSSSA	3.5000	0.7000	17.0000	7.3000	7.7153	3.3502	5.2866	**2994.4711**
SSA	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
HFPSO	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
ALCPSO	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
CLPSO	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
SADE	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
RDWOA	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
I-GWO	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097
SOGWO	3.5028	0.7002	17.0000	7.4308	7.7667	3.3567	5.2875	3000.7795
AOSMA	3.5000	0.7000	17.0000	7.3002	7.7164	3.3502	5.2872	2994.7221
CKGSA	3.5926	0.7134	17.1221	7.7464	8.1030	3.4464	5.3013	3163.2207
MSBSO	3.5000	0.7000	17.0000	7.3000	7.7159	3.3502	5.2872	2994.7097

Best result is in bold

Table 5 Statistical results of all the methods on the speed reducer design problem

Algorithm	Best	Mean	Worst	Std
MSSSA	**2994.4711**	**2994.6003**	2995.1814	0.2369
SSA	2994.7097	2995.0208	3005.0435	1.7041
HFPSO	2994.7097	3001.0011	3033.9863	13.5509
ALCPSO	2994.7097	2994.8501	2998.8993	0.7648
CLPSO	2994.7097	2994.7097	2994.7098	0.0000
SADE	2994.7097	2994.7097	**2994.7097**	**0.0000**
RDWOA	2994.7097	2994.7097	2994.7098	0.0000
I-GWO	2994.7097	2994.7097	2994.7100	0.0001
SOGWO	3000.7795	3006.2565	3014.5684	3.6924
AOSMA	2994.7221	2999.0901	3013.5460	5.0783
CKGSA	3163.2207	3635.4198	4666.9643	378.3087
MSBSO	2994.7097	2994.7097	**2994.7097**	**0.0000**

Best results are in bold. The actual variances of the CLPSO and RDWOA are 0.000 01, so they are not marked in bold

Front Inform Technol Electron Eng

Conclusions

1. We propose an enhanced SSA by integrating TMOM, an adaptive parameter control strategy, and a hybrid disturbance mechanism. Specifically, TMOM combines the TM and OBL to generate high-quality initial sparrow populations. The adaptive parameter control strategy is designed to adjust the ratio of producers to scroungers with an increased number of iterations, which contributes to establishing a balance between exploration and exploitation. The hybrid disturbance mechanism aims to facilitate the MSSSA, strengthening local exploration capability, and effectively jumping out of the local optimal region.
2. Two benchmark function sets (IEEE CEC2014 and IEEE CEC2019) and 10 classical functions are used to evaluate the performance of the proposed MSSSA. Compared with the SSA and 10 state-of-the-art algorithms, the MSSSA has superior performance in terms of solution accuracy, convergence speed, scalability, and stability. Moreover, the proposed MSSSA is applied to deal with two real-world optimization problems. Experimental results indicate that the MSSSA is a practicable and efficient method for complex engineering optimization problems.

Front Inform Technol Electron Eng

Chen CHEN was born in 1982. She received her PhD degree from Beijing Institute of Technology. She is a professor in Beijing Institute of Technology. Her research interests are intelligent optimization and decision-making of complex systems, and military operations research.

Front Inform Technol Electron Eng