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Soccer league optimization-based championship algorithm (SLOCA): A fast novel meta-heuristic technique for optimization problems

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Abstract. Due to their natural and social revelation, also their ease and flexibility, human collective behavior and teamwork sports are inspired to introduce optimization algorithms to solve various engineering and scientific problems. Nowadays, meta-heuristic algorithms are becoming some striking methods for solving complex real-world problems. In that respect in the present study, the authors propose a novel meta-innovative algorithm based on soccer teamwork sport, suitable for optimization problems. The method may be referred to as the Soccer League Optimization-based Championship Algorithm, inspired by the Soccer league. This method consists of two main steps, including: 1. Qualifying competitions and 2. Main competitions. To evaluate the robustness of the proposed method, six different benchmark mathematical functions, and two engineering design problem was performed for optimization to assess its efficiency in achieving optimal solutions to various problems. The results show that the proposed algorithm may well explore better performance than some well-known algorithms in various aspects such as consistency through runs and a fast and steep convergence in all problems towards the global optimal fitness value.

Keywords: championship; GA; meta-heuristic; optimization algorithm; PSO; soccer league

1. Introduction

Nowadays, due to the complexity of real-world problems, the need for efficient meta-innovative methods is greater than ever to handle such thorny problems. Ultra-innovative methods have received more attention than other techniques due to their high efficiency and easy implementation (Varaee and Ghasemi 2017). These methods are used to solve applied engineering problems as well as to find optimal solutions to problems in a given time frame (Salarnia and Ghasemi 2021). The popularity of this type of algorithm is not limited to computers or other engineering fields. These algorithms can be used in various fields of economics and industry, science, and other real-world regions (Hayyolalam and Kazem 2020). The methods of meta-heuristic algorithms are classified into three groups including physics-based, congestion-based, and evolution-based groups. Physics-based algorithms are inspired by physical laws such as electromagnetic force, inertial force, gravitational force, etc. By considering these rules, the search

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agents of algorithms communicate and move in the search space. Algorithms that fall into this category include GSA (Rashedi *et al*. 2009), BBBC (Erol and Eksin 2006) and SA (Kirkpatrick *et al*. 1983), etc. Congestion-based algorithms are inspired by the collective manner of social beings, which refers to how members of a group or colony interact with their environment. Algorithms that fall into this category include PSO (Kennedy and Eberhart 1995), ACO (Dorigo *et al*. 1996) and DPO (Shiqin *et al*. 2009), etc. Evolution-based algorithms are more inspired by nature and biological evolution such as selection, reproduction, cross-over and mutation. These algorithms are inspired by Darwin's theory of natural selection and are defined as the idea of species changing over time and creating new species (Beddall 1968). Some of the most important algorithms in this regard are Genetic Algorithm (GA) (Holland 1975), Evolutionary Strategies (Beyer and Schwefel 2002) and Genetic Programming (Koza and Poli 2005). Over the past few years, nature-inspired algorithms have experienced great success in the industrial world, where they have been shown to be very useful in solving real-world optimization problems (Ghasemi *et al*. 2022). Also, in line with various issues, the performance of these algorithms has greatly improved over the past decades, or even the structure of some parts of these algorithms to solve these problems has changed and has been published under various articles, such as (Kim and Lee 2017, Gujarathi *et al*. 2020). In the present work, a new population-based optimization algorithm in the sports arena, called the Soccer League Optimization-based Championship Algorithm (SLOCA), will be introduced. This algorithm attempts to form a football championship league by forming a set of teams each of which represents a design, and a total of which defines a season or an iteration. The score received by each team equate to the value of the fitness function according to the optimization of the champion team.

The remaining sections of the paper are as follows; In the first part, a brief review of the common terms used in sports leagues are given, followed by the second part where the SLOCA algorithm is described step by step. In the last part, the efficiency of the algorithm will be examined through some mathematical and engineering benchmark problems.

1.1 A review of terms related to sports Champions League

Sports League is an organization to provides a regulated competition for a number of people in a certain sport. Leagues are generally used to refer to competitions related to team sports (Khaji 2014). A league championship can be discussed in several ways. Teams may compete with each other several times in which the team with the best record wins, or based on a scoring system in which a certain number of points are awarded for a win, lose or draw. The team with the highest score is declared as the league champion. After each match, every coach analyzes his team and that of his opponent to plan how they can improve their style of play and remedy their weaknesses to reinforce their strengths for the next play. This analysis also includes the assessment of opportunities and threats to the team along with the dynamics of each individual in the team (Alatas 2019). This type of analysis is commonly known as the analysis of strengths, weaknesses, opportunities, and threats, which explicitly links internal factors like strengths and weaknesses, and also external aspects such as opportunities and threats. After analyzing the game, coaches must change their game system to develop areas that strengthen players and the team (Kashan 2009). Many soccer-based algorithms have been introduced in the literature such as (Kashan 2009, Hatamzadeh and Khayyambashi 2012, Purnomo and Wee 2013, Fadakar and Ebrahimi 2016, Bouchekara 2020). Researchers have used specific soccer concepts in all of these algorithms to write optimization algorithms. For example, in Kashan (2009), an artificial league (population of solutions) is formed in which teams compete weekly (iterations). The game schedule is such that each team competes with all other teams (winner/loser system). In the end, the winning team is introduced. Another example is the study by Hatamzadeh *et al*. (2012). In that work, first a team is created and its players are divided into two groups; main and reserving players. In each iteration, the position of each player in the crowd is calculated, the player with the best position is selected from the current leading players, and parameters are exchanged between the passer and the player with the best position. When a player passes the ball, the other players move to positions where they can receive the ball and move then towards the best player. Then, at the same time, the strength of the players who participated in the previous game reduces, which indicates that the ability of the fixed players changes each time. This alteration of tactics and games will continue until the end of the season (iterations), and the winning team will be declared as the league champion. One of the main features of the proposed algorithm is the effective use of reserved players. It could weaken or strengthen the team accordingly. At the same time, it allows the algorithm experiencing different solutions. Details of the steps are given in the next section.

2. The proposed SLOCA algorithm

Similar to many other evolutionary algorithms, SLOCA works with a population of solutions. An illustrative description of the algorithm may be summarized as in the flowchart of Fig. 1. A detailed explanation of the steps taken in the SLOCA algorithm during the optimization procedure and in accordance with the above figure, may be given as in the subsequent sub-sections.

2.1 Generate initial teams

To solve an optimization problem, the variables for the problem must be properly and explicitly located within a problem-solving structure. In SLOCA, this structure is called a Team, and the problem variables represent the number of players on each team. To solve a standard problem, the structure of each team (a design) must be specified as an array. In an optimization problem with the number of variables being equal to N, each team is specified as an array 1× N.

$$\text{Team} \equiv Design \ = \ [p_1 . p_2 . \cdots . p_N] \tag{1}$$

Also, the fitness function of each team is defined as follows:

$$\text{Fitness Function} = f(\text{Team}\ ) \ = \ f(p_1 . p_2 . \cdots . p_N) \tag{2}$$

Also, as above, a group of reserve players is produced for each team.

$$\text{Reserved\_Team} = \ [p_1 . p_2 . \cdots . p_N] \tag{3}$$

Because half of the participating teams are eliminated in the Qualifying Competitions stage, the algorithm starts with twice the number of teams meant to enter, so that by eliminating the teams in this stage, it continues to work with the same number of the desired population.

2.2 Qualifying competitions

At this stage, a matrix is formed with the number of rows and columns being equal to the total number of teams and players (N_T × N_P), respectively. Before the main competition starts, the teams are first randomly placed in groups of four at random and compete with each other, and the

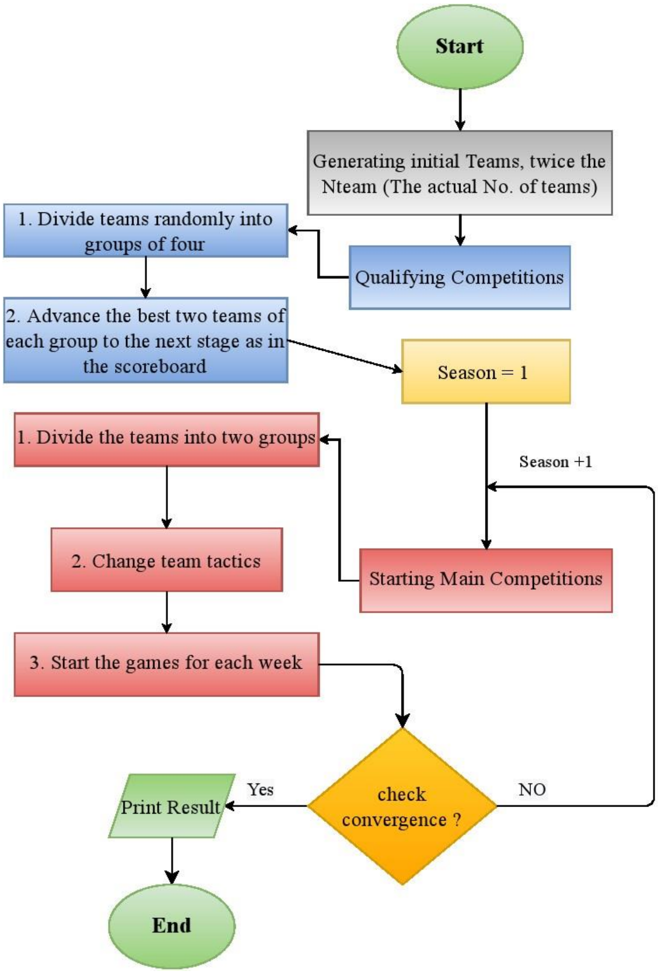


Fig. 1 Flowchart of the soccer league optimization-based championship algorithm

two teams scored the highest will advance to the main (elimination) stage of the competition. This competition is defined by the following equation

$$\mathrm{Winner} = \mathrm{Team_i} \ \rightarrow \mathrm{if} \rightarrow \frac{\mathrm{T\_Score_i}}{\mathrm{T\_Score_j} + \mathrm{T\_Score_i}} \geq 0.5 \tag{4}$$

where $\mathrm{T\_Score_i}$ equals the score of the first team ($\mathrm{Team_i}$) and $\mathrm{T\_Score_j}$ equals the score of the second team ($\mathrm{Team_j}$).

2.3 Main competitions

In the main stage, the winning teams in the previous stage are divided into two groups of R and L, which represent the right and left sides of the championship schedule table, respectively. In each of these groups, every two teams selected randomly, face each other and the winning team is advanced to the next stage while the losing team is eliminated from the stage. In real-world matches, it is possible for players to be injured or fired in each game. Besides, the ability of the players in each game could slightly be different from the previous games, and also changes may well be made to the team composition by the coach, where it is possible to use reserve players. In the SLOCA algorithm, these changes of composition and use of reserve players are defined by the following equations:

$$\mathrm{P} = \mathrm{P}_1, \mathrm{P}_2, \mathrm{P}_3, \cdots, \mathrm{P}_\mathrm{m} \tag{5}$$

$$\alpha \ = 0.01(\mathrm{VarMax} - \mathrm{VarMin}) \tag{6}$$

$$\mathrm{P}_{\mathrm{New}} = \mathrm{P} \ \times \ \alpha \ \times \ \beta \tag{7}$$

$$\mathrm{Team}_{\mathrm{new}} = \mathrm{P}_{\mathrm{New}} \times \beta + (1 - \beta)\mathrm{R\_team} \tag{8}$$

where P refers to the players of the main team and P_{New} denotes to the players after the preliminary game applied upon by the coefficients of fatigue and injury. $Team_{new}$ represents a new team to which reserve and fresh players have been added. R_team is the symbol of the reserve team players. Where α is a fatigue coefficient that if the players are not swapped to another player in the main lineup, this value will increase in the next game compared to the original value. β refers to a random number in the range of zero to one, which indicates the number of players who are replaced in this section and join the main team. This procedure continues until only two teams reach the final stage, after which the league champion team is acknowledged and the first season ends. After the end of the first season and the introduction of the league champion, if the convergence conditions are not satisfied, all the teams will enter the second season of the competition, and this stage will continue until the convergence conditions are satisfied.

2.4 Convergence criteria

For this purpose, either of the following five different convergence criteria may favor completion of the optimization procedure: 1. A maximum number of iterations is confined. 2. The obtained optimum solution to the problem does not change for a certain number of iterations. 3. A certain predefined level of answer accuracy is achieved. 4. A certain time to execute an optimum solution is reached. 5. The average fitness of all the fitnesses reaches a certain level of approval to the fittest.

2.5 Parameters setting

There are two parameters in the SLOCA algorithm that need to be adjusted to find a better answer. These coefficients are determined based on how much they alter in real-world games mentioned by Colwell (2000). These parameters include the rate of preliminary games or the rate of teams leaving the qualifying round (Lt) and the rate of Main Competitions (MC). *Lt* represents the percentage of teams that proceed to the next stage, which is generally equal to 0.5, meaning that only teams that have won the qualifying round can advance to the main stage of the league.
But if this amount is higher, it means that in addition to the winning teams, a number of teams that have lost but scored more points than the other losing teams will also advance to the main competition. MC represents the percentage of teams competing in the league each week. (Colwell 2000, Gilis *et al*. 2006, Armenteros and Curca 2008). Fig. 2 shows the pseudocode of proposed algorithm.

Pseudo Code of Soccer League Optimization-based Championship Algorithm
Input: Maximum number of seasons (Max_It), Rates of teams leaving the qualifying round, Number of players, rate of Main Competitions ***Output***: Near-optimal solution for the objective function

// initialization
1. initial teams
Each team is a N-dimensional array of players for a N-dimensional problem;
2. Qualifying competitions
Grouping teams in groups of four teams at random and based on qualifying competitions rate, calculate the fitness function and choose the winning teams for the main competition (using Eq. 4);
//Loop until the terminal convergence conditions
3. For i=1: (Lt*number of teams);
// Main competitions
4.Divide the teams into two groups at random;
5. Change tactics and players. (using Eq8);
6. start the games for each week;
7. When all the teams have played together, introduce the top team based on the highest score;
8.End for;
// Updating
9.Updating the participating teams;
10.Returning the best team(solution);

Fig. 2 Pseudo code of soccer league optimization-based championship algorithm

Table 1 Benchmark functions to evaluate the speed and accuracy of the SLOCA

Function	Equation	Range	Characteristic
F1: Ackley	$f_1(x) = -20\exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right) - \exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right) + 20 + e$	$-35 \le x_i \le 35$	MN
F2: Rastrigin	$f_7(x) = \sum_{i=1}^{n}(x_i^2 - 10\cos(2\pi x_i) + 10)$	$-5.12 \le x_i \le 5.12$	MS
F3: Cigar	$f_3(x) = x_1^2 + 10^6\sum_{i=2}^{n} x_i^2$	$-5.12 \le x_i \le 5.12$	N/A
F4: Csendes	$f_4(x) = \sum_{i=1}^{n} x_i^6\left(2 + \sin\frac{1}{x_i}\right)$	$-1 \le x_i \le 1$	M
F5: Sphere	$f_{11}(x) = \sum_{i=1}^{n} x_i^2$	$-5.12 \le x_i \le 5.12$	US

Table 2 Parameters values

Algorithm	Parameter	Value	Parameter	Value
GA	crossover rate	0.6	Mutation rate	0.4
PSO	Inertia weight	2	Best global experience	2
	Best personal experience	2	w-damp	0.98
SLOCA	MC	0.5	Lt	0.5

Table 3 Comparing the results in different dimensions with some well-known optimization algorithms

Function		F1			F2		
Nplayers		10	20	50	10	20	50
Nteam		100	150	200	100	150	200
GA	Best	4.82E−05	3.40E−07	2.92E−12	4.81E−10	3.29E−08	4.01E−06
	Mean	4.97E−02	1.05E−01	4.62E−02	5.73E−01	4.94E−02	1.12E−01
	Median	1.22E−02	2.05E−02	1.76E−02	7.90E−03	1.75E−03	5.97E−02
PSO	Best	8.44E−05	9.86E−01	7.10E+00	2.03E−01	1.75E+01	1.56E+02
	Mean	4.43E−03	2.50E+00	1.01E+01	7.90E+00	5.11E+01	3.28E+02
	Median	2.68E−03	2.52E+00	1.02E+02	6.09E+00	5.80E+01	3.43E+02
SLOCA	Best	**8.88E-16**	**8.88E-16**	**2.79E-15**	**0**	**0**	**0**
	Mean	**8.88E-16**	**4.79E-15**	**3.98E-15**	**0**	**0**	**0**
	Median	**8.88E-16**	**4.44E-15**	**3.45E-15**	**0**	**0**	**0**
The best result by		SLOCA	SLOCA	SLOCA	SLOCA	SLOCA	SLOCA

Function		F3			F4		
Nplayers		10	20	50	10	20	50
Nteam		100	150	200	100	150	200
GA	Best	1.11E−01	3.81E−01	1.87E+01	8.93E−23	2.19E−21	2.85E−17
	Mean	8.24E−01	1.39E+00	2.66E+01	1.03E−20	1.73E−20	7.01E−17
	Median	6.17E−01	1.34E+00	2.63E+01	2.79E−21	1.62E−20	6.52E−17
PSO	Best	9.07E−04	5.88E+00	3.76E+05	2.13E−20	3.04E−10	2.73E−04
	Mean	16.6E+00	2.12E+02	1.65E+06	3.23E−14	2.05E−07	1.07E−03
	Median	26.2E+00	1.01E+02	1.54E+06	9.45E−15	4.72E−08	8.00E−04
SLOCA	Best	**1.13E-191**	**1.22E−42**	**2.22E−42**	**0**	**1.44E−43**	**3.23E-24**
	Mean	**2.54E-189**	**4.59E−38**	**3.69E−38**	**0**	**3.68E−33**	**1.21E-19**
	Median	**1.25E-189**	**9.89E−36**	**7.79E−36**	**0**	**2.89E-33**	**4.63E-22**
The best result by		SLOCA	SLOCA	SLOCA	SLOCA	SLOCA	SLOCA

Function		F5		
Nplayers		10	20	50
Nteam		100	150	200
GA	Best	1.30E−11	5.86E−15	1.39E−15
	Mean	6.15E−04	6.82E−04	6.46E−04
	Median	7.90E−06	1.77E−05	2.23E−05
PSO	Best	8.33E−05	2.75E−03	9.66E−01
	Mean	8.60E−03	1.33E−02	3.52E+00
	Median	3.72E−03	7.55E−03	3.39E+00
SLOCA	Best	**2.17E-208**	**5.59E-296**	**6.49E-280**
	Mean	**1.49E-200**	**7.25E-107**	**7.25E-127**
	Median	**1.61E-205**	**3.06E-165**	**3.26E-155**
The best result by		SLOCA	SLOCA	SLOCA

OF-1*: NPlayers=Number of Variables, Nteam = Number of Designs, NSeason= Maximum Number of Iterations

3. SLOCA competence over some benchmark functions and engineering problem

In this section, the SLOCA optimization algorithm is tested with 6 benchmark functions, all of which are minimization functions. Since the final solution of the benchmark functions is already known, assessing the specified level of accuracy of the proposed algorithm may well be detected. To evaluate the performance of the proposed algorithm when compared with other known metaheuristic algorithms, the maximum number of iterations is considered as a stopping criterion in this section. These benchmark functions are classical functions used by various researchers that can be mentioned to (Kaveh and Bakhshpoori 2016, Varaee and Ghasemi 2017, Gupta *et al*. 2020, Hayyolalam and Kazem 2020). Table 1 and Eqs. (9)-(10) lists all the 6 benchmark functions under study. The results obtained from the SLOCA algorithm are compared with the standard form of the GA, the PSO algorithms.

3.1 Benchmark functions_results and discussions

To explore the ability of the proposed SLOCA algorithm, two different types of problems namely as unconstrained and constrained functions were attempted.

3.1.1 Unconstrained functions

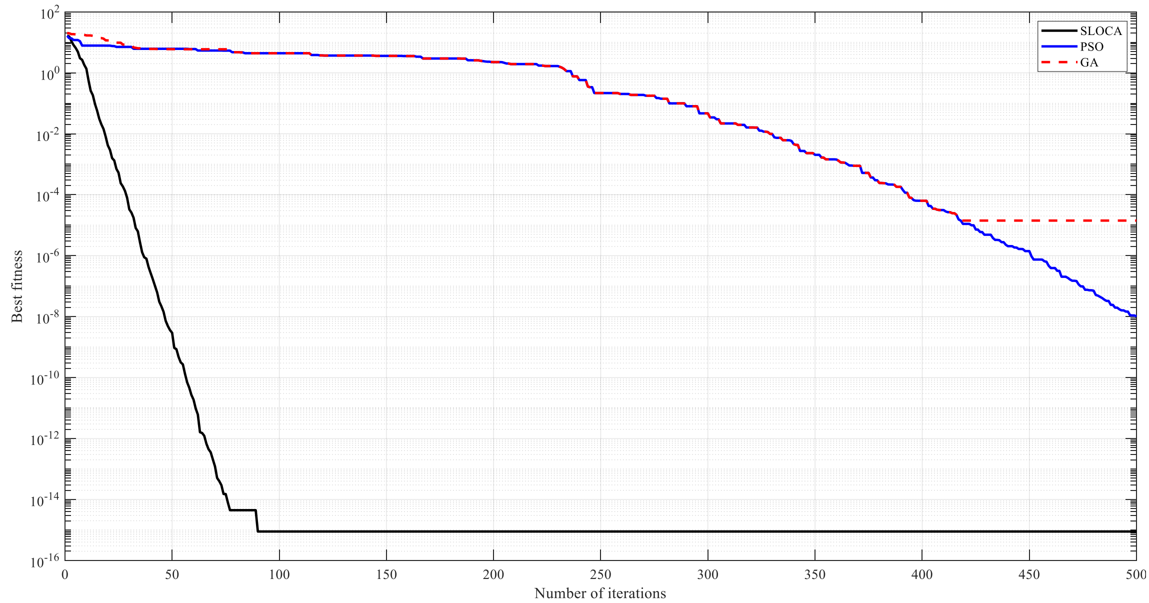
First, some nonlinear benchmark functions were attempted for unconstrained optimization. These functions are listed in Table 1 with their characteristics denoted as M, U, C, S, N. They are signified for Multi-modal, Uni-modal, Composition, Separable and Non-separable, respectively. Apart from SLOCA algorithm, two other metaheuristic technique based on GA and PSO concepts were used for comparison. However, prior to executing each program, the related parameters of the algorithms were set as listed in Table 2.

The results reported in Table 3 were obtained after 30 runs for each algorithm. Number of variables were also categorized distinctly as 10, 20 and 50. Also, the population size was allowed to differ in order to study the sustainability and standard deviation of each algorithm. The maximum number of iterations for all cases was set to 500 as a termination criterion in case not converged earlier. "Best" indicates the best answer of the function in 30 runs of codes execution, "Mean" and "Median" are computed according to the "$\text{Mean} = \frac{\text{SUM of the terms}}{\text{number of terms}}$" and "$\text{Median} = \text{middle of the set of numbers}$" related to each function in 30 times of running the optimization procedure. As shown in Table 3, SLOCA exhibits more accurate results than other algorithms for all functions, especially when a greater number of variables is involved.

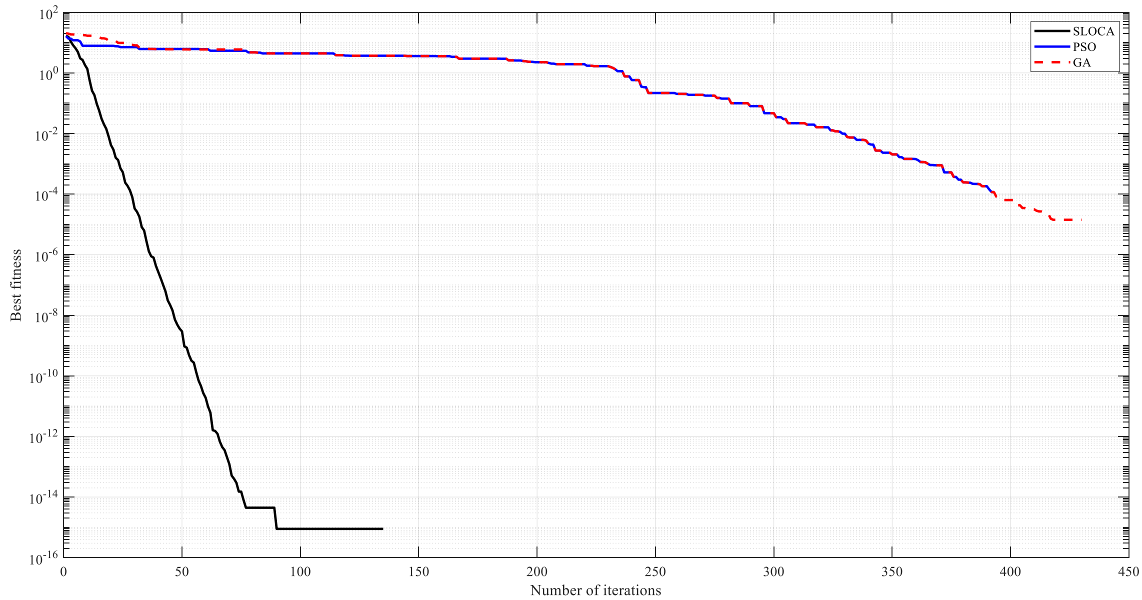
3.1.1.1 Comparison on the convergence histories

For the case where Nteam is equal to 100, a number of convergence studies are performed in this section. Fig. 3(a) illustrates the convergence history on the optimization performance of F1 function using GA, PSO and the proposed SLOCA algorithms. An obvious high speed and a sudden convergence to the global optimum solution is apparent with the SLOCA algorithm compared to the other two approaches. Evidently, the SLOCA algorithm managed to reach the global minimum after 15 iterations, where the other two required at least twenty times more analyses to converge, indicating a convergence experience for SLOCA with a significantly lower number of analyses needed. Fig. 3(a) presents the convergence history with a forced termination criterion at a maximum of 500 iterations to all procedures to make sure of the global convergence. As shown in Fig. 4, the same behavior is apparent when running optimization for the F2 function.

Another study was carried out here for only two of the functions F1 and F5 when Nteam was kept as 50 and only allowed to experience optimization procedure for up to 15 iterations. As shown in Fig. 8 and the results of which are recorded in Table 4, the SLOCA algorithm performed



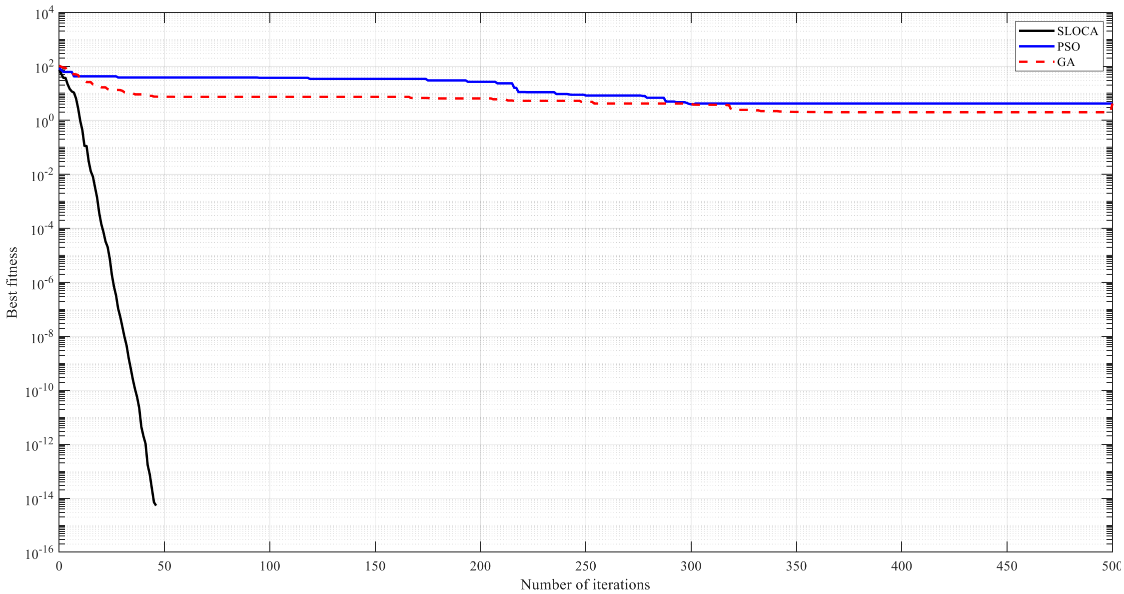
(a) Terminated after 500 iterations



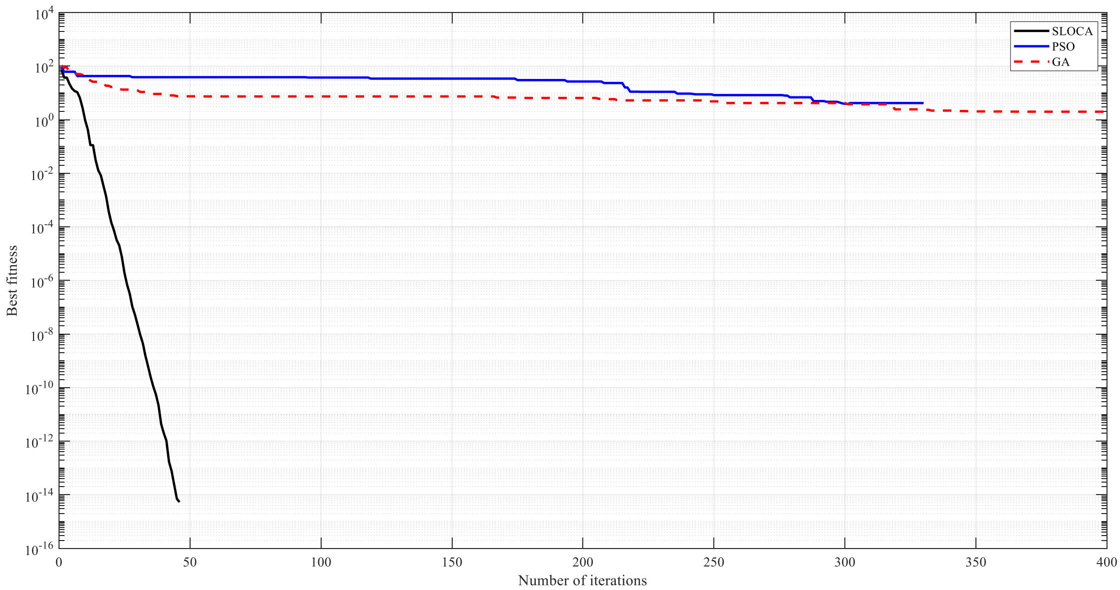
(b) Terminated after 30 iterations without improvement

Fig. 3 Convergence histories for F1 (n = 10)

a convergence to the global minimum, many times faster and more accurate than the other two algorithms within the 15 iterations. For the F5 function, as shown in Fig. 9, the SLOCA even explored a faster convergence to the global optimum after 7 iterations, a clear advancement to the other two metaheuristic algorithms. Thus, as far as even a certain imposed number of analyses to all approaches is concerned, a significant superiority of the SLOCA algorithm to other methods



(a) *Terminated after 500 iterations



(b) Terminated after 30 iterations without improvement

Fig. 4 Convergence of F2 (n = 10)

*OF-2: By reason of the semi-logarithmic scale of the figure, showing zero in the figure was incomprehensible. Therefore, the convergence curve for SLOCA did not continue after reaching the zero point.

was evident.

Also, in Table 5, a symbolic study on the standard deviations (STD) over the same two functions F1 and F5 was carried out using SLOCA, while ten variables were involved and the

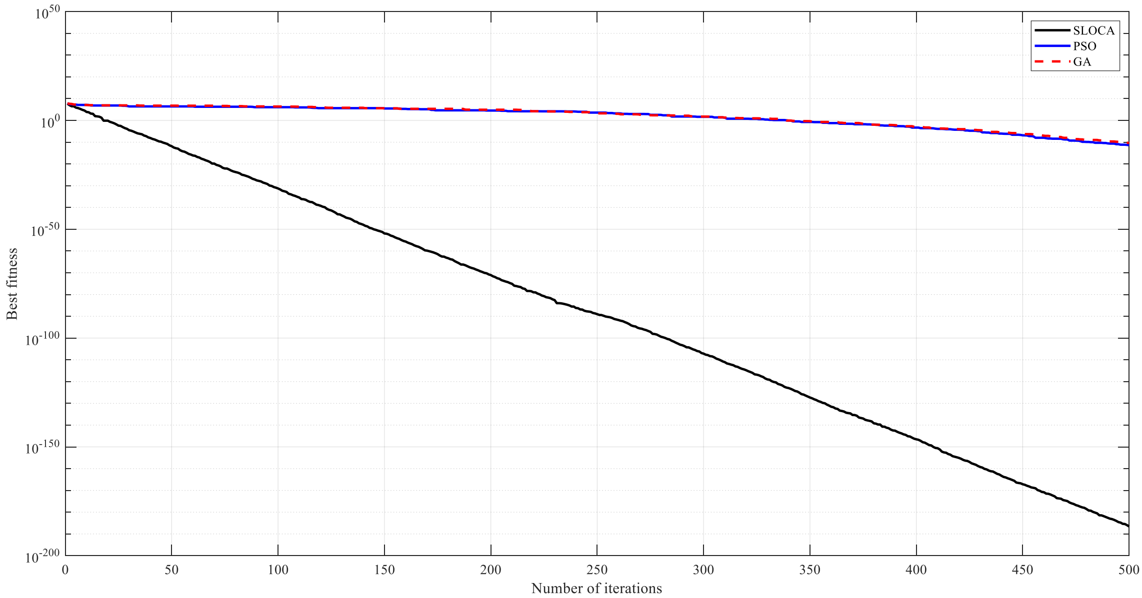


Fig. 5 Convergence of F3 (n = 10)

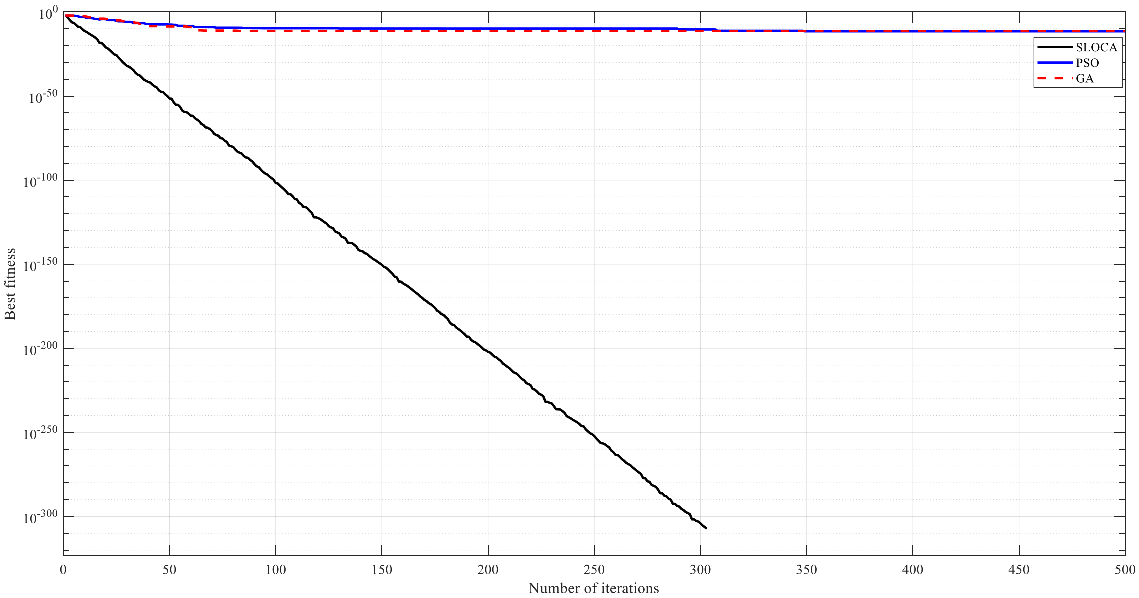


Fig. 6 Convergence of F4 (n = 10)

Nteam was set to 200 for a maximum of 10 iterations throughout the optimization procedure and for a total of 30 runs. As shown in Table 5, compared with those of GA and PSO, the SLOCA algorithm displayed significantly higher stability and firmness in finding the global optimal solution.

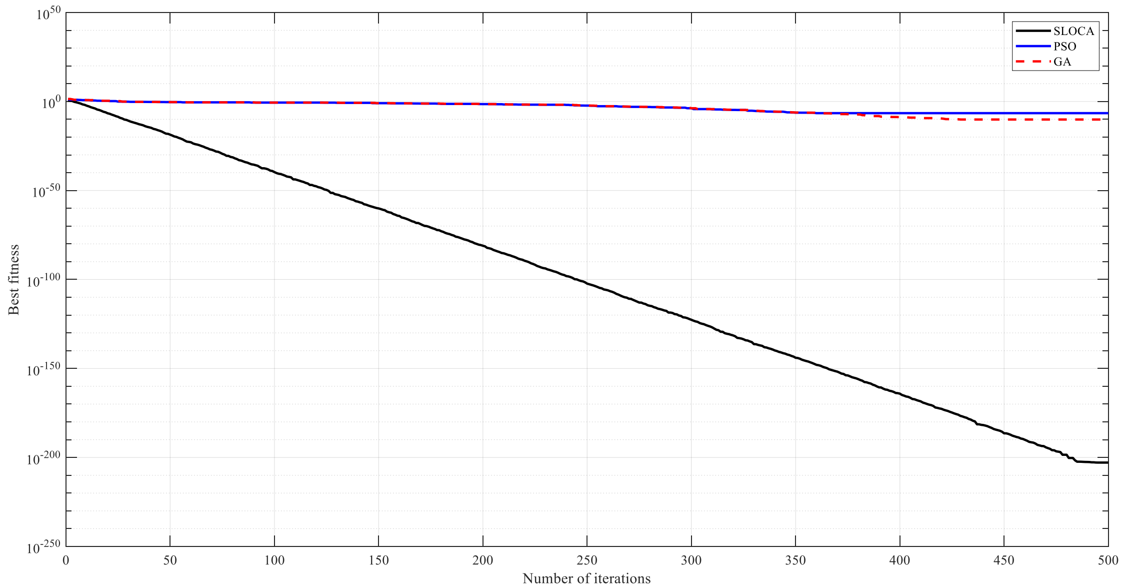


Fig. 7 Convergence of F5 (n = 10)

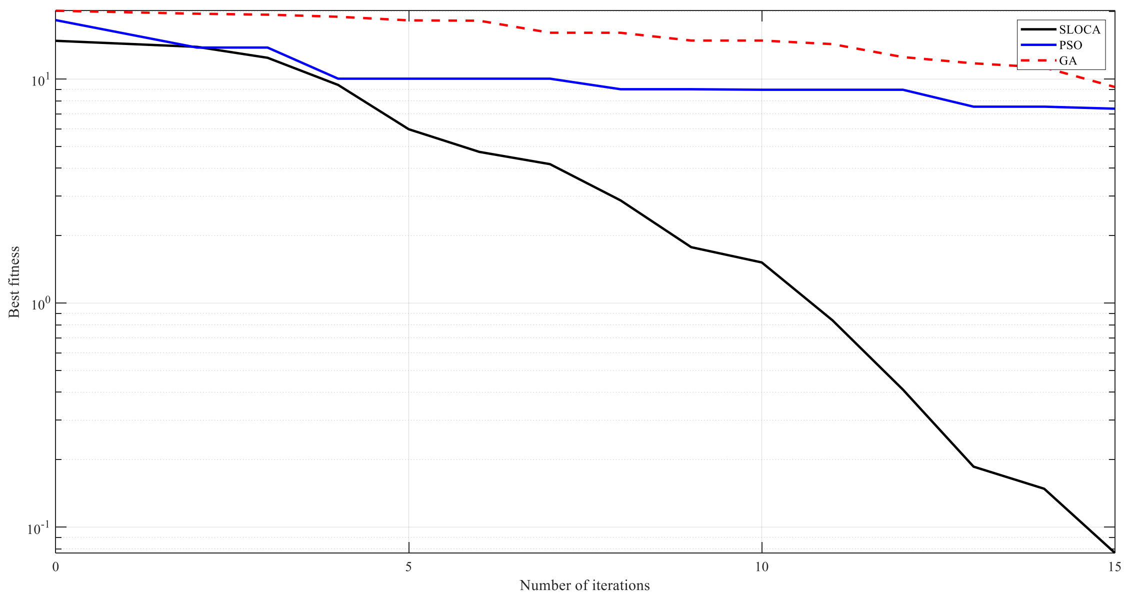


Fig. 8 Convergence of F1 (Number of Analysis = 1000)

3.1.2 Constrained functions

One of the most challenging benchmark functions in optimization is Kean's constrained bump function as defined in Eqs. (9) and (10). It has been attempted by some researchers that can be mentioned to Nestruev *et al*. (2003), Geethaikrishnan *et al*. (2009), and Gupta *et al*. (2020). Here, the aim is to further encounter the SLOCA algorithm for its versatility and globality. Thus, by

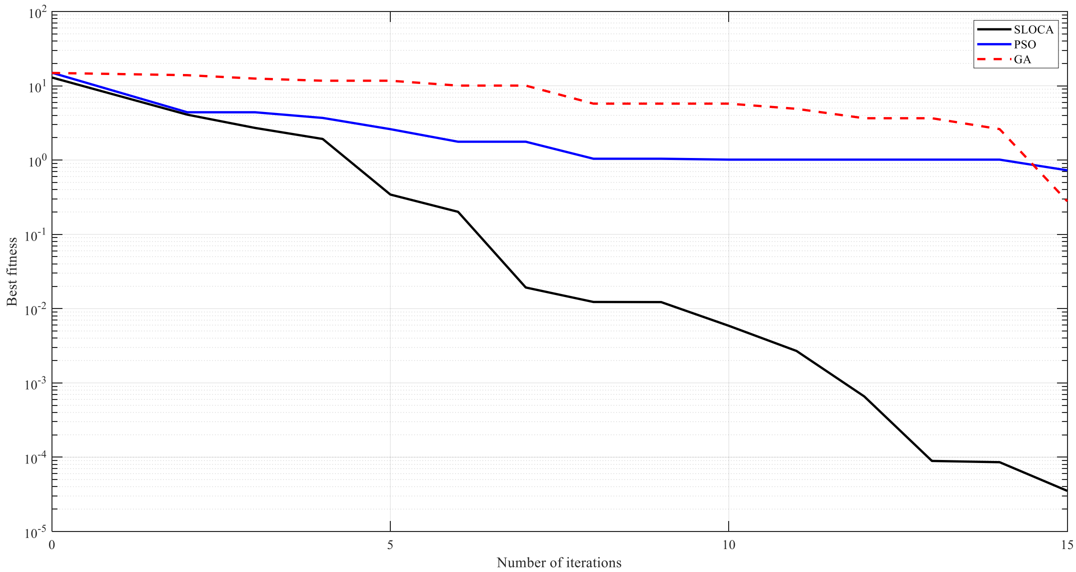


Fig. 9 Convergence of F5 (Number of Analysis = 1000)

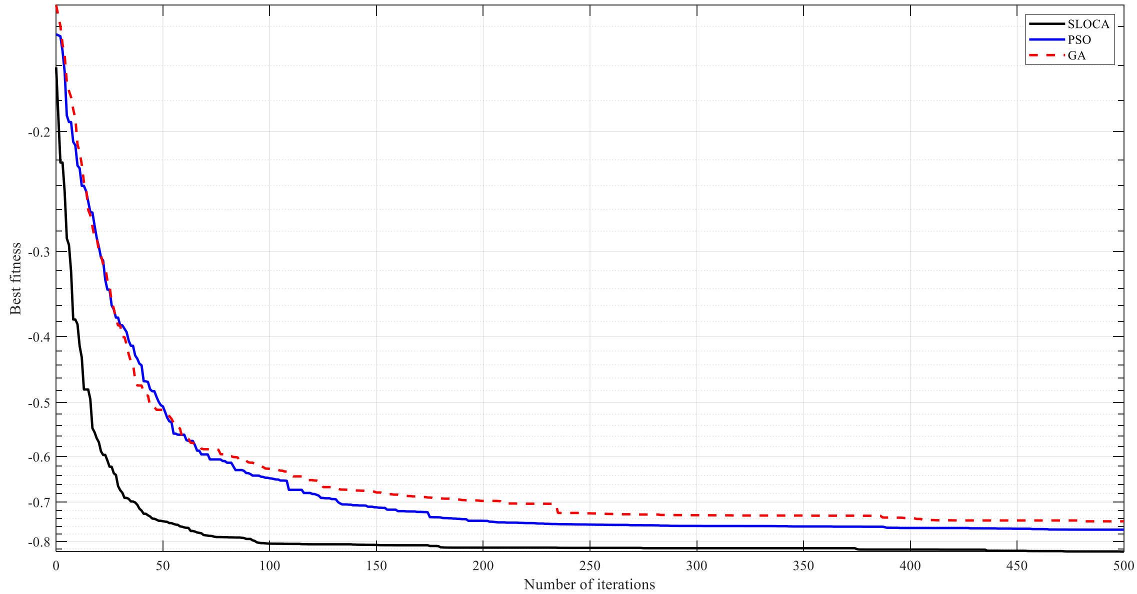
Table 5 Values for standard deviations on the two functions F1 and F5

Function		F1			F5	
Algorithm	GA	PSO	SLOCA	GA	PSO	SLOCA
Best	1.15E-8	8.56E-05	**8.88E-16**	3.63E-16	7.41E-09	**2.14E-208**
Mean	3.65E-02	4.43E-03	**5.96E-15**	2.77E-05	2.15E-05	**7.65E-137**
Median	3.77E-03	2.66E-03	**3.55E-15**	1.96E-07	4.65E-06	**3.99E-155**
STD	8.63E-02	5.89E-03	**7.63E-14**	1.33E-04	2.96E-05	**2.89E-135**

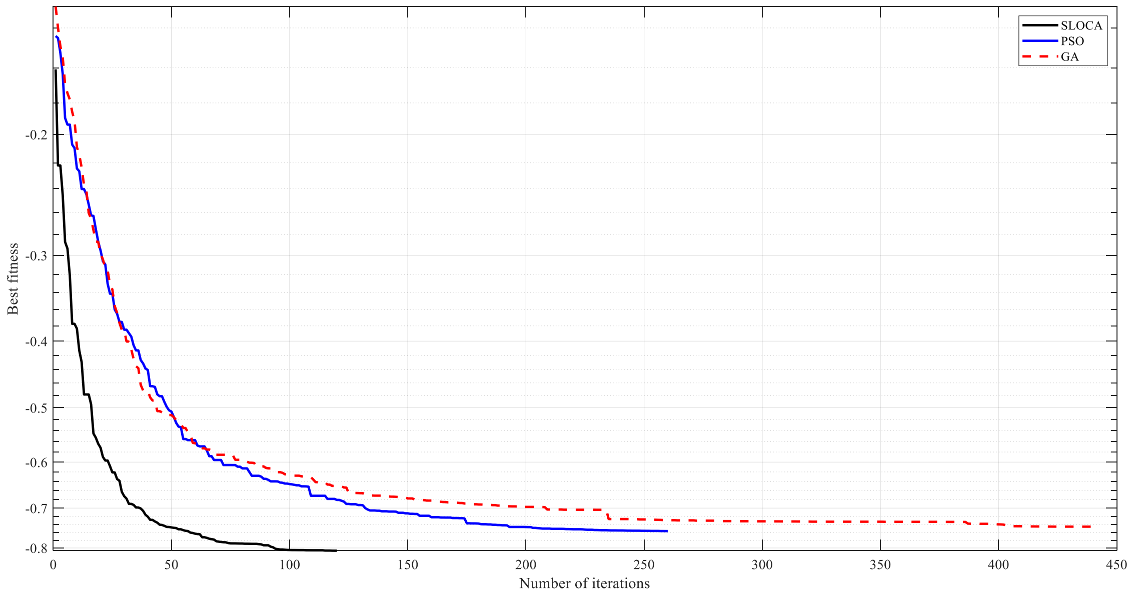
Table 6 Results of bumpy function

Function			Bumpy	
Nplayers	10	20		50
Nteam	100	150		200
GA	Best	-0.71466	-0.73698	-0.75263
	Mean	-0.71532	-0.72698	-0.74466
	Median	-0.69352	-0.71202	-0.72048
PSO	Best	-0.75463	-0.78165	-0.78839
	Mean	-0.75386	-0.77225	-0.76532
	Median	-0.71325	-0.77232	-0.75396
SLOCA	Best	**-0.79213**	**-0.8024**	**-0.82762**
	Mean	**-0.79198**	**-0.8008**	**-0.82762**
	Median	**-0.79165**	**-0.7963**	**-0.82762**
The best result by	SLOCA	SLOCA	SLOCA	SLOCA

employing 20 analyses at each iteration, the GA, PSO, and the SLOCA algorithms were executed, each for 30 times, distinctly under 10, 20, and 50 variables. The parameter characteristic are similar



(a) Terminated after 500 iterations



(b) Terminated after 30 iterations without improvement

Fig. 10 Convergence of Kean Bumpy function)

to unconstrained problems as set up in Table 2 above.The optimum results are listed in Table 6, where it shows a consistency of the solutions in all algorithms, however, the SLOCA could clearly perform the best results in terms of accuracy and speed, with the lowest standard deviation achieved.

Fig. 10(a) illustrates the convergence histories when each of the aforementioned algorithms was allowed for up to 500 iterations. In Fig. 10(b) the convergence criterion on the best solution played a role, causing SLOCA to complete the optimization process after 120 iterations, with a more accurate solution and obviously faster.

$$Minimize\ f(x) = -\left|\left\{\sum_{i=1}^{m} cos^4(x_i) - 2\prod_{i}^{m} cos^2(x_i)\right\} / \left(\sum_{i=1}^{m} ix_i^2\right)^{0.5}\right| \tag{9}$$

$$subject\ to{:}\ g_1(x) = 0.75 - \prod_{i=1}^{m} x_i < 0\,;\ \ g_2(x) = \sum_{i=1}^{m} x_i - 7.5m < 0; x_i < 10 \tag{10}$$

4. Engineering design problems_results and discussions

In this section, the SLOCA algorithm is applied to another benchmark problem, this time to evaluate its performance in handling engineering problems. Engineering problems related to the design of steel bending frames are known problems in engineering design that many researchers including Salarnia and Ghasemi (2021), Kaveh *et al*. (2020) and Khaje *et al*. (2017).

4.1 Frame optimization problems

In most studies on steel frames, the goal is to find the optimal design with the least possible weight. This design is expressed as the following equation:

$$f(X) = \sum_{i=1}^{n} \gamma_i A_i L_i \tag{11}$$

where f (X) is the objective function and represents the optimum weight of the structure. γ is the density of the material, A is the cross-sectional area of the elements and L is the length of the element. i represents the desired element number and n represents the total number of structural elements. According to AISC-LRFD (2001), structures should follow some design constraints. These constraints may include the following:

Stress limits for each element may be given by Eq. (12)

$$v_i^{\sigma} = \left|\frac{\sigma_i}{\sigma_i^{\alpha}}\right| - 1 \le 0 \qquad i = 1,2,\dots,n \tag{12}$$

And maximum lateral displacement limit states that

$$v^{\Delta} = \frac{\Delta_T}{H} - R \le 0 \tag{13}$$

Restrictions on the drifts of floors relative to each other is given by:

$$16v_j^d = R_I - \frac{d_j}{h_j} \le 0 \qquad j = 1,2,\dots,n_s \tag{14}$$

where σ_i and σ_i^{α} are the current and allowable stresses for each element, respectively. R is equal to

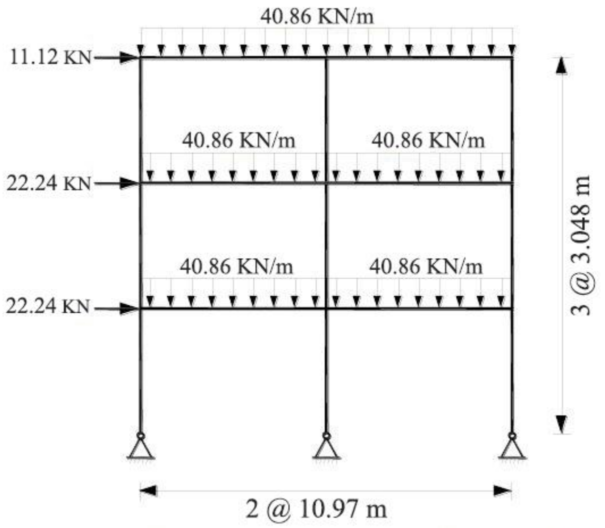


Fig. 11 Two-bay, three-story planar frame

the maximum amount of drift allowed. Δ_T is equal to the maximum lateral displacement the structure experiences at each design interval. H is equal to the height of the whole structure and d_j is equal to the drift between the floors. h_j is equal to the height of the j^{th} floor. n_s denotes the total number of floors and R_I is equal to the allowable drift between floors. Also, i signifies to the current frame member and n is the total number of frame members. According to the AISC regulations, the permissible drift between floors is 1⁄300 and the LRFD limit is defined according to the following equation:

$$v_i^I = 1 - \frac{P_u}{2\varphi_c P_n} - \left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) \geq 0 \qquad For\ \frac{P_u}{\varphi_c P_n} < 0.2 \tag{15}$$

$$v_i^I = 1 - \frac{P_u}{\varphi_c P_n} - \frac{8}{9}\left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) \geq 0 \qquad For\ \frac{P_u}{\varphi_c P_n} \geq 0.2 \tag{16}$$

where P_u is equal to the required strength and P_n is equal to the nominal axial strength. φ_c denotes to the coefficient of resistance (0.9 for tension and 0.85 for pressure). M_{ux} and M_{uy} are equal to the required flexural strength in the X and Y directions, respectively. M_{nx} and M_{ny} are the nominal flexural strength in the X and Y directions, respectively (for the two-dimensional frames, $M_{uy} = 0$). φ_b is equal to the coefficient of reduction of flexural strength. ($\varphi_b = 0.90$). In this paper, the main formula for effective length is determined, which is between -1% and 2% of accurate results.

$$K = \sqrt{\frac{1.6G_A G_B + 4(G_A G_B) + 7.5}{G_A + G_B + 7.5}} \geq 1 \tag{17}$$

In the above equation, G_A and G_B refer to the coefficient of stiffness or relative stiffness of the column at both ends.

According to the findings of the above studies on the benchmark functions where a fast convergence to the global optimum solution was inevitable using the proposed technique.

Table 7 Optimum results of the two-bay, three-story planar frame

Element Group no.	Element Type	Algorithm		
		GA	ACO	SLOCA
1	Beams	W24X62	W24X62	W24X62
2	Columns	W10X60	W10X60	W10X60
Optimum weight(kN)		83.7759	83.7759	83.7759
No. of required analyses		1800	3000	800

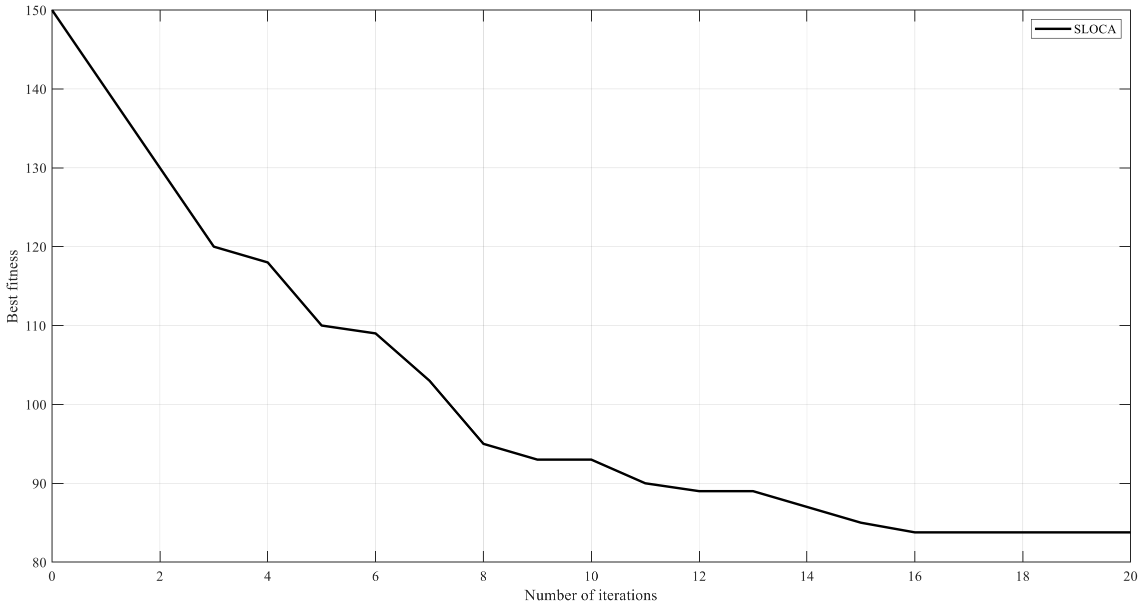


Fig. 12 Convergence history diagram of the two-bay, three-story planar frame

4.1.1 Two-bay, three-story planar frame

A two-span, three-story engineering frame problem is also investigated here. The structure is shown in Fig. 11. The design constraints for the problem are based according to the AISC-LRFD regulations, mentioned in the previous section. The modulus of elasticity is E = 200 GPa (29000 Ksi) and the yield stress is F_y = 248.2 MPa (36 Ksi) and the density of the material is γ = 7861 Kg/m^3 (0.284 lb/in^3). The coefficient of unrestrained length of the beam is set at 0.167. The group of columns is selected from a catalogue list of seventeen W10 sections from within the AISC regulations, and for the beams W sections are used without limit from a catalogue list of 267 sections. It has been attempted by some researchers that can be mentioned to Mahallati *et al.* (2018), and Pezeshk *et al.* (2000).

According to Table 7, the procedure reached the converging global optimum solution after 800 analyzes (16 replications with an initial population of 50), while the GA and ACO required in order, 2.25 times and 3.75 times more analyses to globalize the solution.

Fig. 12 represents the convergence history diagram towards the optimum design for the frame structure using the proposed SLOCA algorithm, a performance of which coincides with the data listed in Table 7.

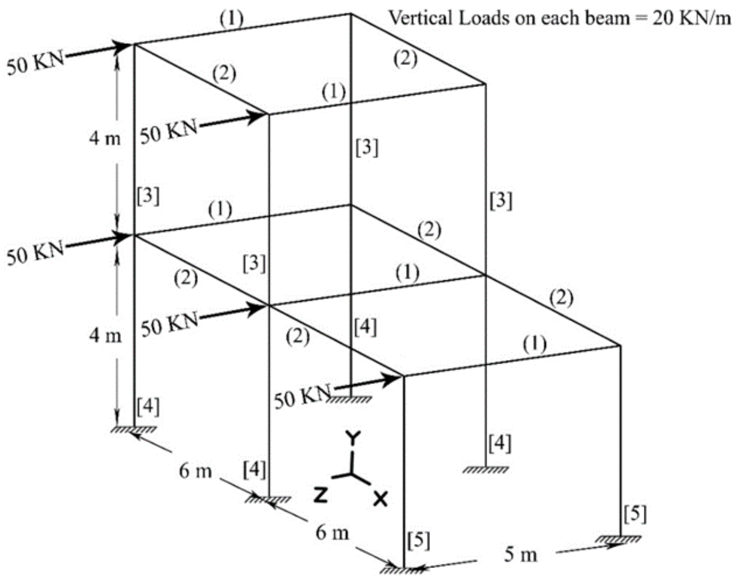


Fig. 13 Two-Story, Two bay irregular steel space frame

Table 8 Optimum results of Two-Story, Two bay irregular steel space frame

Element Group no.	Algorithm		
	ACO	HS	SLOCA
1	W18X40	W18X40	W18X35
2	W14X22	W12X19	W16X26
3	W18X35	W16X40	W14X22
4	W18X46	W18X40	W16X40
5	W12X30	W16X26	W16X26
Weight (KN)	48.68	46.63	45.54

4.1.2 Two-story, Two bay irregular steel space frame

The two-story, two-bay irregular steel space frame has 21 members that are collected in two-beam and three-column design groups. The dimensions and member groupings in the frame are shown in Fig. 13. The frame is subjected to wind loading of 50kN along the Z-axis in addition to the 20kN/m gravity load, which is applied to all beams. The drift ratio limits are defined as 1 cm for inter story drift 4 cm for top story drift where H is the height of the frame. The maximum deflection of beam members is restricted to 1.39 cm. (Aydoğdu 2010)

As shown in Table 8, the proposed algorithm performed slightly lighter weight as the optimal design for the frame structure within the maximum range of analyses allowed (5000).When the maximum number of analyses allowed to exceed up to 10000, as shown in Fig. 14, there was only a minor reduction with SLOCA reaching the global optimum weight of 45.54 KN after 5100 analyses, whereas the other algorithms converged after 8000 and 6700 analyses, respectively and slightly heavier.

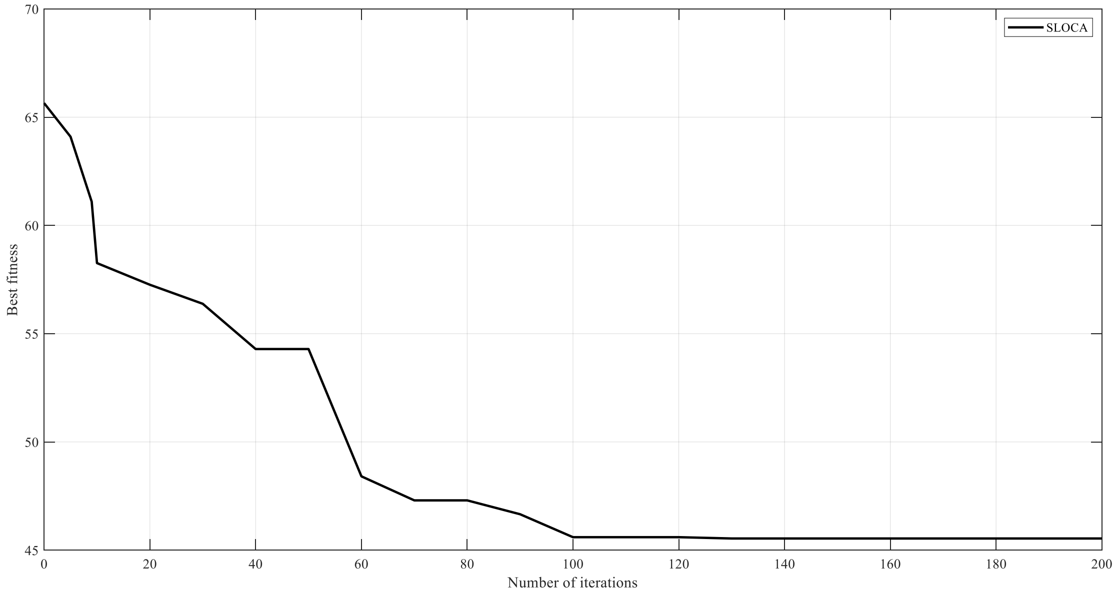


Fig. 14 Convergence history diagram of Two-Story, Two bay irregular steel space frame

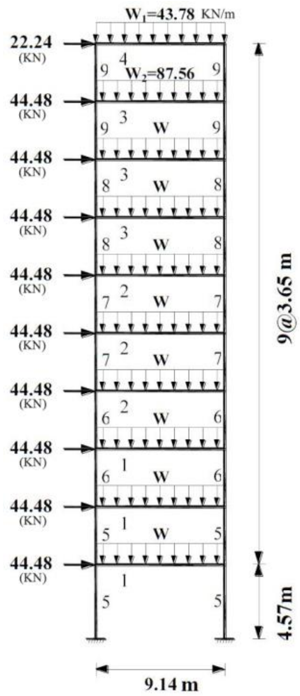


Fig. 15 One-bay ten-story planar frame

4.1.3 One-bay ten-story frame optimum design

Fig. 15 shows a schematic representation of the second engineering problem for optimization; a one-span ten-story frame with the predefined boundary conditions and loading. This frame is one

Table 9 Optimum results of one-bay ten-story planar frame

Element Group no.	Element Type	Algorithm				
		GSU-PSO	CPA	ACO	BB-BC	SLOCA
1	Beam	W40X167	W40X149	W30X108	W33X118	W33X118
2	Beam	W30X90	W30X108	W30X90	W30X90	W30X90
3	Beam	W24X76	W30X90	W27X84	W30X99	W24X76
4	Beam	W10X68	W21X55	W21X44	W18X60	W14X30
5	Column	W12X210	W12X279	W14X233	W14X283	W14X233
6	Column	W12X136	W12X252	W14X176	W12X252	W14X176
7	Column	W12X132	W14X211	W14X145	W14X211	W14X145
8	Column	W12X96	W14X176	W14X99	W12X190	W14X90
9	Column	W12X58	W14X145	W12X65	W14X145	W12X65
Best weight (kN)		293.66	281.65	278.48	280.13	274.99

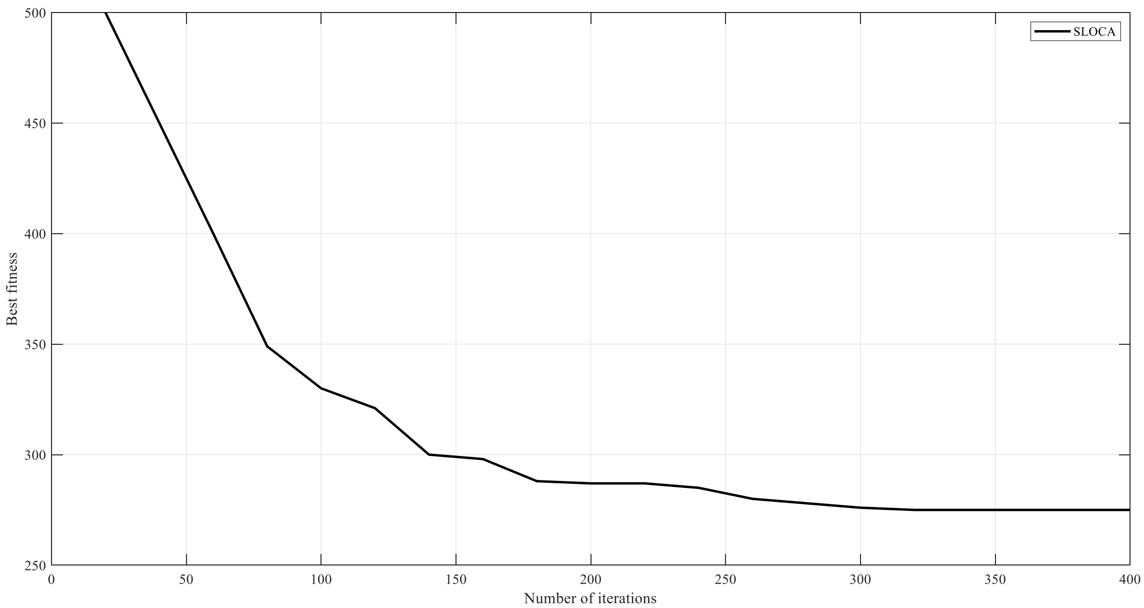


Fig. 16 Convergence history diagram of One-bay ten-story planar frame

of the standard design problems that has been used by several researchers (Pezeshk *et al*. 2000, Mahallati *et al*. 2018, Kaveh *et al*. 2020). In this problem, beams utilized W sections without restriction according to AISC regulations, but the columns are limited to groups W12 and W14. The frame is also designed according to AISC-LRFD regulations and the drift of floors is constrained smaller than the height of the floor divided by 300. The modulus of elasticity is set to 200GPa and the yield stress is fy = 248.2 MPa. The convergence history diagram and the arrangement of the beams and columns are also specified in Figs. 15 and 16, respectively. As is evident in Table 9, the proposed SLOCA algorithm explored a highly satisfactory performance in finding the optimal solution in relatively lower number of analyses.

Table 10 Comparison of SLOCA with other soccer-inspired methods

Function	Sphere	Rastrigin	Ackley
Algorithm			
LCA	1.02E-14	0	2.58E-13
SGO	1.15E-12	7.0231	0.0008
FOA	2.21E-24	0.8891	1.26E-13
FGA	2.13E-28	5.1254	0.0013
MVPA	1.10E-28	0	7.15E-21
SLOCA	**6.59E-279**	**0**	**2.66E-21**

For this frame, 20,000 analyzes have been set for the algorithm (population equal to 50 and 400 repetitions). As shown in Fig. 16, the proposed algorithm obtained less weight in 300 replications (15,000) of the analysis than other comparable algorithms.

5. Related works

This section references to the differences and advantages of SLOCA compared to soccer-inspired methods such as LCA by Kashan (2009), SGO introduced by Purnomo and Wee (2013), FGA presented by Fadakar and Ebrahimi (2016), FOA proposed by Hatamzadeh *et al*. (2012a, b) and MVPA presented by Bouchekara (2017). In this comparison, in conjunction with Alatas (2019), 30 runs are executed with fixed 90.000 function evaluations at each run to compare the comprehensive performance of algorithms within the global unconstrained benchmark optimization problems. The best values for every problem are illustrated in Table 10. The advantages of SLOCA compared to other methods may be summarized as follows: 1. SLOCA is able to solve problems in all three types of variable modes: discrete, semi-discrete and continuous, 2. It has only two main fixed parameters, including initial population and convergence criteria, unlike LCA, SGO, FGA, and FOA, which mainly have 3 to 4 fixed parameters. 3. One of the main differences of SLOCA compared to other methods is that it is much easier to implement on optimization problems than different algorithms and finally 4. Applying a fatigue factor to the players and randomly using the reserve players allows the proposed algorithm to avoid premature convergence because the teams' tactics change uniquely at the start of each game. Thus, the search space is globally observed and the feasible space is explored faster.

6. Conclusions

This paper presents a new meta-heuristic optimization algorithm inspired by the Soccer League Championship Competition (SLOCA). In order to investigate on the accuracy and convergence speed of the algorithm, its performance has been examined on six benchmark functions and two engineering frame problems. Comparison of SLOCA with some well-known algorithms showed that SLOCA has a very promising performance in finding the final optimal solution with high accuracy and fast convergence. Besides, in addition to a set of leading and main solutions (main players), SLOCA uses adjacent responses (reserve players) to determine the location of the next solution. This feature allows each response to take advantage of other solutions. At the same time, this strategy allows the proposed algorithm to maintain diversity in new findings, and this brings the optimal solution obtained by the SLOCA closer to the final and the global optimal response, creating assuring and reliable solutions.

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