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Improving DE-based cooperative coevolution for constrained large-scale global optimization problems using an increasing grouping strategy

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Abstract. Nowadays, high-dimensional constrained «Black-Box» (BB) optimization problems has become more urgent. At the same time, the constrained large-scale global optimization (cLSGO) problems are not well studied and many modern optimization approaches demonstrate low performance when dealing with cLSGO problems. Evolution algorithms (EAs) has proved their efficiency in solving low-dimensional constrained optimization problems and high-dimensional single-objective optimization problems. In this study, we have proposed a new approach based on the cooperative coevolution (CC) framework and an algorithm for increasing size of variables grouping on the decomposition stage (iCC) when solving cLSGO problems. We have proposed a novel EA that combines SHADE, iCC and ε constrained method (E-iCC-SHADE). The proposed optimization algorithm has been investigated using a new cLSGO benchmark, which is based on scalable problems from IEEE CEC 2017 Competition on Constrained Real-Parameter Optimization. The numerical experiments have shown that ε -iCC-SHADE outperforms the early proposed ε -CC-SHADE algorithm which operates with the fixed number of subcomponents.

1. Introduction

The technical progress does not stay still. The complexity of modern problems in different spheres of human activity grows rapidly [1]. As a result, we can observe increasing the number of variables in actual optimization problems. Global BB optimization problems with the number of variables greater than a thousand are called large-scale global optimization problems (LSGO). In [2], the overview of current state of LSGO is presented. Dealing with the high-dimensionality is a challenging task for many optimization techniques. Usually LSGO deals with single objective and no constraints, at the same time, many real-world optimization problems are the constrained optimization problems [3, 4]. The constrained optimization problems (COPs) are known as optimization problems which contain additional requirements and limitations that divide the search space into feasible and infeasible subsets. Many complex COPs deal with both BB objective and BB constraints. Searching for simultaneously the global-best and feasible solution is known as a hard optimization problem. The constrained large-scale global BB optimization combines features of LSGO and COPs and still is not studied. The constrained large-scale global optimization (cLSGO) problem can be formulated as follows:

$$f(\bar{x}) \to \min_{\bar{x}} f(x) \tag{1}$$

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$$x_i^L \le x_i \le x_i^U, i = \overline{1, n} \tag{2}$$

$$g_j(\bar{x}) \le 0, j = \overline{1, p} \tag{3}$$

$$h_i(\bar{x}) = 0, j = \overline{1, k} \tag{4}$$

where \bar{x} is vector of objective variables, $f(\bar{x}): \mathbb{R}^n \to \mathbb{R}$, $g(\bar{x})$ and $h(\bar{x})$ are the objective (fitness) function with *n* objective variables, inequality constraints and equality constraints respectively, *p* and *k* are the numbers of inequality and equality constraints, x_i^L and x_i^U are lower and upper bounds for *i*-th variable.

According to LSGO survey [2], there exist two popular and effective ways for solving LSGO problems: non-decomposition methods and cooperative coevolution (CC) methods. Non-decomposition methods use special operators and techniques for EAs for dealing with the large number of variables at once [5, 6]. The main idea of CC techniques [7, 8] is to divide the objective vector into smaller parts and to optimize them independently using EAs. For many problems approaches based on CC show better results in solving LSGO problems. CC framework provides a decomposition of a LSGO problem and helps to overcome the «curse of dimension» (CoD) [9].

In this paper, we have proposed and investigated a novel CC approach for solving cLSGO problems, which is able to increase the number of subcomponents during an EA run. The approach is title «iCC». We have chosen SHADE (Success-history based parameter adaptation for Differential Evolution) [10] as the main optimizer in CC. The SHADE approach can effectively self-adapt its parameters, namely *F* (scale factor) and *CR* (crossover rate). There exist a number of EA modifications for solving constrained optimization problems [11, 12, 13, 14]. A good survey on constrained-handling approaches is proposed in [15]. In our study, we will use the well-known and well-studied ε -DE method [16]. The whole approach that combines SHADE, iCC and ε -DE is title as ε -iCC-SHADE. In this study, we have compared the performance of the proposed algorithm with the previously proposed ε -CC-SHADE with the fixed number of subcomponents.

The rest of the paper is organized as follows. Section 2 describes related work. In Section 3, the proposed approach is described. In Section 4, the experimental setups and results of numerical experiments are discussed. In the Conclusion the results and further research are discussed.

2. Related work

2.1. SHADE algorithm

Differential evolution (DE) is a powerful approach for solving optimization problems of various complexity levels. This approach, first introduced by Storn and Price [17, 18]. DE algorithm and its variants have proved effectiveness many times [19, 20]. Classic DE has three main control parameters: pop_size (population size), F — scale factor, CR — crossover rate. SHADE is one of DE variants with self-adaptive mechanisms of F and CR parameters was created by Tanabe and Fukunaga [10]. SHADE records successful parameter values and use this information to generate new values of F, CR. Besides, SHADE transfers replaced individuals into external archive to maintain previous experience and use they in mutation stage.

2.2. Cooperative Coevolution framework

For today, Cooperative Coevolution is one of the high-performance frameworks for solving LSGO problems. CC was proposed by Potter and De Jong [21, 22]. The main idea of CC is optimization solution vector sequentially in parts with core of some EA (in this paper, we have used SHADE algorithm as a core of CC). As a result, dimension and complexity of LSGO problem decreases. CC has important controlling parameter, the CC performance strongly dependents on the number of its subcomponents. As we noted before, LSGO problems are BB problems, the structure of problem is unknown. Thus, in this study, CC performs with equal size of subcomponents. In our study, we have

used the following rule: $s \cdot m = N$, where *s* is number of variables into one subcomponent, *m* is the number of subcomponents and *N* is total number of variables in the optimization task.

2.3. *EDE constrained handlings*

In fact, that, there are a lot of constrained-handlings techniques for today [15]. In this study, we have used εDE [16] for constrained-handling. εDE transforms of «Selection» operator in DE using formula (5).

$$(f(X_1), v(X_1)) <_{\varepsilon} (f(X_2), v(X_2)) \leftrightarrow \begin{cases} f(X_1) < f(X_2) \text{ if } v(X_1), v(X_2) \le \varepsilon \\ f(X_1) < f(X_2) \text{ if } v(X_1) = v(X_2) \\ v(X_1) < v(X_2), \text{ otherwise} \end{cases}$$
(5)

Where f(X) is fitness value of X solution, v(X) is value of violation which defines as (6):

$$\nu(X) = \frac{\sum_{i=1}^{p} G_i(X) + \sum_{j=1}^{k} H_j(X)}{p+k}$$
(6)

$$G_i(X) = \begin{cases} g_i(X), & \text{if } g_i(X) > 0\\ 0, & \text{otherwise} \end{cases}$$
(7)

$$H_i(X) = \begin{cases} |h_j(X)|, if |h_j(X)| - \epsilon > 0\\ 0, otherwise \end{cases}$$
(8)

In (8) ϵ is the tolerance threshold, for all equality constraints it is equal to 0.0001. Analyzing the formula (5), we can conclude that violation values have higher priority than fitness function values in comparing two solutions between each other. To control ϵ parameter in (5), we have used modified (9) formula. We were inspired by [23].

$$\varepsilon = \begin{cases} E, if FEV \le 0.8 \cdot MaxFEV \\ 0, otherwise \end{cases}$$

$$E = \left(\left(1 - \frac{FEV}{MaxFEV} \right)^{c_p} \cdot v(X_{[\theta \cdot pop_size]}) \right)$$
(9)

Where *FEV*, *MaxFEV* are current number of fitness evaluations and maximum budget of fitness evaluation for current run, respectively. $v(X_{[\theta \cdot pop_size]})$ is a violation value for solution X with index $[\theta \cdot pop_size]$ after sorting (from best to worse solution). c_p is a parameter to control the speed of constraints, c_p is equal to 3. *pop_size* is a number means population size, θ is equal to 0.8. We have tried use different values for c_p and θ parameters, this set of parameters has shown better performance. In (9), we set *E* is equal to 0 after evaluated of 80% of total FEV budget, because in the last generations EA has to concentrate search focus in local region.

3. Proposed increasing grouping strategy for Cooperative Coevolution framework

In this section, we will describe our proposed and improved CC approach which is named as «iCC». It is a known fact that EA shows quite good performance, for solving optimization problems, if it is guided the following behavior. In the first iterations, EA should use principles of global search, but near the end of FEV budget, EA should use methods of searching near best found solutions. To control decreasing the number of subcomponents we have used simple rules, see formula (10). Where m is the number of subcomponents in CC.

$$m = \begin{cases} 10, if \ FEV \in [0, t_1] \\ 8, if \ FEV \in [t_1 + 1, t_2] \\ 4, if \ FEV \in [t_2 + 1, t_3] \\ 2, if \ FEV \in [t_3 + 1, t_4] \\ 1, if \ FEV \in [t_4 + 1, maxFEV] \\ \forall \ i: \ t_{i+1} - t_i = 0.2 \cdot maxFEV \end{cases}$$
(10)

When we provide decomposition into small groups of variables, an EA is able to converge faster to a perspective region of the search space, especially, if the EA has found an appropriate grouping of interacting variables. At the same time, such a coordinate-wise-like search can be too "greedy", and larger grouping is more preferable. We will increase sizes of subcomponents during the EA run, and finally, we will finish the search using the whole solution vector (m = 1). We will set the equal fitness evaluation budget for each CC stage.

4. Experimental setup and discussion numerical results

4.1. Benchmark set for Constrained Large-scale Global Optimization Problems

Today no benchmark problems for cLSGO is proposed. In this paper, we have proposed a new benchmark based on scalable problems from IEEE CEC 2017 Competition on Constrained Single Objective Real-Parameter Optimization (CSORPO) [24]. All problems from IEEE CEC 2017 benchmark which do not use low-dimensional transformation matrixes, are scaled up to 1000 dimensions and are included in the new set of cLSGO problems. Detailed information on the cLSGO benchmark is shown in table 1.

cLSGO	CEC'2017 CSODDO	Type of	The number and type of constraint	
problem	CEC 2017 CSORPO	objective	Equality	Inequality
cLSGO01	C01	Non Separable	0	1, Separable
cLSGO02	C03	Non Separable	1, Separable	1, Separable
cLSGO03	C04	Separable	0	2, Separable
cLSGO04	C06	Separable	6	0, Separable
cLSGO05	C07	Separable	2, Separable	0
cLSGO06	C08	Separable	2, Non Separable	0
cLSGO07	C09	Separable	2, Non Separable	0
cLSGO08	C10	Separable	2, Non Separable	0
cLSGO09	C11	Separable	1, Non Separable	0
cLSGO10	C12	Separable	0	2, Separable
cLSGO11	C13	Non Separable	0	3, Separable
cLSGO12	C14	Non Separable	1, Separable	1, Separable
cLSGO13	C15	Separable	1	1
cLSGO14	C16	Separable	1, Non Separable	1, Separable
cLSGO15	C17	Non Separable	1, Non Separable	1, Separable
cLSGO16	C18	Separable	1	2, Non Separable
cLSGO17	C19	Separable	0	2, Non Separable
cLSGO18	C20	Non Separable	0	2

 Table 1. Benchmark problems for cLSGO

4.2. Software implementation and setups

- All numerical experiments were executed using the following system:
 - OS: Ubuntu Linux 18.04 LTS
 - CPU: Ryzen 7 1700x (8C/16T) and Ryzen 2700 (8C/16T)
 - RAM: 16 GB
 - IDE: Code::Blocks 17.12

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- Programming Language: C++
- Compiler: g++ (gcc) with -O3 optimization flag

We have used the following main settings for all numerical experiments: the number of variables for all problems is D=1000, the number of independent runs is 25 runs per a benchmark problem, the maximum number of fitness evaluations is Max FEV = 3E+6 in each independent run.

In this study, we use the following notation, ε -CC-SHADE (m) means that ε -CC-SHADE algorithm uses *m* subcomponents for CC. The population size is equal to 25, 50, 75 and 100, and *m* is equal to 1, 2, 4, 8, 10. For decreasing computation time, we have applied parallel computing with 32 threads using Ryzen 7 1700X and 2700 with 8 CPU cores and 16 threads.

Table 2, table 3, table 4 and table 5 show results of numerical experiments for population size equal to 25, 50, 75 and 100, respectively. The first column is cLSGO problem number. The next columns contain the ε -CC-SHADE (m) and ε -iCC-SHADE performance values. Each cell contains two values: the median and the constrains violation, evaluated over 25 independent runs. The Figures 1-4 demonstrate ranking results for the EAs performance with population size equal to 25, 50, 75 and 100, respectively. The best EA has the smallest rank, the ranking is based on the median best-found values averaged over all cLSGO benchmark problems.

Table 2. The experimental results for ε -CC-SHADE and ε -iCC-SHADE on the cLSGO benchmark problems, population size is 25

	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-iCC-
N⁰	SHADE (1)	SHADE (2)	SHADE (4)	SHADE (8)	SHADE (10)	SHADE
1	1.04E+06	7.55E+05	4.48E+05	2.10E+05	1.72E+05	2.50E+05
1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	1.47E+08	1.74E+08	1.59E+08	1.93E+08	2.05E+08	1.51E+08
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	3.34E+04	2.89E+04	1.91E+04	1.02E+04	8.19E+03	8.25E+03
3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
4	1.84E+05	1.91E+05	1.52E+05	1.81E+05	1.80E+05	1.80E+05
4	3.23E-03	1.88E-02	2.36E-02	3.84E-02	5.72E-02	7.40E-03
5	-1.07E+04	-2.27E+03	-4.50E+02	1.64E+02	1.24E+02	-3.50E+03
3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
6	1.78E+02	1.53E+02	1.59E+02	1.59E+02	1.45E+02	1.55E+02
0	7.38E+05	5.23E+05	3.48E+05	2.65E+05	3.57E+05	2.81E+05
7	1.87E+01	1.95E+01	1.74E+01	1.73E+01	1.77E+01	1.80E+01
	5.72E+02	2.84E+02	9.48E+00	0.00E+00	0.00E+00	0.00E+00
0	1.35E+02	1.41E+02	1.11E+02	9.38E+01	1.40E+02	9.32E+01
0	1.81E+06	1.34E+06	5.96E+05	2.79E+05	3.24E+05	3.93E+05
0	-2.70E+03	-5.80E+03	-1.09E+04	-5.02E+03	-4.76E+03	-8.48E+03
9	4.05E+04	2.77E+04	1.39E+04	6.92E+03	1.43E+04	9.11E+03
10	2.72E+04	1.57E+04	8.45E+03	6.77E+02	1.42E+02	3.75E+01
10	1.30E+04	7.52E+03	4.13E+03	2.67E+02	5.45E+01	1.63E+01
11	2.51E+09	2.73E+09	1.22E+09	4.10E+08	2.66E+08	3.38E+08
11	1.15E+04	1.28E+04	8.87E+03	6.26E+03	5.38E+03	5.44E+03
12	2.03E+01	2.01E+01	2.01E+01	2.00E+01	2.00E+01	2.00E+01
12	2.10E+04	2.05E+04	7.88E+03	6.49E+02	8.25E+01	2.16E+02
13	1.06E+02	1.06E+02	9.03E+01	9.03E+01	7.46E+01	1.12E+02
15	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
1/	3.30E+03	4.19E+03	4.71E+03	5.93E+03	6.31E+03	6.13E+03
14	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
15	3.92E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00
15	4.33E+03	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02
16	4.66E+04	2.50E+04	9.30E+03	3.32E+03	3.11E+03	7.37E+03
10	1.14E+09	3.55E+08	6.44E+07	1.35E+06	1.35E+05	8.59E+03

1.5	1.40E+03	1.70E+03	1.69E+03	1.81E+03	1.62E+03	1.54E+03
17	7.38E+05	7.38E+05	7.38E+05	7.38E+05	7.38E+05	7.38E+05
10	1.24E+02	1.51E+02	1.73E+02	1.85E+02	1.88E+02	1.86E+02
18	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00



Figure 1. The ranking of ϵ -CC-SHADE (m) and ϵ -iCC-SHADE on cLSGO, pop_size is 25.

Table 3. The experimental results for ε -CC-SHADE and ε -iCC-SHADE on the cLSGO benchmark problems, population size is 50.

No	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-iCC-
JN≌	SHADE (1)	SHADE (2)	SHADE (4)	SHADE (8)	SHADE (10)	SHADE
1	9.71E+05	5.87E+05	2.52E+05	8.97E+04	6.78E+04	1.35E+05
1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	8.70E+07	1.04E+08	1.51E+08	1.11E+08	1.90E+08	9.89E+07
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	2.75E+04	1.97E+04	9.95E+03	5.39E+03	4.66E+03	4.72E+03
3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
4	1.61E+05	1.74E+05	1.64E+05	1.79E+05	1.65E+05	1.34E+05
4	1.96E-03	1.39E-02	4.28E-02	8.48E-02	9.98E-02	5.23E-03
5	-1.08E+04	-4.00E+02	-3.42E+02	-4.14E+02	8.49E+02	-1.43E+03
3	0.00E+00	4.94E-03	1.07E+04	1.90E+04	2.19E+04	0.00E+00
6	1.51E+02	1.44E+02	1.40E+02	1.27E+02	1.11E+02	1.08E+02
	5.64E+05	3.25E+05	1.99E+05	1.71E+05	2.45E+05	1.91E+05
-	1.74E+01	1.76E+01	1.59E+01	1.51E+01	1.56E+01	1.48E+01
/	3.47E+01	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
0	1.00E+02	8.09E+01	5.12E+01	4.28E+01	6.14E+01	2.75E+01
0	1.62E+06	6.70E+05	1.80E+05	7.27E+04	7.89E+04	8.30E+04
0	-9.67E+03	5.43E+02	-5.95E+03	-4.74E+03	-8.26E+03	-8.23E+03
9	1.61E+04	4.67E+03	1.33E+03	9.04E+02	4.25E+03	1.57E+03
10	6.33E+03	5.87E+02	4.44E+00	3.33E+00	3.22E+00	2.86E+00
10	2.82E+03	2.60E+02	0.00E+00	0.00E+00	4.54E+00	0.00E+00
11	5.54E+08	4.42E+08	2.51E+08	4.47E+07	3.80E+07	2.13E+07
11	1.03E+04	8.69E+03	5.34E+03	2.29E+03	1.69E+03	1.75E+03
12	2.01E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01
12	4.61E+03	2.59E+02	0.00E+00	0.00E+00	0.00E+00	0.00E+00
12	9.35E+01	8.09E+01	6.20E+01	4.95E+01	4.32E+01	4.63E+01
15	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
11	4.68E+03	5.99E+03	6.75E+03	7.10E+03	7.13E+03	7.14E+03
14	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
15	5.42E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00
15	7.33E+03	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02

1	16	1.16E+04	4.40E+03	1.97E+03	1.06E+03	1.01E+03	8.39E+02
10	10	5.68E+07	8.43E+04	4.02E+02	2.33E+02	2.12E+02	1.91E+02
1	17	1.06E+03	8.73E+02	6.60E+02	5.82E+02	5.69E+02	5.20E+02
1	1/	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05
1	10	1.69E+02	2.01E+02	2.21E+02	2.27E+02	2.30E+02	2.42E+02
18	18	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00



Figure 2. The ranking of ε -CC-SHADE (m) and ε -iCC-SHADE on the cLSGO 2017, pop_size is 50

Table 4. The experimental results for E-CC-SHADE and E-iCC-SHA	٩DE
on the cLSGO benchmark problems, population size is 75	

No	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-iCC-
JN⊻	SHADE (1)	SHADE (2)	SHADE (4)	SHADE (8)	SHADE (10)	SHADE
1	8.76E+05	5.22E+05	2.06E+05	7.13E+04	3.28E+04	8.54E+04
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	7.67E+07	8.01E+07	1.50E+08	1.54E+08	2.20E+08	1.13E+08
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
r	2.40E+04	1.47E+04	7.16E+03	4.40E+03	3.85E+03	3.84E+03
3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
4	1.37E+05	1.45E+05	1.56E+05	1.68E+05	1.77E+05	1.36E+05
4	0.00E+00	1.96E-02	6.02E-02	1.11E-01	1.37E-01	8.25E-03
5	-1.12E+04	-4.18E+02	2.49E+02	-1.45E+03	-4.09E+02	-2.18E+02
3	0.00E+00	1.01E+04	2.26E+04	3.07E+04	3.33E+04	1.47E+03
6	1.24E+02	1.24E+02	1.44E+02	1.02E+02	1.67E+02	1.08E+02
	4.77E+05	2.78E+05	1.33E+05	1.11E+05	3.10E+05	1.55E+05
7	1.81E+01	1.62E+01	1.49E+01	1.34E+01	1.44E+01	1.36E+01
/	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
0	9.96E+01	8.05E+01	6.01E+01	3.15E+01	7.04E+01	2.77E+01
0	1.40E+06	5.03E+05	9.50E+04	1.65E+04	6.84E+04	5.67E+04
0	-8.88E+03	-4.59E+03	-2.67E+03	-5.36E+03	-4.48E+03	-6.71E+03
9	8.75E+03	2.02E+03	3.95E+02	8.33E+02	4.45E+03	9.21E+02
10	9.20E+02	3.20E+01	3.23E+00	2.96E+00	3.28E+00	3.19E+00
10	3.62E+02	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
11	5.14E+08	4.13E+08	9.10E+07	8.29E+06	6.45E+06	6.14E+06
11	1.05E+04	7.64E+03	3.16E+03	1.24E+03	9.62E+02	1.02E+03
12	2.01E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01
12	7.96E+02	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
12	8.09E+01	6.52E+01	5.58E+01	3.69E+01	3.38E+01	3.38E+01
13	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
14	5.67E+03	6.68E+03	7.16E+03	7.11E+03	7.05E+03	7.05E+03
14	0.00E+00	0.00E + 00	0.00E+00	0.00E + 00	0.00E+00	0.00E+00
15	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00
15	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02

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14	5.48E+03	2.34E+03	1.41E+03	6.86E+02	3.02E+02	4.80E+02
10	2.17E+06	5.12E+02	2.95E+02	1.36E+02	6.36E+01	1.06E+02
17	8.78E+02	6.75E+02	4.50E+02	3.60E+02	3.64E+02	3.42E+02
17	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05
10	2.02E+02	2.32E+02	2.47E+02	2.55E+02	2.55E+02	2.75E+02
10	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00



Figure 3. The ranking of ϵ -CC-SHADE (m) and ϵ -iCC-SHADE on the cLSGO, pop_size is 75

Γable 5 . The experimental results for ε-CC-SHADE and ε-iCC-SHADE
on the cLSGO benchmark problems, population size is 100

No	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-CC-	ε-iCC-
J¶≌	SHADE (1)	SHADE (2)	SHADE (4)	SHADE (8)	SHADE (10)	SHADE
1	7.79E+05	4.61E+05	1.66E+05	5.57E+04	4.06E+04	8.53E+04
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	9.64E+07	8.13E+07	1.51E+08	1.37E+08	1.83E+08	1.04E+08
	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
2	2.12E+04	1.16E+04	5.97E+03	3.92E+03	3.35E+03	3.31E+03
3	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
4	1.32E+05	1.51E+05	1.74E+05	1.78E+05	1.66E+05	1.34E+05
4	0.00E+00	1.75E-02	8.07E-02	1.81E-01	2.03E-01	1.19E-02
5	-1.12E+04	-1.05E+03	7.31E+02	1.73E+02	-3.32E+02	2.47E+02
3	0.00E+00	1.69E+04	3.04E+04	3.69E+04	3.80E+04	9.31E+03
6	1.29E+02	1.26E+02	8.37E+01	1.02E+02	1.63E+02	9.82E+01
6	4.97E+05	2.80E+05	1.21E+05	1.46E+05	1.46E+06	1.40E+05
7	1.65E+01	1.46E+01	1.38E+01	1.25E+01	1.94E+01	1.23E+01
/	0.00E+00	0.00E+00	0.00E+00	0.00E+00	4.38E+04	0.00E+00
0	9.06E+01	6.43E+01	3.35E+01	1.28E+01	6.08E+01	2.18E+01
0	1.26E+06	4.31E+05	6.05E+04	6.72E+03	7.52E+04	3.99E+04
0	-7.41E+03	-2.49E+03	-4.81E+03	-4.89E+03	-3.95E+03	-4.29E+03
9	5.86E+03	8.90E+02	2.58E+02	2.70E+02	1.81E+04	5.19E+02
10	3.53E+02	5.10E+00	2.99E+00	3.22E+00	3.23E+00	3.18E+00
10	1.05E+02	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
11	4.79E+08	3.68E+08	2.96E+07	3.25E+06	6.23E+06	2.17E+06
11	1.02E+04	5.98E+03	2.16E+03	8.47E+02	6.12E+02	7.42E+02
12	2.00E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01	2.00E+01
12	1.71E+02	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
12	7.46E+01	6.20E+01	4.32E+01	3.38E+01	3.38E+01	3.06E+01
13	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
14	6.33E+03	7.09E+03	7.16E+03	7.03E+03	6.90E+03	6.88E+03
14	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
15	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00	2.00E+00
15	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02	5.01E+02

	16	4.28E+03	1.77E+03	8.71E+02	3.26E+02	1.63E+02	1.53E+02
1	10	1.18E+04	3.90E+02	1.91E+02	6.36E+01	2.12E+01	2.12E+01
	17	8.21E+02	5.99E+02	3.34E+02	2.36E+02	1.91E+02	2.15E+02
	1/	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05	7.37E+05
	10	2.25E+02	2.55E+02	2.68E+02	2.75E+02	2.77E+02	3.01E+02
I	18	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00



Figure 4. The ranking of ε -CC-SHADE (m) and ε -iCC-SHADE on the cLSGO, pop size is 100

As we can see in Figures 1-4, the proposed ε -iCC-SHADE performs better than ε -CC-SHADE (m) with different number of subcomponents. Tables 6-9 prove difference in the results of estimation the performance of ε -iCC-SHADE and ε -CC-SHADE (m) using Mann–Whitney U test with normal approximation and tie correction with p value is equal to 0.01. The first column contains algorithms, the second, third and fourth columns contain the numbers of benchmark problems when the first EA has better, worse and equal performance. We have compared proposed ε -iCC-SHADE versus ε -CC-SHADE (m) algorithms. Tables 6-9 show that ε -iCC-SHADE is statistically better than ε -CC-SHADE (m).

ε-iCC-SHADE vs.	+ (better)	- (worse)	\approx (no. sig)
ε-CC-SHADE (1)	11	3	4
ε-CC-SHADE (2)	14	2	2
ε-CC-SHADE (4)	13	2	3
ε-CC-SHADE (8)	7	3	8
ε-CC-SHADE (10)	5	2	11
Total sum	50	12	28

Table 6. Mann–Whitney U test, population size is 25

ε-iCC-SHADE vs.	+ (better)	- (worse)	\approx (no. sig)	
ε-CC-SHADE (1)	13	4	1	
ε-CC-SHADE (2)	14	2	2	
ε-CC-SHADE (4)	13	2	3	
ε-CC-SHADE (8)	5	2	11	
ε-CC-SHADE (10)	6	2	10	
Total sum	51	12	27	

Table 7. Mann–Whitney U test, population size is 50

ε-iCC-SHADE vs.	+ (better)	- (worse)	\approx (no. sig)
ε-CC-SHADE (1)	12	5	1
ε-CC-SHADE (2)	14	3	1
ε-CC-SHADE (4)	11	2	5
ε-CC-SHADE (8)	6	3	9
ε-CC-SHADE (10)	7	2	9
Total sum	50	15	25

Table 8. Mann–Whitney U test, population size is 75

Table 9. Mann–Whitney U test, population size is 100

ε-iCC-SHADE vs.	+ (better)	- (worse)	\approx (no. sig)
ε-CC-SHADE (1)	12	4	2
ε-CC-SHADE (2)	15	2	1
ε-CC-SHADE (4)	11	2	5
ε-CC-SHADE (8)	9	3	6
ε-CC-SHADE (10)	7	3	8
Total sum	54	14	22

5. Conclusions

In this study, we have proposed a novel ε -iCC-SHADE algorithm for constrained large-scale global BB optimization. We have investigated the performance of ε -iCC-SHADE with different population sizes. The experimental results have shown that the proposed iCC approach demonstrates better results than CC with fixed number of subcomponents. At the same time, iCC still has the great potential for improvement, thus in our further works we will try to modify it for adaptive dynamic sizing of groups.

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