

RESEARCH ARTICLE

Improved ensemble of differential evolution variants

Juan Yao¹, Zhe Chen^{2,3*}, Zhenling Liu⁴

1 College of Informatics, Huazhong Agricultural University, Wuhan, Hubei, China, **2** School of Computer Science, China University of Geosciences, Wuhan, Hubei, China, **3** Hubei Key Laboratory of Intelligent Geo-Information Processing, China University of Geosciences, Wuhan, Hubei, China, **4** Network Management Department, Wuhan Information Center of Real Estate, Wuhan, Hubei, China

* chenzhe@cug.edu.cn



Abstract

In the field of Differential Evolution (DE), a number of measures have been used to enhance algorithm. However, most of the measures need revision for fitting ensemble of different combinations of DE operators—ensemble DE algorithm. Meanwhile, although ensemble DE algorithm may show better performance than each of its constituent algorithms, there still exists the possibility of further improvement on performance with the help of revised measures. In this paper, we manage to implement measures into Ensemble of Differential Evolution Variants (EDEV). Firstly, we extend the collecting range of optional external archive of JADE—one of the constituent algorithm in EDEV. Then, we revise and implement the Event-Triggered Impulsive (ETI) control. Finally, Linear Population Size Reduction (LPSR) is used by us. Then, we obtain Improved Ensemble of Differential Evolution Variants (IEDEV). In our experiments, good performers in the CEC competitions on real parameter single objective optimization among population-based metaheuristics, state-of-the-art DE algorithms, or up-to-date DE algorithms are involved. Experiments show that our IEDEV is very competitive.

OPEN ACCESS

Citation: Yao J, Chen Z, Liu Z (2021) Improved ensemble of differential evolution variants. PLoS ONE 16(8): e0256206. <https://doi.org/10.1371/journal.pone.0256206>

Editor: Diego Oliva, Universidad de Guadalajara, MEXICO

Received: April 6, 2021

Accepted: August 2, 2021

Published: August 20, 2021

Copyright: © 2021 Yao et al. This is an open access article distributed under the terms of the [Creative Commons Attribution License](https://creativecommons.org/licenses/by/4.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Data Availability Statement: The data sets and majority of algorithms used in this study are available at Github at https://github.com/luozero0/Differential_Evolution/.

Funding: The author(s) received no specific funding for this work.

Competing interests: The authors have declared that no competing interests exist.

Introduction

Differential evolution (DE), a type of population-based metaheuristic, is reliable and powerful for global numerical optimization. DE incorporates mutation, crossover and selection operators to move population gradually toward a global optimum [1]. At beginning of execution, target vectors $\vec{x}_{i,0} = (x_{1,i,0}, x_{2,i,0}, \dots, x_{D,i,0})$ ($i = 1, 2, \dots, NP$), where NP denotes population size and D is dimensionality, are initialized randomly. Then, mutant vectors $\vec{v}_{i,g}$ are produced based on target vectors $\vec{x}_{i,g}$ by mutation in a generation g . Different mutation strategies are used in different DE algorithms. Three widely used mutation strategies—DE/rand/1, DE/best/1, and DE/current-to-best/1—are listed below for example,

$$\vec{v}_{i,g} = \vec{x}_{r1,g} + F \cdot (\vec{x}_{r2,g} - \vec{x}_{r3,g}), \tag{1}$$

$$\vec{v}_{i,g} = \vec{x}_{best,g} + F \cdot (\vec{x}_{r1,g} - \vec{x}_{r2,g}), \tag{2}$$

and

$$\vec{v}_{i,g} = \vec{x}_{i,g} + F \cdot (\vec{x}_{best,g} - \vec{x}_{i,g}) + F \cdot (\vec{x}_{r1,g} - \vec{x}_{r2,g}). \tag{3}$$

In the equations, the distinct integers different from $i-r1$, $r2$, and $r3$ —are randomly chosen from the range $[1, NP]$. F is the scaling factor, while $\vec{x}_{best,g}$ denotes the individual with the best fitness in the generation g . After mutation, crossover is executed based on $\vec{x}_{i,g}$ and $\vec{v}_{i,g}$ to generate trial vectors $\vec{u}_{i,g} = (u_{1,i,g}, u_{2,i,g}, \dots, u_{D,i,g})$. Binomial crossover,

$$u_{j,i,g} = \begin{cases} v_{j,i,g}, & \text{if } rand(0, 1) \leq Cr \text{ or } j = randn(i), \\ x_{j,i,g}, & \text{otherwise,} \end{cases} \tag{4}$$

is widely used in DE algorithms. In Eq 4, $Cr \in [0, 1]$ is the crossover rate, and $randn(i)$ is an integer randomly generated from the range $[1, NP]$ to ensure that $\vec{u}_{i,g}$ has at least one component from $\vec{v}_{i,g}$. In selection,

$$\vec{x}_{i,g+1} = \begin{cases} \vec{u}_{i,g}, & \text{if } f(\vec{u}_{i,g}) \leq f(\vec{x}_{i,g}), \\ \vec{x}_{i,g}, & \text{otherwise,} \end{cases} \tag{5}$$

where $f(\vec{u}_{i,g})$ and $f(\vec{x}_{i,g})$ represent fitness of $\vec{u}_{i,g}$ and $\vec{x}_{i,g}$, respectively. By this means, $\vec{u}_{i,g}$ competes with $\vec{x}_{i,g}$ for survival. The winner becomes the target vector of the next generation, $\vec{x}_{i,g+1}$.

For years, DE is improved in various ways. Recently, methods for improving DE include

- The improved trial vector generation strategies [2–10]
- The hybridizations of DE and other techniques [7, 9, 11–17]; and
- The developed types of ensemble of different combinations of operators [18–27]

It can be seen that ensemble is one of the active type of method for improving DE. All the types of ensemble listed above are be further introduced in our section for related work. Essentially, ensemble of different combinations of DE operators still belongs to DE algorithm and so called ensemble DE algorithm in this paper.

The motivation of this paper is given below. A number of measures have been used in DE algorithms. However, most of the measures need revision for fitting ensemble DE algorithm. Meanwhile, although ensemble DE algorithm may show better performance than each of its constituent algorithms, there still exists the possibility of further improvement on performance with the help of revised measures.

In this paper, we enhance Ensemble of Differential Evolution Variants (EDEV) [21], an ensemble DE algorithm, by measures listed below. Firstly, we revise the organization of optional external archive in one of the constituent DE algorithms of EDEV—JADE [28]. In detail, when JADE is used as a constituent algorithm, the individuals eliminated from other constituent algorithms are also sent to optional external archive. Then, we add Linear Population Size Reduction (LPSR), the widely used technique in the field of DE, into algorithm. Under the control of LPSR, population size is linearly reduced. Finally, we implement the Event-Triggered Impulsive (ETI) control, which is firstly introduced from control theory to DE by [12]. Here, the ETI control is implemented to the two inefficient constituent DE algorithms in ensemble confirmed by comparison at intervals. That is, after each time of performance comparison, not only the best performer among the three constituent algorithms as before, but also the other two constituent algorithms, are pointedly treated. Thus, we obtain

our Improved Ensemble of Differential Evolution Variants (IEDEV). Our experiments are based on the CEC 2013, 2014 and 2017 benchmark testing suites. Nine peers are involved in experiment. Experimental results show that our IEDEV is competitive.

The rest of the paper is organized as follows. In Section II, related work is presented. In Section III, our IEDEV is given. Then, experimental results are shown and analyzed in Section IV. Finally, a conclusion and a prospect are dealt with in Section V.

Related work

Here, related work includes two aspects. Firstly, we list existing ensemble DE algorithms including EDEV. Then, we review existing techniques for improving DE, including the measures taken by us—optional external archive, LPSR, and the ETI control.

In SaDE [29], each individual make a choice from multiple mutation strategies based on previous experiences of generating promising solutions. In EPSDE [30], recorded successful combinations of strategy and parameter are employed at high probability. In mDE-bES [31], population is divided into subpopulations. Each subpopulation are different in operators. After every certain number of generations, individuals are exchanged between subpopulations. MPEDE [32] has three mutation strategies. There are three equally sized smaller indicator subpopulations and one much larger reward subpopulation in population of MPEDE. Each constituent mutation strategy controls one indicator subpopulation. After every certain number of generations, the current best performing mutation strategy will be determined according to the ratios between fitness improvements and consumed function evaluations. Then, the reward subpopulation will be allocated dynamically to the determined best performing mutation strategy. In sTDE-dR [18], population is clustered in multiple tribes in which different mutation and crossover strategies are utilized. In each tribe, scaling factor and crossover rate are controlled by a different adaptive scheme. The mean success of each tribe is used to calculate the participation ratio for the next generation. In L-SHADE-SPA [33], there are two combinations of setting for both the parameter for mutation F and the one for crossover CR . L-SHADE-SPACMA [33] is a hybridization framework between LSHADE-SPA and a modified version of CMA-ES. In [34], a memetic framework for solving large-scale global optimization problems is proposed. In the framework, L-SHADE-SPA is used for global exploration, while a modified version of multiple trajectory search is used for local exploitation. In EL-SHADE-SPACMA [35], based on L-SHADE-SPACMA, the greediness of the mutation strategy is changed to be dynamic. Furthermore, another directed mutation strategy is integrated into framework. In the DE algorithm proposed by [19], both fitness landscapes and performance history of the operators to dynamically selecting the most suitable operator. In AMECODEs [20], two elites-guided trial vector generation strategies may be both employed for each target vector in a generation to generate two trial vectors accordingly. In fact, only the better one can participate in selection. EDEV [21] consists of three highly popular and efficient DE algorithms—JADE [28], CoDE [1], and EPSDE. Similar with population of MPEDE, there are three indicator subpopulations and a reward subpopulation in population of EDEV. Also, the competition mechanism for the four subpopulations are similar with that in MPEDE. MLCC framework [22] implements a parallel structure with the entire population simultaneously monitored by multiple DE algorithms assigned to different layers. A target vector can store, utilize and update its evolution information in different layers. EMMSIQDE [23] is quantum-inspired DE based on mixing multiple strategies. In detail, a new multipopulation mutation evolution mechanism is designed. Meanwhile, the feasible solution space transformation strategy is used. IPOQEA [24] is ensemble based on quantum evolutionary algorithm

and particle swarm optimization. This algorithm is proposed for gate allocation of airport. MSQCCEA [25] is an improved quantum-inspired cooperative co-evolution algorithm based on combining the strategies of cooperative co-evolution, random rotation direction and Hamming adaptive rotation angle. Also, the algorithm is proposed for gate allocation. HMCQDE [26] is ensemble of quantum evolutionary algorithm(QEA) and cooperative coevolution evolutionary algorithm, which is based on a new hybrid mutation strategy consisting of local neighborhood mutation and SaNSDE. The coastal ship path planning model based on the optimized deep Q network (DQN) algorithm [27] is proposed for path planning in the field of coastal ships. In essence, the model is ensemble of environment status information and the DQN algorithm. The former provides training space for the latter.

JADE is a famous DE algorithm based on optional external archive. SHADE [36], which is also base on optional external archive, is revised from JADE and has many variants. For example, L-SHADE-SPA, L-SHADE-SPACMA, EL-SHADE-SPACMA, L-SHADE-RSP and EB-L-SHADE are all variants of SHADE. Under the control of the ETI scheme [12], stabilizing impulses and destabilizing impulses are executed based on the event-triggered mechanism. In fact, destabilizing impulses are essentially partial restarts. In [12], the ETI scheme is used in ten DE algorithms. The adaptive social learning strategy [14] can extract the neighborhood relationship information of individuals. Multi-topology-based DE [15], which is based on multiple population topologies, the individual-dependent adaptive topology selection scheme, and the topology-dependent mutation strategy, can utilize the information derived from the differences in fitness. Since [37], LPSR, which means linear decrease in population size, began to be employed in DE algorithms. Recently, LPSR is at least employed in [7, 9, 34, 35, 38].

Our proposed algorithm

Firstly, we discuss EDEV, optional external archive, the ETI control, and LPSR for improvement. Then, we propose our IEDEV based on discussion in this section.

Discussion on the involved methods

EDEV. EDEV [21] is a powerful ensemble DE algorithm. There are three constituent DE algorithms—JADE [28], CoDE [1], and EPSDE [30]—in EDEV. Population of EDEV is partitioned into four subpopulations, including three indicator subpopulations and a reward subpopulation. Each of the three constituent DE algorithms in EDEV owns an indicator subpopulation. After every predefined generations, the most efficient constituent DE algorithm is determined based on comparison. Then, the reward subpopulation is assigned to the determined one as an extra reward. In detail, at the beginning of execution, the reward subpopulation is allocated to one of the three constituent algorithm randomly. At intervals, the most efficient DE algorithm A_k ($k = 1, 2, 3$) is determined by

$$A_k = \operatorname{argmax}_{k=1,2,3} \frac{\Delta f_k}{\Delta FES_k}, \quad (6)$$

where Δf_k denotes improvement of the k th constituent algorithm in fitness and ΔFES_k indicates consumed function evaluations of the k th constituent algorithm. After that, the reward subpopulation is reallocated to the most efficient DE algorithm. More details of EDEV can be seen in [21].

It can be seen that there exists a paradox in EDEV. In detail, the best performing constituent algorithm obtains the reward, while the rewarded constituent algorithm may continue

performing best with the help of the reward. In fact, no measure is adopted for the other two constituent algorithms to enhance them.

Optional external archive

In JADE, SHADE and the most variants of SHADE, individuals eliminated by selection are all sent to the archive. However, the archive never accepts duplicated individuals. Furthermore, when the archive is full, randomly chosen individuals in it are replaced by new comers. The above method to organize the archive is simple and effective for maintaining diversity to resist stagnation.

In EDEV, the constituent algorithm—JADE—employs the archive. According to [28], the paper proposed JADE, the motivation of applying the archive is to give more choices when selecting individual for difference in mutation. Thus, diversity can be better maintained. In EDEV, compared with just using individuals eliminated from JADE, using individuals eliminated from all the three constituent algorithms to organizing the archive may be a better method for maintaining diversity.

The ETI control. The ETI control, which comes from the field of control theory, can be widely used in DE algorithms. The update rate (UR) of the population in the current generation needs to be observed during execution. UR is illustrated by Eq 7

$$UR = \frac{UP}{NP}, \quad (7)$$

where NP is the population size, and UP is the number of individuals updated in the current generation. When UR begins to decrease, for enhancing exploitation, stabilizing impulses drive the individuals with lower rankings in the current population to approach the individuals with better fitness values. When UR drops to zero or stabilizing impulses fail to take effect, to improve exploration, destabilizing impulses randomly adjust the positions of the individuals with lower rankings in the current population within the area of the current population. More details of stabilizing impulses and destabilizing impulses can be found in [12]. The ranking of each individual for exposed to the two types of impulses is given below. For $\vec{x}_{i,g}$,

$$R_{i,g} = \tilde{R}_{i,g} + \bar{R}_{i,g}, \quad (8)$$

where $\tilde{R}_{i,g}$ denotes the ranking of $\vec{x}_{i,g}$ according to fitness and $\bar{R}_{i,g}$ denotes the ranking of that based on the number of consecutive stagnation generation. In the experiments of [12], the ETI control is applied on many DE algorithms including JADE, CoDE, and EPSDE and leads to significant improvement. In fact, the three DE algorithms are constituent algorithms of EDEV.

Although the ETI control can be widely used in DE algorithms, so far, it can be hardly seen that the technique is implemented in ensemble DE algorithm. In ensemble DE algorithm, the cooperation of different combinations of operators makes that the simple scheme for calling the two types of impulses in [12] becomes invalid. At least, Eq 7 cannot be valid for EDEV to control the two types of impulses because, in a moment, the three constituent DE algorithms may be different in state. For example, when one constituent algorithm leads to little update and need impulses, the other two constituent algorithms may be still active. In this case, UR may still not decrease, or even increase. Therefore, the two types of impulses cannot executed at all. In brief, a new scheme for calling the two types of impulses need be proposed for implementing the ETI control in EDEV.

LPSR. So far, LPSR has many applications in the field of DE. For example, L-SHADE [37], L-SHADE-EpSin [39], jSO [2], L-SHADE-SPACMA [33], L-SHADE-RSP [7], EAGDE [38], and EB-L-SHADE [40] are famous DE algorithms with LPSR. The algorithms are all good performers in competitions of real parameter single objective optimization among population-based metaheuristics held by the series of IEEE Congress on Evolutionary Computation (CEC). It can be seen that LPSR is useful for improving solution.

IEDEV proposed by us

As mentioned before, in EDEV, no measure is adopted for the two constituent algorithms worse in performance to enhance them. Provided that another strategy, e.g., the ETI control, is employed the two constituent algorithms, competition among all the three constituent algorithms may become more intense than before. In this case, reallocation of the reward subpopulation becomes more frequent. Thus, algorithm performance may be further improved.

In our IEDEV, firstly, organization of optional external archive is changed. As mentioned before, individuals eliminated from all the three constituent DE algorithms are all sent to the archive. Moreover, the ETI control is applied in the two constituent DE algorithms not best in efficiency. In detail, after each time of reallocation of the reward subpopulation to the best performer among the three constituent DE algorithms, the ETI control is implemented in the other two ones. Here, the parameters for the ETI control, such as UR and $R_{i,g}$, are computed just based on individuals in constituent DE algorithm. By this means, all constituent DE algorithms are all treated by different means according to their rank in comparison. That is, the most efficient constituent algorithm still obtains the reward subpopulation, while the other two constituent algorithms are supported by the ETI control. In addition, LPSR is applied here. That is, during the course of run, population size is decreased linearly.

The pseudo-code of our IEDEV is given in Algorithm 1. Nevertheless, the change in organization of optional external archive for JADE is not reflected by Algorithm 1 directly. In our algorithm, the simple multiple relation between generations and function evaluations in EDEV is not used any more. As shown in Step 7, the main loop is counted by function evaluations but not generations as EDEV any more.

Algorithm 1 The pseudo-code of L-ETI-EDEV

Input:

NP_{max} , the maximum value of NP
 NP_{min} , the minimum value of NP
 $MaxFES$, the maximum number of function evaluations;
 λ_k ($k = 1, 2, 3, 4$), the proportion between size of the k th subpopulation and NP
 ng , interval for determining the most efficient constituent DE algorithm

Parameter:

NP , population size;
 A_k ($k = 1, 2, 3$), the k th constituent DE algorithm (A_1 , A_2 , and A_3 are JADE, CoDE, and EPSDE, respectively)
 FES , fitness evaluations
 FES_k ($k = 1, 2, 3$), consumed fitness evaluations of A_k
 1: Initialize population, pop
 2: Set $\Delta f_k = 0$ and $\Delta FES_k = 0$ ($k = 1, 2, 3$)
 3: Randomly divide pop into four subpopulations, pop_k ($k = 1, 2, 3, 4$), whose size is $NP_k = \lambda_k \cdot NP$
 4: Randomly select a integer m from $[1, 3]$.
 5: Let $pop_m = pop_m \cup pop_4$ and $NP_m = NP_m + NP_4$

```

6:  $FES = NP$ ,  $r = 0$ , and  $r' = 0$ 
7: while  $FES \leq MaxFES$  do
8:   for  $k = 1$  to 3 do
9:     Execute  $A_k$  on  $pop_k$ 
10:    calculate  $\Delta f_k$  and  $\Delta FES_k$ 
11:   end for
12:    $FES = FES + \sum_{k=1}^3 \Delta FES_k$ 
13:    $pop = \cup_{k=1,2,3} pop_k$ 
14:    $r' = r$  and  $r = \text{mod}(MaxFES, ng \cdot NP)$ 
15:   if  $r' > r$  then
16:     Determine the most efficient constituent DE algorithm  $A_m$  by Eq 6
17:   end if
18:   Randomly divide  $pop$  into four subpopulations,  $pop_k$  ( $k = 1, 2, 3, 4$ ), whose size are  $NP_k = \lambda_k \cdot NP$ 
19:   Let  $pop_m = pop_m \cup pop_4$  and  $NP_m = NP_m + NP_4$ 
20:   Add the ETI control into the two constituent DE algorithms other than  $A_m$ 
21:    $NP = ((NP_{min} - NP_{max}) / MaxFES) \cdot FES + NP_{max}$ 
22: end while
23: Report solution

```

Experimental study

In the section, we list and compare computational results of the proposed algorithm and other algorithms. Firstly, we describe setup in experiment. Then, an experiment based on the CEC 2013 benchmark testing suite is executed to investigate the effect of each of the measures taken by us. After that, a comparative comparison against existing algorithms is executed based on the CEC 2014 and 2017 benchmark testing suites. In detail, we compare out IEDEV with EBOwithCMAR [41], jSO, L-SHADE-SPACMA, ETI-JADE, L-SHADE-RSP, EDEV, EAGDE, EB-L-SHADE, and NDE [9]. Among the peers, at least L-SHADE-SPACMA, ETI-JADE, L-SHADE-RSP, EB-L-SAHDE employ optional external archive, while ETI-JADE implement the ETI control. The all peers except EBOwithCMAR, ETI-JADE, and EDEV are all based on LPSR.

Experimental settings

Settings of all the algorithms are shown in Table 1. Here, D denotes dimensionality, while $MaxFES$ represents maximum number of function evaluations. The parameters for IEDEV are

Table 1. Settings for algorithms.

Algorithm	Parameters
EBOwithCMAR	$NP_{1,max} = 18 \cdot D$, $NP_{1,min} = 4$, $NP_{2,max} = 46.8 \cdot D$, $NP_{2,min} = 10$, $NP_3 = 4 + 3 \cdot \log(D)$, $H = 6$, $\sigma = 0.3$, $CS = 200$ when $D = 30$, $CS = 300$ when $D = 100$, $prob_{ls} = 0.1$ and $cfel_s = 0.25 \cdot MaxFES$
jSO	$NP_{max} = 25 \cdot \log(D) \cdot \sqrt{D}$, $NP_{min} = 4$, $p_{max} = 0.25$, $p_{min} = \frac{p_{max}}{2}$, $ A = 1404$, $H = 5$
L-SHADE-SPACMA	$NP_{max} = 18 \cdot D$, $Pbest = 0.11$, $H = 1.4$, $Arc_rate = 5$, $F_{CP} = 0.5$, $c = 0.8$, $T = 0.5 \cdot MaxFES$
ETI-JADE	$NP = 100$, $LN = 1$, $UN = NP$, $\mu_F = 0.5$, $\mu_{CR} = 0.5$, $c = 0.1$, $ A = 100$, and $p = 0.05$ [12]
L-SHADE-RSP	$NP_{max} = D^2 \cdot 75$, $NP_{min} = 4$, $ A = NP$, $H = 5$, and $k = 3$ [7]
EDEV	$NP = 60$ when $D = 30$, $NP = 100$ when $D = 50, 100$, $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$, and $ng = 20$ [21]
EAGDE	$NP_{max} = 180$ when $D = 30$, $NP_{max} = 400$ when $D = 100$, $NP_{min} = 12$, $p = 0.1$
EBL-SHADE	$NP_{max} = 18 \cdot D$, $NP_{min} = 4$, $Pbest = 0.11$, $EDE_best = 0.10$, $ A = 1.4$
NDE	$NP_{max} = 10 \cdot D$, $NP_{min} = 5$, $\mu_F = 0.5$, $\mu_{CR} = 0.5$, $gm = 10$, and $c = 0.1$ [9]
IEDEV	$NP_{max} = 300$, $NP_{min} = 4$, $\lambda_1 = \lambda_2 = \lambda_3 = 0.1$, $ng = 20$, $LN = 1$, and $UN = NP$

<https://doi.org/10.1371/journal.pone.0256206.t001>

Table 2. Result of the experiment to investigate the effect of measures.

Function	Average (standard deviation) of algorithms				
	EDEV	IEDEV-1	IEDEV-2	IEDEV-3	IEDEV
F1	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)
F2	1.58E+04	1.35E+04	9.57E+03	1.34E+04	5.60E+03
	(1.01E+04)	(8.35E+03)	(7.38E+03)	(1.25E+04)	(6.91E+03)
F3	1.89E+05	1.92E+05	1.24E+05	1.76E+05	1.18E+05
	(7.23E+05)	(6.82E+05)	(3.58E+05)	(4.63E+05)	(2.76E+05)
F4	8.90E+00	8.16E+00	7.67E+00	1.17E+01	4.72E+00
	(7.16E+00)	(5.81E+00)	(9.34E+00)	(9.25E+00)	(7.28E+00)
F5	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)
F6	6.71E-01	6.82E-01	8.18E-01	5.84E-01	6.62E-01
	(1.35E+00)	(8.46E-01)	(9.81E-01)	(7.94E-01)	(1.31E+00)
F7	3.06E+00	2.81E+00	1.79E+00	2.91E+00	1.35E+00
	(5.16E+00)	(4.78E+00)	(2.31E+00)	(7.24E+00)	(6.34E+00)
F8	2.09E+01	2.10E+01	2.03E+01	2.07E+01	2.03E+01
	(6.00E-02)	(7.24E-02)	(5.27E-02)	(3.71E-03)	(5.41E-03)
F9	2.54E+01	2.48E+01	2.85E+01	2.84E+01	2.66E+01
	(2.27E+00)	(3.57E+00)	(3.39E+00)	(5.48E+00)	(2.13E+00)
F10	3.88E-02	3.25E-02	2.57E-02	2.67E-02	2.46E-02
	(2.42E-02)	(3.84E-02)	(1.86E-02)	(5.82E-03)	(4.27E-03)
F11	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)
F12	2.68E+01	2.73E+01	2.18E+01	2.59E+01	2.16E+01
	(7.17E+00)	(5.75E+00)	(8.64E+00)	(8.57E+00)	(6.73E+00)
F13	4.32E+01	4.39E+01	3.27E+01	3.97E+01	2.59E+01
	(1.71E+01)	(2.38E+01)	(1.37E+01)	(1.52E+01)	(1.37E+01)
F14	1.72E-01	1.64E-01	2.67E-01	1.68E-01	1.82E-01
	(1.07E-01)	(3.57E-01)	(1.58E-01)	(1.39E-01)	(2.25E-01)
F15	4.19E+03	4.28E+03	3.87E+03	3.53E+03	3.21E+03
	(4.96E+02)	(5.91E+02)	(5.61E+02)	(2.97E+02)	(1.78E+02)
F16	2.27E+00	1.76E+00	1.95E+00	1.81E+00	1.58E+00
	(3.79E-01)	(2.61E-01)	(4.27E-01)	(4.38E-01)	(3.64E-01)
F17	3.04E+01	3.04E+01	3.04E+01	3.04E+01	3.04E+01
	(2.54E-13)	(4.58E-12)	(1.57E-14)	(3.71E-13)	(8.49E-14)
F18	9.21E+01	9.35E+01	9.07E+01	7.24E+01	7.03E+01
	(8.61E+00)	(7.71E+00)	(5.67E+00)	(6.34E+00)	(5.75E+00)
F19	1.98E+00	1.75E+00	1.83E+00	1.52E+00	1.42E+00
	(1.56E-01)	(3.56E-01)	(2.43E-01)	(3.67E-01)	(5.73E-01)
F20	1.10E+01	1.08E+01	1.27E+01	1.08E+01	1.17E+01
	(3.99E-01)	(2.58E-01)	(4.97E-01)	(4.41E-02)	(3.96E-01)
F21	2.99E+02	2.86E+02	2.58E+02	2.75E+02	2.45E+02
	(7.01E+01)	(8.21E+01)	(6.61E+01)	(5.87E+01)	(8.63E+01)
F22	1.16E+02	1.28E+02	8.25E+01	1.37E+02	1.03E+02
	(2.72E+01)	(3.77E+01)	(3.78E+01)	(3.64E+01)	(2.95E+01)
F23	4.40E+03	4.46E+03	4.12E+03	4.37E+03	4.28E+03
	(7.69E+02)	(6.72E+02)	(3.97E+02)	(9.37E+02)	(6.52E+02)

(Continued)

Table 2. (Continued)

Function	Average (standard deviation) of algorithms				
	EDEV	IEDEV-1	IEDEV-2	IEDEV-3	IEDEV
F24	2.37E+02	2.46E+02	2.21E+02	2.16E+02	2.05E+02
	(3.22E+01)	(2.46E+01)	(1.58E+01)	(5.28E+01)	(1.83E+01)
F25	2.76E+02	2.65E+02	2.72E+02	2.75E+02	2.70E+02
	(6.85E+00)	(5.82E+02)	(4.23E+00)	(7.82E+00)	(5.85E+00)
F26	2.00E+02	2.00E+02	2.00E+02	2.00E+02	2.00E+02
	(8.13E-03)	(7.58E-03)	(5.48E-05)	(5.54E-05)	(8.32E-07)
F27	6.90E+02	5.68E+02	4.28E+02	6.22E+02	4.79E+02
	(2.19E+02)	(3.71E+02)	(3.41E+02)	(5.48E+02)	(6.62E+02)
F28	3.00E+02	3.00E+02	3.00E+02	3.00E+02	3.00E+02
	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)	(0.00E+00)

<https://doi.org/10.1371/journal.pone.0256206.t002>

further explained as below. NP_{max} and NP_{min} is for LPSR. λ_1 , λ_2 , and λ_3 are inherited from EDEV to define ratio of each constituent DE algorithm, while LN and UN are redefined by us for the ETI control. Details can be found in the last subsection of the previous section. In all experiments, $MaxFES$ is set $10000 \cdot D$. We use two non-parametric statistical hypothesis tests to compare and analyze solution. In detail, the Friedman test is used for multiple comparison, while the Wilcoxon's rank sum test for pairwise comparison.

Experiment to investigate the effect of our measures

This experiment is based on the CEC 2013 benchmark testing suite which consists of 28 benchmark functions. In this experiment, D is set 30. For each function in the suite, EDEV, IEDEV-1 (EDEV changed in organization of the archive), IEDEV-2 (EDEV with the ETI control), IEDEV-3 (EDEV with LPSR), and our IEDEV are all executed 30 times, respectively. Results are given in Table 2. Then, in Table 3, we lists Friedman test ranks based on the results in Table 2. From the table, it can be seen that p-value is less than 0.05. That is, there exists significant difference on performance. According to Table 3, each measure taken by us enhances EDEV. Therefore, our IEDEV which integrates all the three measures performs much better than EDEV.

Experiment for comparative comparison

Based on the CEC 2014 benchmark test suite and the CEC 2017 benchmark test suite, when dimensionality is set 30 and 100, our algorithm is compared with the nine peers listed above. Furthermore, we give convergence graphs. Details are listed below.

Table 3. Friedman test ranks of EDEV and its variants proposed by us.

Algorithm	Ranking	Rank
IEDEV	1.9107	1
IEDEV-2	2.8036	2
IEDEV-3	2.9821	3
IEDEV-1	3.4464	4
EDEV	3.8571	5
Friedman p value	3.18E-06	

<https://doi.org/10.1371/journal.pone.0256206.t003>

Table 4. Results for CEC 2014 suites with 30 in dimensionality.

Function	Average (standard deviation) of algorithms									
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV
F1	4.76E-06 (6.95E-06)+	0.00E+00 (0.00E+00)+	0.00E+00 (0.00E+00)+	7.09E+02 (1.43E+03)-	2.46E-14 (2.45E-14)+	3.26E+03 (9.10E+03)-	0.00E+00 (0.00E+00)+	0.00E+00 (0.00E+00)+	5.50E+02 (1.31E+03)-	8.70E+01 (1.67E+02)
F2	2.18E-14 (1.22E-14)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈
F3	1.33E-14 (2.45E-14)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	4.00E-04 (6.09E-04)-	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈
F4	5.87E+01 (1.01E+00)-	0.00E+00 (0.00E+00)+	5.86E+01 (1.06E-14)-	2.11E+00 (1.16E+01)-	4.74E-14 (3.37E-14)+	6.86E-03 (2.55E-02)-	5.86E+01 (1.06E-14)-	5.86E+01 (1.01E+00)-	7.74E-04 (1.53E-03)≈	8.37E-05 (7.37E-04)
F5	2.00E+01 (9.18E-06)+	2.08E+01 (2.42E-01)-	2.02E+01 (2.35E-02)≈	2.00E+01 (1.91E-02)+	2.02E+01 (4.93E-02)≈	2.04E+01 (5.11E-02)-	2.01E+01 (2.51E-02)≈	2.01E+01 (3.42E-02)≈	2.02E+01 (8.50E-02)≈	2.01E+01 (5.30E-02)
F6	1.16E-01 (3.19E-01)-	8.52E-06 (1.26E-05)+	9.32E-02 (4.32E-01)-	4.90E-01 (7.92E-01)-	3.59E-02 (1.96E-01)-	5.21E-01 (1.16E+00)-	6.90E-01 (2.00E+00)-	0.00E+00 (3.30E-01)+	2.38E+00 (2.29E+00)-	5.63E-05 (7.28E-04)
F7	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈
F8	9.47E-14 (4.31E-14)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	4.11E-09 (7.73E-09)-	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (5.24E-14)≈	2.32E+00 (2.93E+00)-	0.00E+00 (0.00E+00)
F9	1.38E+01 (2.93E+00)-	8.38E+00 (1.87E+00)-	5.39E+00 (2.13E+00)≈	4.25E+01 (4.91E+00)≈	9.13E+00 (1.98E+00)-	3.49E+01 (5.46E+00)-	7.82E+00 (1.55E+00)-	3.21E+00 (1.40E+00)≈	5.12E+01 (2.15E+01)-	4.19E+00 (3.61E+00)
F10	2.01E-02 (2.08E-02)+	1.63E+00 (1.17E+00)-	1.11E-02 (1.52E-02)+	4.37E-02 (3.43E-02)+	6.32E+00 (2.37E+00)-	2.14E+00 (9.49E+00)-	2.78E-03 (7.20E-03)-	1.82E-12 (1.48E-02)+	4.37E+00 (2.27E+01)-	5.93E-02 (7.56E-02)
F11	1.71E+03 (2.51E+02)-	1.31E+03 (2.29E+02)-	1.54E+03 (3.51E+02)-	1.15E+03 (3.69E+02)-	1.20E+03 (2.18E+02)-	2.51E+03 (6.79E+02)-	1.86E+03 (1.73E+02)-	1.39E+03 (1.80E+02)-	2.10E+03 (5.59E+02)-	8.50E+01 (3.67E+02)
F12	9.29E-02 (3.65E-02)+	4.27E-01 (3.53E-01)-	2.25E-01 (3.27E-02)-	7.33E-02 (2.77E-02)+	2.39E-01 (5.01E-02)-	5.53E-01 (1.66E-01)-	2.42E-01 (3.89E-02)-	1.56E-01 (4.07E-02)-	1.55E-01 (1.02E-01)-	1.31E-01 (6.18E-02)
F13	1.36E-01 (2.72E-02)-	1.35E-01 (2.13E-02)-	1.08E-01 (1.76E-02)+	1.39E-01 (3.53E-02)+	1.29E-01 (1.40E-02)≈	1.94E-01 (3.36E-02)-	1.30E-01 (1.82E-02)-	8.29E-02 (1.16E-02)≈	9.90E-02 (3.03E-02)≈	9.51E-02 (4.62E-02)
F14	1.78E-01 (1.75E-02)-	2.24E-01 (3.46E-02)-	1.80E-01 (2.14E-02)-	1.63E-01 (2.73E-02)-	1.41E-01 (2.05E-02)+	1.75E-01 (2.56E-02)-	2.11E-01 (2.38E-02)-	1.52E-01 (2.55E-02)≈	2.26E-01 (3.66E-02)-	1.52E-01 (2.85E-02)
F15	2.13E+00 (3.86E-01)-	2.22E+00 (3.21E-01)-	2.19E+00 (3.51E-01)≈	2.61E+00 (5.72E-01)-	2.39E+00 (3.62E-01)-	4.03E+00 (4.78E-01)-	2.48E+00 (3.43E-01)-	1.99E+00 (2.47E-01)≈	3.10E+00 (8.71E-01)-	2.03E+00 (1.56E-01)
F16	9.80E+00 (4.71E-01)-	8.72E+00 (7.48E-01)-	8.77E+00 (6.34E-01)-	8.32E+00 (5.62E-01)≈	8.31E+00 (4.39E-01)≈	9.86E+00 (4.19E-01)-	9.92E+00 (4.75E-01)-	8.59E+00 (4.63E-01)-	1.00E+01 (7.26E-01)≈	8.27E+00 (3.76E-01)
F17	2.72E+02 (1.12E+02)+	6.74E+01 (1.52E+01)+	3.81E+02 (1.45E+02)+	2.19E+04 (6.44E+04)-	6.67E+01 (3.88E+01)+	4.52E+03 (8.35E+03)≈	3.67E+02 (1.38E+02)+	5.70E+01 (9.93E+01)+	1.91E+02 (1.19E+02)+	4.16E+03 (4.28E+03)
F18	1.29E+01 (7.35E+00)-	2.21E+00 (1.18E+00)+	1.36E+01 (5.23E+00)-	1.05E+02 (2.09E+02)-	2.70E+00 (1.54E+00)+	2.44E+01 (1.58E+01)-	9.70E+00 (4.25E+00)≈	3.16E+00 (2.42E+00)+	8.58E+00 (3.77E+00)≈	8.60E+00 (3.67E+00)
F19	3.78E+00 (1.90E+00)-	1.99E+00 (6.54E-01)+	2.37E+00 (9.99E-01)-	3.83E+00 (7.95E-01)-	1.92E+00 (8.18E-01)+	3.65E+00 (2.26E+00)-	7.95E+00 (1.71E+00)-	3.43E+00 (1.52E+00)-	2.69E+00 (7.11E-01)-	2.16E+00 (3.95E+00)

(Continued)

Table 4. (Continued)

Function	Average (standard deviation) of algorithms									
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV
F20	3.65E+00 (1.73E+00)+	2.02E+00 (6.92E-01)+	3.80E+00 (1.86E+00)+	1.52E+02 (1.09E+02)-	1.94E+00 (6.42E-01)+	1.47E+01 (3.60E+00)-	4.13E+00 (1.45E+00)+	1.18E+00 (1.22e+00)+	5.30E+00 (1.70E+00)+	8.49E+00 (2.57E+00)
F21	1.70E+02 (7.50E+01)-	2.62E+01 (3.90E+01)-	1.77E+02 (9.89E+01)-	2.06E+03 (7.27E+03)-	1.58E+01 (3.17E+01)≈	3.62E+02 (1.71E+02)-	1.84E+02 (9.88E+01)-	2.17E+00 (8.50e+01)+	4.06E+01 (5.14E+01)-	1.58E+01 (6.82E+01)
F22	2.51E+01 (1.57E+00)+	2.91E+01 (2.18E+01)+	2.22E+01 (1.53E+00)+	1.03E+02 (7.91E+01)≈	2.77E+01 (2.21E+01)+	1.03E+02 (6.14E+01)≈	2.87E+01 (2.33E+00)+	2.42E+01 (1.19e+00)+	6.40E+01 (6.83E+01)+	9.23E+01 (1.84E+01)
F23	3.36E+02 (8.44E-14)-	3.15E+02 (1.09E-13)-	3.36E+02 (0.00E+00)-	3.15E+02 (1.11E-13)-	3.15E+02 (5.78E-14)-	3.14E+02 (1.57E-13)≈	3.36E+02 (8.44E-14)-	3.36E+02 (8.44E-14)-	3.15E+02 (1.45E-13)-	3.14E+02 (2.44E-14)
F24	1.97E+02 (1.84E+01)+	2.07E+02 (1.02E+01)≈	2.01E+02 (3.94E-02)≈	2.25E+02 (2.42E+00)-	2.06E+02 (1.02E+01)≈	2.24E+02 (9.60E-01)-	2.01E+02 (5.50E-02)+	2.01E+02 (4.80e-02)+	2.21E+02 (6.99E+00)-	2.05E+02 (6.35E+00)
F25	2.00E+02 (9.77E-01)≈	2.03E+02 (2.79E-02)≈	2.01E+02 (1.24E+00)≈	2.04E+02 (1.20E+00)-	2.03E+02 (1.89E-02)-	2.00E+02 (2.74E-02)≈	2.02E+02 (1.41E+00)-	2.00E+02 (1.05e+00)≈	2.03E+02 (2.88E-01)-	2.00E+02 (3.76E-02)
F26	1.00E+02 (2.51E-02)≈	1.00E+02 (2.22E-02)≈	1.00E+02 (2.33E-02)≈	1.00E+02 (3.70E-02)≈	1.00E+02 (1.56E-02)≈	1.00E+02 (3.86E-02)≈	1.00E+02 (1.41E-02)≈	1.00E+02 (1.51e-02)≈	1.00E+02 (5.82E-02)≈	1.00E+02 (5.39E-02)
F27	3.01E+02 (1.74E+00)+	3.00E+02 (1.71E-13)+	3.02E+02 (2.83E+00)+	3.32E+02 (4.50E+01)≈	3.01E+02 (6.80E+00)+	3.60E+02 (4.95E+01)-	3.02E+02 (3.04E+00)+	3.00E+02 (1.69e+00)+	4.00E+02 (2.40E-01)-	3.37E+02 (4.53E+01)
F28	4.14E+02 (2.16E+01)≈	8.25E+02 (1.94E+01)-	4.19E+02 (2.40E+00)+	7.63E+02 (3.57E+01)-	8.18E+02 (1.85E+01)-	3.83E+02 (6.52E+00)+	4.21E+02 (3.98E+00)-	4.15E+02 (3.08e+00)-	8.26E+02 (2.68E+01)-	4.09E+02 (2.17E+01)
F29	4.33E+02 (1.37E+01)-	7.16E+02 (2.48E+00)-	4.96E+02 (1.16E+01)≈	7.44E+02 (1.13E+02)-	7.15E+02 (1.63E+00)-	2.14E+02 (9.65E-01)+	4.32E+02 (1.03E+01)-	4.26E+02 (5.89e+00)-	6.46E+02 (1.84E+02)-	4.06E+02 (6.84E+00)
F30	4.43E+02 (1.33E+01)-	6.53E+02 (2.19E+02)-	4.63E+02 (5.51E+01)-	1.43E+03 (4.60E+02)-	2.01E+03 (7.02E+02)-	3.66E+02 (1.07E+02)≈	4.43E+02 (7.94E+01)-	3.87E+02 (1.44e+01)-	5.62E+02 (1.86E+02)-	3.26E+02 (3.49E+02)
-	14	14	11	18	12	18	17	9	18	18
+	9	9	8	4	9	2	6	10	3	3
≈	7	7	11	8	9	10	7	11	9	9

“+” or “-” denotes that the current result is significantly better or statistical worse than the result of our algorithm in terms of Wilcoxon’s rank sum test at a 0.05 significance level, respectively. Meanwhile, “≈” represents that there is no significant difference.

<https://doi.org/10.1371/journal.pone.0256206.t004>

Table 5. Results for CEC 2014 suites with 100 in dimensionality.

Function	Average (standard deviation) of algorithms										
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBI-SHADE	NDE	IEDEV	
F1	1.66E-02 (6.38e-03)+	1.37E+05 (4.54E+04)≈	1.03E+04 (8.52E+03)+	1.39E+05 (1.07E+05)≈	6.95E+04 (3.89E+04)+	1.07E+05 (5.69E+04)+	1.39E+05 (4.31E+04)≈	6.68E+04 (5.49e+04)+	9.90E+05 (2.69E+05)-	1.68E+05 (8.57E+04)	
F2	1.46E-04 (1.66e-04)-	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	1.56E-10 (3.74E-10)≈	2.56E-13 (1.04E-13)≈	2.39E-10 (3.81E-10)-	0.00E+00 (0.00E+00)≈	1.42E-13 (8.50e-14)≈	3.98E+03 (5.04E+03)-	0.00E+00 (0.00E+00)	
F3	3.16E-09 (3.76e-09)≈	0.00E+00 (0.00E+00)+	0.00E+00 (0.00E+00)≈	1.84E+02 (1.56E+02)-	4.26E-13 (1.37E-13)≈	4.84E+00 (1.04E+01)-	0.00E+00 (0.00E+00)≈	1.14E-13 (1.97e-13)≈	1.26E+01 (2.12E+01)-	7.31E-11 (5.47E-11)	
F4	1.77E+02 (6.04e+01)-	1.56E+02 (2.80E+01)-	2.05E+02 (1.04E+01)-	9.50E+01 (4.44E+01)-	1.77E+02 (3.28E+01)-	5.45E+01 (6.85E+01)-	1.85E+02 (2.95E+01)-	6.84E+01 (3.84e+01)-	1.62E+02 (2.95E+01)-	3.27E+01 (3.98E+01)	
F5	2.00E+01 (1.39e-06)≈	2.08E+01 (3.15E-01)-	2.05E+01 (3.67E-02)-	2.00E+01 (6.98E-03)≈	2.07E+01 (2.16E-01)-	2.08E+01 (2.96E-01)-	2.06E+01 (3.30E-02)-	2.05E+01 (2.67e-02)-	2.05E+01 (3.04E-01)-	2.00E+01 (7.24E-04)	
F6	1.14E+00 (1.10e+00)+	4.01E+00 (1.76E+00)-	7.75E-01 (6.24E-01)+	2.38E+01 (9.22E+00)-	1.31E+00 (1.17E+00)+	3.65E+01 (4.21E+00)-	1.23E+01 (2.62E+00)-	6.99E+00 (2.71e+00)-	6.18E+01 (1.38E+01)-	1.68E+00 (1.49E+00)	
F7	1.97E-13 (5.11e-14)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	9.04E-04 (2.86E-03)-	1.59E-13 (5.66E-14)≈	1.40E-03 (3.75E-03)-	8.21E-04 (3.19E-03)-	1.14E-13 (1.35e-03)≈	1.23E-03 (4.13E-03)-	7.56E-14 (2.57E-14)	
F8	1.86E-01 (3.96e-01)-	4.20E-03 (2.53E-03)-	4.34E+00 (2.11E+00)-	1.14E-13 (0.00E+00)≈	2.47E+00 (1.35E+00)-	0.00E+00 (0.00E+00)≈	1.04E-01 (5.10E-02)-	6.04E-04 (9.27e-04)-	2.78E+01 (2.62E+01)-	0.00E+00 (0.00E+00)	
F9	5.16E+01 (1.25e+01)-	4.45E+01 (6.75E+00)-	1.16E+01 (2.75E+00)+	1.46E+02 (2.47E+01)-	3.70E+01 (8.51E+00)≈	1.71E+02 (2.57E+01)-	5.72E+01 (5.25E+00)-	2.59E+01 (7.24e+00)+	8.95E+01 (3.83E+01)-	3.87E+01 (6.54E+00)	
F10	8.56E+01 (1.50e+02)-	8.01E+01 (2.59E+01)-	1.72E+01 (3.45E+00)-	1.46E+02 (2.68E+01)-	2.64E+02 (5.27E+01)-	7.15E-01 (2.27E-01)-	6.68E+01 (1.16E+01)-	1.63E+01 (4.69e+00)-	3.83E+01 (1.51E+01)-	5.24E-01 (7.27E-01)	
F11	1.14E+04 (1.26e+03)≈	1.01E+04 (7.02E+02)+	1.14E+04 (1.12E+03)-	9.41E+03 (8.88E+02)≈	1.08E+04 (8.09E+02)≈	1.11E+04 (3.50E+03)≈	1.54E+04 (6.18E+02)-	1.20E+04 (6.58e+02)-	1.30E+04 (1.47E+03)≈	1.06E+04 (9.14E+02)	
F12	6.80E-02 (2.87e-02)-	4.60E-01 (8.64E-02)-	9.74E-01 (9.45E-02)-	1.04E-01 (5.14E-02)+	4.77E-01 (4.46E-02)-	8.30E-01 (6.83E-01)-	1.09E+00 (9.91E-02)-	7.61E-01 (8.96e-02)-	3.52E-01 (2.34E-01)≈	3.48E-01 (5.57E-02)	
F13	2.84E-01 (2.49e-02)≈	3.09E-01 (4.29E-02)+	3.04E-01 (2.45E-02)+	3.22E-01 (5.38E-02)≈	2.66E-01 (2.46E-02)+	3.64E-01 (3.43E-02)≈	2.41E-01 (1.82E-02)+	1.87E-01 (1.67e-02)+	2.75E-01 (4.64E-02)+	3.37E-01 (2.47E-02)	
F14	2.47E-01 (1.39e-02)-	2.10E+02 (3.97E+01)-	2.27E-01 (1.67E-02)-	1.14E-01 (1.21E-02)+	1.08E-01 (9.94E-03)+	2.09E-01 (1.69E-02)-	3.06E-01 (1.51E-02)-	2.65E-01 (1.27e-02)-	1.38E-01 (1.64E-02)+	1.52E-01 (1.59E-02)	
F15	1.06E+01 (3.02e+00)+	1.55E+01 (1.93E+00)≈	1.27E+01 (2.58E+00)+	1.88E+01 (3.36E+00)-	1.68E+01 (9.89E-01)-	2.12E+01 (3.99E+00)-	1.92E+01 (1.30E+00)-	1.34E+01 (1.38e+00)+	1.18E+01 (1.62E+00)+	1.61E+01 (1.54E+00)	
F16	4.06E+01 (1.33e+00)-	3.89E+01 (7.05E-01)-	3.88E+01 (6.52E-01)-	3.85E+01 (1.84E+00)-	3.89E+01 (4.19E-01)-	4.04E+01 (5.51E-01)-	4.05E+01 (5.36E-01)-	3.86E+01 (6.83e-01)-	4.23E+01 (1.76E+00)≈	3.67E+01 (7.28E-01)	
F17	3.88E+03 (6.92e+02)+	3.52E+03 (7.34E+02)+	3.30E+03 (4.47E+02)+	1.25E+04 (4.79E+03)+	3.99E+03 (5.40E+02)+	4.59E+04 (1.89E+05)-	5.21E+03 (7.45E+02)+	4.04E+03 (7.04e+02)+	9.81E+03 (4.94E+03)+	3.42E+04 (2.51E+04)	
F18	1.61E+02 (1.93e+01)+	2.17E+02 (2.04E+01)≈	2.05E+02 (2.61E+01)≈	6.40E+02 (5.70E+02)-	2.61E+02 (3.34E+01)≈	3.05E+02 (6.52E+01)-	2.54E+02 (2.78E+01)-	2.08E+02 (2.03e+01)≈	2.53E+02 (5.25E+01)-	2.11E+02 (6.75E+01)	
F19	1.04E+06 (7.94e+05)-	9.11E+01 (1.19E+00)-	5.93E+01 (1.37E+00)-	9.75E+01 (1.76E+01)-	9.12E+01 (1.24E+00)-	4.33E+01 (2.87E+01)≈	7.04E+01 (2.03E+00)-	6.34E+01 (2.42e+00)-	9.23E+01 (1.99E+00)-	3.76E+01 (2.49E+01)	

(Continued)

Table 5. (Continued)

Function	Average (standard deviation) of algorithms										
	EBOwith CMAR	JSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV	
F20	3.38E+03 (4.84E+02)-	4.87E+01 (1.14E+01)+	3.07E+01 (7.22E+00)+	1.12E+03 (1.21E+03)-	3.52E+01 (8.30E+00)+	3.30E+02 (9.56E+01)+	1.73E+02 (4.49E+01)+	7.44E+01 (2.73E+01)+	3.15E+02 (6.82E+01)+	4.43E+02 (1.28E+02)	
F21	6.56E+02 (6.80E+01)+	9.04E+02 (3.73E+02)+	1.40E+03 (3.86E+02)+	4.22E+03 (1.91E+03)+	1.03E+03 (3.55E+02)+	7.47E+03 (1.95E+04)-	2.96E+03 (6.02E+02)+	1.08E+03 (4.91E+02)+	1.88E+03 (6.12E+02)+	5.47E+03 (4.43E+04)	
F22	1.89E+04 (5.45E+03)-	1.05E+03 (2.43E+02)+	8.66E+02 (3.96E+02)+	1.53E+03 (3.84E+02)≈	1.10E+03 (2.51E+02)+	1.43E+03 (3.46E+02)≈	7.37E+02 (2.07E+02)+	2.79E+02 (1.73E+02)+	1.46E+03 (5.28E+02)-	1.27E+03 (5.41E+02)	
F23	2.49E+04 (6.34E+03)-	3.48E+02 (0.00E+00)-	3.38E+02 (1.95E+00)-	3.48E+02 (1.89E-13)-	3.48E+02 (0.00E+00)-	3.45E+02 (5.40E-12)-	3.38E+02 (1.95E+00)-	3.38E+02 (1.95E+00)-	3.48E+02 (2.94E-12)+	3.06E+02 (0.00E+00)	
F24	2.00E+02 (2.05E+00)≈	3.84E+02 (2.66E+00)-	2.03E+02 (1.22E-01)-	3.99E+02 (5.67E+00)-	3.87E+02 (2.06E+00)-	3.94E+02 (3.79E+00)-	2.03E+02 (1.69E-01)-	2.03E+02 (9.72E-02)-	3.80E+02 (2.96E+00)-	2.00E+02 (2.41E+00)	
F25	1.39E+05 (3.47E+04)-	2.02E+02 (4.79E+00)+	2.14E+02 (2.08E-01)≈	2.71E+02 (8.10E+00)-	2.16E+02 (9.80E-01)-	2.41E+02 (2.16E+01)-	2.17E+02 (1.36E+00)≈	2.15E+02 (1.27E+00)-	2.29E+02 (1.26E+01)-	2.10E+02 (3.57E+01)	
F26	4.25E+04 (1.55E+03)-	2.00E+02 (1.99E-13)≈	1.00E+02 (2.25E-02)+	2.00E+02 (1.69E-02)≈	2.00E+02 (2.25E-02)≈	2.00E+02 (1.59E-02)≈	1.00E+02 (1.48E-02)+	1.00E+02 (1.56E-02)+	1.37E+02 (4.89E+01)+	2.00E+02 (1.84E-02)	
F27	2.09E+03 (2.59E+03)-	3.43E+02 (3.14E+01)+	3.15E+02 (1.41E+01)+	1.09E+03 (1.15E+02)≈	3.08E+02 (1.64E+01)+	1.10E+03 (5.03E+02)≈	5.04E+02 (5.99E+01)+	4.02E+02 (4.95E+01)+	6.77E+02 (8.92E+01)+	9.47E+02 (3.57E+02)	
F28	2.89E+04 (5.80E+04)-	2.14E+03 (7.33E+01)-	5.26E+02 (1.47E+01)+	2.30E+03 (2.58E+02)-	2.11E+03 (5.34E+01)-	6.80E+02 (8.14E+01)≈	5.83E+02 (1.60E+01)≈	5.31E+02 (1.51E+01)+	2.30E+03 (7.44E+01)-	6.68E+02 (2.87E+01)	
F29	4.40E+03 (6.91E+02)-	7.36E+02 (3.06E+01)-	9.27E+02 (6.72E+00)-	1.35E+03 (2.03E+02)-	7.74E+02 (5.94E+01)-	2.51E+02 (5.09E+00)+	9.31E+02 (5.99E+00)-	9.20E+02 (7.08E+00)-	1.22E+03 (2.49E+02)-	2.87E+02 (4.26E+00)	
F30	1.51E+11 (1.51E+10)-	4.73E+03 (1.01E+03)-	5.70E+03 (6.83E+02)-	8.36E+03 (1.13E+03)-	7.96E+03 (7.57E+02)-	2.67E+03 (6.61E+02)-	5.96E+03 (7.12E+02)-	3.83E+03 (5.89E+02)-	3.95E+03 (6.70E+02)-	2.33E+03 (4.39E+02)	
-	18	15	13	17	14	19	18	15	18		
+	6	9	12	4	9	3	7	11	9		
≈	6	6	5	9	7	8	5	4	3		

“+” or “-” denotes that the current result is significantly better or statistical worse than the result of our algorithm in terms of Wilcoxon’s rank sum test at a 0.05 significance level, respectively. Meanwhile, “≈” represents that there is no significant difference.

<https://doi.org/10.1371/journal.pone.0256206.t005>

Table 6. Friedman test ranks for the CEC 2014 experiment.

Algorithm	30D	100D	Mean Ranking	Rank
EBL-SHADE	3.33	3.88	3.61	1
IEDEV	3.92	4.08	4.00	2
L-SHADE-SPACMA	5.23	3.85	4.54	3
jSO	5.23	4.85	5.04	4
L-SHADE-RSP	4.97	5.38	5.18	5
EAGDE	5.95	5.97	5.96	6
EBOwithCMAR	5.55	6.40	5.98	7
EDEV	6.80	6.70	6.75	8
NDE	7.00	6.85	6.93	9
ETI-JADE	7.02	7.03	7.03	10
Friedman p value	2.76E-08	2.85E-07		

<https://doi.org/10.1371/journal.pone.0256206.t006>

The results of CEC 2014 functions are given in Tables 4 and 5. The Table 4 is for the comparison when dimensionality is set 30, while Table 5 is for 100. In Table 6, we lists Friedman test ranks based on the result in Tables 4 and 5. From the table, it can be seen that p-value is always less than 0.05. That is, there exists significant difference on performance. In Fig 1, convergence graph of the ten algorithms are plotted for five functions int the CEC 2014 suite. For these functions, our algorithm never performs worse than the peers.

The results of CEC 2017 functions are given in Tables 7 and 8. The former is for the comparison when dimensionality is set 30, while the latter is for 100. In Table 9, we lists Friedman test ranks based on the result in Tables 7 and 8. From the table, it can be seen that p-value is always less than 0.05. That is, there exists significant difference on performance.

According to Table 4, in term of Wilcoxon's rank sun test, our algorithm performs worse than EBL-SHADE for the CEC 2014 suite with 30 in dimensionality but better than all the other peers. According to Table 5, in term of Wilcoxon's rank sun test, our algorithm defeats all the peers for the CEC 2014 suite with 100 in dimensionality. It can be seen from Table 6 that, in term of Friedman test, our algorithm ranks second. That is, our algorithm defeats all the peers except EBL-SHADE. Fig 1 demonstrates that our algorithm does not performs outstanding at all at the initial stage but show make a greater progress than most of the peers in the latter stage.

According to Table 7, in term of Wilcoxon's rank sun test, our algorithm performs worse than EBL-SHADE for the CEC 2017 suite with 30 in dimensionality but better than all the other peers. According to Table 8, in term of Wilcoxon's rank sun test, our algorithm performs worse than L-SHADE-SPACMA and EBL-SHADE for the CEC 2017 suite with 100 in dimensionality but better than all the other peers. It can be seen from Table 9 that, in term of Friedman test, our algorithm ranks second. That is, our algorithm defeats all the peers except EBL-SHADE.

Discussion

In fact, the peers selected by us are good performers in the CEC competitions on real parameter single objective optimization among population-based metaheuristics, state-of-the-art algorithms, or up-to-date algorithms. According to the results of our experiments, our IEDEV is competitive among DE algorithms. Based on EDEV, we integrate three measures. Firstly, individuals in optional external archive of the constituent algorithm JADE is collected from a wider range to maintain diversity. Then, the fiercer competition among the three constituent

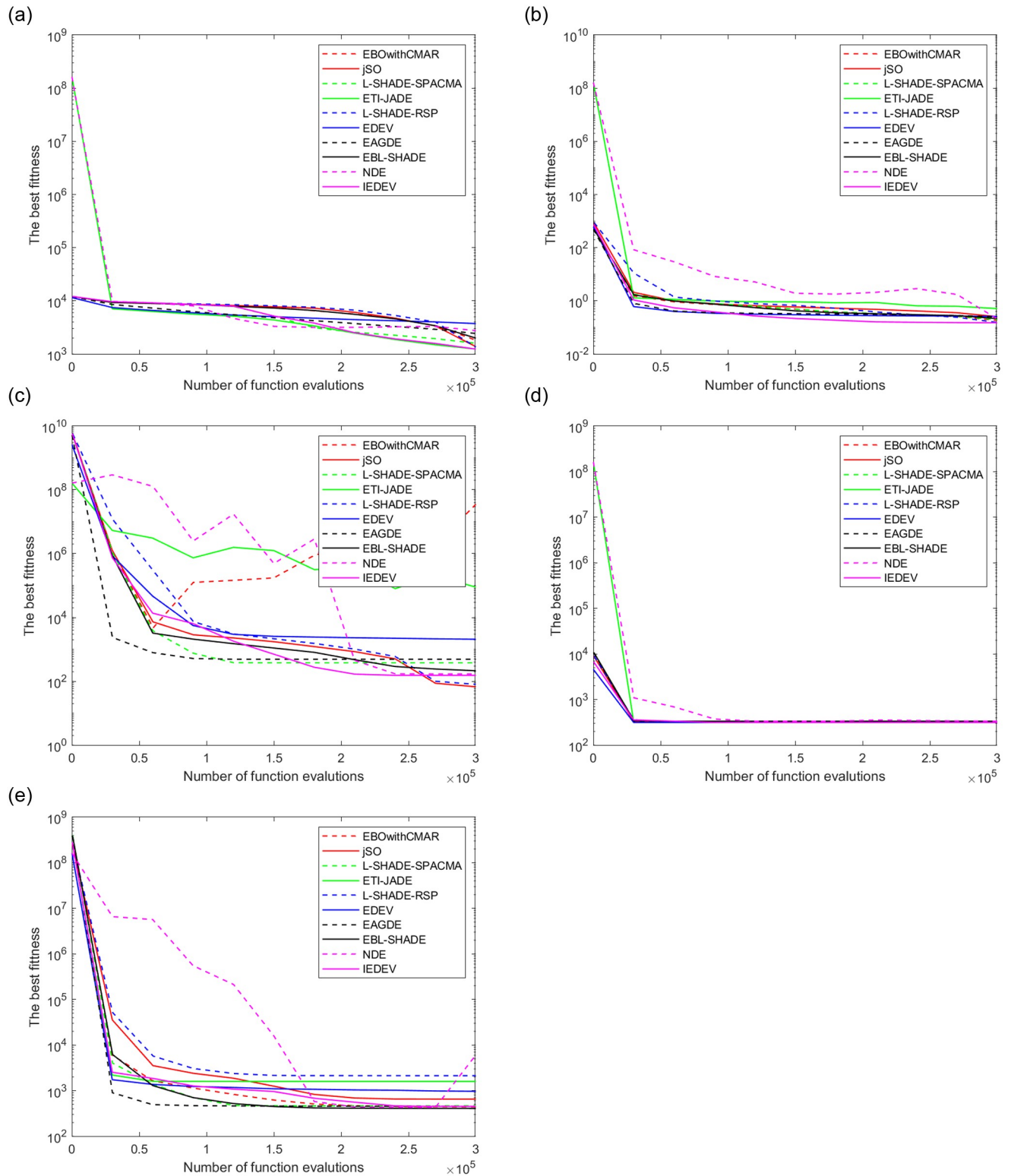


Fig 1. Convergence graphs of the ten algorithms for the five functions from the CEC 2014 suite. (a): F11, (b): F14, (c): F17, (d): F23, (e): F30.

<https://doi.org/10.1371/journal.pone.0256206.g001>

Table 7. Results for CEC 2017 suites with 30 in dimensionality.

Function	Average (standard deviation) of algorithms										
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETL-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV	
F1	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (2.59e-15)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)	
F2	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	3.71E-13 (4.09E-13)≈	1.42E-14 (1.94E-14)≈	1.97E-12 (4.82E-12)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (7.21e-15)≈	0.00E+00 (2.46E-08)–	4.84E-09 (3.57E-14)	
F3	7.39E-14 (3.39E-14)≈	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	6.59E+03 (6.52E+03)–	2.27E-14 (2.83E-14)≈	5.96E-02 (1.96E-01)–	0.00E+00 (0.00E+00)≈	0.00E+00 (2.79e-14)≈	0.00E+00 (3.39E-03)–	6.18E-04 (7.67E-14)	
F4	5.93E+01 (1.92e+00)–	5.86E+01 (2.08E-14)–	5.86E+01 (0.00E+00)–	4.25E+01 (2.43E+01)–	5.86E+01 (2.11E-14)–	4.00E+00 (1.72E+00)–	5.86E+01 (1.49E-14)–	5.86E+01 (3.17e-14)–	5.91E+01 (1.70E+00)–	5.91E+01 (8.96E-01)	
F5	2.69E+00 (1.59e+00)+	8.79E+00 (1.56E+00)–	3.37E+00 (2.06E+00)+	2.21E+01 (5.60E+00)–	8.65E+00 (1.67E+00)–	3.27E+01 (6.29E+00)–	7.18E+00 (1.39E+00)≈	3.11E+00 (1.48e+00)+	3.98E+01 (1.98E+01)–	5.46E+00 (2.37E+00)	
F6	1.14E-13 (0.00e+00)≈	1.14E-08 (3.46E-08)–	0.00E+00 (0.00E+00)+	1.14E-13 (0.00E+00)≈	8.50E-08 (2.11E-07)–	1.14E-13 (0.00E+00)≈	5.70E-09 (2.55E-08)–	1.14E-13 (2.50e-08)≈	4.56E-09 (2.50E-08)–	1.14E-13 (0.00E+00)	
F7	3.35E+01 (8.12e-01)+	3.92E+01 (1.70E+00)–	3.40E+01 (9.41E-01)+	5.14E+01 (4.62E+00)–	4.02E+01 (1.65E+00)–	6.38E+01 (5.60E+00)–	3.86E+01 (1.13E+00)≈	3.52E+01 (1.27e+00)≈	5.96E+01 (1.03E+01)–	3.57E+01 (3.27E+00)	
F8	2.49E+00 (1.58e+00)–	9.33E+00 (1.72E+00)+	3.64E+00 (2.50E+00)+	2.30E+01 (5.68E+00)+	9.82E+00 (2.62E+00)+	3.33E+01 (5.60E+00)+	8.50E+00 (1.88E+00)+	5.03E+00 (1.47e+00)+	5.25E+01 (1.91E+01)+	7.63E+01 (4.27E+00)	
F9	0.00E+00 (0.00e+00)+	0.00E+00 (0.00E+00)+	0.00E+00 (0.00E+00)+	2.98E-03 (1.63E-02)–	0.00E+00 (0.00E+00)+	2.98E-03 (1.63E-02)–	0.00E+00 (0.00E+00)+	0.00E+00 (0.00e+00)+	0.00E+00 (0.00E+00)+	4.63E-05 (5.73E-04)	
F10	1.42E+03 (2.38e+02)–	1.51E+03 (2.21E+02)–	1.47E+03 (3.09E+02)–	1.27E+03 (3.75E+02)–	1.38E+03 (3.13E+02)–	2.81E+03 (6.02E+02)–	1.48E+03 (2.03E+02)–	9.54E+02 (1.91e+02)–	2.55E+03 (6.49E+02)–	7.28E+02 (3.48E+02)	
F11	1.11E+01 (2.01e+01)–	7.01E+00 (1.48E+01)+	1.07E+01 (1.75E+01)–	2.24E+01 (2.39E+01)–	1.27E+01 (2.17E+01)–	2.00E+01 (1.70E+01)–	2.83E+01 (2.89E+01)–	1.99E+00 (2.75e+01)+	1.35E+01 (1.44E+01)+	7.36E+00 (3.76E+01)	
F12	4.29E+02 (2.50e+02)≈	1.92E+02 (1.03E+02)+	4.69E+02 (2.45E+02)≈	1.35E+03 (4.10E+02)–	3.58E+02 (2.20E+02)+	1.24E+03 (5.42E+02)–	1.06E+03 (3.44E+02)–	3.41E+02 (2.83e+02)≈	4.92E+02 (2.28E+02)+	5.39E+02 (1.43E+02)	
F13	1.30E+01 (6.76e+00)+	1.51E+01 (5.99E+00)≈	1.28E+01 (6.51E+00)≈	2.77E+02 (1.69E+01)–	2.01E+01 (3.67E+00)–	9.06E+01 (6.27E+01)–	1.71E+01 (5.93E+00)≈	9.95E-01 (5.62e+00)+	1.70E+01 (8.07E+00)–	1.57E+01 (8.48E+00)	
F14	2.28E+01 (1.48e+00)–	2.23E+01 (9.77E-01)–	2.31E+01 (1.51E+00)–	1.33E+03 (2.76E+03)–	2.02E+01 (5.41E+00)+	3.09E+01 (1.00E+01)–	2.20E+01 (3.68E+00)≈	5.63E-02 (4.35e+00)+	2.05E+01 (1.00E+01)+	2.08E+01 (1.00E+01)	
F15	3.14E+00 (1.63e+00)–	1.03E+00 (5.41E-01)–	5.06E+00 (3.07E+00)–	5.56E+02 (1.57E+03)–	1.81E+00 (9.90E-01)–	1.53E+01 (1.06E+01)–	4.19E+00 (2.41E+00)–	3.00E-01 (1.37e+00)–	4.85E+00 (1.87E+00)–	2.42E-01 (4.83E-01)	
F16	6.88E+01 (7.60e+01)≈	6.72E+01 (8.71E+01)≈	6.13E+01 (8.12E+01)≈	3.17E+02 (1.96E+02)–	2.44E+01 (2.35E+01)+	4.06E+02 (1.33E+02)–	9.61E+01 (7.58E+01)–	1.41E+01 (3.94e+01)+	2.66E+02 (2.49E+02)–	5.96E+01 (4.98E+01)	
F17	3.20E+01 (6.65e+00)≈	2.93E+01 (7.51E+00)+	3.19E+01 (7.79E+00)≈	4.44E+01 (4.24E+01)–	3.38E+01 (7.78E+00)≈	5.52E+01 (9.71E+00)–	3.58E+01 (6.46E+00)–	1.24E+01 (5.74e+00)+	6.04E+01 (3.75E+01)–	3.25E+01 (4.68E+00)	
F18	2.25E+01 (1.34e+00)≈	2.01E+01 (3.66E+00)+	2.37E+01 (2.16E+00)≈	6.47E+03 (1.98E+04)–	2.08E+01 (5.60E-01)+	4.81E+01 (2.92E+01)–	2.34E+01 (4.39E+00)≈	2.03E+01 (9.07e-01)≈	2.31E+01 (5.64E+00)+	2.31E+01 (5.90E+01)	
F19	8.71E+00 (2.22e+00)–	4.41E+00 (1.67E+00)–	1.08E+01 (3.08E+00)–	6.56E+02 (4.47E+03)–	4.26E+00 (1.04E+00)–	1.49E+01 (3.38E+00)–	5.29E+00 (1.22E+00)–	2.90E+00 (1.46e+00)–	5.64E+00 (1.30E+00)–	2.14E+00 (1.93E+00)	

(Continued)

Table 7. (Continued)

Function	Average (standard deviation) of algorithms									
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV
F20	3.61E+01 (6.63E+00)≈	2.89E+01 (4.49E+00)+	8.12E+01 (5.27E+01)-	5.07E+01 (5.80E+01)≈	2.80E+01 (6.12E+00)+	8.78E+01 (6.07E+01)-	3.40E+01 (5.81E+00)-	1.64E+01 (6.69E+00)+	7.59E+01 (7.73E+01)-	3.52E+01 (1.64E+01)
F21	2.03E+02 (1.50E+00)≈	2.09E+02 (1.89E+00)-	2.07E+02 (3.58E+00)-	2.26E+02 (6.00E+00)-	2.10E+02 (2.09E+00)-	2.36E+02 (6.75E+00)-	2.08E+02 (1.85E+00)-	2.04E+02 (1.08E+00)-	2.39E+02 (1.93E+01)-	2.03E+02 (1.37E+00)
F22	1.00E+02 (0.00E+00)≈	1.00E+02 (0.00E+00)≈	1.00E+02 (2.12E-13)≈	1.00E+02 (0.00E+00)≈	1.00E+02 (0.00E+00)≈	1.00E+02 (8.30E-14)≈	1.00E+02 (0.00E+00)≈	1.00E+02 (8.30E-14)≈	1.00E+02 (0.00E+00)≈	1.00E+02 (0.00E+00)
F23	3.53E+02 (4.52E+00)-	3.50E+02 (3.52E+00)-	3.56E+02 (3.27E+00)-	3.67E+02 (7.03E+00)-	3.55E+02 (4.15E+00)-	3.79E+02 (1.30E+01)-	3.52E+02 (3.33E+00)-	3.40E+02 (3.07E+00)≈	3.77E+02 (9.20E+00)-	3.40E+02 (2.77E+00)
F24	4.25E+02 (2.31E+00)≈	4.26E+02 (1.75E+00)≈	4.29E+02 (3.04E+00)-	4.40E+02 (5.60E+00)-	4.29E+02 (2.78E+00)-	4.37E+02 (8.71E+00)-	4.27E+02 (2.25E+00)≈	4.23E+02 (1.47E+00)≈	4.51E+02 (1.20E+01)-	4.24E+02 (3.57E+00)
F25	3.87E+02 (1.49E-02)-	3.87E+02 (7.52E-03)-	3.87E+02 (9.42E-03)-	3.87E+02 (2.17E-01)-	3.87E+02 (8.63E-03)-	3.78E+02 (9.56E-02)≈	3.87E+02 (2.03E-02)-	3.87E+02 (2.56E-02)-	3.87E+02 (5.74E-02)-	3.78E+02 (6.44E-02)
F26	5.07E+02 (3.22E+02)+	9.29E+02 (3.74E+01)-	9.54E+02 (4.17E+01)-	1.13E+03 (7.83E+01)-	9.50E+02 (4.13E+01)-	9.17E+02 (4.48E+02)-	9.34E+02 (4.10E+01)-	8.20E+02 (3.83E+01)-	1.12E+03 (3.02E+02)-	8.02E+02 (7.58E+01)
F27	5.04E+02 (4.17E+00)-	4.96E+02 (6.58E+00)+	5.06E+02 (5.13E+00)-	5.04E+02 (8.00E+00)-	5.02E+02 (6.07E+00)-	5.00E+02 (1.54E-04)≈	5.00E+02 (7.13E+00)≈	4.87E+02 (6.75E+00)+	4.94E+02 (9.56E+00)+	5.00E+02 (7.61E-04)
F28	3.10E+02 (3.15E+01)≈	3.00E+02 (2.56E-13)+	3.18E+02 (4.16E+01)-	3.47E+02 (5.51E+01)-	3.04E+02 (2.08E+01)≈	3.48E+02 (5.82E+01)-	3.39E+02 (5.75E+01)-	3.00E+02 (5.27E+01)≈	3.23E+02 (4.74E+01)-	3.01E+02 (2.37E+01)
F29	4.35E+02 (1.02E+01)-	4.34E+02 (6.46E+00)-	4.48E+02 (1.57E+01)-	4.30E+02 (2.53E+01)-	4.38E+02 (1.48E+01)-	4.06E+02 (3.90E+01)+	4.39E+02 (8.64E+00)-	4.17E+02 (5.21E+00)-	4.39E+02 (3.32E+01)-	4.12E+02 (6.54E+01)
F30	2.00E+03 (4.67E+01)-	1.97E+03 (2.40E+01)-	2.00E+03 (7.32E+01)-	2.31E+03 (1.53E+02)-	1.97E+03 (3.77E+01)+	3.64E+02 (6.63E+02)-	1.99E+03 (5.25E+01)-	1.94E+03 (6.42E+01)-	2.01E+03 (5.90E+01)-	2.00E+02 (5.74E+01)
-	12	14	16	24	16	22	17	9	21	
+	5	9	5	1	8	2	2	10	7	
≈	13	7	9	5	6	6	11	11	2	

“+” or “-” denotes that the current result is significantly better or statistical worse than the result of our algorithm in terms of Wilcoxon’s rank sum test at a 0.05 significance level, respectively. Meanwhile, “≈” represents that there is no significant difference.

<https://doi.org/10.1371/journal.pone.0256206.t007>

Table 8. Results for CEC 2017 suites with 100 in dimensionality.

Function	Average (standard deviation) of algorithms										
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETL-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV	
F1	1.22E+02 (1.32e+02)–	0.00E+00 (0.00E+00)≈	0.00E+00 (0.00E+00)≈	2.26E-10 (5.92E-10)≈	9.55E-13 (1.95E-12)≈	3.04E-10 (4.15E-10)≈	0.00E+00 (0.00E+00)≈	7.11E-14 (2.75e-11)≈	1.68E+03 (2.28E+03)–	5.58E-11 (7.83E-11)	
F2	0.00E+00 (0.00e+00)+	1.42E+07 (7.62E+07)≈	3.91E-07 (2.13E-06)+	4.72E+13 (2.58E+14)–	2.52E+03 (8.08E+03)≈	1.77E+09 (9.34E+09)–	2.18E+01 (4.43E+01)+	1.42E-13 (7.61e+05)+	6.07E+39 (3.33E+40)–	5.49E+08 (7.34E+08)	
F3	3.22E-06 (5.87e-06)+	1.86E-06 (1.23E-06)+	0.00E+00 (0.00E+00)+	1.37E+05 (1.01E+05)–	3.92E-08 (2.68E-08)+	7.94E+01 (1.70E+02)–	4.86E-07 (5.23E-07)+	1.22E-07 (1.69e-06)+	1.87E+04 (8.30E+04)–	3.43E+01 (1.50E+02)	
F4	1.95E+02 (1.69e+01)–	1.91E+02 (3.15E+01)–	2.00E+02 (1.27E+01)–	8.59E+01 (5.74E+01)–	2.00E+02 (9.87E+00)–	2.77E+01 (5.21E+01)≈	1.90E+02 (2.50E+01)–	7.48E+01 (3.87e+01)–	2.11E+02 (2.47E+01)–	2.39E+01 (4.68E+01)	
F5	2.51E+03 (1.79e+02)–	4.35E+01 (5.54E+00)≈	1.08E+01 (2.60E+00)+	1.42E+02 (2.58E+01)–	4.16E+01 (7.94E+00)≈	1.82E+02 (2.56E+01)–	5.64E+01 (5.71E+00)≈	3.26E+01 (4.58e+00)+	8.87E+01 (1.80E+01)–	4.28E+01 (2.73E+01)	
F6	5.00E+01 (2.06e+01)–	3.68E-04 (6.50E-04)–	0.00E+00 (0.00E+00)+	2.05E-03 (3.44E-03)–	3.85E-05 (1.49E-04)+	3.28E-04 (1.52E-03)–	2.24E-02 (1.65E-02)–	1.49E-04 (7.26e-03)≈	1.12E-05 (1.02E-05)+	1.56E-04 (8.49E-04)	
F7	6.53E-12 (1.71e-12)+	1.46E+02 (5.73E+00)–	1.12E+02 (1.34E+00)+	2.66E+02 (2.57E+01)–	1.48E+02 (5.49E+00)–	3.01E+02 (2.90E+01)–	1.64E+02 (4.34E+00)–	1.31E+02 (4.37e+00)–	1.84E+02 (2.56E+01)–	1.27E+02 (3.87E+00)	
F8	8.79E+01 (1.53e+02)≈	4.32E+01 (6.89E+00)+	1.09E+01 (3.00E+00)+	1.37E+02 (1.91E+01)–	4.20E+01 (7.36E+00)+	1.73E+02 (2.22E+01)–	5.64E+01 (4.78E+00)+	3.74E+01 (3.77e+00)+	9.51E+01 (4.32E+01)≈	8.57E+01 (1.35E+01)	
F9	4.66E+03 (7.76e+02)–	8.45E-02 (1.77E-01)+	0.00E+00 (0.00E+00)+	5.47E+01 (2.75E+01)–	2.98E-03 (1.63E-02)+	9.46E+01 (6.56E+01)–	2.03E+00 (1.09E+00)+	1.14E-13 (6.88e-01)+	8.23E+00 (4.54E+00)≈	6.59E+00 (3.67E+00)	
F10	3.51E+04 (1.34e+03)–	9.85E+03 (5.81E+02)≈	9.89E+03 (8.19E+02)≈	8.91E+03 (1.31E+03)≈	1.02E+04 (8.43E+02)–	1.09E+04 (2.15E+03)≈	1.15E+04 (5.59E+02)–	8.96E+03 (5.46e+02)≈	1.15E+04 (1.46E+03)≈	9.82E+03 (4.34E+02)	
F11	9.97E+02 (3.22e+02)–	1.08E+02 (3.03E+01)+	4.91E+01 (2.49E+01)+	5.43E+02 (2.38E+02)–	7.86E+01 (2.80E+01)+	6.38E+02 (2.77E+02)≈	5.93E+02 (9.87E+01)≈	1.41E+02 (1.30e+02)+	5.01E+02 (1.60E+02)≈	5.26E+02 (6.76E+02)	
F12	3.13E+11 (4.16e+10)–	1.66E+04 (6.12E+03)–	4.63E+03 (6.80E+02)+	5.48E+03 (1.66E+03)+	1.32E+04 (6.18E+03)≈	1.58E+04 (6.44E+03)–	2.30E+04 (1.42E+04)–	8.76E+03 (7.97e+03)+	1.69E+05 (9.22E+04)–	1.35E+04 (4.94E+03)	
F13	4.84E+09 (9.28e+08)–	1.44E+02 (3.36E+01)+	1.28E+02 (2.97E+01)+	2.10E+03 (1.08E+03)–	1.69E+02 (3.69E+01)+	1.11E+03 (9.57E+02)–	4.15E+02 (1.97E+02)+	1.13E+02 (7.47e+01)+	3.57E+02 (1.25E+02)+	8.61E+02 (4.82E+01)	
F14	1.55E+08 (9.82e+07)–	6.39E+01 (1.21E+01)≈	7.04E+01 (9.15E+00)–	6.22E+02 (1.41E+02)–	5.92E+01 (9.86E+00)–	1.23E+04 (4.81E+04)–	2.93E+02 (5.48E+01)–	1.81E+02 (2.89e+01)–	1.48E+02 (3.42E+01)–	5.76E+01 (2.81E+01)	
F15	3.68E+09 (1.27e+09)–	1.51E+02 (2.68E+01)–	1.02E+02 (2.27E+01)+	4.69E+02 (1.38E+02)–	1.80E+02 (3.99E+01)–	3.17E+02 (1.24E+02)–	2.76E+02 (5.66E+01)–	1.60E+02 (5.07e+01)–	2.85E+02 (5.98E+01)–	1.46E+02 (2.34E+01)	
F16	2.59E+04 (4.76e+03)–	1.90E+03 (2.80E+02)≈	1.29E+03 (4.61E+02)+	2.05E+03 (4.00E+02)≈	1.55E+03 (3.25E+02)+	2.35E+03 (3.71E+02)–	1.80E+03 (2.75E+02)≈	8.40E+02 (2.11e+02)+	2.19E+03 (4.34E+02)–	1.92E+03 (6.12E+02)	
F17	3.29E+03 (5.77 e+02)–	1.31E+03 (1.76E+02)–	9.25E+02 (3.39E+02)≈	1.03E+03 (2.55E+02)≈	1.06E+03 (3.03E+02)≈	1.63E+03 (2.29E+02)–	1.31E+03 (1.84E+02)–	6.38E+02 (1.90e+02)+	1.60E+03 (4.93E+02)–	1.07E+03 (3.18E+02)	
F18	1.67E+02 (3.42e+01)≈	1.83E+02 (2.34E+01)≈	1.35E+02 (3.38E+01)+	2.18E+03 (1.60E+03)–	2.02E+02 (4.44E+01)≈	2.23E+03 (1.65E+03)–	2.72E+02 (4.88E+01)≈	1.26E+02 (4.53e+01)+	3.64E+02 (9.59E+01)–	1.98E+02 (4.18E+03)	
F19	8.36E+05 (6.77e+05)–	1.03E+02 (2.33E+01)≈	7.47E+01 (1.31E+01)≈	1.55E+03 (1.23E+03)–	1.20E+02 (2.57E+01)–	4.27E+02 (4.05E+02)–	1.95E+02 (3.24E+01)–	1.19E+02 (2.14e+01)≈	1.75E+02 (4.43E+01)≈	1.12E+02 (3.65E+02)	

(Continued)

Table 8. (Continued)

Function	Average (standard deviation) of algorithms									
	EBOwith CMAR	jSO	L-SHADE-SPACMA	ETI-JADE	L-SHADE-RSP	EDEV	EAGDE	EBL-SHADE	NDE	IEDEV
F20	3.42E+03 (3.94E+02)-	1.34E+03 (2.43E+02)-	1.39E+03 (3.36E+02)-	1.07E+03 (5.27E+02)+	1.29E+03 (3.45E+02)-	1.51E+03 (2.91E+02)-	1.77E+03 (1.89E+02)-	1.21E+03 (1.84E+02)≈	2.08E+03 (3.29E+02)-	1.16E+03 (2.57E+02)
F21	6.60E+02 (5.39E+01)-	2.65E+02 (6.81E+00)-	2.41E+02 (4.12E+00)+	3.76E+02 (6.17E+01)-	2.68E+02 (8.89E+00)-	3.96E+02 (2.59E+01)-	2.76E+02 (8.91E+00)-	2.38E+02 (7.28E+00)+	3.12E+02 (2.20E+01)-	2.58E+02 (8.54E+00)
F22	1.73E+04 (1.04E+03)-	1.06E+04 (7.45E+02)-	9.89E+03 (1.20E+03)≈	1.33E+04 (5.16E+03)-	1.08E+04 (7.53E+02)-	1.32E+04 (4.93E+03)-	1.24E+04 (5.45E+02)-	1.02E+04 (4.96E+02)≈	1.32E+04 (8.34E+02)≈	1.02E+04 (6.86E+02)
F23	2.62E+04 (3.79E+03)-	5.71E+02 (1.03E+01)-	5.82E+02 (7.17E+00)-	1.24E+03 (4.72E+01)-	5.62E+02 (1.00E+01)-	6.84E+02 (3.52E+01)-	5.74E+02 (1.21E+01)-	5.56E+02 (9.28E+00)-	6.46E+02 (2.46E+01)-	5.42E+02 (2.61E+01)
F24	2.00E+02 (2.68E+00)+	9.00E+02 (8.13E+00)≈	9.14E+02 (2.11E+01)-	2.14E+02 (3.45E+01)+	9.07E+02 (9.49E+00)-	1.10E+03 (4.70E+01)-	9.17E+02 (9.77E+00)-	8.90E+02 (9.22E+00)+	9.71E+02 (2.22E+01)-	9.00E+02 (7.65E+00)
F25	1.54E+05 (5.54E+04)-	7.31E+02 (3.63E+01)-	6.93E+02 (4.74E+01)≈	8.14E+02 (5.62E+01)≈	7.01E+02 (4.27E+01)≈	7.70E+02 (6.08E+01)-	7.47E+02 (3.39E+01)-	6.98E+02 (3.00E+01)≈	7.38E+02 (4.58E+01)-	7.09E+02 (4.66E+01)
F26	4.30E+04 (1.75E+03)-	3.25E+03 (9.40E+01)+	3.13E+03 (9.23E+01)+	7.53E+03 (4.49E+03)-	3.24E+03 (1.00E+02)+	4.91E+03 (3.16E+02)-	3.39E+03 (9.02E+01)+	3.05E+03 (7.02E+01)+	3.83E+03 (1.97E+02)+	4.27E+03 (2.21E+02)
F27	2.98E+03 (2.96E+03)-	5.87E+02 (2.28E+01)+	5.99E+02 (2.07E+01)≈	1.79E+03 (1.81E+02)-	6.02E+02 (1.46E+01)≈	6.93E+02 (1.76E+02)-	6.45E+02 (2.47E+01)-	5.86E+02 (1.80E+01)+	6.53E+02 (2.87E+01)-	6.03E+02 (3.64E+01)
F28	1.04E+04 (3.78E+04)-	5.26E+02 (2.50E+01)-	5.12E+02 (1.50E+01)-	5.00E+02 (2.06E+01)-	5.25E+02 (2.64E+01)-	4.19E+02 (8.65E+01)+	5.24E+02 (2.03E+01)-	5.03E+02 (2.61E+01)-	5.68E+02 (3.34E+01)-	4.36E+02 (3.28E+01)
F29	4.29E+03 (6.03E+02)-	1.27E+03 (1.71E+02)+	1.52E+03 (3.60E+02)≈	1.49E+03 (2.90E+02)+	1.44E+03 (1.79E+02)≈	1.76E+03 (3.27E+02)-	1.35E+03 (1.82E+02)+	8.61E+02 (1.55E+02)+	1.67E+03 (3.54E+02)≈	1.64E+03 (4.66E+02)
F30	1.57E+11 (2.06E+10)-	2.31E+03 (1.22E+02)-	2.39E+03 (2.06E+02)-	6.23E+03 (5.82E+03)-	2.55E+03 (2.27E+02)-	8.81E+02 (2.60E+02)≈	2.45E+03 (1.74E+02)-	2.16E+03 (1.32E+02)-	2.51E+03 (1.45E+02)-	7.24E+02 (3.57E+02)
-	24	13	7	21	13	24	18	7	20	
+	4	8	15	4	8	1	7	16	3	
≈	2	9	8	5	9	5	5	7	7	

“+” or “-” denotes that the current result is significantly better or statistical worse than the result of our algorithm in terms of Wilcoxon’s rank sum test at a 0.05 significance level, respectively. Meanwhile, “≈” represents that there is no significant difference.

<https://doi.org/10.1371/journal.pone.0256206.t008>

Table 9. Friedman test ranks for the CEC 2017 experiment.

Algorithm	30D	100D	Mean Ranking	Rank
EBL-SHADE	2.62	2.55	2.58	1
IEDEV	3.73	4.23	3.98	2
L-SHADE-SPACMA	5.52	2.85	4.18	3
jSO	4.38	4.37	4.38	4
L-SHADE-RSP	5.35	4.38	4.87	5
EAGDE	5.87	6.03	5.95	6
EBOwithCMAR	4.73	8.50	6.62	7
NDE	7.45	7.43	7.44	8
ETI-JADE	7.92	6.97	7.44	9
EDEV	7.43	7.68	7.56	10
Friedman p value	0.00E+00	0.00E+00		

<https://doi.org/10.1371/journal.pone.0256206.t009>

DE algorithms than ever brought by the ETI control contributes to improvement on solution. Moreover, LPSR further improves overall performance. Hence, our algorithm performs much better than EDEV and becomes so competitive.

Conclusion

Most existing measures for improving DE algorithm need be revised for fitting ensemble DE algorithm. In this paper, we propose IEDEV—an ensemble DE algorithm with three measures. To obtain the algorithm, firstly, we extend the collecting range of optional external archive of JADE—one of the constituent algorithm in EDEV. Then, we revise the ETI control and implement it into algorithm. Finally, LPSR is used by us. In our experiments, we compare our IEDEV with nine peers. Experimental results show that our algorithm is competitive.

Our IEDEV shows that, measures for DE algorithm may be used in ensemble DE algorithm although revision is needed in many occasions. We will continue our research in the future to consider more techniques.

Author Contributions

Conceptualization: Juan Yao.

Data curation: Juan Yao.

Formal analysis: Zhenling Liu.

Methodology: Juan Yao.

Project administration: Zhe Chen.

Software: Zhenling Liu.

Validation: Zhe Chen.

Writing – original draft: Zhe Chen.

References

1. Wang Y, Cai Z, Zhang Q. Differential evolution with composite trial vector generation strategies and control parameters. *IEEE Trans on Evo Comput.* 2011; 15(1):55–66. <https://doi.org/10.1109/TEVC.2010.2087271>

2. Brest J, Maučec MS, Bošković B. Single objective real-parameter optimization: Algorithm jSO. In: Proc of CEC. IEEE; 2017. p. 1311–1318.
3. Qiu X, Tan KC, Xu JX. Multiple exponential recombination for differential evolution. *IEEE Trans on Cybernetics*. 2017; 47(4):995–1006. <https://doi.org/10.1109/TCYB.2016.2536167>
4. Zheng LM, Zhang SX, Tang KS, Zheng SY. Differential evolution powered by collective information. *Information Sciences*. 2017; 399:13–29. <https://doi.org/10.1016/j.ins.2017.02.055>
5. Zhou YZ, Yi WC, Gao L, Li XY. Adaptive differential evolution with sorting crossover rate for continuous optimization problems. *IEEE Trans on Cybernetics*. 2017; 47(9):2742–2753. <https://doi.org/10.1109/TCYB.2017.2676882> PMID: 28362602
6. Meng Z, Pan JS, Kong L. Parameters with adaptive learning mechanism (PALM) for the enhancement of differential evolution. *Knowledge-Based Systems*. 2018; 141:92–112. <https://doi.org/10.1016/j.knsys.2017.11.015>
7. Stanovov V, Akhmedova S, Semenkin E. LSHADE Algorithm with Rank-Based Selective Pressure Strategy for Solving CEC 2017 Benchmark Problems. In: Proc of CEC. IEEE; 2018. p. 1–8.
8. Meng Z, Pan JS, Tseng KK. PaDE: An enhanced Differential Evolution algorithm with novel control parameter adaptation schemes for numerical optimization. *Knowledge-Based Systems*. 2019; 168:80–99. <https://doi.org/10.1016/j.knsys.2019.01.006>
9. Tian M, Gao X. Differential evolution with neighborhood-based adaptive evolution mechanism for numerical optimization. *Information Sciences*. 2019; 478:422–448. <https://doi.org/10.1016/j.ins.2018.11.021>
10. Mohamed AW, Hadi AA, Mohamed AK. Differential Evolution Mutations: Taxonomy, Comparison and Convergence Analysis. *IEEE Access*. 2021. <https://doi.org/10.1109/ACCESS.2021.3077242>
11. Awad NH, Ali MZ, Suganthan PN, Reynolds RG. CADE: A hybridization of Cultural Algorithm and Differential Evolution for numerical optimization. *Information Sciences*. 2017; 378:215–241 <https://doi.org/10.1016/j.ins.2016.10.039>
12. Du W, Leung SYS, Tang Y, Vasilakos AV. Differential evolution with event-triggered impulsive control. *IEEE Trans on Cybernetics*. 2017; 47(1):244–257 <https://doi.org/10.1109/TCYB.2015.2512942> PMID: 26800559
13. Awad NH, Ali MZ, Mallipeddi R, Suganthan PN. An improved differential evolution algorithm using efficient adapted surrogate model for numerical optimization. *Information Sciences*. 2018; 451:326–347 <https://doi.org/10.1016/j.ins.2018.04.024>
14. Cai Y, Liao J, Wang T, Chen Y, Tian H. Social learning differential evolution. *Information Sciences*. 2018; 433:464–509. <https://doi.org/10.1016/j.ins.2016.10.003>
15. Sun G, Cai Y, Wang T, Tian H, Wang C, Chen Y. Differential evolution with individual-dependent topology adaptation. *Information Sciences*. 2018; 450:1–38. <https://doi.org/10.1016/j.ins.2018.02.048>
16. Huang Q, Zhang K, Song J, Zhang Y, Shi J. Adaptive differential evolution with a Lagrange interpolation argument algorithm. *Information Sciences*. 2019; 472:180–202. <https://doi.org/10.1016/j.ins.2018.09.004>
17. Zhou XG, Zhang GJ. Differential evolution with underestimation-based multimutation strategy. *IEEE Transactions on Cybernetics*. 2019; 49(4):1353–1364. <https://doi.org/10.1109/TCYB.2018.2801287> PMID: 29994744
18. Ali MZ, Awad NH, Suganthan PN, Reynolds RG. An adaptive multipopulation differential evolution with dynamic population reduction. *IEEE Trans on Cybernetics*. 2017; 47(9):2768–2779. <https://doi.org/10.1109/TCYB.2016.2617301> PMID: 28113798
19. Sallam KM, Elsayed SM, Sarker RA, Essam DL. Landscape-based adaptive operator selection mechanism for differential evolution. *Information Sciences*. 2017; 418:383–404. <https://doi.org/10.1016/j.ins.2017.08.028>
20. Cui L, Li G, Zhu Z, Lin Q, Wong KC, Chen J, et al. Adaptive multiple-elites-guided composite differential evolution algorithm with a shift mechanism. *Information Sciences*. 2018; 422:122–143 <https://doi.org/10.1016/j.ins.2017.09.002>
21. Wu G, Shen X, Li H, Chen H, Lin A, Suganthan P. Ensemble of differential evolution variants. *Information Sciences*. 2018; 423:172–186. <https://doi.org/10.1016/j.ins.2017.09.053>
22. Zhang SX, Zheng LM, Tang KS, Zheng SY, Chan WS. Multi-layer competitive-cooperative framework for performance enhancement of differential evolution. *Information Sciences*. 2019; 482:86–104 <https://doi.org/10.1016/j.ins.2018.12.065>
23. Deng W, Xu J, Gao XZ, Zhao H. An enhanced MSIQDE algorithm with novel multiple strategies for global optimization problems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*. 2020 <https://doi.org/10.1109/TSMC.2020.3030792>

24. Deng W, Xu J, Zhao H, Song Y. A novel gate resource allocation method using improved PSO-based QEA. *IEEE Transactions on Intelligent Transportation Systems*. 2020. <https://doi.org/10.1109/TITS.2020.3025796>
25. Cai X, Zhao H, Shang S, Zhou Y, Deng W, Chen H, et al. An improved quantum-inspired cooperative co-evolution algorithm with multi-strategy and its application. *Expert Systems with Applications*. 2021; 171:114629 <https://doi.org/10.1016/j.eswa.2021.114629>
26. Deng W, Shang S, Cai X, Zhao H, Zhou Y, Chen H, et al. Quantum differential evolution with cooperative coevolution framework and hybrid mutation strategy for large scale optimization. *Knowledge-Based Systems*. 2021; 224:107080. <https://doi.org/10.1016/j.knosys.2021.107080>
27. Guo S, Zhang X, Du Y, Zheng Y, Cao Z. Path planning of coastal ships based on optimized DQN reward function. *Journal of Marine Science and Engineering*. 2021; 9(2):210. <https://doi.org/10.3390/jmse9020210>
28. Zhang J, Sanderson AC. JADE: adaptive differential evolution with optional external archive. *IEEE Trans on Evo Comput*. 2009; 13(5):945–958. <https://doi.org/10.1109/TEVC.2009.2014613>
29. Qin AK, Huang VL, Suganthan PN. Differential evolution algorithm with strategy adaptation for global numerical optimization. *IEEE Transactions on Evolutionary Computation*. 2009; 13(2):398–417. <https://doi.org/10.1109/TEVC.2008.927706>
30. Mallipeddi R, Suganthan PN, Pan QK, Tasgetiren MF. Differential evolution algorithm with ensemble of parameters and mutation strategies. *Applied Soft Computing*. 2011; 11(2):1679–1696. <https://doi.org/10.1016/j.asoc.2010.04.024>
31. Ali MZ, Awad NH, Suganthan PN. Multi-population differential evolution with balanced ensemble of mutation strategies for large-scale global optimization. *Applied Soft Computing*. 2015; 33:304–327. <https://doi.org/10.1016/j.asoc.2015.04.019>
32. Wu G, Mallipeddi R, Suganthan PN, Wang R, Chen H. Differential evolution with multi-population based ensemble of mutation strategies. *Information Sciences*. 2016; 329:329–345. <https://doi.org/10.1016/j.ins.2015.09.009>
33. Mohamed AW, Hadi AA, Fattouh AM, Jambi KM. LSHADE with semi-parameter adaptation hybrid with CMA-ES for solving CEC 2017 benchmark problems. In: 2017 IEEE Congress on evolutionary computation (CEC). IEEE; 2017. p. 145-152.
34. Hadi AA, Mohamed AW, Jambi KM. LSHADE-SPA memetic framework for solving large-scale optimization problems. *Complex & Intelligent Systems*. 2019; 5(1):25–40. <https://doi.org/10.1007/s40747-018-0086-8>
35. Hadi AA, Mohamed AW, Jambi KM. Single-objective real-parameter optimization: Enhanced LSHADE-SPACMA algorithm. In: *Heuristics for Optimization and Learning*. Springer; 2021. p. 103-121.
36. Tanabe R, Fukunaga A. Success-history based parameter adaptation for differential evolution. In: *Proc of CEC*. IEEE; 2013. p. 71-78.
37. Tanabe R, Fukunaga AS. Improving the search performance of SHADE using linear population size reduction. In: *Proc of CEC*. IEEE; 2014. p. 1658-1665.
38. Mohamed AK, Mohamed AW. Real-parameter unconstrained optimization based on enhanced AGDE algorithm. In: *Machine Learning Paradigms: Theory and Application*. Springer; 2019. p. 431–450.
39. Awad NH, Ali MZ, Suganthan PN, Reynolds RG. An ensemble sinusoidal parameter adaptation incorporated with L-SHADE for solving CEC2014 benchmark problems. In: *Proc of CEC*. IEEE; 2016. p. 2958-2965.
40. Mohamed AW, Hadi AA, Jambi KM. Novel mutation strategy for enhancing SHADE and LSHADE algorithms for global numerical optimization. *Swarm and Evolutionary Computation*. 2019; 50:100455. <https://doi.org/10.1016/j.swevo.2018.10.006>
41. Kumar A, Misra RK, Singh D. Improving the local search capability of effective butterfly optimizer using covariance matrix adapted retreat phase. In: *Proc of CEC*. IEEE; 2017. p. 1835-1842.