

IEEE CEC Competition Report: A Fitness-assignment Method for Evolutionary Constrained Multi-objective Optimization

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Abstract—This report presents I_{cSDE}^+ , a single-population fitness-assignment-based algorithm designed for constrained multi-objective optimization. The method effectively integrates constraint violation, sum of objectives, and shift-based density estimation to guide the search toward feasible regions while preserving diversity and convergence.

I. THE PROPOSED METHOD

We present a constrained multi-objective evolutionary algorithm based on a novel fitness-assignment strategy, named I_{cSDE}^+ . The algorithm balances constraint satisfaction, convergence, and diversity within a single-population framework. It integrates three core components: constraint violation (CV), sum of objectives (SOB), and shift-based density estimation (SDE). Solutions are ranked first by feasibility, then by normalized SOB, with SDE guiding toward sparse, feasible areas.

The fitness value $I_{cSDE}^+(x)$ for a solution x is defined as [1]:

$$I_{SDE}^+(x) = \min_{y \in P_{SC}(x)} \|f(x) - \hat{f}(y)\| \quad (1)$$

where $P_{SC}(x) \subseteq P$ and $y \in P_{SC}(x)$ such that

$$\begin{cases} CV(y) < CV(x) \\ SOB(y) < SOB(x) \text{ if } CV(y) = CV(x) \end{cases} \quad (2)$$

By setting CV of solutions to zero, which is the case in UMOPs, (1) degenerates into (3), and I_{SDE}^+ can be viewed as a generalized version of I_{SDE}^+ [2].

$$I_{SDE}^+(x) = \min_{y \in P_{SOB}(x)} \|f(x) - \hat{f}(y)\| \quad (3)$$

where $P_{SOB}(x) \subseteq P$ and $y \in P_{SOB}(x)$ such that $SOB(y) < SOB(x)$.

A. Framework of the proposed I_{cSDE}^+ algorithm

Algorithm 1 presents the general structure of CMOEA with I_{cSDE}^+ . After the initial parameter setting (Line 1), starting with a uniformly initialized population (P) of size N (Line 2), I_{cSDE}^+ values are evaluated (Line 3). Until a predefined stopping criterion is met, operations such as mating selection, variation, fitness evaluation and environmental

selection are iterated (Lines 4-9). Finally, the population (P) is returned.

Algorithm 1: Framework of I_{cSDE}^+

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1 Input:  $N$ 
2  $P \leftarrow \text{InitializePopulation}(N)$ 
3  $I_{cSDE}^+ \leftarrow \text{FitnessEvaluation}(P)$ 
4 while not done do
5    $P' \leftarrow \text{MatingSelection}(P, N, I_{cSDE}^+)$ 
   // Algorithm 2
6    $Q \leftarrow P \cup \text{Variation}(P', N)$ 
7    $I_{cSDE}^+ \leftarrow \text{FitnessEvaluation}(Q)$ 
8    $[P, I_{cSDE}^+] \leftarrow \text{EnvironmentalSelection}(Q, N, I_{cSDE}^+)$ 
   // Algorithm 3
9 end
10 Output:  $P$ 

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Algorithm 2: I_{cSDE}^+ based Mating Selection

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1 Input:  $P, N, I_{cSDE}^+$ 
2  $P' \leftarrow \emptyset$ 
3 while  $|P'| < N$  do
4   select two individuals  $x$  and  $y$  randomly from  $P$ 
5   if  $I_{cSDE}^+(x) > I_{cSDE}^+(y)$  then
6      $P' \leftarrow P' \cup \{x\}$ 
7   else
8      $P' \leftarrow P' \cup \{y\}$ 
9   end
10 end
11 Output:  $P'$ 

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Algorithm 3: I_{cSDE}^+ based Environmental Selection

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1 Input:  $Q, N, I_{cSDE}^+$ 
2 sort solutions in  $Q$  in descending order of  $I_{cSDE}^+$ 
3  $[P, I_{cSDE}^+] \leftarrow N$  solutions with large fitness values are selected
   and ties are resolved randomly
4 Output:  $P, I_{cSDE}^+$ 

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As in Algorithm 2, during mating selection, based on I_{cSDE}^+ promising solutions from the immediate population are selected through binary tournament selection. In binary tournament selection, out of the two randomly selected solutions, the solution with highest I_{cSDE}^+ -based fitness value is preferred (lines 4–9). The solutions selected during mating selection are used to produce new solutions using the Differential Evolution (DE) operator and polynomial mutation. Finally, during environmental selection (Algorithm 3), N individuals with the highest I_{cSDE}^+ -based fitness values

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are picked from the union of the current population and offspring population produced through mating and variation operators.

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