THE EFFECT OF CONTROL PARAMETERS ON NOVEL DOMINANCE-BASED DIFFERENTIAL EVOLUTION METHOD: AN EMPIRICAL STUDY

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ABSTRACT

To find and extract the optimal or near-optimal results to solve multi-objective optimization problems (MOOP), optimization algorithms are found to apply various methods. Moreover, the majority of the algorithms possess several control parameters that have an impact on the performance and quality of the extracted Pareto-fronts (PF). It is noteworthy to remember that Differential Evolution (DE) algorithm, possesses three main control parameters, namely Crossover (CR) Rate, Fitness (F) Scaling Factor, and Population (NP) size. The magnitudes of the control parameters (CP) previously mentioned seeming to have a significant effect on the performance of DE. Hence, the adjustment of F, CR, and NP values is a productive method to enhance the achievement of the DE algorithm. This paper probes into the extraction of optimum values for control parameters (F,CR,NP) between the selected numerical intervals. DE Algorithm is a popular approach inspired by nature in the field of evolutionary computing. In this work, the Dominance Based DE Method (DBDE) tests and finds the optimum magnitude for the chosen CP. The proposed novel DBDE method is the enhanced type of the mainly accepted DE algorithm. This paper investigates how the control parameters affect DBDE.

Furthermore, the Inverted Generational Distance (IGD) metric is employed in the measure and calculation of the quality of results obtained in DBDE. Similarly, as in the state-of-the-art methods, the Fitness function is invoked by DBDE in this paper and runs the algorithm 30 times with 300.000 function evaluations in each run. Finally, the well-known CEC2009 benchmark problem set is used in the experimental evaluation of the tuned DBDE. From the analysis of the obtained results, the performance of the DBDE is shown to improve depending on the values of CP. However, compared with F and CR values, the selected NP values have lower effects on the performance of DBDE.

Keywords: Multi Objective Optimization Problems, Control Parameters, Crossover, Inverted Generational Distance, Differential Evolution.

1. INTRODUCTION

Over the recent decades, nature-inspired methods have been broadly utilized in solving the issues related to multi objective optimization problems. Multi objective optimization is concurrently enhancing a set of objective functions (Marler & Arora, 2004). Multi objective optimization (MOO) methods are being investigated in a variety of scientific and technical aspects. Naturally, MOO issues arise through a wide range of areas, and finding solutions for the issues has been a severe difficulty for researchers (Coello et al., 2006). Over the latest years, an extensive diversity of techniques to overcome the single and multi objective optimization problems have been suggested by researchers (Salomon et al., 2006). It can be claimed that multi-objective optimization methods have become at the same time complicated and robust. To solve MOO problems, a chosen number of appropriate and suitable values must be chosen for the Control Parameters. The best trade-off method of control parameters can differ from an optimization problem to another one (Mallipeddi et al., 2011). Differential Evolution algorithm applies sensitive CP's such as NP, F, and CR to discover the optimal or near-optimal Pareto-fronts. Choosing a good trade-off for scaling factor values in each generation is a practical action to enhance the results of the DE method (Zhu et al., 2020). Based on the mutant vector, the crossover operator (CRO) is used in constructing a trial vector (TriV); also According to the CP, the CRO assembles the components of the present element and mutant vector, $CR \in [0,1]$ called crossover rate (Zaharie, 2009). As well, the control parameter F is a control parameter in DE referred to as the amplification constant. (Zielinski et al., 2006). The scale factor inflicts an effect on the magnitude of the perturbation that was applied to the initial vector and has an essential part in having a diverse population (Zaharie, 2009).

The IGD values are used to assess the excellence of the outputs generated and extracted Pareto-front. The primary objective of MOO is to investigate the solution space and discover the optimal solution set (Pareto-front) by considering all objectives into account. MOO is of great importance in several fields of engineering applications. Objective optimization problems, both single- and multi- are solved successfully using the Differential Evolution algorithm. DE is established as a fast and efficient algorithm in solving MOO problems. Many researchers are continually working on introducing improvements to the performance of the DE algorithm and seeking a better non-dominated solution set. The three parameters Population size N, scaling factor F, and crossover rate CR are indispensably involved in DE (Xia et al., 2021). The DBDE method checks and tests the CP (F,CR,NP). Besides optimization process, the combinations of the parameters were measured in DBDE. Test results show the effects of variation of the control parameters on the obtained results. Accordingly, the application of the predefined and fixed parameters cannot fulfill several needs of the dynamical optimization process (Xia et al., 2021).

DE algorithms use a randomly determined direct search method inspired by nature, consisting of the initialization phase and Mutation, Crossover and Selection stages. Similarly, most well-known improved DE algorithms apply known mutation strategies, such as; DE/rand/1, DE/rand/2 (Li et al., 2020). DBDE is considered not complicated in terms of implementation and competent in terms of the value of obtained solutions when compared with other methods (Tuncay & Haydar, 2021).

DBDE method is evaluated with the several selected control parameters: F, CR, and NP. Likewise, it is observed that DBDE performance changes depending on the control parameters. Therefore, the DBDE method is tested with several F and CR parameter values to find the optimal control parameter values. In this paper, DBDE is tested with ten unconstrained benchmark problems (CEC 2009). The Selected parameters are applied on DBDE, and the obtained results are explained in detail. Finally, in the experimental part, the quality of obtained results is compared using IGD method. It is imperative to note that the optimal Pareto fronts (PF) of the algorithms must be known in the computation of the IGD values.

The remainder of this paper to follow is structured into five sections: 2nd Section indicates brief explanation of the Differential Evolution Algorithm. An outline of the DBDE method is briefly presented in 3rd Section. Metrics of performance and methods of ranking are stated in 4th Section. 5th Section includes the experimental results and evaluations. Next 6th Section, introduces the discussion of the results. Finally, the conclusion of the study and some future research suggestions are stated in section 7.

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2. DIFFERENTIAL EVOLUTION ALGORITHM

The DE method was presented in 1995, in the form of vector population based stochastic optimization technique. (Reyes-sierra, 2016). DE is a method of evolutionary programming created by Kenneth Price and Rainer Storm (Salomon et al., 2006). Moreover, each actual variable is denoted by a real number for the solution of optimization problems across continuous domains in DE. The DE method possesses a basic structure, and it is straightforward to implement. One cannot overlook the fact that DE is also one of the best algorithms when working with actual variables, and it may be utilized for a wide range of scientific subjects. Different constituents of DE are widely used in solving various interactive issues that do not need a great deal of specialist knowledge. There are four operators in the DE algorithm:

2. 1. Initialization operator

In DE, the first population is initially generated randomly, which represents the initial solution space. The two bounds, Upper (ub) and lower (lb), for each parameter are deemed necessary to be established before the population initialization (Salomon et al., 2006).

2. 2. Mutation operator

The mutation operator must have a diverse population of solutions and escape from local optimal traps (I et al., 2003). Likewise, three distinct random vectors are chosen from the NP. Suppose that Rnd1, Rnd2, and Rnd3 are the random numbers chosen from the population where Rnd1≠Rnd2≠Rnd3. The random numbers are arbitrarily selected from within the population where Rnd1, Rnd2, Rnd3 ϵ [1-NP]. Following formula is used for vector mutation,

$$V = Pop\ (Rnd1) + F\_num \times (\ Pop(Rnd2) - Pop\ (Rnd3)) \tag{1}$$

Where Pop(R1), Pop(R2), and Pop(R3) represent the randomly selected vectors from the population, also, F_num in eqn,(1) is the constant factor. whose value is among 0 and 2. Thus, the transformation generates a mutant vector (V(x)).

2. 3. Crossover operator

This operator is applied to extricate higher quality vectors and to improve the diversity of vectors. An important operator called crossover rate controls the percentage of performing the crossover operator. The permissable interval of CR may be within 0 and 1. "Rand" has an arbitrary value that is used to randomly dispense parameters to construct a test vector (U(p)).

```
For p := 0 to D_num do
begin
   R_num := rand(0,1)
   j_num:=rand(0,D_num)
   if (CR >= R_num) or (p:=j_num) then
      U(p):= V(p)
   Else
      U(p) := A(r)(p)
  end;
```

Figure 1. Sample code for Crossover operator

The crossover operator is performed when the value of "Rand" is less than or equal to CR value, and trial vectors' parameters are transferred to the mutant vector (V(p)). Or else, a

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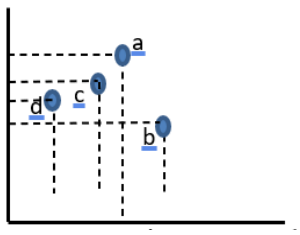
copy of the trial vector parameter is taken from the target vector (TarV), which is A(r)(p). "i" represents the Rnd1, Rnd2, and Rnd3 indexes that are selected from the population. In the above Fig.1 the pseudocode of the Crossover operator is presented.

2. 4. Selection operator

The selection operator regulates if the TriV has replaced the TarV or not.When the TriV's fitness value is less than the TarV's, the TarV is equated to the TriV. Thus, the target becomes fourth randomly selected vector, called Rnd4.

3. NOVEL DOMINANCE BASED DIFFERENTIAL EVOLUTION (DBDE) METHOD

In DBDE, the Selection, Initialization, Crossover operators are altered to enhance the optimization performance. Also, standard methods are applied to the mutation operator in DBDE (Tuncay & Haydar, 2021). In the initialization phase, 1000 numbers are generated randomly. Then, the top 100 solutions from the generated numbers are chosen on the basis of dominance-rank values as a first population. This method is intelligent and more promising. A dominance-rank for solution X is determined as the number of solutions dominating X. In Figure 2, the values of dominance rank are shown for four solutions.



	Dominance Rank
a	2
b	0
c	1
d	0

Figure 2. Dominance-Ranks (DR)
(Tuncay & Haydar, 2021)

Consequently, the initial population is most likely made up of high-quality and prospective solutions. The lower DR values correlate with better solutions; however solutions having DR equal to zero are the best. (Tuncay & Haydar, 2021).

The CR and mutation scale factor (F Value) as two important control parameters are adjusted to have value among 0 and 1. Moreover, the values Rnd1, Rnd2, and Rnd3 are considered as integer numbers randomly chosen among 1 and 100. The size of Population is also defined as 100. Meanwhile, the following formula is used for the mutation operator:

$$V = Pop\,[Rnd1] + F.(\,Pop[Rnd2] - Pop\,[Rnd3]) \qquad (2)$$

The phases of crossover and mutation phases are recurred until the TriV has changed.

Moreover, Pop[Rnd1], Pop[Rnd2],and Pop[Rnd3] are defined as TarV dependent on the chosen section and parameters.

The selection section fulfills the selection under the following three conditions:

1. if the DR of the TriV is more petite than TarV Pop[Rnd1].
2. If the trial vector's DR is more diminutive than TarV Pop[Rnd2], it is completed after 200,000 function evaluations.
3. If the trial vector's DR is more petite than TarV Pop[Rnd3], it is achieved after 200,000 function evaluations.

The fitness values are recorded in an amalgamate at the end of each 500 iterations. The amalgamate is created using an ordinary array. After 300,000 iterations, the amalgamate's

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Pareto front is calculated, and non-dominated solutions are chosen.

Explanation of the DBDE method is shown in Figure 3.

```
1. Starts with 1000 random solutions
  A( i ) ( j ) = rand ( lb_num, ub_num);
2. F(1) and F(2) calculation (fitness vales)
        4.   Eliminates the 1000 solution and selects 100 best solution.
 Do begin
4. Mutation Stage
V1_num = A(Rnd1)(x) + [ A(Rnd2)(x)* F_Value – A(Rnd3)(x)* F_Value ] ;
5. Crossover Stage
for x = 0 to Dimension-1 do begin
    Rand_X := rand(0,1); j_rand:=rand(0, Dimension)
    if (CR_Value >= Rand_X ) or ( x=j_rand )
    Begin
      if ( exceed the lb or ub ) then U(i):=A(Rnd1)(x)
     else U(x) := V(x);
    End
    else U(x) := A(Rnd1)(x);
             end
If U(x) = A(Rnd1)(x) repeats fourth and fifth step.

6. Fitness Calculation (F1(New) and F2(New))
7. Selection Section

a. If ( Dominated(Rnd1)>Dominated(New) ) or (Dominated(New) = 0 )
 F1(Rnd1) := F1(New) and F2(Rnd1) := F2(New)
b. Else If ( Dominated(Rnd2)>Dominated(New) ) and (iteration<100,000 )
 F1(Rnd2) := F1(New) and F2(Rnd2) := F2(New)
c. Else If ( Dominated(R3)>Dominated(New) ) and (iteration<100,000 )
 F1(Rnd3) := F1(New) and F2(Rnd3) := F2(New)

 Count:=Count+1;
If (count=500) begin
Non-dominated fitness values added to the general pool
Count:=0;
end
 Iteration:= iteration-1;
 end
8. If the iterations completed best non-dominated solutions selecting from the general pool.
```

Figure 3. DBDE method explained with pseudocode (Tuncay & Haydar, 2021)

4. METRICS OF PERFORMANCE AND METHODS OF RANKING

The following formula is used to compute the Inverted Generational Distance measure (Sierra & Coello, 2005) utilized in the assessment phase of DBDE. In other words, IGD calculates the average Euclidean distance between two Pareto-fronts.

$$IGD := \frac{\left(\sum_{x=1}^{|k^*|} d_x^k\right)^{\frac{1}{k}}}{|K^*|}. \quad (3)$$

The formula determines the average distance between K* and the closest solution K. (Yu et al., 2018). The d_x value indicates the shortest distance between K* and K. Furthermore, the "k" value is equal to one and the size of K* is denoted by the symbol |K*|. As a result, a lower IGD value implies that the method has achieved excellent convergence and that the solutions produced by the algorithm are evenly distributed.

When IGD = 0, all findings are placed on the real Pareto front in the best possible way (Lwin et al., 2017). Low IGD values in the generated Pareto fronts indicate good algorithm performance.

5. EVALUATION AND EXPERIMENTAL RESULTS

In this part, performance evaluations of the DBDE technique presented, which are based on the control parameter (NP,F,CR) values. DBDE method is tested with a combination of eight CR values and eight F values (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9). Likewise, these combinations of CR and F values are tested with three different population sizes (60, 100, and 140). Multi-objective optimization methods are evaluated in the literature carried out on the basis of certain specified parameters. In general, independently 30 runs of the programs and 300,000 function evaluations are utilized to evaluate algorithms; the testing of algorithms is performed according to these evaluations. In order to assess the performance of the DBDE method, 10 CEC2009 problem sets (UF1-UF10) are used. After each 30 run for each eight F and CR values, the mean and standard deviation values are computed.

Table 1 represents the evaluation of the DBDE method using eight F and CR values. The results are presented in bold text and in a frame are considered the best.

Table 1 (part-1). IGD (means & std. dev.) results for UF10 of CEC 2009, by testing with 60 NP and Eight F and CR values are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, UF10, NP: 60									
CR	**Metrics**	**F(0.2)**	**F(0.5)**	**F(0.7)**	**F(0.9)**	**F(0.1-0.5)**	**F(0.5-0.9)**	**F(0.3-0.7)**	**F(0.1-0.9)**
0.2	Mean	0.09160	0.10200	0.11300	0.12600	$\boxed{\mathbf{0.08790}}$	0.11300	0.10500	0.09700
	Std	0.01250	0.00980	0.01280	0.01450	0.00982	0.01500	0.01460	0.01280
	Best	$\boxed{\mathbf{0.05870}}$	0.08380	0.09160	0.10300	0.06470	0.08060	0.07810	0.07860
0.5	Mean	0.16900	0.13300	0.15700	0.18500	0.13300	0.15900	0.13300	0.13200
	Std	0.03440	0.01460	0.01780	0.01840	0.01170	0.03250	0.01560	0.01350
	Best	0.10700	0.09570	0.12100	0.14500	0.11200	0.11200	0.09550	0.10400
0.7	Mean	0.35600	0.23100	0.27700	0.32700	0.23900	0.28800	0.23000	0.22500
	Std	0.05730	0.01990	0.02810	0.05560	0.02850	0.03510	0.01990	0.02300
	Best	0.26100	0.19800	0.23000	0.24300	0.17900	0.20500	0.19300	0.17400
0.9	Mean	1.76000	0.91000	1.02000	1.16000	1.73000	0.98500	0.95900	1.15000
	Std	0.34100	0.09840	0.12200	0.13300	0.25700	0.11000	0.11200	0.15200
	Best	1.27000	0.69400	0.74700	0.90900	1.09000	0.71900	0.75400	0.86300
0.1-0.5	Mean	0.09990	0.11000	0.11900	0.14000	0.09230	0.11900	0.10700	0.10100
	Std	0.01210	0.01200	0.01480	0.01430	0.01060	0.01470	0.01260	0.01340
	Best	0.08350	0.08480	0.08440	0.11400	0.06610	0.09330	0.08510	0.08070

Table 1 (part-2). IGD (means & std. dev.) results for UF10 of CEC 2009, by testing with 60 NP and Eight F and CR values are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, UF10, NP: 60									
CR	**Metrics**	**F(0.2)**	**F(0.5)**	**F(0.7)**	**F(0.9)**	**F(0.1-0.5)**	**F(0.5-0.9)**	**F(0.3-0.7)**	**F(0.1-0.9)**
0.5-0.9	Mean	0.35000	0.22300	0.28100	0.33300	0.24200	0.28700	0.22200	0.23800
	Std	0.06110	0.02340	0.02970	0.04910	0.02600	0.04220	0.02830	0.02740
	Best	0.25000	0.18100	0.21600	0.25800	0.20200	0.18200	0.16500	0.19200
0.3-0.7	Mean	0.16500	0.13500	0.15500	0.18400	0.12700	0.16000	0.13900	0.13200
	Std	0.01990	0.01550	0.01880	0.02030	0.01600	0.02340	0.01610	0.01550
	Best	0.12800	0.09960	0.11500	0.15100	0.10200	0.12000	0.11000	0.11300
0.1-0.9	Mean	0.16100	0.13800	0.15900	0.17900	0.12600	0.15800	0.13400	0.13300
	Std	0.02180	0.01350	0.01930	0.02380	0.01350	0.02040	0.01520	0.01270
	Best	0.12300	0.11200	0.11200	0.14000	0.09460	0.12000	0.10900	0.10500

Table 2 lists the evaluation of DBDE using eight F and CR values. The favorable results are indicated in bold and framed.

Table 2. IGD (means & std. dev.) results for UF10 of CEC 2009 by testing 100 population and Eight F and CR values are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, UF10, NP: 100									
CR	**Metrics**	**F(0.2)**	**F(0.5)**	**F(0.7)**	**F(0.9)**	**F(0.1-0.5)**	**F(0.5-0.9)**	**F(0.3-0.7)**	**F(0.1-0.9)**
0.2	Mean	0.11800	0.11400	0.13100	0.14700	**0.10000**	0.13100	0.11100	0.10700
	Std	0.01070	0.01180	0.01610	0.01430	0.00902	0.01110	0.01310	0.01070
	Best	0.09230	0.08600	0.10600	0.10500	**0.08300**	0.10600	0.08700	0.09160
0.5	Mean	0.27300	0.17600	0.22300	0.23700	0.17400	0.20600	0.17300	0.17800
	Std	0.04210	0.01910	0.02870	0.02730	0.01600	0.01820	0.01540	0.01270
	Best	0.18700	0.13600	0.17200	0.19000	0.14000	0.17300	0.15100	0.15600
0.7	Mean	0.55300	0.32800	0.39700	0.45200	0.36300	0.37300	0.33100	0.33100
	Std	0.07750	0.03510	0.03860	0.04990	0.04340	0.04150	0.02940	0.02840
	Best	0.40800	0.25800	0.29800	0.37100	0.30300	0.27900	0.27900	0.28200
0.9	Mean	2.48000	1.31000	1.43000	1.63000	2.10000	1.44000	1.33000	1.56000
	Std	0.38900	0.09040	0.13400	0.17000	0.23800	0.12700	0.08730	0.16700
	Best	1.62000	1.15000	1.18000	1.20000	1.63000	1.14000	1.16000	1.13000
0.1-0.5	Mean	0.15200	0.12800	0.14700	0.16800	0.11900	0.14600	0.12300	0.11900
	std	0.02290	0.01190	0.01510	0.01700	0.01380	0.01560	0.00864	0.01430
	best	0.11700	0.10700	0.11000	0.13900	0.08310	0.12100	0.10100	0.08660
0.5-0.9	mean	0.57400	0.33000	0.39200	0.44500	0.36000	0.37600	0.31900	0.33600
	std	0.09220	0.02570	0.04630	0.04990	0.03620	0.03110	0.02540	0.02090
	best	0.34200	0.24200	0.30000	0.37500	0.30100	0.30900	0.27500	0.29900
0.3-0.7	mean	0.25000	0.17100	0.21700	0.24100	0.17600	0.20400	0.16700	0.17900
	std	0.03380	0.01440	0.02130	0.02840	0.01480	0.01860	0.01760	0.01210
	best	0.17800	0.14000	0.18600	0.19200	0.15000	0.17400	0.12700	0.16100
0.1-0.9	mean	0.27500	0.17500	0.20800	0.24000	0.18000	0.20400	0.17400	0.17500
	std	0.04050	0.01520	0.01890	0.03570	0.01710	0.02210	0.01570	0.01630
	best	0.20400	0.14400	0.16800	0.17200	0.14300	0.16600	0.12700	0.13900

Table 3 shows the DBDE technique evaluated across eight F and CR variables. Table 3's top findings are bolded and framed.

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Table 3. IGD (means & std. dev.) results for the CEC 2009 UF10 are measured in eight-population test, as well as using Eight F and CR values (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, UF10, NP: 140									
CR	**Metrics**	**F(0.2)**	**F(0.5)**	**F(0.7)**	**F(0.9)**	**F(0.1-0.5)**	**F(0.5 -0.9)**	**F(0.3 -0.7)**	**F(0.1 -0.9)**
0.2	mean	0.17500	0.13300	0.16300	0.18200	**0.12700**	0.15400	0.13200	0.13000
	std	0.02120	0.01340	0.01510	0.01930	0.01090	0.01810	0.01190	0.01370
	best	0.12400	0.11000	0.12700	0.15100	0.11000	0.11100	0.09510	**0.09370**
0.5	mean	0.39200	0.22700	0.26800	0.30800	0.24800	0.27500	0.23300	0.23300
	std	0.05860	0.01650	0.02820	0.02650	0.02290	0.02370	0.02280	0.02310
	best	0.24900	0.19400	0.21900	0.24500	0.19800	0.21400	0.18700	0.17000
0.7	mean	0.74500	0.41800	0.49600	0.55900	0.52300	0.49200	0.42800	0.45300
	std	0.10000	0.04170	0.04660	0.06500	0.05550	0.04260	0.03650	0.03240
	best	0.50100	0.32400	0.38500	0.43700	0.43000	0.40100	0.36000	0.38800
0.9	mean	2.84000	1.70000	1.76000	2.06000	2.43000	1.77000	1.68000	1.94000
	std	0.41700	0.18400	0.15200	0.21000	0.26900	0.18600	0.16800	0.17200
	best	2.03000	1.20000	1.40000	1.62000	1.86000	1.38000	1.37000	1.67000
0.1-0.5	mean	0.23200	0.15400	0.17700	0.20400	0.15700	0.17600	0.15400	0.14900
	std	0.03360	0.01530	0.02020	0.02190	0.01350	0.02090	0.01450	0.00995
	best	0.17500	0.12500	0.14000	0.16800	0.12300	0.13400	0.12600	0.12300
0.5-0.9	mean	0.79300	0.43400	0.49800	0.56600	0.49300	0.48900	0.43600	0.44600
	std	0.10700	0.04100	0.04900	0.05720	0.05620	0.05290	0.03770	0.03190
	best	0.59200	0.35100	0.39600	0.47300	0.38000	0.39100	0.35700	0.39100
0.3-0.7	mean	0.39900	0.22600	0.27200	0.30000	0.25100	0.27100	0.22900	0.23500
	std	0.04110	0.01410	0.02350	0.03330	0.02130	0.02170	0.02380	0.01740
	best	0.32500	0.19900	0.22900	0.22800	0.20800	0.21900	0.17600	0.20600
0.1-0.9	mean	0.37100	0.22800	0.26800	0.30900	0.24400	0.25200	0.22000	0.22900
	std	0.06020	0.01920	0.02100	0.03270	0.02100	0.02630	0.02220	0.01410
	best	0.27300	0.18900	0.22300	0.22700	0.18600	0.19200	0.17600	0.19500

In Table 4, the best results, obtained by Eight F and CR values, are represented.

Table 4. The best mean of IGD results with unconstrained multi-objective problems (UF1-UF10) of CEC 2009. Tested with 60 NP. Eight F and CR control parameters are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, NP = 60		
Problems	**Best IGD Mean**	**Best IGD Result**
UF1	0.00223 CR/F (0.2, 0.2)	0.00191 CR/F (0.2, 0.2)
UF2	0.00437 CR/F (0.2, 0.5-0.9)	0.00347 CR/F (0.2, 0.5-0.9)
UF3	0.01550 CR/F (0.2, 0.1-05)	0.00883 CR/F (0.2, 0.2)
UF4	0.01940 CR/F (0.2, 0.5-0.9)	0.01860 CR/F (0.2, 0.9)
UF5	0.03160 CR/F (0.2, 0.5)	0.02130 CR/F (0.1-0.5, 0.3-07)
UF6	0.02960 CR/F (0.1-0.5, 0.2)	0.01820 CR/F (0.1-0.5, 0.2)
UF7	0.01550 CR/F (0.1-0.5, 0.1-0.5)	0.00777 CR/F (0.2, 0.5-0.9)
UF8	0.02640 CR/F (0.2, 0.2)	0.02490 CR/F (0.2, 0.2)
UF9	0.06670 CR/F (0.2, 0.9)	0.06490 CR/F (0.2, 0.9)
UF10	0.08790 CR/F (0.2, 0.1-05)	0.05870 CR/F (0.2, 0.2)

In Table 5, the best results obtained by Eight F and CR control values are shown.

Table 5. The best IGD mean results with unconstrained multi-objective problems (UF1-UF10) of CEC 2009, tested with 100 NP and Eight F and CR control parameters are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, NP = 100		
Problems	**Best IGD Mean**	**Best IGD Result**
UF1	0.00195 CR/F (0.2, 0.2)	0.00175 CR/F (0.2, 0.2)
UF2	0.00294 CR/F (0.2, 0.1 – 09)	0.00250 CR/F (0.2, 0.1 – 09)
UF3	0.01410 CR/F (0.1-05, 0.2)	0.00924 CR/F (0.2, 0.2)
UF4	0.02100 CR/F (0.2, 0.5-0.9)	0.02020 CR/F (0.2, 0.9)
UF5	0.04000 CR/F (0.2, 0.5)	0.02820 CR/F (0.2, 0.5)
UF6	0.03130 CR/F (0.2, 0.2)	0.02460 CR/F (0.1-0.5, 0.2)
UF7	0.01510 CR/F (0.3-07, 0.1-0.5)	0.00734 CR/F (0.2, 0.5)
UF8	0.02450 CR/F (0.2, 0.2)	0.02280 CR/F (0.2, 0.2)
UF9	0.06450 CR/F (0.2, 0.9)	0.06200 CR/F (0.2, 0.9)
UF10	0.10000 CR/F (0.2, 0.1-05)	0.08300 CR/F (0.2, 0.1-05)

The best results achieved by Eight F and CR values are given in Table 6.

Table 6. Shows best mean (IGD) outcomes with unconstrained multi-objective problems (UF1-UF10) of CEC 2009, tested with 140 NP and Eight F and CR control parameters are used (0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, 0.1-0.9).

DSDE, NP = 140		
Problems	**Best IGD Mean**	**Best IGD Result**
UF1	0.00190 CR/F (0.2, 0.2)	0.00160 CR/F (0.2, 0.2)
UF2	0.00245 CR/F (0.2, 0.3-07)	0.00206 CR/F (0.2, 0.1-05)
UF3	0.01580 CR/F (0.1-0.5, 0.2)	0.01150 CR/F (0.2, 0.2)
UF4	0.02330 CR/F (0.2, 0.5-0.9)	0.02260 CR/F (0.2, 0.5-0.9)
UF5	0.04930 CR/F (0.2, 0.5)	0.04100 CR/F (0.2, 0.5)
UF6	0.03960 CR/F (0.2, 0.2)	0.02860 CR/F (0.2, 0.1-05)
UF7	0.01390 CR/F (0.3-0.7, 0.1-05)	0.00828 CR/F (0.2, 0.5-0.9)
UF8	0.02340 CR/F (0.2, 0.1-0.9)	0.02280 CR/F (0.2, 0.1-0.9)
UF9	0.06400 CR/F (0.2, 0.9)	0.06170 CR/F (0.2, 0.9)
UF10	0.12700 CR/F (0.2, 0.1-0.5)	0.09370 CR/F (0.2, 0.1-0.9)

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6. DISCUSSION

DBDE method is a novel optimized DE algorithm that uses dominance rank to deal with optimization problems. The DBDE method utilizes three control parameters: NP, F and CR. The performance of the DBDE algorithm can be changed according to the values of control parameters. The performance of DBDE for the UF10 is shown in Tables 1, 2 and 3 for eight distinct F and CR values with identified appropriate parameter settings of 0.2, 0.5, 0.7, 0.9, 0.1-0.5, 0.5-0.9, 0.3-0.7, and 0.1-0.9, respectively. Also, three NP values are used as 60, 100, and 140.

Additionally, for the UF1-UF10 problems, the findings presented in Table 4, 5 and 6 demonstrate that the optimal IGDs vary according to population size. Likewise, the best IGD value is obtained for CR=0.2 and F=0.2. Based on the results, mostly DBDE has better optimization performance with a 0.2 CR value for the selected populations and problems. The performance of DBDE is changeable depending on the F value. For every problem, if the correct F value is selected, the best results can be obtained. CR value is more stable for CEC 2009 problems.

UF1, UF4, UF5, UF9, UF10 problems have stable CR and F values for the selected NP values. Therefore, depending on these results, it can be said that for UF1, UF4, UF5, UF9, and UF10 problems, NP does not affect the selection of F and CR values.

Depends on the IGD mean results;

a. CR/F (0.2, 0.5-0.9) intervals gives the superior optimal values for the UF4 problem,
b. CR/F (0.2, F= 0.5) intervals gives the superior optimal values for the UF5 problem,
c. CR/F (0.2, F= 0.9) intervals gives the superior optimal for the UF9 problem,
d. CR/F (0.2, 0.1-05) intervals gives the superior optimal for the UF10 problem.

UF2, UF3, UF6, UF7, UF8 problems have changeable F value performance for selected populations. However, the CR=0.2 value is stable primarily for all the selected NP values for the mentioned problems.

7. CONCLUSION

The performance of the DBDE algorithm is investigated with respect to the selection of the CR rate, the scale factor(F), and the population size(NP).

Experimental results shows that the performance of the DBDE outperforms with the optimized control parameters. Although convergence happens rapidly in small populations, its consequences are more apparent. Generally, DBDE may produce outstanding outcomes when proper configuration parameters are used to optimize a specific function. If wrong settings are selected, the outcome might not be good. On the other side, a large population with a high exploratory potential reduces the probability of stagnation effects and premature convergence , even if the rate of convergence is slower. By examining additional methods and changes in the CR & F is possible to detect more complex interactions. (Mallipeddi & Suganthan, 2008)

It is clear that when the correct CR and F values are selected, DBDE performance is improved significantly. Depending on the experimental results, The best outcomes are achieved from the most prominent population size NP=140, used with the UF1, UF2, UF7, UF8, and UF9 test problems. In the selected NP=100 size population, also the UF3 test problem gives the best possible results. In addition, UF4, UF5, UF6, and UF10 problems, with the smaller selected population of NP=60, have the best outcomes. The algorithm's performance is directly proportional to the control parameters and the problem's complexity.

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