Motor operation inspired optimization for Hierarchical Influence governed Differential Evolution

ABSTRACT

Operational maturity of biological control systems have fuelled the inspiration for a large number of mathematical and logical models for control, automation and optimisation. The human brain represents the most sophisticated control architecture known to us and is a central motivation for several research attempts across various domains. In the present work, we introduce an algorithm for mathematical optimisation that derives its intuition from the hierarchical and distributed operations of the human motor system. The system comprises global leaders, local leaders and an effector population that adapt dynamically to attain global optimisation via a feedback mechanism coupled with the structural hierarchy. The hierarchical system operation is distributed into local control for movement and global controllers that facilitate gross motion and decision making. We present our algorithm as a variant of the classical Differential Evolution algorithm, introducing a hierarchical crossover operation. The discussed approach is tested exhaustively on standard test functions from the CEC 2017 benchmark. Our algorithm significantly outperforms various standard algorithms as well as their popular variants as discussed in the results.

CCS CONCEPTS

•**Computer systems organization** → **Embedded systems;** *Redundancy;* Robotics; •**Networks** → Network reliability;

KEYWORDS

Hierarchical Optimization

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1 INTRODUCTION

Evolutionary algorithms are classified as meta-heuristic search algorithms, where possible solution elements span the n-dimensional search space to find the global optimum solution. Over the years, natural phenomena and biological processes have laid the foundation for several algorithms for control and optimization that have highlighted their applicability in solving intricate optimization problems in various fields. At the cellular level in the E.Coli Bacterium, there is sensing and locomotion involved in seeking nourishment and avoid harmful chemicals. These behavioral characterisitics have fueled the inspiration for the Bacterial Foraging Optimization algorithm[3]. Ant Colony Optimization [1] deals with behaviour of ants and has been a successful model for solving complex problems. Particle Swarm Optimization [2] is a swarm intelligence algorithm based on behaviour of birds and fishes that models these particles as they traverse an n-dimensional search space and share information in order to obtain global optimum. From a biological control point, the human brain represents one of the most sophesticated architectures and several research attempts seek to mimic its accuracy, precision and efficiency. The brain function activities can be classified into 2 categories: sensory and motor operations. Sensory cortical functions inspired the concept of neural networks and they are being scaled successfully in deep learning to solve vast amount of problems.

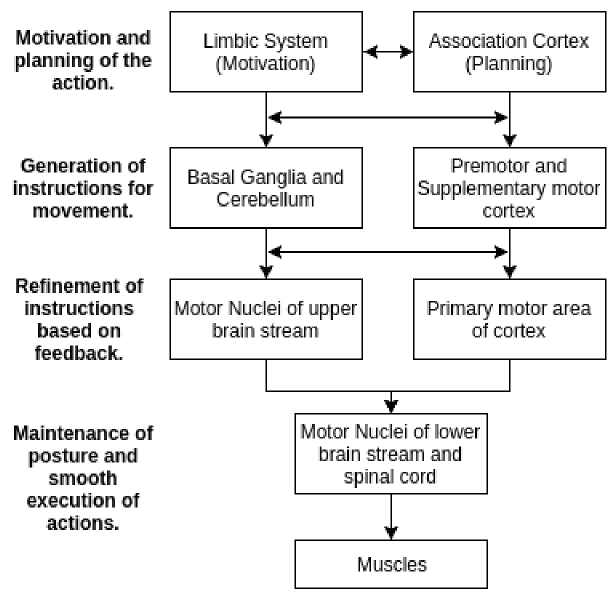

Figure 1: Description of Heirarchical Motor Operations in Humans

The human motor function represents a distributed neural and hierarchical control system. It can be classified as having local control functions for movement as well as higher level controllers for gross motion and decision making for planning actions.The optimal execution of motor operation involves distributed brain structures at different levels of hierarchy.These include the pre-frontal cortex, motor cortex, spinal cord, anterior horn cells etc. For generating an actions sequence, a sequence of actions is implemented by a string of subsequences of actions each implemented in a different part of the body. The operational structure has been depicted in Figure

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1[4]. For optimality of actions, neurons act in unison. The neurons in the motor cortex act like global leaders and send inhibitory or facilitatory influence over the anterior horn cells, local leaders, located in the spinal cord. These local leaders, are connected to the muscle fibres, effectors through a peripheral nerve and neuromuscular junction. Efficient execution of task requires feedback based facilitation and inhibition of the effectors over the anterior horn cells. These sequence of operations consitute the optimal convergence of the system leading to smooth motor execution.

The present paper focusses on introducing an optimisation algorithm modelled intuitively on the distributed and hierarchical operation of the brain motor function.

The Classical Differential Algorithm [5], proposed by Storn and Price has been hailed as one of the best available evolutionary algorithms, owing to it's simple yet effective structure but it has been criticised for it's slow convergence rate. Through this paper, we seek to improve the algorithm's performance by proposing a hierarchical structure in the pipeline of the algorithm. Introduction of a hierarchical architecture in the algorithm enables the algorithm to control the flow of agents based on the influences of local leaders and a global leader, as depicted by the brain motor function in Fig. 1. The algorithmic performance has been exhaustively compared with some popular variants of DE, namely JADE [6], Particle Swarm Optimization-Differential Evolution(PSODE) and the original Classical Differential Evolution (DE) algorithms. Through this exhaustive comparision, we show even with fixed parameters and the introduction of a hierarchical crossover operator, HIDE is able to outperform adaptive architectures such as JADE by a high margin, as discussed in the result sections. This effective behaviour results from the co-ordinated hierarchy between the global and local control, owing to the selected hierarchical function as discussed in the algorithmic approach. The result section () comprises a thorough analysis and comparision on algorithmic performance on the CEC 2017 objective function set, where we report the objective function optimal values and display the convergence plots for each algorithm, while discussing the efficiency of HIDE.

2 CLASSICAL DIFFERENTIAL EVOLUTION

The classical Differential Evolution (DE) algorithm is a population-based global optimization algorithm, utilizing a crossover and mmutation approach to generate new individuals in the population for achieving optimum solutions. For each individual x_i that belongs to the population, DE randomly samples three other individuals from the population a_i, b_i and c_i. Then using the randomly chosen points, a new individual vector is generated using equation (1):

$$u_i = a_i + F(b_i - c_i) \tag{1}$$

Where, F is called the differential weight (Usually lies between $[0, 1]$).
And to obtain the new position of the individual, a crossover operation is implemented between x_i and u_i, controlled by the parameter CR called the crossover probability. The value for CR always lies between $[0, 1]$.

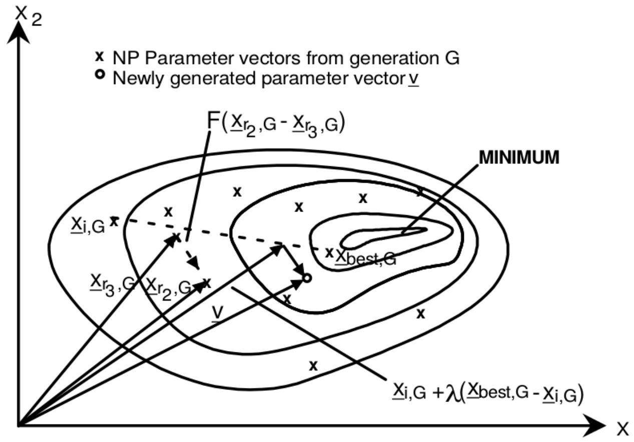

Figure 2: Two dimensional example of an objective function showing its contour lines and the process for generating v in scheme DE2

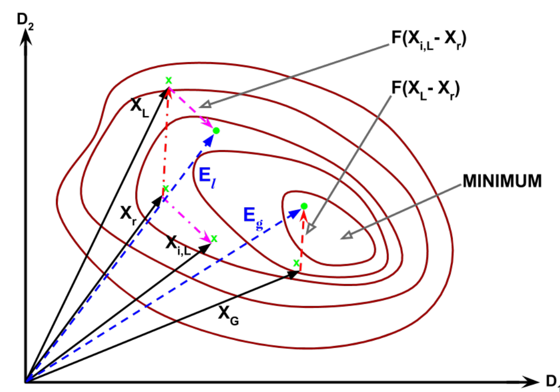

Figure 3: The process for generating generation of E_g and E_l in a 2 dimensional optimization.

3 DISTRIBUTED LEADER OPTIMIZATION

Taking inspiration from the human motor system, we model the hierarchical motor operations in our optimization agents, where we define a global leader which influences the action of several distributed local leaders and the particle agents which act as the effectors. The global leader is analogous to the decision making and planning section in the motor system hierarchy whilst, the local leaders correspond to motion generators acting under the influence of the global leader.

The position of each particle in the population is affected by the influence of global leaders and local leaders, while also being affected by a randomly chosen particle from the population to induce some stochasticity in the optimization pipeline. We first model the influence of the global leader on the local leaders and the influences of the local leaders on each population element using equation (2) and (3). We introduce a hierarchical crossover between the two influencing equations governed by a hierarchical crossover parameter HC.

Algorithm 1 Distributed Leader Optimization

procedure START
  Initialize parameters (HC, P, N_l, N).
  Generate initial global leader g_L as a random point.
  Generate N_l local leader points around g_L.
  Using a Normal distribution, generate N points for population P around the local leaders.
  while termination criteria is not met **do**
    for each individual x_i in P **do**
      compute the corresponding local leader l based on nearest position.
      Let $u = 0$ be an empty vector.
      Let i_c and i_N be the current generation and total generations of the procedure.
      if $i_c < (HC * i_N)$ **then**
        $u = E_g$ from (2).
      else
        $u = E_l$ from (3).
      end if
      for each dimension i **do**
        Generate $r_i = U(0,1)$, a random number between 0 and 1.
        if $r_i < HC$ **then**
          Set $x_i^{'} = x_i$.
        else
          Set $x_i^{'} = u_i$
        end if
      end for
      if $f(x^{'}) < f(x)$ **then**
        Replace x with $x^{'}$ in the population.
      end if
    end for
    Alter local leaders in each population cluster based on objective function value.
    Compute updated global leader g_L.
  end while
end procedure

Analogously to [step 3] in the brain motor operation, the updation of particle positions requires generating feedback for the leaders as a part of the optimization procedure, and hence the local leaders and the global leader are updated based onn their objective function value generated from the perturbations in population particles. This series of events comprise of one optimization pass (one loop step). On execution of several optimization passes as described, the system is able to converge to an optimal configuration, analogous to the successful execution of the required task as shown in [step 4].

The updated position of the particle x is governed by the hierarchical crossover operation and a mutation operation. The hierarchical operation is affected by the global leader g_L and the local leader l through the parametric equations (2) and (3). Switching between the two is governed by the hierarchical crossover parameter HC. The given equations are discussed as follows:

$$E_g = g_L + F(l - c) \tag{2}$$

$$E_l = l + F(x - c) \tag{3}$$

In the algorithm 1, The Hierarchical crossover is controlled by the conditional equation $i_c < (HC * i_N)$. According to this equation, during the initial phases (HC fraction of total generations) of the optimization procedure, only the local leader is responsible for the motion of the agents, and after a certain amount of time has passed, the global leader also takes part in the motion generation process, signifying the motor control operation. Additionaly, The hierarchical crossover parameter HC also influences the mutation process wherein the degree of final mutation is decided based on the probability HC.

Table 1: Test Functions

F_{id}	Problem Function	F*
1	Shifted and Rotated Bent Cigar Function	100
2	Shifted and Rotated Sum of Different Power Function	200
3	Shifted and Rotated Zakharov Function	300
4	Shifted and Rotated Rosenbrockfis Function	400
5	Shifted and Rotated Rastriginfis Function	500
6	Shifted and Rotated Expanded Scafferfis F6 Function	600
7	Shifted and Rotated Lunacek Bi_Rastrigin Function	700
8	Shifted and Rotated Non-Continuous Rastriginfis Function	800
9	Shifted and Rotated Levy Function	900
10	Shifted and Rotated Schwefelfis Function	1000
11	Hybrid Function 1 (N=3)	1100
12	Hybrid Function 2 (N=3)	1200
13	Hybrid Function 3 (N=3)	1300
14	Hybrid Function 4 (N=4)	1400
15	Hybrid Function 5 (N=4)	1500
16	Hybrid Function 6 (N=4)	1600
17	Hybrid Function 7 (N=5)	1700
18	Hybrid Function 8 (N=5)	1800
19	Hybrid Function 9 (N=5)	1900
20	Hybrid Function 10 (N=6)	2000
21	Composition Function 1 (N=3)	2100
22	Composition Function 2 (N=3)	2200
23	Composition Function 3 (N=4)	2300
24	Composition Function 4 (N=4)	2400
25	Composition Function 5 (N=5)	2500
26	Composition Function 6 (N=5)	2600
27	Composition Function 7 (N=6)	2700
28	Composition Function 8 (N=6)	2800
29	Composition Function 9 (N=3)	2900
30	Composition Function 10 (N=3)	3000
Search Range: $[-100,100]^D$		

4 RESULTS AND DISCUSSIONS

All evaluations were performed using Python 2.7.12 with Scipy and Numpy for numerical computations and Matplotlib package for graphical representation of the result data. This section is divided into two sub-sections: Section A provides description about the problem set used for analysis of algorithmic efficiency and accuracy, and section B comprises of tabular and graphical data to support the claim of eminence of the proposed approach.

4.1 Problem Set Description

The set of objective functions considered for testing the proposed algorithm and compare it's performance against classsical DE and it's variants PSODE and Joint Adaptive Differential Evolution (JADE) have been taken from the CEC 2017 [] set of benchmark functions. Exhaustive comparisions and analysis have been depicted on dimensions D = 10, 30, 50 and 100 for a clear understanding of the strengths of the proposed algorithm. Objective functions $f_1 - f_3$ are simple unimodal functions and $f_4 - f_1 0$ are multimodal functions with a high number of local optima values. Functions $f_1 1 - f_2 0$ are all hybrid functions using a combination of functions from $f_1 - f_1 0$. The set of composite function range from $f_2 1 - f_3 0$ and merges the properties of the sub-functions better while incorporating the basic functions as well as hybrid functoins to increase complexity while maintaining continuity around the global optima.

Summarized in Table 1 are the 30 objective functions from the CEC 2017 dataset and the global optimum value for each fuction denoted by $F*$. In all simulation runs, we set the population size NP to a fixed value of 40, and the results are shown in a tabular structure depicting the best and average values of the population individuals for the simulations. Additionally, several graphical results have been discussed to observe the convergence rate and efficiency of the algorithms used in the simulation. These graphs were plotted based on the numerical results obtained from the simulation runs used to build the tables.

4.2 Parameter Settings

For fair comparisions, the parameters for all algorithms are fixed to the values depicted in table 2. As clear from the table, we set the parameters F and CR as 0.4 and 0.48 for DE across all experiments. The parameters for JADE were selected as suggested in the original work. These parameter settiings allow transparency in results and a base for fair and clear comparisions in the analysis of the algorithms.

4.3 Numerical and Graphical Results

In Tables 3-6, the best and mean values obtained for the population agents in the simulation runs have been reported, and the optimum results for each objective function have been highlighted in [bold]. For Clarity, the comparisionn results in each table have been summarized in a "w/t/l" format, depicting the corresponding algorithm wins in 'w' functions, ties in 't' functions and loses in 'l' functions. The utilization of such an evaluation metric facilitates the comparision of different algorithms and clarify the distinction between their performances.

Tables 3 and 4 list the computation results for D=10 and 30, respectively. For D=10, HIDE achieves the maximum number of wins and shows an impressive performance with a 'w/t/l' score of '12/7/11' in the best case and '14/4/12' in the mean of population case. JADE achhieves the second best performance with 5 wins and 7 ties in the best case, and 9 wins and 4 ties in the mean case. JADE shows decent results owing to the adaptive nature of it's parameter selection which also improve it's convergence rate as compared to DE (evident from the graphical plots as well). For D=30, HIDE again achieves the maximum number of wins in both best and mean case with 17 wins in best case and 18 in mean case, followed by JADE with 8 and 9 wins in best and mean cases, respectively.

In tables 5 and 6, the data for D=50 and 100 (higher dimensions) have been summarized. For D=50, HIDE shows 17 wins in the best case and 18 wins in the mean case, depecting exceptional performance capability. Classical DE shows no wins in any case in high dimensional scenarios owing to it's low convergence rate and incapability to reach the global optimum. Similarly, for D=100, HIDE is able to outperform all comparative algorithms by a very high margin showing it's impressive performance on higher dimensions. This efficiency and accuracy of HIDE can be attributed to the hierarchical nature of crossover selection which enables our algorithm to follow two distinct patterns in a hierarchical fashion.

It is clearly evident from the tabular information that HIDE surpasses DE, JADE and PSODE by an exceptionally high margin. On close analysis, it can be seen that HIDE falls behind the other algorithms in a small fraction of functions on lower dimensions objective functions such as f_5, f_7 etc. because of the unimodal and smooth nature of the objective functions where due to fast convergence, the proposed algorithm sometimes converges to a point quickly in the early stages of execution. But it is also evident from the data that HIDE shows remarkable performance on higher dimensions, especially on hybrid and composite objective functions implying it's extensive utility in real world complex problems.

In addition to the tabular information, the plots in Fig. 4 aptly depict the performance of all algorithms across various dimensions and objective functions. On overall compilation of the plots, it is clear that HIDE shows a better convergence rate as compared to rest of the algorithms. Moreover, on higher dimensions, the proposed algorithm evidently outperforms all other algorithms both in terms of convergence rate and optimality. On lower dimensions (D=10, 30), HIDE shows a performance trend similar to PSODE as shown in Fig. 4 (a, b, e, f, i, j, m, n) and can been seen to produce better end-results as compared to PSODE, DE and JADE in almost all these cases, as was evident from the tabular information as well. For problems in higher dimensions (D=50, 100), it is very clear that HIDE optperforms rest of the algorithms by a high margin, especially in Fig. 4 (s, t), where the algorithm displays an impressive convergence rate and a far better optimality than DE, PSODE and JADE. Similarly, in Fig. 4 (k, l, o, p) HIDE shows a faster convergence than any other algorithms considered for comparisions, hence validating the claim that the proposed approach is able to overcome the issue of slow convergence with Differential Evolution algorithm. This remarkable trait in HIDE enhances it's utility for high dimensional problems where fast convergence to global optimum value is required, hence making it superior to the other considered algorithms and several variants of the Differential Algorithm

Table 2: Algorithm Parameter Settings used for comparision

DE		PSODE					JADE		Ours	
F	Cr	w	Cp	Cg	F	Cr	μ_{CR}	μ_F	HC	$n_{leaders}$
0.4	0.48	0.7	2.0	2.0	0.48	0.5	0.5	0.5	0.375	5

4.4 Results

5 CONCLUSION

Differential Evolution has been one of the most successful optimization algorithms and over the years, several variants have been proposed to enhance its convergence time and performance. In the present work, we introduced a hierarchical influence governed variant of the classical Differential Evolution. Our algorithm derives its motivation from the distributed and hierarchical operations of the human motor system, one of the most sophesticated biological control architecture known. Our proposed approach involved introduction of a hierarchical crossover parameter, HC , that has enabled scaling the classical algorithm to more distributed settings. The collaborative influence of the global leader-local leader and local leader-effector interactions resulted in faster and more robust optimization. We exhaustively tested the algorithm performance on transformed hybrid and composite functions introduced in CEC 2017 Benchmark.The results and graphs discussed in Section 4 highlight the particular effectivess of the proposed approach on higher dimensional settings on more involved test functions.

The results observed provide sufficient motivation to extend the work to solving challenging real life problems in future.

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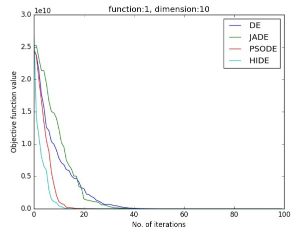
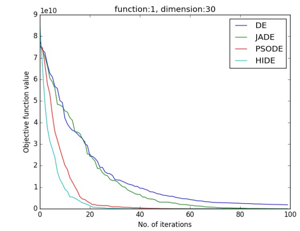
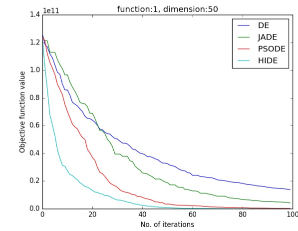


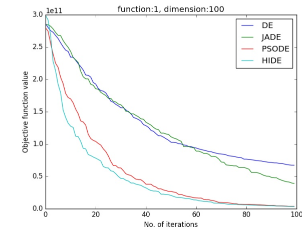
(a) F1D10



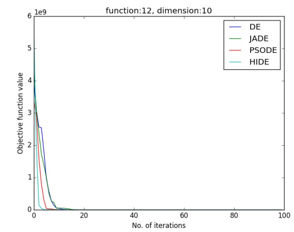
(b) F1D30



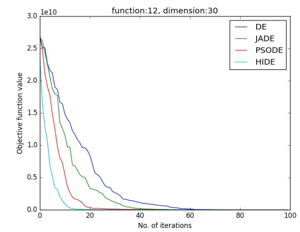
(c) F1D10



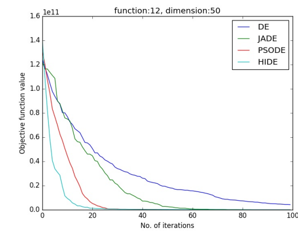
(d) F1D30



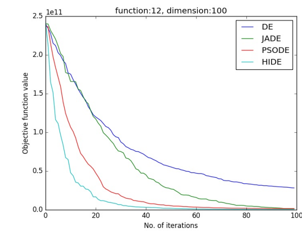
(e) F12D10



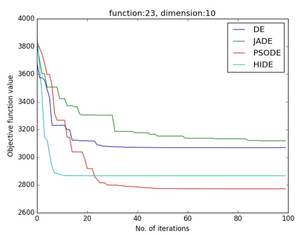
(f) F12D30



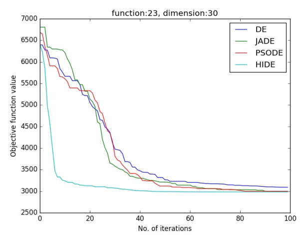
(g) F12D50



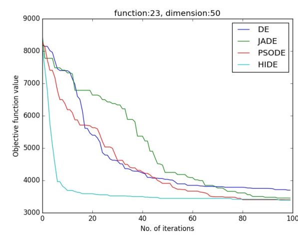
(h) F12D100



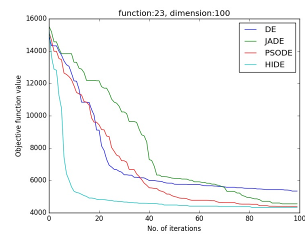
(i) F23D10



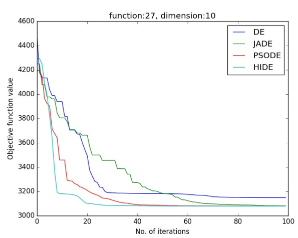
(j) F23D30



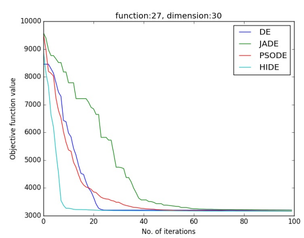
(k) F23D50



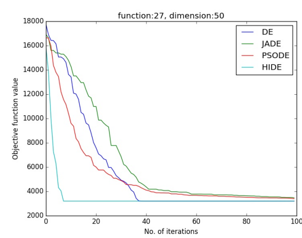
(l) F23D100



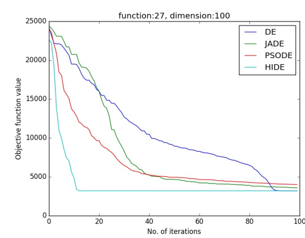
(m) F27D10



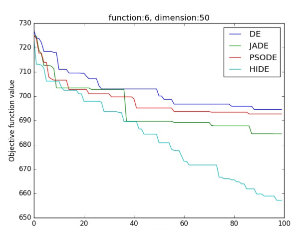
(n) F27D30



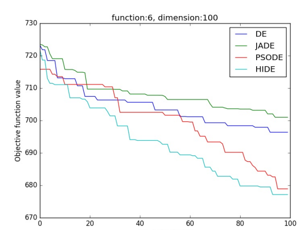
(o) F27D50



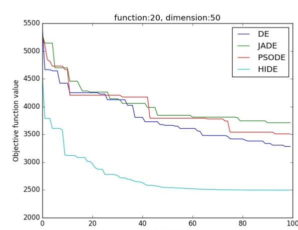
(p) F27D100



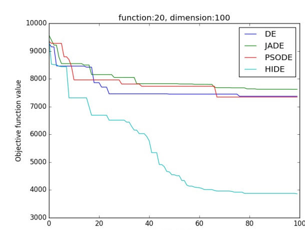
(q) F6D50



(r) F6D100



(s) F20D50



(t) F20D100

Figure 4: Comparision analysis over various functions and dimensions

Table 3: Objective Function Value for Dimension: 10

ID	DE		JADE		PSO-DE		Ours	
	best	mean	best	mean	best	mean	best	mean
1	100.000051	100.011085	**100.0**	**100.0**	100.000712	185.975885	**100.0**	**100.0**
2	**200.0**	200.1	**200.0**	**200.0**	**200.0**	**200.0**	**200.0**	**200.0**
3	300.00134	300.214502	**300.0**	**300.0**	300.000006	300.000985	**300.0**	**300.0**
4	400.042617	403.674837	**400.0**	400.409399	400.064644	404.307763	**400.0**	**400.000003**
5	566.661791	604.867489	**523.908977**	**541.521084**	525.868824	575.61616	533.803201	579.483815
6	621.914237	634.807962	620.878276	636.034759	**603.187964**	635.865001	613.730565	**629.293758**
7	724.831278	739.129935	**717.016542**	**723.983312**	725.44788	733.15638	720.345706	725.233785
8	**818.904202**	829.749207	821.914433	**826.321588**	820.8941	830.246691	821.064763	828.160987
9	**900.0**	908.104383	**900.0**	1084.478253	**900.0**	1124.102561	**900.0**	**903.454324**
10	1911.510092	2447.443751	1760.956867	2162.648588	2049.644727	2518.241095	**1694.437597**	**2049.074266**
11	1102.985708	1113.423105	1105.661676	1117.509748	1105.97013	1120.192974	**1101.769749**	**1108.863598**
12	2531.746305	6509.743078	1438.605713	5430.674683	4089.006352	10810.387667	**1308.438341**	**1327.405881**
13	1313.130226	1404.903601	**1304.681558**	**1328.755262**	1319.839199	1453.340785	1306.682039	1344.282241
14	1409.949612	1426.571937	1412.934432	1428.169439	1420.91065	1434.112884	**1404.928993**	**1410.000769**
15	1504.131392	1521.446614	1502.496189	1508.31154	1501.389515	1518.310358	**1500.08137**	**1503.169264**
16	1958.42062	2104.555728	1958.857997	2094.630816	**1958.411527**	**2048.156879**	1958.433511	2062.385949
17	1728.194973	**1743.155244**	1730.715318	1748.129878	1727.80039	1791.607742	**1723.853972**	1747.589077
18	1801.586012	1838.840555	1804.298538	1825.091639	1817.154641	1840.546923	**1800.235516**	**1804.014301**
19	1901.195482	1903.604767	1900.399786	1902.152965	1902.71174	1906.252333	**1900.005632**	**1901.014116**
20	2204.55412	2289.226577	2148.538938	2178.313173	2140.561308	2261.038768	**2139.915527**	**2172.816519**
21	2337.772994	2387.230357	**2314.421135**	**2338.688719**	2337.207339	2351.898856	2320.496212	2344.61612
22	2300.805852	2304.132879	**2300.0**	**2300.093485**	2300.684181	2301.710478	2300.000015	2301.095975
23	3070.177083	3145.772296	3003.678563	3091.22041	**2773.372859**	3060.022519	2867.020036	**3047.982305**
24	**2500.0**	**2500.0**	**2500.0**	**2500.0**	**2500.0**	**2500.0**	**2500.0**	**2500.0**
25	2899.584968	2933.249812	2899.584968	2930.266506	**2897.742869**	**2921.27479**	2897.833388	2927.976511
26	**2800.0**	4117.597033	**2800.0**	**2956.064173**	**2800.0**	3367.60765	**2800.0**	3161.548079
27	3113.157656	3358.806434	3072.439023	3178.509645	3078.873134	3240.501812	**3071.203569**	**3107.268539**
28	3184.75565	3230.921422	3184.75565	**3195.113042**	3184.755652	3198.370691	**3100.0**	3195.411961
29	**3148.587115**	3266.979786	3172.400194	**3233.707677**	3191.348193	3244.892638	3189.211417	3292.420474
30	3442.555095	11927.404685	3207.766942	4615.591316	4573.358512	16415.162901	**3205.740954**	**3249.710975**
#	2/4/24	1/1/28	5/7/18	9/4/17	4/4/22	2/2/26	12/7/11	14/4/12

Table 4: Objective Function Value for Dimension: 30

ID	DE		JADE		PSO-DE		Ours	
	best	mean	best	mean	best	mean	best	mean
1	100.001508	4334.438478	100.001338	100.056201	364.295574	4236.363207	**100.0**	**100.0**
2	40412441.0	5.129601e+19	**200.0**	1535352368.6	332899.0	9.590679e+11	**200.0**	**159855.5**
3	17926.872873	22131.542719	69304.926091	74080.700372	15792.547575	21683.209092	**3679.811599**	**8999.947269**
4	481.255055	519.422652	403.633939	**442.206911**	468.341175	479.341966	**400.004163**	443.016156
5	689.041352	737.79326	**667.50756**	**735.204027**	715.904429	746.548906	685.40454	738.842184
6	**643.626307**	652.582714	651.39169	655.142819	642.724237	655.106996	644.701241	**652.002395**
7	883.347367	962.591129	**779.907693**	**818.344111**	790.014281	854.285524	812.923573	856.90477
8	923.37426	967.251501	931.500175	**957.362003**	**915.414882**	960.486239	930.288539	964.11663
9	5652.483961	7878.781444	4953.05469	5146.600953	6018.417197	9042.410178	**4003.118072**	**4734.984364**
10	**3596.63104**	4536.989761	4012.723292	**4204.18969**	3934.606704	4863.741107	3793.781776	4346.741344
11	1162.405965	1184.634006	1152.748529	1174.58813	1165.144993	1189.171787	**1149.748499**	**1171.130409**
12	56679.435092	317650.61349	24821.171765	58930.090242	10221.077465	161046.05540	**9208.289246**	**41947.22269**
13	3002.029489	18794.835991	4276.907742	13775.816239	3871.279833	10612.26359	**1664.06241**	**2453.606969**
14	1773.180798	5502.160382	1496.219858	42868.9158	1555.452763	4029.808535	**1462.926848**	**1504.191515**
15	1860.435669	2484.689969	1688.05046	2222.674323	1651.747476	2223.060542	**1611.074402**	**1852.66177**
16	2517.439623	2827.004968	2344.19818	2621.618684	**2239.242719**	**2664.114667**	2298.041965	2691.674809
17	2321.175936	2604.529778	2062.898023	2546.995596	2107.43677	2457.34021	**1820.806639**	**2418.723829**
18	38987.282456	94156.328505	**11841.60813**	184888.162181	62294.853257	118430.28912	12578.003784	**23024.11193**
19	2043.469888	3010.235379	1959.71819	2156.957875	3049.52231	6840.408394	**1949.271714**	**1987.866761**
20	2625.539158	2864.832611	**2706.314441**	**2805.600064**	2619.996493	2895.107238	2753.806213	2966.035793
21	2412.081757	2504.777775	2414.52134	2456.718982	2431.740293	2478.841357	**2200.0**	**2442.734316**
22	2300.481796	5655.569322	**2300.0**	**4157.698784**	2307.721358	6811.069162	2300.009985	6795.24842
23	3050.654508	3572.965066	**2772.002023**	**2946.749322**	2764.922461	3199.874364	2883.276891	3543.839343
24	3104.623692	3290.698756	2891.557648	2965.225566	**2911.63347**	2983.772932	**2500.0**	2940.75997
25	2916.180657	2946.711753	2875.106846	2881.091389	2875.498843	2889.943671	**2874.171109**	**2877.484904**
26	4043.691403	6756.3724	2900.0	**3266.510982**	**2800.007809**	3273.128769	2900.0	3298.490539
27	3200.005857	3998.876498	3145.810354	**3189.82261**	3145.425231	3639.634132	**3132.816283**	3284.28897
28	3290.744025	3326.263983	**3100.0**	3131.027315	3195.486838	3225.594053	**3100.0**	**3115.505829**
29	3720.314598	4115.185803	**3305.310139**	**3626.887552**	3535.952295	3867.593068	3352.845055	3709.102375
30	3359.030768	3900.826662	**3263.496536**	3749.610722	3312.635025	3524.714477	3298.704645	**3421.715322**
#	2/0/28	0/0/30	8/2/20	11/0/19	4/0/26	1/0/29	15/2/13	17/0/13

Table 5: Objective Function Value for Dimension: 50

ID	DE		JADE		PSO-DE		Ours	
	best	mean	best	mean	best	mean	best	mean
1	5884574.87314	367294248.521	136.072384	3708.75086	5811.218992	154233.646744	**106.072862**	**3665.419272**
2	4.718137e+24	3.364977e+44	**2635725.0**	**5.02374e+26**	2.212101e+19	2.544543e+23	2.279950e+17	1.00729e+31
3	45520.966376	62237.296819	143481.793147	156166.762356	52308.42743	64435.24063	**44613.29993**	**58182.83733**
4	574.400328	801.384952	418.580378	470.113207	477.080964	574.528479	**400.005049**	**447.775413**
5	816.394775	843.258843	809.899483	834.131266	**778.59312**	831.066954	791.405194	**830.218472**
6	652.541914	655.794152	**633.217881**	**654.893828**	653.291336	658.183613	645.25633	656.060597
7	1109.02123	1263.038487	**889.036574**	**944.90319**	915.153525	1047.43879	989.957862	1186.248741
8	1139.278925	1175.893113	1118.339103	**1144.604745**	**1092.62639**	1159.032351	1100.476077	1168.529946
9	22196.387817	29218.775982	11958.280061	**13174.66236**	24753.040541	32233.95451	**10251.47631**	14752.7168
10	6228.49289	7289.183679	6054.707691	6833.306317	6207.795302	7055.595231	**6050.434374**	**6609.804567**
11	1170.858603	1258.517635	1202.694857	1232.204268	1206.154564	1252.939541	**1156.439606**	**1205.254497**
12	677263.0799	16987989.981	**74784.6159**	530814.6481	584300.6983	3448448.7906	126908.2157	**494471.0756**
13	6005.535308	16893.949921	2041.488125	4332.5945	1572.252973	**4301.829606**	**1484.761799**	7760.056137
14	38490.532315	174367.45065	**2466.047056**	238838.470051	16327.42317	67939.000264	2967.818485	**26290.31618**
15	2278.141229	26989.255509	13553.041864	25636.769611	3443.587343	**9167.267098**	**1938.200405**	14976.72189
16	2722.026011	3176.916902	**2345.400708**	**2916.561016**	2521.93881	3146.04527	2436.449338	2978.37746
17	2799.949776	3289.61565	2568.383575	2907.869272	2887.281107	3236.957928	**2561.370306**	**2874.965038**
18	264037.12570	872072.47739	36176.58677	**113941.3176**	**26965.28512**	114846.121366	260540.781819	536454.326476
19	10051.912407	20380.25713	2089.172253	7763.17234	9905.850822	16555.756926	**2013.126904**	**3609.258962**
20	2950.923195	3274.334015	3041.81309	3113.289461	2991.589293	3361.823946	**2495.031774**	**3080.137478**
21	2596.725663	2689.688363	2526.190898	2597.677199	2555.8788	2642.381597	**2447.758274**	**2570.911014**
22	9713.993241	10803.653732	10759.59674	11032.880953	8918.436264	10465.022457	**8181.446081**	**9755.070369**
23	3451.104943	4200.174424	2971.160647	3237.778662	2977.554961	3490.639751	**2851.650254**	**3162.313622**
24	3434.465028	3682.846708	3103.955173	3185.382676	**3036.799607**	**3158.330504**	3136.927747	3284.656095
25	3141.144886	3292.303449	2931.162959	2962.471758	2931.926959	3008.895353	**2931.142314**	**2954.767839**
26	4906.132848	7989.490966	**2900.0**	3346.874039	2900.441895	3653.757741	**2900.0**	**3262.668498**
27	3200.010703	3792.645588	3143.038057	3184.646353	3158.178238	3397.130323	**3141.010872**	**3176.011524**
28	3300.010827	3431.570911	**3240.725865**	**3288.253039**	3263.207144	3300.257609	3243.631996	3294.373237
29	3812.475517	4605.349537	**3533.945743**	**3956.835243**	3955.324537	4364.18129	3653.675553	3966.471956
30	3673.711968	5813.173755	3916.725719	4869.089335	3730.309354	5143.078706	**3346.483679**	**4747.88675**
#	0/0/30	0/0/30	8/1/21	9/0/21	4/0/26	3/0/27	17/1/12	18/0/12

Table 6: Objective Function Value for Dimension: 100

ID	DE		JADE		PSO-DE		Ours	
	best	mean	best	mean	best	mean	best	mean
1	3427212811.79	13807281895.7	141.263356	13516.698933	6067123.52108	29751976.5091	**122.398748**	**11708.82360**
2	4.19617e+84	1.54741e+112	8.73752e+74	2.54362e+87	**6.1536e+66**	**3.2118e+73**	3.8835e+80	8.8914e+114
3	208808.969094	242699.687639	312244.360944	332179.290693	241427.723667	257462.977885	**220765.0838**	**251901.1093**
4	1975.651157	2752.246068	539.386275	677.054657	777.314462	836.965399	**531.169819**	**621.219143**
5	1223.536503	1286.153332	1249.195036	1307.110127	1248.410134	1310.887657	**1068.11742**	**1272.47682**
6	651.650133	657.84974	654.709342	659.421427	656.877048	662.318417	**642.33355**	**654.132758**
7	1614.003864	1920.797726	1367.066537	1536.357878	**1311.849757**	**1534.207764**	1562.379772	2076.702502
8	1595.418732	1736.367379	1672.567849	1768.082435	1678.127263	1761.94051	**1293.552115**	**1592.162983**
9	59726.514621	71986.043905	28906.90908	30336.745335	63640.331351	74961.220998	**23466.57501**	**27067.02959**
10	12005.889721	14725.348334	14227.801909	15355.621891	12937.027857	14972.950738	**11153.58683**	**13298.09210**
11	7540.617987	11481.260145	40447.548688	57228.683666	**3521.901521**	**4544.804011**	5380.432052	9916.347692
12	529993877.325	1881773956.29	2893556.27222	6415173.6097	26105108.937	41876679.0862	**3680108.181**	**10059039.63**
13	7943.9249	508209.562668	4622.698553	**8892.775994**	8246.515295	12675.845535	**2976.841354**	11376.986338
14	728122.833253	1329183.17224	**132194.7952**	**365560.8816**	548410.338286	941547.524763	234045.940166	867160.306892
15	2660.465784	181957.060133	**1799.506503**	3362.509604	1899.073444	**2914.44348**	1976.789124	4485.415275
16	4749.254663	5847.826738	4817.483738	5632.3022	3852.700054	5228.663526	**3519.494945**	**4796.802728**
17	4397.496352	4958.418182	3842.206015	**4450.177422**	3790.72056	4730.994585	**3582.785882**	5463.216947
18	1357845.39305	1938893.27972	**146426.2736**	**763318.8226**	1004224.20385	2315010.29868	631040.14635	1335739.59138
19	2482.170159	26455.706954	2098.9496	4767.529535	2263.725158	3927.459947	**2071.077067**	**3664.159878**
20	4968.497438	5436.604051	5231.026486	5690.748998	5109.460563	5781.300835	**3627.777893**	**5228.430669**
21	3180.746656	3355.4783	2921.900122	**3085.692252**	**2885.574085**	3127.356835	2926.350399	3199.986183
22	17808.897744	19562.986646	19213.375668	20278.929093	18695.522312	20167.413741	**17548.33905**	**19547.15124**
23	4907.519646	5819.207866	**3352.556985**	4222.436894	3582.043556	4779.921248	3418.983204	**3609.098575**
24	5173.249408	5946.12042	4060.951302	4095.429519	**3801.368588**	**4042.426859**	3998.054028	4216.824895
25	4089.118918	4548.285768	**3153.485413**	**3236.61784**	3348.382262	3407.526581	3176.3038	3264.318532
26	8557.498566	20159.11458	2900.077371	11924.799473	3021.136025	4682.035439	**2900.000382**	**9867.5518**
27	3200.023355	3772.409153	**3194.809213**	3201.670732	3200.024171	3494.618132	3200.023542	**3200.023953**
28	4947.745152	5948.213156	**3295.122914**	**3340.280383**	3456.828432	3542.571307	3300.807691	3354.717338
29	6004.774424	7090.642544	5208.711727	5970.628689	5462.328635	6178.559061	**4541.195471**	**5739.291549**
30	7798.106217	202435555.594	**3584.974771**	10674.217331	3920.327039	**7139.460728**	3850.317099	15318.554601
#	0/0/30	0/0/30	8/0/22	7/0/23	5/0/25	6/0/24	17/0/13	17/0/13