Supplemental materials for “Performance assessment and exhaustive listing of 500+ nature-inspired metaheuristic algorithms”

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Note: An online updated list of 500+ meta-heuristic algorithms is available at: https://github.com/P-N-Suganthan/MHA-500Plus. Please send you feedbacks to epnsugan@ntu.edu.sg or p.n.suganthan@qu.edu.qa.

Appendix A

1 Friedman test and Holm post hoc test

The statistical results of the Friedman test and the Holm post hoc test are shown in Table S4 and Tables S5-S7. The number in brackets of Table S4 is the rank index. The observations results are as follows:

1) CEC 2017 functions with 10 variables: In Table S4, MPA achieves the lowest rank with a score of 3.85 and surpasses all the 4 state-of-the-art algorithms. EBCM also outperforms all the 4 state-of-the-art algorithms with a score of 4.1833. MFLA is superior to NLSHADE and HSES by achieving a score of 5.68. The other 8 newly named algorithms achieve the highest ranks compared with 5 state-of-the-art algorithms. In more detail, the scores of GSK, SDCS, IMFO, AO, MSCA, EO, HGSA, and IGOA are 7.75, 7.65, 8.7667, 13.8667, 10.4333, 11.0333, 12, and 12.4667, respectively. It can be found in Table S5 that there is no significant difference among MPA, MFLA, and 3 state-of-the-art algorithms (except for HSES) in terms of algorithm performance. It is can be concluded that MPA, EBCM and MFLA are competitive algorithms in solving CEC 2017 functions with 10 variables and can be considered as high-performance optimizers. On the contrary, the overall performance of GSK, SDCS, IMFO, AO, MSCA, EO, HGSA, and IGOA are significantly worse than the 4 state-of-the-art algorithms in dealing with CEC 2017 functions with 10 variables.

2) CEC 2017 functions with 30 variables: It can be found in the results reported in Table S4 that the scores of EBCM, MFLA and GSK are 7.3667, which is the same as the 4 state-of-the-art algorithms. The other 8 newly named algorithms IMFO, MPA, AO, EO, SDCS, HGSA, IGOA, and MSCA achieve the highest ranks, and the scores are 7.5, 7.55, 9.85, 8.1167, 8.25, 8.5333, 9.0833, and 9.55, respectively. But the results of the Holm post hoc test in Table S6 suggest that the performance between the other 10 newly named algorithms (except for EBCM) and the 4 state-of-the-art algorithms are significantly similar on CEC 2017 functions with 30 variables.

3) CEC 2017 functions with 50 variables: It is observed from Table S4 that AO and HSES achieve the highest ranks and the scores are 8.1667 and 8.23, respectively. The scores of the other 10 newly named algorithms MFLA, GSK, IMFO, MPA, AO, EO, SDCS, HGSA, IGOA, and EBCM are 7.95, which is the same as the scores achieved by ED-EB, LS-SPA, and NLSHADE. Table S7 shows that there is no statistically significant difference between the 11 newly named algorithms and the 4 state-of-the-art algorithms in dealing with CEC 2017 functions with 50 variables.

In conclusion, EBCM, MPA and MFLA demonstrate high performance compared with the 4 state-of-the-art algorithms in CEC 2017 functions with 10 variables. In the cases of the functions with 30 variables, EBCM, MFLA and GSK achieve the same ranking as the 4 state-of-the-art algorithms. This is consistent with the observations of the Bayesian rank-sum test. Moreover, except for AO, the other 10 newly named algorithms (i.e., MFLA, GSK, IMFO, MPA, MSCA, EO, SDCS, HGSA, EBCM, and IGOA) have the same ranking as the 5 state-of-the-art algorithms in solving the function with 50 variables.

2 Bayesian signed-rank test

The results of the Bayesian signed-rank test are shown in Figs.S1-S3. In the diagram of the Bayesian signed-rank test (i.e., Fig.7), the value in each cell represents the comparison result between the two algorithms. The color depends on the results of the comparisons and indicates if the greater probability belongs to the region of an algorithm or the rope. The probability of the hypothesis is written in the cell and represented in the opacity of the color to highlight the greater probabilities.

As it can be seen from Fig.7, the performance of many pairs of algorithms is a tie when solving the CEC 2017 functions with 10 variables. Particularly, there is a high probability that EBCM, MPA, MFLA, IMFO, and GSK have similar performance to the 4 state-of-the-art algorithms. In Fig.8, EBCM, MFLA, MPA, and GSK have promising performance among the 11 newly named algorithms compared with the 4 state-of-the-art algorithms in solving CEC 2017 functions with 30 variables. In the cases of the functions with 50 variables, it is a high probability that the other 10 newly named algorithms (except for EBCM) are inferior to the 4 state-of-the-art algorithms. It is also can be found from Figs. S1-S3 that the performance of the other 10 newly named algorithms become deteriorate as the dimension of the functions increases. The conclusions drawn in this section are similar to the observations from the Wilcoxon signed-rank test and CD plot.

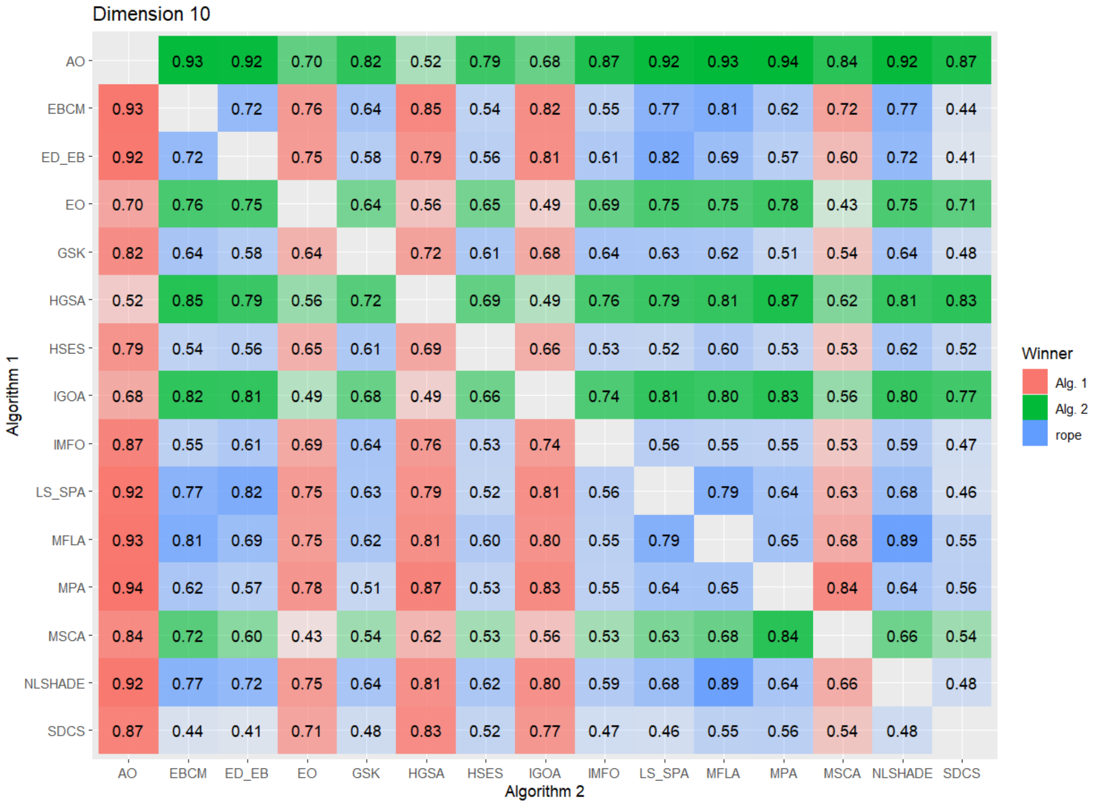


Fig.S1 Bayesian signed-rank test of 10 variables

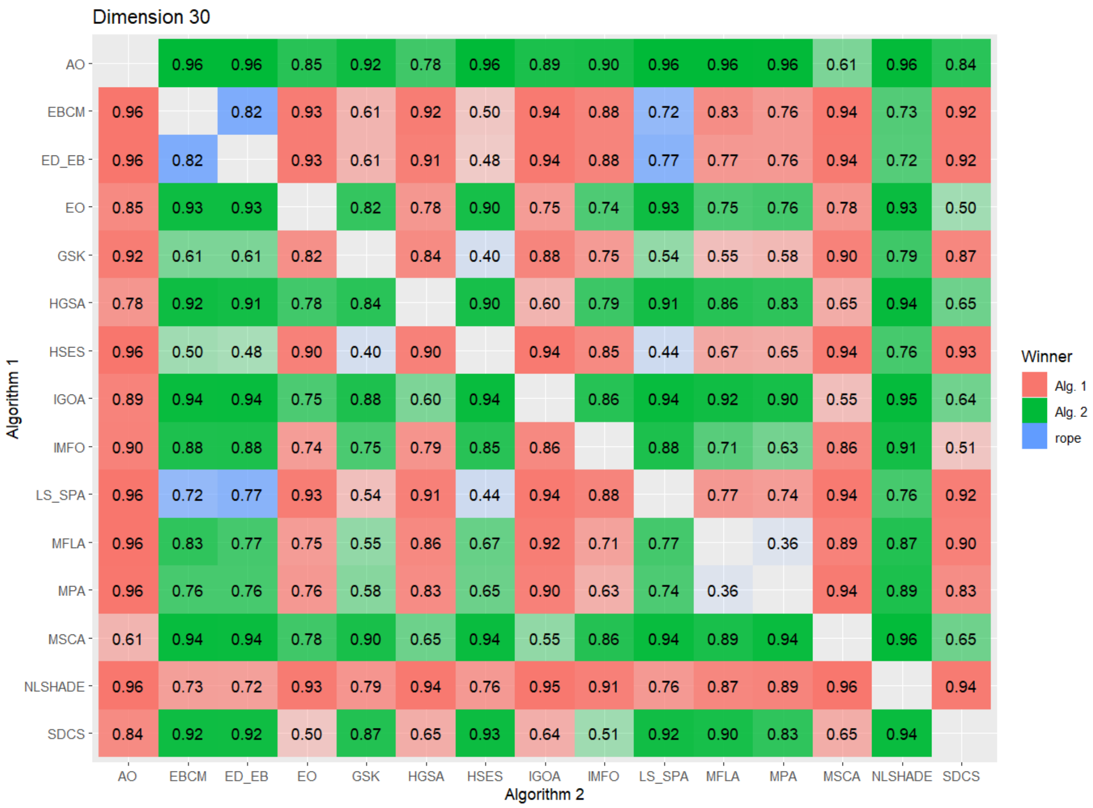


Fig.S2 Bayesian signed-rank test of 30 variables

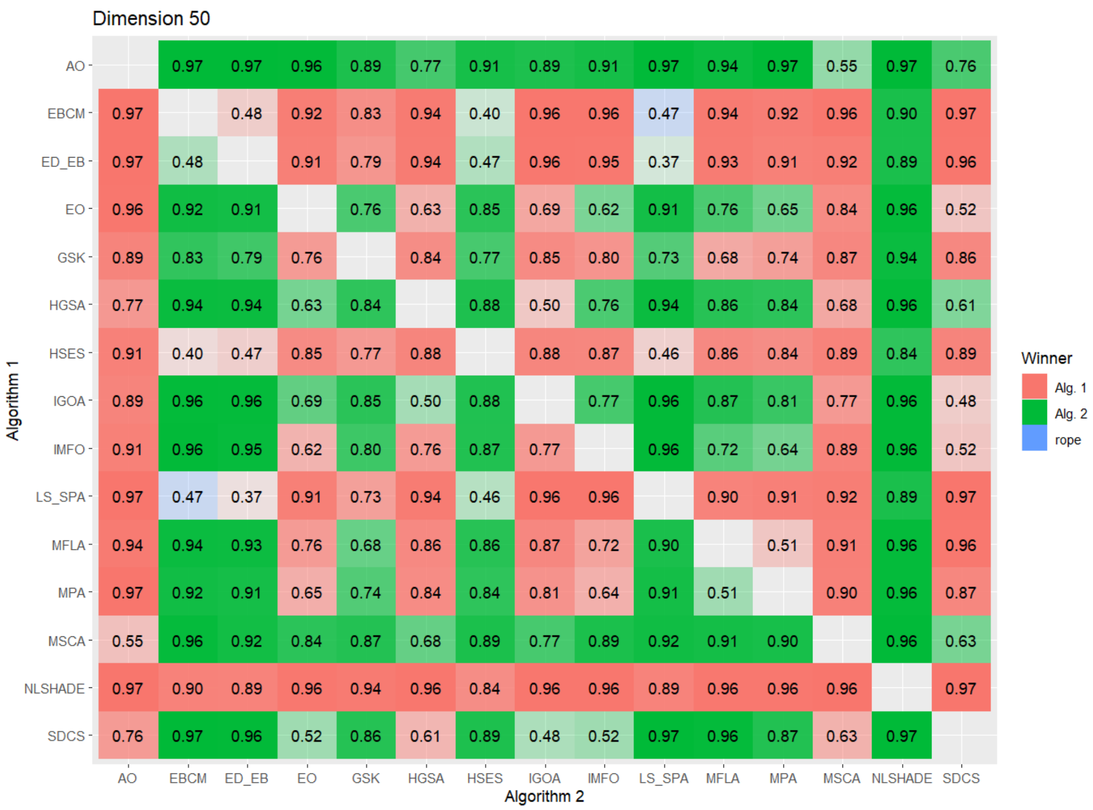


Fig.S3 Bayesian signed-rank test of 50 variables

3 Benchmark functions with 10 variables

(1) Comparison of each function

Several observations can be obtained from the statistics results of the functions with 10 variables reported in Table S1. It can be found that the overall performance of MPA and EBCM are the best two among the 11 recent algorithms since they outperform 4 state-of-the-art algorithms in more than half of the functions. In more detail, MPA outperforms HSES, ED-EB, LS-SPA and NLSHADE on twenty-four (F1-F4, F9, and F12-F30, eighteen (F1-F4, F9, F12-F13, F15, F18, F21-F28, and F30), eighteen (F1-F4, F9, F12-F13, F15, F18, F21-F28, and F30), and sixteen (F12-F15, F18-F19, F21-F30) functions, respectively. Besides, MPA is comparable to ED-EB, LS-SPA, and NLSHADE on five (F1-F4 and F9), five (F1-F4 and F9), and five (F1-F4 and F9) functions, respectively. Particularly, MPA beats all the 4 state-of-the-art algorithms for solving unimodal functions F1-F3, multimodal functions F4 and F9, hybrid functions F12-F13, F15 and F18, and composition functions F21-F28 and F30.

EBCM is another efficient newly proposed algorithm. It is superior to HSES, ED-EB, LS-SPA and NLSHADE on twenty-two (F2, F5, F7-F8, F10-F11, F13-F17, F19-F23, and F25-F30), thirteen (F5, F7-F8, F14, F17, F21-F23, F25-F26, F28, and F30), thirteen (F5, F7-F8, F11, F14-F16, F20, F22-F23, F25-F26, and F30), and sixteen (F5, F7-F8, F10-F11, F14-F17, F19-F21, F23, F26-F27, and F29) functions, respectively. Besides, EBCM is comparable to ED-EB, LS-SPA and NLSHAD on one (F2), one (F2), and one (F2) function, respectively.

MFLA outperforms HSES, ED-EB, LS-SPA and NLSHADE on twenty (F1-F3, F9, F14-F22, and F24-F30), eight (F21-F22, F24-F28, and F30), eight (F18, F22, F24-F28 and F30) and twelve (F12, F14, F18, F20-F22, F24-F28 and F30) functions, respectively. Moreover, the performance of MFLA is equivalent to ED-EB, LS-SPA, and NLSHADE on two (F3 and F9) functions. It is worth noting that MFLA exhibits significantly better performance than the 4 state-of-the-art algorithms on the composition functions F22 and F25-F28.

GSK, IMFO, and SDCS also demonstrate promising performance compared with the 4 state-of-the-art algorithms. In more detail, GSK is better than HSES, ED-EB, LS-SPA and NLSHADE on seventeen (F1-F4, F6, F9, F11, F14-F15, F19-F21, F24-F25, and F27-F29), four (F11, F14, F28 and F30), five (F11, F15, F25, F28 and F30), and eight (F6, F11, F14-F15, F19, F27, F29 and F30) functions, respectively. Besides, GSK has similar performance to HSES, ED-EB, LS-SPA, and NLSHADE on one (F26), five (F1, F3-F4, F9, and F26), five (F1, F3-F4, F9, and F26), and five (F1, F3-F4, F9, and F26) functions, respectively.

IMFO achieves better results than HSES, ED-EB, LS-SPA, and NLSHADE on thirteen (F1-F3, F6, F15, F17, F20-F22, F25, F27-F28, and F29), one (F22), one (F22) and two (F22 and F29) functions, respectively. Particularly, IMFO exhibits better performance on the composition function F22 and surpasses all the 4 state-of-the-art algorithms. In addition, it is comparable to ED-EB, LS-SPA, and NLSHADE on two (F3 and F6), two (F3 and F6), and two (F3 and F6) functions, respectively.

SDCS is superior to HSES, ED-EB, LS-SPA and NLSHADE on twelve (F3-F4, F14-F15, F21-F22, F24-F28 and F30), six (F21-F22, F24-F26 and F30)), six (F21-F22, F24-F26 and F30) and seven (F12, F18, F21-F22, F24-F26) functions. Particularly, SDCS exhibits significantly better performance on the composition functions F21-F22 and F24-F26 which surpasses all the 4 state-of-the-art algorithms. On the contrary, the other 5 recent algorithms (i.e., EO, AO, HGSA, IGOA, and MSCA) are less efficient than the 4 state-of-the-art algorithms in solving the majority of the functions with 10 variables.

To summarize, the results of the Bayesian rank-sum test are given in the last rows of Table S1. It can be found that the 11 recent algorithms can be divided into three levels based on the performance in solving CEC 2017 functions with 10 variables. First, MPA, EBCM and MFLA exhibit competitive overall performance compared with the 4 state-of-the-art algorithms. MPA is significantly better than

HSES, ED-EB, LS-SPA, and NLSHADE on 24, 13, 13, and 16 functions, EBCM outperforms them on 22, 13, 13, 16 functions, while MFLA significantly outperforms them on 20, 12, 8, 8, and 12 functions. In addition, MPA is comparable to ED-EB, LS-SPA, and NLSHADE on 5, 5, and 5 functions. MFLA has a similar performance to ED-EB, LS-SPA, and NLSHADE on 2, 2, and 2 functions. Then, GSK, IMFO, and SDCS demonstrate better performance than the 4 state-of-the-art algorithms, and they outperform HSES in more than 10 functions while are better than the other four comparative algorithms in less than 10 functions. Concretely, GSK, IMFO, and SDCS are significantly better than HSES, ED-EB, LS-SPA, and NLSHADE on 17/4/5/8, 13/1/1/2, and 12/6/6/7 functions, while it is comparable to them on 1/5/1/5, 0/2/2/2, and 0/1/1/1 function(s). Finally, EO, AO, HGSA, IGOA, and MSCA are significantly less efficient performance and are inferior to the 4 state-of-the-art algorithms in the majority of the CEC 2017 functions with 10 variables.

(2) Results of Wilcoxon signed-rank test

We further use the Wilcoxon signed-rank test to analyze the significant difference between the 10 recent algorithms and the 4 state-of-the-art algorithms that are considered to be control algorithms. The statistical results are shown in Table S0, where R^+ denotes the sum of ranks, which means the control algorithm (i.e., 4 state-of-the-art algorithms) outperforms the comparative algorithm. R^- is the sum of ranks for the opposite condition. The results (i.e., *p-value*) are in **bold** when a significant difference existed. Some interesting observations obtained from the results of functions with 10 variables are summarized as follows:

MPA, EBCM and MFLA are competitive algorithms compared with the 4 state-of-the-art algorithms in solving CEC 2017 functions with 10 variables. This is consistent with the conclusions of the Bayesian rank-sum test and the Friedman test. Besides, SDCS and GSK also demonstrate promising efficiency in dealing with CEC2017 functions with 10 variables. Most statistical results suggest that there is no significant difference between SDCS and 4 state-of-the-art algorithms, and the performance of GSK is similar to HSES. On the contrary, IMFO, AO, MSCA, EO, HGSA, and IGOA are significantly worse than the 4 state-of-the-art algorithms since the 5 comparative algorithms get higher R^+ values than R^- in all functions.

Table S0 The results with significant differences of the Wilcoxon signed-rank test in 10, 30, and 50 variables

Algorithms	10 variables			30 variables			50 variables		
	R^+	R^-	*p-value*	R^+	R^-	*p-value*	R^+	R^-	*p-value*
HSES VS EO	396.0	69.0	**0.000743**	444.0	21.0	**0.000013**	414.0	51.0	**0.000182**
HSES VS AO	412.0	53.0	**0.000214**	465.0	0.0	**0.000002**	435.0	30.0	**0.00003**
HSES VS GSK	216.0	219.0	1	230.0	205.0	0.778632	388.0	77.0	**0.001334**
HSES VS HGSA	384.0	81.0	**0.00177**	449.0	16.0	**0.000008**	425.0	40.0	**0.000072**
HSES VS IGOA	387.0	78.0	**0.001432**	465.0	0.0	**0.000002**	429.0	36.0	**0.000051**
HSES VS IMFO	267.0	198.0	0.471592	436.0	29.0	**0.000027**	426.0	39.0	**0.000066**
HSES VS MFLA	144.0	321.0	1	346.0	89.0	**0.005281**	420.0	45.0	**0.00011**
HSES VS MPA	80.0	385.0	1	375.0	90.0	**0.003269**	409.0	56.0	**0.000272**
HSES VS MSCA	320.0	145.0	0.070294	458.0	7.0	**0.000003**	431.0	34.0	**0.000043**
HSES VS SDCS	256.0	209.0	0.62156	465.0	0.0	**0.000002**	429.0	36.0	**0.000051**
HSES VS EBCM	53.0	412.0	1	53.0	412.0	1	285.0	180.0	0.275659
ED-EB VS EO	447.0	18.0	**0.000009**	460.0	5.0	**0.000003**	443.0	22.0	**0.000014**
ED-EB VS AO	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**
ED-EB VS GSK	356.0	79.0	**0.00265**	388.0	47.0	**0.000218**	412.0	53.0	**0.000214**
ED-EB VS HGSA	440.0	25.0	**0.000019**	449.0	16.0	**0.000008**	452.0	13.0	**0.000006**
ED-EB VS IGOA	455.0	10.0	**0.000005**	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**
ED-EB VS IMFO	445.5	19.5	**0.000011**	454.0	11.0	**0.000005**	465.0	0.0	**0.000002**
ED-EB VS MFLA	279.5	185.5	0.328571	386.0	49.0	**0.000258**	458.0	7.0	**0.000003**
ED-EB VS MPA	172.0	263.0	1	426.0	39.0	**0.000066**	445.0	20.0	**0.000012**
ED-EB VS MSCA	353.0	112.0	**0.012819**	465.0	0.0	**0.000002**	446.0	19.0	**0.000011**
ED-EB VS SDCS	287.0	148.0	0.130121	458.0	7.0	**0.000003**	465.0	0.0	**0.000002**
ED-EB VS EBCM	153.0	282.0	1	153.0	282.0	1	133.0	332.0	1
LS-SPA VS EO	454.0	11.0	**0.000005**	460.0	5.0	**0.000003**	443.0	22.0	**0.000014**
LS-SPA VS AO	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**
LS-SPA VS GSK	354.0	81.0	**0.003053**	347.0	88.0	**0.004939**	391.0	74.0	**0.001074**
LS-SPA VS HGSA	440.0	25.0	**0.000019**	448.0	17.0	**0.000009**	451.0	14.0	**0.000007**
LS-SPA VS IGOA	453.0	12.0	**0.000005**	465.0	0.0	**0.000002**	465.0	0.0	**0.000002**
LS-SPA VS IMFO	445.5	19.5	**0.000011**	454.0	11.0	**0.000005**	465.0	0.0	**0.000002**
LS-SPA VS MFLA	290.5	174.5	0.22888	385.0	50.0	**0.00028**	436.0	29.0	**0.000027**
LS-SPA VS MPA	170.0	265.0	1	410.0	55.0	**0.000251**	442.0	23.0	**0.000016**

LS-SPA VS MSCA	376.0	89.0	**0.003058**	461.0	4.0	**0.000002**	447.0	18.0	**0.00001**
LS-SPA VS SDCS	296.0	139.0	0.087593	458.0	7.0	**0.000003**	465.0	0.0	**0.000002**
LS-SPA VS EBCM	184.0	251.0	1	184.0	251.0	1	189.0	276.0	1
NLSHADE VS EO	439.0	26.0	**0.000021**	435.0	0.0	**0.000002**	435.0	0.0	**0.000002**
NLSHADE VS AO	465.0	0.0	**0.000002**	463.0	2.0	**0.000002**	465.0	0.0	**0.000002**
NLSHADE VS GSK	353.0	82.0	**0.003274**	417.0	18.0	**0.000015**	465.0	0.0	**0.000002**
NLSHADE VS HGSA	440.0	25.0	**0.000019**	460.0	5.0	**0.000003**	435.0	0.0	**0.000002**
NLSHADE VS IGOA	458.0	7.0	**0.000003**	462.0	3.0	**0.000002**	465.0	0.0	**0.000002**
NLSHADE VS IMFO	377.5	58.0	**0.000541**	459.0	6.0	**0.000003**	465.0	0.0	**0.000002**
NLSHADE VS MFLA	189.5	245.5	1	450.0	15.0	**0.000007**	465.0	0.0	**0.000002**
NLSHADE VS MPA	112.0	323.0	1	428.0	7.0	**0.000005**	465.0	0.0	**0.000002**
NLSHADE VS MSCA	392.0	73.0	**0.000999**	463.0	2.0	**0.000002**	465.0	0.0	**0.000002**
NLSHADE VS SDCS	272.0	163.0	0.234331	460.0	5.0	**0.000003**	465.0	0.0	**0.000002**
NLSHADE VS EBCM	83.0	352.0	1	121.0	314.0	1	220.0	245.0	1

(3) Results of CD plot

Furthermore, we use the critical differences (CD) plot to analyze the significance of the difference between the 11 recent algorithms and the 4 state-of-the-art algorithms. In the CD plot, the algorithms are sorted by their Ranks, and they are linked by a line when the test rejects the null hypothesis of their significant differences. The CD plots of 15 algorithms on the CEC 2017 functions with 10 variables are shown in Figs.S0.

It can be seen from Fig.S0 that MPA and EBCM have significantly similar performance compared with the ED-EB, LS-SPA, and NLSHADE in solving the CEC 2017 functions with 10 variables. Moreover, the performance of MFLA, GSK, and SDCS is not significantly different from the 4 state-of-the-art algorithms. By contrast, the other 6 recent algorithms (i.e., IMFO, MSCA, AO, EO, HGSA, and IGOA) are significantly inferior to the 4 state-of-the-art algorithms on the functions with 10 variables. This is consistent with the conclusion drawn by the Bayesian rank-sum test, the Friedman test, and the Wilcoxon signed-rank test.

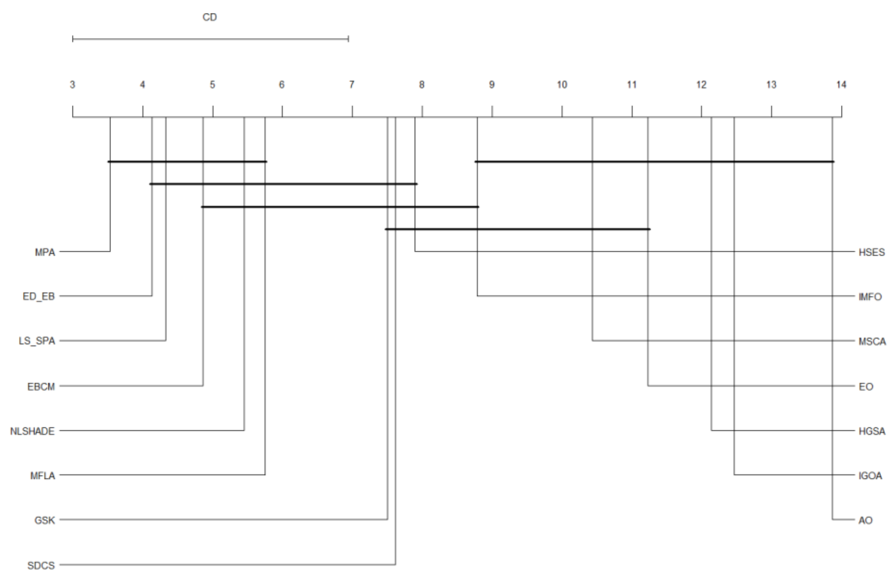


Fig.S0 The CD plot of algorithms on the CEC 2017 functions with 10 variables

(4) Convergence analysis

In order to study the convergence speed of the 15 algorithms on CEC 2017 functions with 10 variables, two unimodal functions (i.e., F1 and F3), two multimodal functions (i.e., F4 and F7), two hybrid functions (i.e., F11 and F19), and two composition functions (i.e., F21 and F24) are considered. The convergence plots of the 15 algorithms on these eight functions with 10 variables are presented in Fig.S4. As can be seen from Fig.S4, AO and MFLA have the slowest convergence speed among all 15 algorithms on all functions. By contrast, EBCM and MPA has better convergence speed and global search ability (i.e., in terms of the solution quality) similar to the 4 state-of-the-art algorithms. Moreover, EO, GSK, IMFO, and SDCS also have similar or slightly slower convergence speeds compared with the 4 state-of-the-art algorithms, but the global search ability of these four algorithms is inferior to the 4 state-of-the-art algorithms. Except that HSES shows a slightly slower convergence speed on functions F3, F11, and F19. The other four state-of-the-art algorithms perform best in terms of convergence speed and global search ability.

(5) The trade-off of exploration and exploitation analysis

We consider the method proposed in Ref. [93] to evaluate the trade-off between exploration and exploitation of the 15 algorithms. Particularly, the percentage of exploration (i.e., XPL%) and the percentage of exploitation (i.e., XPT%) are used to evaluate the trade-off response. XPL% represents the level of exploration as the relationship between the diversity in each iteration and the maximum reached diversity. XPT% corresponds to the level of exploitation. Both elements XPL% and XPT% are mutually conflicting and complementary. For more information about how to evaluate the trade-off of algorithms, please refer to [93].

To analyze the trade-off between exploration and exploitation of the 15 algorithms on CEC 2017 functions with 10 variables, two unimodal functions (i.e., F1 and F3), two multimodal functions (i.e., F4 and F7), two hybrid functions (i.e., F11 and F19), and two composition functions (i.e., F22 and F24) are considered. The evolution effects of the exploration and the exploitation obtained by the 15 algorithms are shown in Fig.S7. In order to visualize exploration and exploitation effects as a characteristic, a new graph called incremental-decremental has been also added. In this graph, an increment is presented when the value of the exploration effect is higher or equal to the exploitation action. On the contrary, a decrement is produced when the exploitation value is superior to the exploration effect [93].

According to Fig.S7 and Table S1, the exploration and exploitation trade-off analysis of 15 algorithms based on function classification is as follows. Due to space limitations, we only analyze one function in each function type (i.e., F1, F7, F11, and F22). For detailed information on the trade-off analysis of other functions, please read the supplementary materials.

- Unimodal function F1: GSK, MPA, ED-EB, LS-SPA, and NLSHADE surpasses all other algorithms and obtained optimal solutions on function F1, they exploited the search space equal to or more than 96.7816% of the time and explored equal to or less than 3.2184% of the time. IMFO and MFLA perform slightly worse than the aforementioned best five algorithms, among which IMFO with the exploitation of 98.631% and 1.369% exploration, and MFLA employed a trade-off of 69.4461% exploitation and 30.5539% exploration. Although HSES and EBCM with less exploitation of 94.9457% and 93.1149%, their performance is similar to that of IMFO and MFLA. Moreover, AO, EO, SDCS, and HGSA obtain the same trade-off level as the best five algorithms but are far from the optimal solution. Among the remaining algorithms like IGOA and MSCA, they are less efficient and with a larger exploration of more than 16% (i.e., 16.8373 % and 38.0725%). In all cases, the incremental-decremental graph shows that the effect of the exploration effect is very short while the exploitation action is prolonged most of the time in the search. These results suggest that the best trade-off for unimodal functions is closer to 98% exploitation and 2% exploration. Particularly, algorithms like MPA, MFLA, and EBCM have multiple exploration peaks appear along the optimization process. Morales-Castañeda et al.[93] believe that an algorithm like these has multiple operators and considers multiple attraction points would be beneficial for finding better solutions. It should be noted that MPA is well trade-off, but it is a roughly trade-off response. In spite of AO, EO, SDCS, and HGSA having a good trade-off level, it seems that it is also important for the search mechanisms to obtain a better performance.

- Multimodal function F7: EBCM finds the best solution among all the 15 algorithms. It is exploited the search space 89.9166% of the time and explored 10.0834% of the time. Compared with the other 4 state-of-the-art algorithms, the other 10 new algorithms (i.e., except for EBCM) performs less efficient on function F7 with 10 variables. ED-EB, HSES, LS-SPA, and NLSHADE exploited the search space 92.96%, 96.6598%, 96.0401%, and 88.5274% of the time, respectively. On the contrary, they explored the search space 7.04%, 3.3402%, 3.9599%, and 11.4726% of the time, respectively. Compared with the 4 state-of-the-art algorithms, the performance of 10 new algorithms on function F7 is slightly worst and AO achieved the worst performance with the exploitation of 89.2456% and 10.7554% exploration. According to the incremental-decremental graph, all 15 algorithms with a short exploration effect while the exploitation action is extremely long. Once again, the bottom algorithms IGOA and MSCA with less exploitation compared with the best performing algorithm EBCM, and they spent 82.2936% and 75.3964% of the time exploiting respectively. The AO, GSK, MPA, and SDCS trade-off between exploration and exploitation is close to the one employed by EBCM but less efficient. As previously mentioned, the reason for this difference is the search mechanism used for exploration and exploitation.
- Hybrid function F11: The most prominent algorithm is newly proposed algorithm EBCM, which exploited the search space 93.6396% of the time and explored 6.3607% of the time. GSK, LS-SPA, HSES, and ED-EB perform slightly worse than EBCM and spent 94.64765, 97.3335%, 94.5047%, and 97.477% of the time exploiting respectively. MPA, MFLA, and SDCS also have similar performance to the aforementioned four algorithms but with different trade-offs, such as with a balance of 88.3831%, 56.071%, and 89.4454% of the time exploring and 11.6169%, 43.929%, and 10.5546% exploiting. As previously mentioned, MPA and MFLA with multiple exploration peaks can jump into different zones to find potential solutions. Although MSCA and IGOA have similar characteristics, they present a bad performance in terms of solution quality. Particularly, MSCA with the exploitation of 53.415% and exploitation 46.585% is close to the one employed by MFLA, but MSCA is inferior to MFLA on function F7. Once again, it is emphasized how the difference in the quality of the specific search mechanism of each algorithm affects greatly the performance. According to the incremental-decremental graph, all better-performed algorithms spent above 93% of the runtime exploited the search space.
- Composition function F22: SDCS is the best performing algorithm with a trade-off of 98.9975% of the time exploited and 1.0025% explored. EBCM, MPA, MFLA, IMFO, and NLSHADE are very close to SDCS in terms of solution quality, and they spent time of 99.2526%, 97.8179%, 81.6935%, 81.22%, and 96.818% on exploitation respectively. Except for NLSHADE, the other 3 state-of-the-art algorithms HSES, ED-EB, and LS-SPA are slightly worse than SDCS but they maintain a behavior very close to the SDCS. Moreover, the bottom algorithms EO, GSK, and HGSA also have a similar trade-off behavior to SDCS. Once again, it seems that the search mechanism is also important for better performance. The incremental-decremental graph shows that exploiting the search space above 98% and less than 1% explored may be the best trade-off for composition functions.

(6) Diversity analysis

In order to complement the analysis, an experimental of diversity on functions F3, F7, F11, and F24 with 10 variables is conducted and the results are present in Fig.S10. As can be seen from Fig.S10, it is clear that all 13 algorithms (i.e., except for HSES and AO) begin with a big diversity as a consequence of their random initialization. As the iteration increase, the population diversity diminishes. Since the diversity value of HSES varies below the order of magnitude of 10^{-4}, its population diversity variation is not obvious in the figure. Moreover, the diversity of AO is not diminished as the iteration increase, it still has certain population diversity in the final stage of iteration. According to Morales-Castañeda [93], the diversity of algorithms such as AO, MPA, MSCA, MFLA, IGOA, and HGSA present high oscillations which reflex its better conduction of exploration-exploitation. On the other hand, the other algorithms present different diversity levels. Particularly, EO, HSES, ED-EB, EBCM, LS-SPA, and NLSHADE show the smoothest diversity responses, but EBCM presents more oscillation on function F24.

4 Benchmark functions with 50 variables

(1) Comparison of each function

From the statistics results of the functions with 50 variables reported in Table S3, it can be observed that 11 recent algorithms (except for EBCM) exhibit less efficiency compared with the 4 state-of-the-art comparative algorithms. But EO, GSK, MPA, and MSCA have better performance among these 11 algorithms.

EBCM shows competitive performance compared to HSES, ED-EB, LS-SPA, and NLSHADE on ten (F2, F4, F6, F9, F13, F16-F17, F25, and F27-F28), eighteen (F4-F8, F10-F13, F15, F18, F20, F22, F25-F26, F28, and F30), fourteen (F4-F5, F7-F8, F10-F11, F16, F21-F24, F26, and F29-F30), and one (F6) functions, respectively. EO is superior to HSES, ED-EB, LS-SPA, and NLSHADE on four (F2, F4, F26, and F28), three (F4, F26, and F28), two (F4 and F26), and zero functions. In more detail, EO demonstrates the best performance in dealing with multimodal function F4 and composition function F26 since it surpasses all 4 state-of-the-art algorithms (except NLSHADE) in both functions. GSK achieves better results than HSES, ED-EB, LS-SPA, and NLSHADE on six (F2, F4, F9, F16-F17, and F28), three (F4, F11, and F30), five (F4, F23, F24, F26, and F30), and zero functions. MPA outperforms HSES, ED-EB, LS-SPA, and NLSHADE on five (F2, F4, F25-F26, and F28), one (F26), one (F26), and zero functions, while MSCA is superior to HSES, ED-EB, LS-SPA and NLSHADE on three (F2 and F27-F28), two (F22 and F27), two (F22 and F27), and zero functions. On the contrary, AO, HGSA, IGOA, IMFO, MFLA, and SDCS are less efficient in dealing with the functions with 50 variables, and they only better than the 4 state-of-the-art algorithms on the less function (i.e., less three functions).

In summary, EBCM shows similar performance with HSES, ED-EB, and LS-SPA, but the other 10 recent algorithms demonstrate less efficiency compared with the 4 state-of-the-art comparative algorithms in dealing with CEC 2017 functions with 50 variables. The results of the Bayesian rank-sum test show more detailed comparative information that EO, GSK, MPA, MSCA, and EBCM are significantly superior to HSES, ED-EB, LS-SPA, and NLSHADE on 4/3/2/0/10, 6/3/5/0/18, 5/1/1/0/14, and 3/2/2/0/1 functions. AO, HGSA, IGOA, IMFO, MFLA, and SDCS exhibits better performance than HSES, ED-EB, LS-SPA, and NLSHADE on 1/0/0/0, 2/1/1/0, 3/0/0/0, 4/0/0/0, 4/1/1/0, and 4/0/0/0 functions. It is worth mentioning that the performance of all the 10 recent algorithms become deteriorates as the dimension of CEC 2017 functions increases. Particularly, some algorithms (i.e., MPA, MFLA, and GSK) exhibit significantly high efficiency in dealing with the functions with 10 and 30 variables and are less efficient in solving the same functions with 50 variables. This shows that the 10 recent algorithms have less efficiency and robustness to solve large-scale optimization problems.

(2) Results of Wilcoxon signed-rank test

As can be seen from Table S0, EBCM shows similar performance to the 4 state-of-the-art algorithms, but the other 10 recent algorithms are less efficient compared with the 4 state-of-the-art algorithms in solving CEC 2017 functions with 50 variables. In other words, there has a significant difference between the 4 state-of-the-art algorithms and the 10 new algorithms (i.e., except for EBCM). The conclusion drawn in this case is consistent with the Bayesian rank-sum test. Besides, it is can be seen that the performance of the 10 new algorithms become deteriorated as the dimension of the functions from 10 variables to 50 variables.

(3) Result of CD plot

Fig.SI shows that there is no significant difference among EBCM, GSK and the 3 state-of-the-art algorithms (except NLSHADE) in dealing with the functions with 50 variables. This is different from the conclusions drawn by the Friedman test and the Wilcoxon signed-rank test. It can also be concluded from the CD diagrams that the performance of the 10 recent algorithms become deteriorates as the dimension of the CEC 2017 functions increases from 10 variables to 50 variables, which is consistent with the observation of the Bayesian rank-sum test and the Wilcoxon signed-rank test.

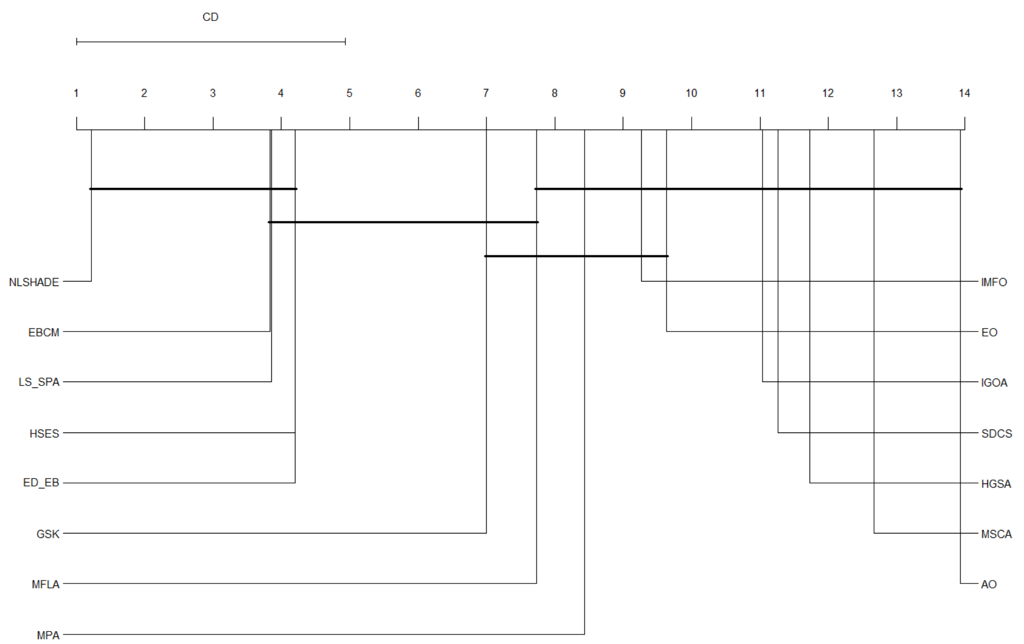


Fig.SI The CD plot of algorithms on the CEC 2017 functions with 50 variables

(4) Convergence analysis

Fig.S6 shows the convergence plots of the 15 algorithms on functions F1, F3, F4, F10, F11, F19, F21, and F24 with 50 variables. As can be seen from Fig.S6, EBCM and 4 state-of-the-art algorithms have the best performance in terms of convergence speed and global search ability. Concerning the other 10 new algorithms, AO, MFLA, and MSCA have the slowest convergence speed and the worst global search ability on all selected functions. Although EO, GSK, MPA, HGSA, IGOA, IMFO, and SDCS have a similar convergence speed to the 4 state-of-the-art algorithms, they are inferior to the 4 state-of-the-art algorithms on almost all selected functions. In other words, they have a worse global search ability.

(5) The trade-off of exploration and exploitation analysis

The experimental results of the exploration and exploitation trade-off of the 15 algorithms on functions F1, F3, F4, F7, F11, F19, F22, and F24 with 50 variables are presented in Fig.S9. Due to space limitations, we only consider functions F1, F7, F11, and F22 in this section. According to Fig.S9 and Table 3, The analysis results are as follows.

- Unimodal function F1: EBCM and the 4 state-of-the-art algorithms are the top five algorithms for solving the function F1 and MFLA being the distant sixth. HSES, EBCM, ED-EB, LS-SPA, and NLSHADE focused less on exploration and show the smoothest trade-off response. They spent

95.3143%, 98.3741%, 99.2259%, 98.1125%, and 98.3668% of their time exploring the search space, respectively. Especially NLSHADE obtains the best solution that is equal to the optimal solution of function F1 with 50 variables. Concerning the other 10 new algorithms, MFLA is best than the other new algorithms with a trade-off of 88.9295% exploitation and 11.0705% exploration. The other new algorithms including AO, EO, GSK, MPA, IMFO, HGSA, IGOA, MSCA, and SDCS perform less efficiently in terms of the solution quality and they present a rough trade-off response. Particularly, MPA, IGOA, and MSCA present trade-off responses with high oscillation. Although EO, GSK, and HGSA trade-off between exploration and exploitation are close to the one employed by the 4 state-of-the-art algorithms, maybe the search mechanisms used by them affects greatly the performance. Interestingly, SDCS is the worst algorithm and presents excessive 100% exploration. These results suggest that the best trade-off for unimodal function F1 with 50 variables is closer to 99% exploitation and 1% exploration. In all cases, the incremental-decremental graph shows that the effect of the exploration effect is very short while the exploitation action is prolonged during most of the time in the search strategy.

- Multimodal function F7: EBCM and the 4 state-of-the-art algorithms are once again the top five algorithms and they spent a high amount of time exploiting (i.e., more than 91% of the time) and very little time exploring, among which NLSHADE is the best algorithm. In terms of the other 10 new algorithms, HGSA is slightly worse than the 4 state-of-the-art algorithms with a trade-off of 99.6981% exploitation and 0.30194% exploration. AO, EO, GSK, MPA, IMFO, and SDCS maintain a behavior very close to the one used by the 4 state-of-the-art algorithms, but they are inferior to these top algorithms. As previously mentioned, the reason for this difference is the search mechanisms used for exploration and exploitation. Moreover, IGOA, MFLA, and MSCA focused more on exploration compared with the 4 state-of-the-art algorithms and present trade-off responses with high oscillation. They spent the time of 76.7191%, 83.9714%, and 79.5579% on exploitation respectively. On the contrary, EO, GSK, IMFO, and SDCS have a smoother trade-off response similar to the 4 state-of-the-art algorithms. According to the incremental-decremental graph, all best-performing algorithms spent above 91% of the runtime exploiting the search space.

- Hybrid function F11: EBCM, GSK, and the 4 state-of-the-art algorithms are the top six algorithms for solving the function F11. HSES, EBCM, ED-EB, LS-SPA, and NLSHADE exploited the search space using 93.2975%, 92.1969%, 97.5919%, 96.602%, and 96.3223% of the time. EBCM has better performance than the other new algorithms with a trade-off of 92.1969% exploitation and 7.8031% exploitation. GSK also shows better performance and spent the time of 96.3237% on exploitation and the time of 3.6763% on exploitation. The other 9 new algorithms are inferior to the 4 state-of-the-art algorithms and present different trade-off levels. These 9 algorithms produce a rougher trade-off response than 4 state-of-the-art algorithms. Especially AO, MPA, IGOA, MFLA, and MSCA present in their behavior high oscillation, and IGOA, MFLA, and MSCA focused less on exploitation (i.e., less than 71% of the time) than the 4 state-of-the-art algorithms. These results suggest that the best trade-off for hybrid function F11 is closer to 97% exploitation and 3% exploration. The incremental-decremental graph shows that all 14 algorithms (i.e., except for MSCA) with a short exploration effect while the exploitation action is extremely long. Particularly, MACA is the worst algorithm with similar exploitation (i.e., 48.9211% of the runtime) and exploration (i.e., 51.0789% of the runtime) rate.

- Composition function F22: The six top algorithms for solving the function F22 are the 4 state-of-the-art algorithms, EBCM, and MSCA, in which HSES is the best one with a trade-off of 95.4105% exploitation and 4.5895% exploration. In terms of the other 3 state-of-the-art algorithms, LS-SPA maintains a trade-off behavior very close to the one used by HSES. ED-EB and NLSHADE seem to focus less on the exploitation on the function F22. They spent 50.3806%, 80.3491%, and 80.5332% of the time exploring the search space, respectively. In terms of the 11 new algorithms, EBCM and MSCA have better performance with the exploitation of 49.6194% and 46.3255%, respectively. But the other new algorithms are all inferior to the 4 state-of-the-art algorithms. Particularly, EO and HGSA have a similar trade-off behavior to the top algorithm HSES. They exploited the search space 96.6097% and 99.7002% of the time respectively. Once again, it is a good example of how the difference in the quality of the specific search mechanism affects greatly the performance. Moreover, AO, MPA, IGOA, IMFO, and SDCS focused less on exploitation compared to HSES. They spent 84.4127%, 69.645%, 79.0503%, 75.1791%, and 69.14355 of the time exploiting the search space, respectively. On the contrary, GSK, MFLA, and MSCA focused more on exploration compared to the HSES. They spent the time of 76.5211%, 75.2899%, and 53.6745 on exploration, respectively. Except for HSES, all 14 algorithms produce a rougher trade-off response for solving the function F22 than solving the functions F1, F7, and F11.

(6) Diversity analysis

Fig.S12 shows the experiment results of the 15 algorithms related to the diversity on functions F3, F7, F11, and F24 with 50 variables. According to Fig.S12, it is a clear trend that all 15 algorithms begin with a significant diversity as a consequence of their random initializations. As the iteration increase, the population diversity diminishes. EBCM and the 4 state-of-the-art algorithms present the smoothest diversity response. Concerning the other 10 new algorithms, the algorithms like EO, GSK, IGOA, IMFO, SDCS, and HGSA produce a diversity response that is similar to the 4 state-of-the-art algorithms. But AO, MPA, MSCA, and MFLA are present in their behaviors with high oscillations. Especially the diversity of AO continuously increases and decreases with iteration increase. Maybe this is one of the reasons why AO is inefficient in all functions.

In Table S1-S3, “Best”, “Worst” and “Mean” are the best, worst, and mean values of the produced results on each function over 31 times, and “SD” is the related standard deviation. BRT: Bayesian rank-sum test are conducted between the 10 newly named algorithms and the 5 state-of-the-art algorithms.

Table S1 The computational results on benchmark functions with 10 variables

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
1	Worst	2.3923E+03	3.5341E+05	**0.0000E+00**	3.6933E+03	2.1438E+04	2.1036E-10	1.4211E-14	**0.0000E+00**	3.3157E+06	4.6469E-05	9.8267E-09	1.6763E-10	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	2.3923E+03	5.7785E+04	**0.0000E+00**	2.5750E-01	1.4531E+02	0.0000E+00	0.0000E+00	**0.0000E+00**	6.1464E+05	0.0000E+00	4.1797E-09	1.3941E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	2.3923E+03	1.7606E+05	**0.0000E+00**	8.9940E+02	6.0933E+03	1.0973E-11	4.5841E-16	**0.0000E+00**	2.0705E+06	3.0321E-06	8.0218E-09	6.2343E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	SD	0.0000E+00	7.8922E+04	**0.0000E+00**	9.5436E+02	5.6111E+03	3.9755E-11	2.5523E-15	**0.0000E+00**	7.3080E+05	1.0516E-05	1.5389E-09	3.9036E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/=/=/=	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/=/=/=	−/−/−/−	−/−/−/−	−/−/−/−	6/0/4 (+/=/−)	8/2/0 (+/=/-)	8/2/0 (+/=/-)	8/2/0 (+/=/-)
	Rank	8	10	1	7	9	3	2	1	11	6	5	4	1	1	1
2	Worst	8.5703E-06	1.2794E+04	2.8422E-14	4.9091E-05	6.2880E-04	5.5242E-09	4.8317E-13	**0.0000E+00**	4.0123E+03	1.0000E+10	**0.0000E+00**	4.4503E+06	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	8.5703E-06	1.1263E+00	0.0000E+00	2.3271E-06	1.0578E-06	3.9563E-11	0.0000E+00	**0.0000E+00**	1.1372E+01	2.2737E-13	**0.0000E+00**	0.0000E+00	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	8.5703E-06	1.5449E+03	9.1683E-16	1.6683E-05	1.8111E-04	1.1679E-09	2.2004E-14	**0.0000E+00**	9.5497E+02	9.9438E+08	**0.0000E+00**	3.7922E+05	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	SD	0.0000E+00	3.1758E+03	5.1047E-15	1.2898E-05	1.7525E-04	1.3882E-09	8.6429E-14	**0.0000E+00**	1.2947E+03	2.9989E+09	**0.0000E+00**	1.0757E+06	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/=/=/=	+/−/−/−	−/−/−/−	+/=/=/=	1/0/9 (+/=/−)	9/1/0 (+/=/-)	9/1/0 (+/=/-)	9/1/0 (+/=/-)
	Rank	5	9	2	6	7	4	3	1	8	11	1	10	1	1	1
3	Worst	5.6843E-14	6.3894E+00	**0.0000E+00**	5.6843E-14	3.1756E-02	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	3.4406E+01	**0.0000E+00**	9.9367E-09	9.6918E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	5.6843E-14	1.7045E-01	**0.0000E+00**	0.0000E+00	1.1195E-05	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	6.6194E+00	**0.0000E+00**	3.7983E-09	0.0000E+00	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	5.6843E-14	1.8254E+00	**0.0000E+00**	1.2836E-14	3.4719E-03	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	1.9589E+01	**0.0000E+00**	8.3224E-09	2.3177E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	SD	0.0000E+00	1.5146E+00	**0.0000E+00**	2.4160E-14	6.6652E-03	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	6.7545E+00	**0.0000E+00**	1.4591E-09	2.7712E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	+/−/−/−	−/−/−/−	+/=/=/=	+/−/−/−	−/−/−/−	+/=/=/=	+/=/=/=	+/=/=/=	−/−/−/−	+/=/=/=	−/−/−/−	3/0/7 (+/=/-)	5/5/0 (+/=/-)	5/5/0 (+/=/-)	5/5/0 (+/=/-)
	Rank	3	7	1	2	6	1	1	1	8	1	5	4	1	1	1
4	Worst	3.2414E+00	7.8401E+00	**0.0000E+00**	1.1057E+00	3.4593E+00	2.1699E-02	1.2597E-09	**0.0000E+00**	7.1314E+00	1.9327E-12	9.7809E-09	4.6214E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	3.2414E+00	1.5136E+00	**0.0000E+00**	1.9093E-02	1.3377E-01	2.3154E-05	0.0000E+00	**0.0000E+00**	3.2063E+00	0.0000E+00	3.5820E-09	0.0000E+00	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	3.2414E+00	6.2187E+00	**0.0000E+00**	6.3787E-01	2.3489E+00	9.0496E-03	8.6771E-11	**0.0000E+00**	5.5235E+00	2.1454E-13	7.5029E-09	1.5637E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	SD	0.0000E+00	1.4259E+00	**0.0000E+00**	2.6468E-01	1.0073E+00	6.1730E-03	2.4251E-10	**0.0000E+00**	1.1488E+00	4.4462E-13	1.7225E-09	1.2745E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/=/=/=	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/=/=/=	−/−/−/−	+/−/−/−	−/−/−/−	7/0/3 (+/=/-)	8/2/0 (+/=/-)	8/2/0 (+/=/-)	8/2/0 (+/=/-)
	Rank	9	11	1	7	8	6	4	1	10	2	5	3	1	1	1
5	Worst	7.9597E+00	4.0454E+01	2.8609E+01	3.2834E+01	2.3468E+01	1.3929E+01	1.1948E+01	7.9597E+00	2.7888E+01	1.3180E+01	**2.6546E-11**	8.9546E+00	3.9824E+00	9.9496E+00	5.1536E+00
	Best	7.9597E+00	7.0419E+00	7.3419E+00	3.9798E+00	3.9806E+00	3.9798E+00	3.2919E+00	1.9899E+00	5.0257E+00	2.9941E+00	7.9581E-13	**0.0000E+00**	9.9524E-01	9.9496E-01	2.1346E+00
	Mean	7.9597E+00	2.3998E+01	1.7740E+01	1.7075E+01	1.3711E+01	7.5382E+00	6.2882E+00	5.2316E+00	1.6071E+01	7.4698E+00	**3.3593E-12**	1.9578E+00	2.5047E+00	3.1157E+00	3.2070E+00
	SD	**0.0000E+00**	9.0762E+00	4.1277E+00	6.3765E+00	4.8682E+00	2.5214E+00	2.0794E+00	1.7034E+00	5.8986E+00	2.8723E+00	5.2940E-12	1.8253E+00	9.5672E-01	2.0000E+00	7.6575E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)
	Rank	10	15	14	13	11	9	7	6	12	8	1	2	3	4	5
6	Worst	1.1369E-13	2.9136E+01	1.1369E-13	9.5995E-01	2.6866E+00	**0.0000E+00**	4.1987E-08	7.8821E-04	2.0976E+00	1.0639E+00	9.9611E-09	2.2055E-10	**0.0000E+00**	**0.0000E+00**	7.6628E-08
	Best	1.1369E-13	8.1845E-01	0.0000E+00	1.1369E-13	5.2990E-03	**0.0000E+00**	3.7289E-11	2.4600E-06	4.2961E-01	6.5059E-04	4.4498E-09	1.1255E-11	**0.0000E+00**	**0.0000E+00**	1.6712E-11
	Mean	1.1369E-13	1.2006E+01	7.3346E-14	3.1023E-02	3.8274E-01	**0.0000E+00**	7.5278E-09	6.2711E-05	1.1957E+00	8.0336E-02	8.6065E-09	4.9157E-11	**0.0000E+00**	**0.0000E+00**	6.1987E-09
	SD	0.0000E+00	7.3374E+00	5.5294E-14	1.7240E-01	7.3928E-01	**0.0000E+00**	9.8114E-09	1.4680E-04	3.5175E-01	1.9654E-01	1.3824E-09	4.3206E-11	**0.0000E+00**	**0.0000E+00**	1.4133E-08
	BRT	+/−/−/+	−/−/−/−	+/−/−/+	−/−/−/−	−/−/−/−	+/=/=/=	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	7/0/3 (+/=/-)	9/1/0 (+/=/-)	9/1/0 (+/=/-)	7/1/2 (+/=/-)
	Rank	3	13	2	9	11	1	6	8	12	10	7	4	1	1	5
7	Worst	2.1777E+01	7.4571E+01	3.6714E+01	2.3426E+01	3.7971E+01	2.2285E+01	2.3841E+01	2.0894E+01	4.1393E+01	2.9824E+01	**1.1188E+01**	2.2315E+01	1.3468E+01	1.6580E+01	1.5312E+01
	Best	2.1777E+01	2.4636E+01	2.1940E+01	1.2516E+01	1.3828E+01	**3.6024E+00**	1.3868E+01	1.1618E+01	2.0859E+01	1.3015E+01	1.0367E+01	1.0924E+01	1.1082E+01	1.0503E+01	1.1692E+01
	Mean	2.1777E+01	4.6087E+01	2.9837E+01	1.6612E+01	2.2504E+01	1.6078E+01	1.8486E+01	1.6300E+01	2.9538E+01	2.0689E+01	**1.0533E+01**	1.3447E+01	1.2316E+01	1.2530E+01	1.3194E+01
	SD	**0.0000E+00**	1.1867E+01	3.2446E+00	2.8862E+00	5.1794E+00	3.9334E+00	2.7364E+00	2.2937E+00	5.2945E+00	4.5887E+00	1.8837E-01	2.6415E+00	6.6743E-01	1.4170E+00	8.5423E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	14	8	12	6	9	7	13	10	1	5	2	3	4
8	Worst	6.9647E+00	4.1848E+01	2.8085E+01	2.6864E+01	2.8820E+01	1.5919E+01	9.0023E+00	1.0945E+01	2.1155E+01	1.6914E+01	**3.8654E-12**	4.9748E+00	4.9794E+00	7.9597E+00	4.3202E+00
	Best	6.9647E+00	9.0454E+00	1.1816E+01	1.9899E+00	2.9901E+00	2.9849E+00	1.9905E+00	2.9849E+00	6.7707E+00	3.9878E+00	4.5475E-13	**0.0000E+00**	9.9501E-01	9.9496E-01	1.2688E+00
	Mean	6.9647E+00	2.2854E+01	1.9845E+01	1.0046E+01	1.7502E+01	7.2536E+00	4.6572E+00	5.5525E+00	1.4182E+01	9.2057E+00	**9.7551E-13**	8.9867E-01	2.4412E+00	3.5987E+00	2.8743E+00
	SD	**0.0000E+00**	7.7119E+00	3.6882E+00	5.3786E+00	7.6722E+00	3.6257E+00	1.7739E+00	2.2801E+00	3.4844E+00	3.3497E+00	6.2736E-13	1.0702E+00	1.0228E+00	1.6964E+00	7.7433E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	15	14	11	13	9	6	7	12	10	1	2	3	5	4
9	Worst	1.1369E-13	3.6905E+02	**0.0000E+00**	1.1369E-13	9.2348E-03	4.5432E-01	**0.0000E+00**	**0.0000E+00**	1.3244E+00	2.1836E+00	9.7854E-09	2.5011E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	1.1369E-13	1.4852E-01	**0.0000E+00**	0.0000E+00	1.7606E-04	0.0000E+00	**0.0000E+00**	**0.0000E+00**	2.2592E-01	0.0000E+00	3.4236E-09	0.0000E+00	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	1.1369E-13	5.6851E+01	**0.0000E+00**	3.6673E-15	1.5039E-03	1.4656E-02	**0.0000E+00**	**0.0000E+00**	7.8557E-01	8.5094E-02	7.1489E-09	1.9693E-12	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	SD	0.0000E+00	7.0167E+01	**0.0000E+00**	2.0419E-14	1.8947E-03	8.1599E-02	**0.0000E+00**	**0.0000E+00**	2.7739E-01	3.9791E-01	1.6833E-09	5.5566E-12	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	+/−/−/−	−/−/−/−	+/=/=/=	+/−/−/−	−/−/−/−	−/−/−/−	+/=/=/=	+/=/=/=	−/−/−/−	−/−/−/−	−/−/−/−	5/0/5 (+/=/-)	7/3/0 (+/=/-)	7/3/0 (+/=/-)	7/3/0 (+/=/−)
	Rank	3	10	1	2	6	7	1	1	9	8	5	4	1	1	1
10	Worst	4.5752E+02	1.2766E+03	1.3543E+03	1.5037E+03	9.1605E+02	5.2386E+02	4.3596E+02	5.4520E+02	6.4536E+02	8.2035E+02	2.1745E+02	5.9234E+02	1.3451E+02	2.4751E+02	2.7324E+02
	Best	4.5752E+02	3.4046E+02	6.2874E+02	1.2185E+02	1.3350E+02	1.2204E+02	5.6358E+00	1.1895E+02	2.5391E+01	1.6397E+02	3.1227E-01	3.7473E-01	2.0901E-01	6.4632E-01	3.3482E+01
	Mean	4.5752E+02	7.5558E+02	1.0345E+03	8.7332E+02	5.0039E+02	2.6865E+02	2.0492E+02	2.5467E+02	3.6643E+02	4.2997E+02	4.0516E+01	1.2459E+02	3.0363E+01	2.1481E+01	1.4771E+02
	SD	**3.4670E-13**	2.4081E+02	1.8541E+02	2.6227E+02	2.2442E+02	1.1834E+02	1.1200E+02	1.1203E+02	1.5433E+02	1.5032E+02	5.9784E+01	1.6950E+02	4.4340E+01	4.7697E+01	6.6533E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	13	15	14	12	8	6	7	9	10	3	4	2	1	5
11	Worst	3.0271E+00	1.6981E+02	9.9496E-01	8.6011E+01	2.6283E+01	5.9697E+00	4.0484E+00	3.7014E+00	1.8432E+01	4.4258E+00	**9.9531E-09**	1.9899E+00	1.9835E+00	1.9112E+00	3.7204E+00
	Best	3.0271E+00	9.3398E+00	0.0000E+00	1.0379E+01	3.2233E+00	0.0000E+00	5.0941E-04	0.0000E+00	2.9083E+00	3.9919E-08	1.5916E-12	0.0000E+00	0.0000E+00	0.0000E+00	1.0550E+00
	Mean	3.0271E+00	5.2549E+01	3.2095E-02	3.9475E+01	1.0018E+01	1.5868E+00	9.1498E-01	5.1641E-01	9.3527E+00	9.6741E-01	**4.0987E-09**	2.5676E-01	4.9077E-01	6.1651E-02	2.5439E+00
	SD	**0.0000E+00**	3.1863E+01	1.7870E-01	2.0788E+01	5.7482E+00	1.6904E+00	9.1782E-01	1.0122E+00	4.5760E+00	1.1927E+00	3.9210E-09	5.1172E-01	6.7613E-01	3.4326E-01	7.4442E-01
	BRT	−/−/−/−	−/−/−/−	+/+/+/+	−/−/−/−	−/−/−/−	−/−/−/+	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	8/0/2 (+/=/−)
	Rank	11	15	2	14	13	9	7	6	12	8	1	4	5	3	10
12	Worst	4.0160E+03	8.6660E+06	2.3838E+02	1.3615E+04	5.7974E+04	7.7577E+02	1.5034E+02	**2.3970E-01**	8.6987E+05	1.2120E+02	2.3688E+02	1.1865E+02	1.1995E+02	1.3486E+02	1.2961E+02
	Best	4.0160E+03	1.5302E+04	1.1551E-10	1.0206E+03	1.3135E+03	4.1746E-01	5.2572E+00	2.3647E-11	1.4443E+04	2.2136E-01	2.0814E-01	6.4837E-05	**0.0000E+00**	**0.0000E+00**	4.4017E-02
	Mean	4.0160E+03	2.2284E+06	8.5575E+01	7.7122E+03	2.0835E+04	3.6795E+02	4.6132E+01	**2.2771E-02**	2.9872E+05	4.2142E+01	9.3855E+01	9.7574E+00	2.3348E+01	3.6233E+01	6.2862E+01
	SD	**0.0000E+00**	2.6161E+06	7.8168E+01	3.2555E+03	1.6745E+04	2.0922E+02	3.6763E+01	6.5772E-02	2.3496E+05	4.9454E+01	5.8381E+01	2.7429E+01	4.7981E+01	5.7156E+01	5.6854E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/+	+/+/+/+	−/−/−/−	−/−/−/+	−/−/−/−	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	7/0/3 (+/=/−)
	Rank	11	15	8	12	13	10	6	1	14	5	9	2	3	4	7
13	Worst	1.1736E+03	3.2099E+04	8.3179E+00	1.5868E+04	2.7590E+04	9.4449E+00	9.5790E+00	5.7741E+00	3.8122E+03	1.0357E+01	7.9510E+00	7.2689E+00	**5.2373E+00**	5.3941E+00	9.6608E+00
	Best	1.1736E+03	1.6169E+03	5.7350E-09	1.1143E+03	2.5026E+02	9.9496E-01	1.3819E+00	**0.0000E+00**	1.8135E+02	5.2827E-02	4.0638E-09	2.6603E-11	**0.0000E+00**	**0.0000E+00**	2.3257E-01
	Mean	1.1736E+03	1.5350E+04	5.1682E+00	8.3347E+03	8.5808E+03	5.3955E+00	5.5236E+00	**1.5987E+00**	1.6794E+03	4.8897E+00	3.2820E+00	3.4590E+00	3.1584E+00	2.3989E+00	2.9995E+00
	SD	**2.3113E-13**	9.4640E+03	1.3058E+00	3.8579E+03	8.7738E+03	2.2938E+00	1.7161E+00	1.8873E+00	1.0819E+03	2.5805E+00	2.5215E+00	2.4243E+00	2.2348E+00	2.4018E+00	2.6885E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	−/−/−/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/−)
	Rank	11	15	8	13	14	9	10	1	12	7	5	6	4	2	3
14	Worst	4.2902E+01	1.2555E+03	1.1204E+00	4.2430E+03	1.5829E+02	2.2985E+01	2.3421E+00	3.9798E+00	5.8828E+01	6.0959E+00	**1.8191E-01**	4.6898E+01	9.9496E-01	9.9496E-01	3.9001E+00
	Best	4.2902E+01	9.1968E+01	0.0000E+00	2.3820E+01	1.7028E+01	**0.0000E+00**	3.9144E-03	**0.0000E+00**	2.3562E+01	4.5869E-06	3.7733E-09	6.1164E-11	**0.0000E+00**	**0.0000E+00**	2.1144E-01
	Mean	4.2902E+01	3.0332E+02	2.9449E-01	5.7309E+02	5.5855E+01	4.9942E+00	1.1071E+00	6.0981E-01	3.9884E+01	1.8622E+00	**1.6001E-02**	3.8535E+00	3.0671E-01	1.2838E-01	1.5018E+00
	SD	**0.0000E+00**	2.8795E+02	4.6854E-01	7.8786E+02	3.7399E+01	8.2768E+00	5.7059E-01	8.7788E-01	8.2078E+00	1.6542E+00	3.5848E-02	1.1776E+01	4.1839E-01	3.3906E-01	1.0883E+00
	BRT	−/−/−/−	−/−/−/−	+/+/-/+	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/+	+/−/−/+	−/−/−/−	+/−/−/−	+/+/+/+	6/0/4 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/-)	7/0/3 (+/=/−)
	Rank	12	14	3	15	13	10	6	5	11	8	1	9	4	2	7
15	Worst	1.2048E+02	3.6678E+03	5.0000E-01	4.4305E+03	1.3366E+02	1.9908E+00	1.0064E+00	1.0052E+00	1.0366E+02	1.4740E+00	4.9991E-01	4.0921E+00	**4.9953E-01**	5.0000E-01	6.7187E-01
	Best	1.2048E+02	4.6228E+02	2.8751E-04	4.7522E+01	2.2840E+00	3.7039E-04	6.4823E-02	**1.2386E-04**	1.9809E+01	3.5318E-02	2.0504E-03	6.0745E-02	1.6661E-04	3.8532E-04	4.7612E-02
	Mean	1.2048E+02	1.8090E+03	2.0539E-01	5.9161E+02	3.6295E+01	5.2509E-01	2.9237E-01	**6.0971E-02**	4.0530E+01	4.2284E-01	2.2551E-01	5.9480E-01	1.8367E-01	2.4901E-01	3.2229E-01
	SD	**1.1557E-13**	9.7611E+02	2.1675E-01	8.0285E+02	3.6755E+01	5.7794E-01	2.1490E-01	1.8064E-01	1.6221E+01	3.4874E-01	2.2624E-01	6.8933E-01	2.0612E-01	2.1458E-01	1.6979E-01
	BRT	−/−/−/−	−/−/−/−	+/-/+/+	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/+	+/+/+/+	−/−/−/−	+/−/−/−	+/−/+/+	5/0/5 (+/=/-)	9/0/1 (+/=/-)	8/0/2 (+/=/-)	7/0/3 (+/=/−)
	Rank	13	15	3	14	11	9	6	1	12	8	4	10	2	5	7
16	Worst	3.8612E+01	3.8662E+02	1.2392E+01	4.6226E+02	5.0502E+02	1.4605E+02	9.6573E-01	1.8862E+00	2.0683E+01	1.2229E+02	9.1621E-01	1.8993E+00	**9.1587E-01**	1.1436E+00	3.5520E+00
	Best	3.8612E+01	9.8225E+00	3.5285E-01	1.2405E+02	1.8078E+00	2.0058E-02	2.6803E-01	1.0334E-01	2.6396E+00	1.0138E+00	2.1040E-02	1.7106E-01	**1.1756E-03**	1.9469E-02	1.0448E+00
	Mean	3.8612E+01	1.0979E+02	4.4518E+00	3.5519E+02	2.4299E+02	2.0742E+01	7.0398E-01	6.0838E-01	7.7596E+00	8.2432E+00	4.4826E-01	7.0804E-01	**3.9235E-01**	5.9265E-01	1.9189E+00
	SD	**0.0000E+00**	1.0708E+02	5.0723E+00	9.2079E+01	1.2757E+02	3.9880E+01	1.8315E-01	3.8756E-01	3.9548E+00	2.1974E+01	2.2614E-01	3.4039E-01	2.1999E-01	3.1123E-01	6.7943E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/+	+/−/−/−	−/−/−/−	−/−/−/−	+/−/+/+	5/5 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	9/0/1 (+/=/−)
	Rank	12	13	8	15	14	11	5	4	9	10	2	6	1	3	7
17	Worst	3.8846E+01	1.1883E+02	4.1833E+01	3.1243E+02	1.9968E+02	3.7772E+01	1.8619E+01	2.4000E+01	4.9461E+01	4.6226E+01	6.3779E-01	3.9033E+01	7.5157E-01	**3.4476E-01**	5.7957E+00
	Best	3.8846E+01	3.2537E+01	2.4217E+01	4.1355E+01	1.6861E+01	**0.0000E+00**	1.3980E+00	6.4408E-01	1.2818E+01	1.1901E+01	1.9729E-02	1.9054E+00	2.7304E-03	1.0627E-02	1.5743E+00
	Mean	3.8846E+01	6.0829E+01	3.1645E+01	1.0201E+02	7.6443E+01	1.4550E+01	5.0576E+00	5.3226E+00	3.1830E+01	3.0617E+01	1.5410E-01	1.7948E+01	1.6366E-01	**1.1968E-01**	3.0719E+00
	SD	**0.0000E+00**	2.0960E+01	4.2182E+00	9.2622E+01	5.4261E+01	9.8662E+00	3.2236E+00	5.9140E+00	1.0180E+01	7.4889E+00	1.7639E-01	9.2448E+00	1.9721E-01	1.1837E-01	1.0852E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/+/−/+	7/0/3 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	13	10	15	14	7	5	6	11	9	2	8	3	1	4
18	Worst	3.0419E+03	4.4198E+04	2.0543E+01	1.4243E+04	3.6646E+04	4.8999E+01	1.3187E+00	1.4469E+00	1.9454E+04	2.0488E+01	2.0452E+01	1.4950E+00	**5.0000E-01**	2.0037E+01	1.2962E+00
	Best	3.0419E+03	1.3765E+03	5.6738E-04	3.6781E+02	5.5396E+02	3.3389E-04	8.7554E-02	1.5552E-03	4.4500E+02	2.5960E-02	6.7192E-04	8.3409E-03	**2.3629E-05**	4.3388E-03	1.0659E-02
	Mean	3.0419E+03	2.3639E+04	4.2599E+00	4.9069E+03	1.1628E+04	9.6130E+00	4.2702E-01	**2.0609E-01**	6.8867E+03	1.1203E+00	1.0239E+00	4.8643E-01	2.6178E-01	9.7625E-01	3.8614E-01
	SD	**9.2453E-13**	1.5682E+04	8.0381E+00	3.7722E+03	9.5942E+03	1.2082E+01	3.0083E-01	2.7714E-01	5.0314E+03	3.6115E+00	3.6101E+00	2.1411E-01	2.2375E-01	3.5415E+00	3.1561E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	+/+/+/+	−/−/−/−	−/−/−/+	−/−/−/−	8/0/2 (+/=/-)	9/0/1 (+/=/-)	8/0/2 (+/=/-)	8/0/2 (+/=/−)
	Rank	11	15	9	12	14	10	4	1	13	8	7	5	2	6	3
19	Best	1.0848E+02	2.8711E+04	1.5194E+00	4.0317E+03	8.5041E+01	2.6216E+00	5.0421E-01	4.4712E-01	9.2724E+01	1.5809E+00	3.9422E-02	1.5351E+00	**2.5059E-02**	3.9214E-02	4.3842E-01

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	Worst	1.0848E+02	1.1843E+02	2.5368E-03	1.6874E+01	3.4653E+00	3.4561E-11	2.4447E-02	2.2999E-05	1.6086E+01	1.0490E-01	7.5670E-09	3.1694E-02	2.2557E-07	**0.0000E+00**	2.7691E-02
	Best	1.0848E+02	4.0988E+03	9.9150E-02	7.4148E+02	1.9878E+01	8.9291E-01	2.1643E-01	5.5260E-02	3.6505E+01	8.7369E-01	1.9350E-02	3.3298E-01	**7.5198E-03**	1.7676E-02	1.1144E-01
	SD	**0.0000E+00**	6.0430E+03	2.6857E-01	9.7841E+02	1.5262E+01	8.1840E-01	1.0537E-01	8.3656E-02	1.5853E+01	4.7460E-01	1.0269E-02	3.4113E-01	9.6824E-03	1.4540E-02	7.8358E-02
	BRT	−/−/−/−	−/−/−/−	+/-/-/+	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/+	−/−/−/−	−/−/−/−	+/−/−/+	7/0/3 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	8/0/2 (+/=/−)
	Rank	13	15	5	14	11	10	7	4	12	9	3	8	1	2	6
20	Worst	1.8029E+01	2.3783E+02	2.9284E+01	3.5755E+02	1.6844E+02	2.0624E+01	1.3682E+00	2.3980E+01	4.0752E+01	3.6669E+01	3.1217E-01	1.1943E+02	**0.0000E+00**	3.1217E-01	3.0679E+00
	Best	1.8029E+01	3.8772E+01	3.1217E-01	3.6722E+01	1.6259E+00	0.0000E+00	2.9680E-05	1.0232E-11	7.7696E+00	4.2903E+00	4.5616E-09	7.9065E-08	**0.0000E+00**	**0.0000E+00**	1.3707E-01
	Mean	1.8029E+01	1.1733E+02	6.5643E+00	1.5701E+02	4.6205E+01	4.7709E+00	2.3873E-01	3.0317E+00	2.3986E+01	2.1945E+01	1.2084E-01	1.7278E+01	**0.0000E+00**	1.3091E-01	9.0668E-01
	SD	**0.0000E+00**	5.8599E+01	9.6159E+00	4.4568E+01	4.5918E+01	7.9277E+00	3.3226E-01	5.7173E+00	8.9726E+00	8.5323E+00	1.5457E-01	2.2148E+01	**0.0000E+00**	1.5659E-01	7.7139E-01
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/+	+/−/−/−	−/−/−/−	−/−/−/−	+/−/+/+	6/0/4 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	9/0/1 (+/=/−)
	Rank	10	14	8	15	13	7	4	6	12	11	2	9	1	3	5
21	Worst	**1.0000E+02**	2.4346E+02	2.2592E+02	2.3237E+02	2.4530E+02	2.1896E+02	2.1230E+02	**1.0000E+02**	1.0200E+02	**1.0000E+02**	2.0293E+02	2.0996E+02	2.0497E+02	2.0473E+02	2.0488E+02
	Best	**1.0000E+02**	1.0625E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02	**1.0000E+02**	1.0027E+02	**1.0000E+02**	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02
	Mean	**1.0000E+02**	2.1532E+02	1.7641E+02	2.0863E+02	1.8483E+02	1.6158E+02	1.2102E+02	**1.0000E+02**	1.0067E+02	**1.0000E+02**	1.2969E+02	1.9695E+02	1.5381E+02	1.0712E+02	1.3913E+02
	SD	**0.0000E+00**	3.0401E+01	5.7764E+01	3.6647E+01	5.4470E+01	5.5577E+01	4.3626E+01	8.1676E-14	3.8654E-01	2.4402E-07	4.6905E+01	2.6014E+01	5.2154E+01	2.6070E+01	3.3862E+01
	BRT	+/+/+/+	−/−/−/−	+/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/+/−/+	+/+/+/+	+/+/+/+	+/+/+/+	+/+/−/+	2/0/8 (+/=/-)	5/0/5 (+/=/-)	6/0/4 (+/=/-)	5/0/5 (+/=/−)
	Rank	1	13	9	12	10	8	4	1	2	1	5	11	7	3	8
22	Worst	1.0035E+02	1.1006E+02	1.0050E+02	1.0300E+02	9.6618E+02	1.0355E+02	1.0095E+02	1.0060E+02	1.1011E+02	1.0073E+02	**1.0000E+02**	**1.0000E+02**	1.0045E+02	1.0035E+02	1.0011E+02
	Best	1.0035E+02	1.0307E+02	1.0000E+02	1.0000E+02	1.7887E+01	1.9224E+01	**4.5475E-13**	1.2847E+01	1.0452E+02	3.1378E-11	4.1511E+01	1.0000E+02	1.0000E+02	1.0000E+02	2.4244E+01
	Mean	1.0035E+02	1.0651E+02	1.0017E+02	1.0057E+02	1.5509E+02	9.3890E+01	9.3848E+01	8.1629E+01	1.0831E+02	**5.9591E+01**	9.8113E+01	1.0000E+02	1.0001E+02	1.0002E+02	9.7568E+01
	SD	**0.0000E+00**	1.5963E+00	1.9277E-01	6.4348E-01	2.1207E+02	2.3752E+01	2.5054E+01	3.2514E+01	1.1027E+00	3.9037E+01	1.0505E+01	**0.0000E+00**	8.0944E-02	7.9650E-02	1.3608E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	+/+/+/+	+/+/+/+	−/−/−/−	+/+/+/+	+/+/+/−	6/0/4 (+/=/-)	6/0/4 (+/=/-)	6/0/4 (+/=/-)	6/0/4 (+/=/−)
	Rank	11	13	10	12	15	4	3	2	14	1	6	7	8	9	5
23	Worst	3.1989E+02	3.6775E+02	3.2117E+02	3.6026E+02	3.2743E+02	3.2414E+02	3.1261E+02	3.1701E+02	3.2900E+02	3.1507E+02	**3.0321E+02**	3.1256E+02	3.0443E+02	3.0890E+02	3.0743E+02
	Best	3.1989E+02	3.1943E+02	3.0000E+02	3.0691E+02	3.0432E+02	3.0713E+02	3.0067E+02	**0.0000E+00**	3.0959E+02	3.0287E+02	3.0000E+02	3.0000E+02	3.0002E+02	3.0000E+02	3.0044E+02
	Mean	3.1989E+02	3.3804E+02	3.0854E+02	3.2892E+02	3.1662E+02	3.1307E+02	3.0790E+02	**2.9827E+02**	3.1511E+02	3.0953E+02	3.0037E+02	3.0457E+02	3.0276E+02	3.0431E+02	3.0393E+02
	SD	**0.0000E+00**	1.2030E+01	6.2131E+00	1.4365E+01	6.0165E+00	4.5772E+00	2.9530E+00	5.5471E+01	4.1408E+00	2.9720E+00	9.8770E-01	2.9538E+00	1.3873E+00	2.5468E+00	1.9712E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	−/−/−/−	−/−/−/−	+/+/+/+	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/−)
	Rank	13	15	8	14	12	10	7	1	11	9	2	6	3	5	4
24	Worst	3.4642E+02	3.8765E+02	3.4835E+02	3.5123E+02	3.7394E+02	3.5528E+02	3.3924E+02	2.0096E+02	3.4408E+02	**1.0000E+02**	3.2956E+02	3.3653E+02	3.3202E+02	3.3950E+02	3.3221E+02
	Best	3.4642E+02	1.0064E+02	1.0000E+02	1.0000E+02	1.0008E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0150E+02	**3.7163E-06**	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02	5.1098E-04
	Mean	3.4642E+02	3.2725E+02	3.1601E+02	2.2236E+02	3.2742E+02	3.3615E+02	2.5891E+02	1.0971E+02	1.4644E+02	**9.6774E+01**	1.6042E+02	3.2126E+02	2.7910E+02	2.9597E+02	2.7286E+02
	SD	**2.3113E-13**	9.1022E+01	6.3186E+01	1.1565E+02	7.6083E+01	4.4102E+01	1.1150E+02	3.0150E+01	9.1087E+01	1.7961E+01	8.6574E+01	4.1094E+01	9.5346E+01	8.7407E+01	8.0428E+01
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	+/+/+/+	−/−/−/−	−/−/−/−	+/+/+/+	+/+/+/+	+/+/+/+	+/+/+/+	−/−/−/−	4/0/6 (+/=/-)	5/0/5 (+/=/-)	5/0/5 (+/=/-)	5/0/5 (+/=/−)
	Rank	15	12	10	5	13	14	6	2	3	1	4	11	8	9	7
25	Worst	4.4369E+02	4.5028E+02	4.4579E+02	4.4583E+02	5.2417E+02	4.4602E+02	4.4349E+02	**3.9958E+02**	4.4395E+02	4.4351E+02	4.4337E+02	4.4830E+02	4.4579E+02	4.4580E+02	4.4581E+02
	Best	4.4369E+02	3.9793E+02	3.9774E+02	3.9775E+02	1.0076E+02	3.9776E+02	3.9774E+02	**1.0000E+02**	3.9828E+02	**1.0000E+02**	3.9774E+02	3.9774E+02	3.9801E+02	3.9801E+02	3.9774E+02
	Mean	4.4369E+02	4.2751E+02	4.1945E+02	4.3636E+02	4.0449E+02	4.2083E+02	4.0098E+02	**3.6902E+02**	4.0093E+02	3.8324E+02	4.1409E+02	4.4519E+02	4.1718E+02	4.2012E+02	4.1152E+02
	SD	**2.8892E-13**	2.3498E+01	2.2848E+01	1.6561E+01	7.4881E+01	2.3882E+01	1.1365E+01	8.9512E+01	8.0086E+00	7.6823E+01	2.2059E+01	8.8425E+00	2.2930E+01	2.3207E+01	2.1066E+01
	BRT	+/−/−/−	+/−/−/−	+/-/+/−	+/−/−/−	+/+/+/+	+/−/−/−	+/+/+/+	+/+/+/+	+/+/+/+	+/+/+/+	+/+/+/−	0/0/10 (+/=/-)	5/0/5 (+/=/-)	5/0/5 (+/=/-)	5/0/5 (+/=/−)
	Rank	14	12	9	13	5	11	4	1	3	2	7	15	8	10	6
26	Worst	4.0118E+02	7.3229E+02	3.0000E+02	1.2508E+03	1.4206E+03	1.2077E+03	**3.0000E+02**	**3.0000E+02**	3.0819E+02	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	3.0000E+02
	Best	4.0118E+02	3.2088E+00	3.0000E+02	2.0000E+02	2.0032E+02	3.0000E+02	4.5475E-13	**0.0000E+00**	1.0919E+01	1.5552E-10	2.0000E+02	3.0000E+02	3.0000E+02	3.0000E+02	3.0000E+02
	Mean	4.0118E+02	3.3587E+02	3.0000E+02	2.8551E+02	4.9759E+02	3.4956E+02	2.8390E+02	**2.1613E+02**	2.7355E+02	2.5810E+02	2.8437E+02	3.0000E+02	3.0000E+02	3.0000E+02	3.0000E+02
	SD	3.4670E-13	1.9962E+02	1.8565E-13	1.8598E+02	3.9157E+02	1.6284E+02	5.8245E+01	8.6011E+01	8.7703E+01	8.0699E+01	3.6326E+01	2.6722E-13	**0.0000E+00**	**0.0000E+00**	0.0000E+00
	BRT	−/−/−/−	−/−/−/−	=/=/=/=	+/+/+/+	−/−/−/−	−/−/−/−	+/+/+/+	+/+/+/+	+/+/+/+	+/+/+/+	+/+/+/+	4/1/5 (+/=/-)	4/1/5 (+/=/-)	4/1/5 (+/=/-)	4/1/5 (+/=/−)
	Rank	10	8	7	6	11	9	4	1	3	2	5	7	7	7	7
27	Worst	3.9236E+02	4.0664E+02	3.8995E+02	4.6003E+02	4.8813E+02	3.9268E+02	3.9382E+02	3.8971E+02	**3.8751E+02**	3.9268E+02	3.9507E+02	4.0588E+02	3.8952E+02	3.8952E+02	3.9634E+02
	Best	3.9236E+02	3.8912E+02	3.8901E+02	3.9427E+02	3.8829E+02	3.8689E+02	3.8731E+02	3.8689E+02	**3.7915E+02**	3.8887E+02	3.8952E+02	3.9038E+02	3.8901E+02	3.8732E+02	3.9196E+02
	Mean	3.9236E+02	3.9776E+02	3.8948E+02	4.1877E+02	3.9969E+02	3.9002E+02	3.8938E+02	3.8893E+02	**3.8296E+02**	3.8949E+02	3.9066E+02	3.9773E+02	3.8943E+02	3.8940E+02	3.9401E+02
	SD	**0.0000E+00**	4.5015E+00	1.7699E-01	2.0473E+01	2.2056E+01	1.1205E+00	1.2412E+00	6.9791E-01	2.0847E+00	8.0333E-01	1.8557E+00	3.9896E+00	1.9229E-01	4.1449E-01	8.9849E-01
	BRT	+/−/−/+	−/−/−/−	+/−/−/+	−/−/−/−	−/−/−/−	+/−/−/+	+/+/+/+	+/+/+/+	+/+/+/+	+/−/−/−	+/−/−/+	3/0/7 (+/=/-)	7/0/3 (+/=/-)	7/0/3 (+/=/-)	4/0/6 (+/=/−)
	Rank	10	13	6	15	14	8	3	2	1	7	9	12	5	4	11
28	Worst	6.1182E+02	6.6954E+02	3.9657E+02	7.0584E+02	6.1182E+02	6.1182E+02	**3.0000E+02**	**3.0000E+02**	4.9611E+02	6.1182E+02	5.8375E+02	6.4648E+02	6.1182E+02	6.1182E+02	3.0000E+02
	Best	6.1182E+02	3.0118E+02	3.0000E+02	3.0000E+02	1.5394E+00	3.0000E+02	3.0000E+02	**0.0000E+00**	3.0266E+02	3.0000E+02	3.0000E+02	5.8373E+02	3.0000E+02	3.0000E+02	3.0000E+02
	Mean	6.1182E+02	5.3761E+02	3.0312E+02	5.6565E+02	4.7140E+02	4.4625E+02	3.0000E+02	**2.9032E+02**	3.4817E+02	3.9053E+02	3.1289E+02	5.9299E+02	3.5673E+02	3.1006E+02	3.0000E+02
	SD	4.6226E-13	1.1605E+02	1.7344E+01	1.1048E+02	1.6075E+02	1.3929E+02	**1.7085E-13**	5.3882E+01	6.6640E+01	1.4388E+02	5.4393E+01	2.0197E+01	1.1786E+02	5.6005E+01	0.0000E+00
	BRT	−/−/−/−	+/−/−/−	+/+/+/−	+/−/−/−	+/−/−/−	+/−/−/−	+/+/+/=	+/+/+/+	+/+/−/−	+/−/−/−	+/+/−/−	1/0/9 (+/=/-)	6/0/4 (+/=/-)	7/0/3 (+/=/-)	8/1/1 (+/=/−)

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	Rank	14	11	3	12	10	9	2	1	6	8	5	13	7	4	2
29	Worst	4.1337E+02	3.7461E+02	2.5461E+02	7.2676E+02	4.1235E+02	2.9904E+02	2.7489E+02	2.6040E+02	2.9545E+02	3.1753E+02	2.4463E+02	2.7182E+02	2.4148E+02	2.3841E+02	2.7216E+02
	Best	4.1337E+02	2.7200E+02	2.3735E+02	2.6055E+02	2.3433E+02	2.3031E+02	2.3311E+02	**2.2225E+02**	2.4845E+02	2.3755E+02	2.2746E+02	2.3438E+02	2.2797E+02	2.2708E+02	2.4161E+02
	Mean	4.1337E+02	3.0548E+02	2.4658E+02	3.3425E+02	3.1441E+02	2.4146E+02	2.4778E+02	2.3669E+02	2.6802E+02	2.5937E+02	2.3355E+02	2.5752E+02	2.3327E+02	**2.3070E+02**	2.5586E+02
	SD	**0.0000E+00**	2.7994E+01	5.1269E+00	1.0086E+02	5.2786E+01	1.4652E+01	1.0183E+01	8.1012E+00	1.3149E+01	1.7363E+01	3.1139E+00	8.7440E+00	2.7890E+00	2.4482E+00	7.0252E+00
	BRT	−/−/−/−	−/−/−/−	+/−/−/+	−/−/−/−	−/−/−/−	+/−/−/+	+/−/−/+	+/−/−/+	−/−/−/−	−/−/−/−	+/−/−/+	6/0/4 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	6/0/4 (+/=/−)
	Rank	15	12	6	14	13	5	7	4	11	10	3	9	2	1	8
30	Worst	8.1758E+05	1.0804E+06	5.0032E+02	5.6166E+06	1.2488E+06	8.1758E+05	4.5029E+02	4.4266E+02	1.1809E+04	5.1675E+02	4.4291E+02	4.6413E+02	8.1758E+05	8.1758E+05	4.4270E+02
	Best	8.1758E+05	2.8775E+03	3.9450E+02	5.7698E+03	2.0052E+03	4.0578E+02	3.9757E+02	3.9450E+02	**2.7195E+02**	3.9460E+02	3.9450E+02	3.9450E+02	3.9450E+02	3.9450E+02	3.9455E+02
	Mean	8.1758E+05	2.1092E+05	4.4025E+02	4.1658E+05	3.0903E+05	1.0597E+05	4.0990E+02	**3.9689E+02**	2.7729E+03	4.0705E+02	4.0574E+02	4.1301E+02	2.6758E+04	5.3122E+04	4.0446E+02
	SD	**4.7336E-10**	3.0162E+05	3.5170E+01	1.2976E+06	4.1983E+05	2.7843E+05	1.0717E+01	9.0877E+00	3.2105E+03	2.7358E+01	1.5700E+01	2.3075E+01	1.4677E+05	2.0407E+05	1.7678E+01
	BRT	−/−/−/−	−/−/−/−	−/+/+/+	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	+/+/+/+	−/+/+/+	+/+/+/−	+/+/+/−	7/0/3 (+/=/-)	5/0/5 (+/=/-)	5/0/5 (+/=/-)	8/0/2 (+/=/−)
	Rank	15	12	7	14	13	11	5	1	8	4	3	6	9	10	2
+/=/−		7/0/23 4/0/26 1/0/29 1/0/29 3/0/27	3/0/27 0/0/30 0/0/30 0/0/30	17/1/12 4/5/21 5/5/20 8/5/17	7/0/23 2/0/28 2/0/28 2/0/28	4/0/26 1/0/29 1/0/29 1/0/29	13/0/17 1/2/27 1/2/27 2/2/26	20/0/10 8/2/20 8/2/20 12/3/15	24/0/6 13/5/12 13/5/12 16/5/9	7/0/23 7/0/23 6/0/24 6/0/24	12/0/18 6/1/24 6/1/24 7/1/23	22/0/8 13/1/16 13/1/16 16/1/13	185/1/33	258/16/56	258/16/56	271/17/72

Table S2 The computational results on benchmark functions with 30 variables

No	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
1	Worst	1.1285E+01	4.5954E+06	1.1369E-13	9.6973E+03	1.8588E+06	8.7529E-10	7.1054E-14	2.0842E+04	1.4962E+08	1.0000E+10	9.9966E-09	1.7116E-09	1.4211E-14	**0.0000E+00**	**0.0000E+00**
	Best	1.1285E+01	1.2096E+06	1.4211E-14	4.0569E+00	1.1590E+05	1.4211E-14	1.4211E-14	1.9526E-01	4.3673E+07	1.0000E+10	6.1999E-09	6.4915E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	1.1285E+01	2.8983E+06	5.5468E-14	3.2012E+03	8.1083E+05	5.0255E-11	3.2547E-14	6.6689E+03	9.0374E+07	1.0000E+10	9.1231E-09	3.2484E-10	3.2089E-15	**0.0000E+00**	**0.0000E+00**
	SD	7.2229E-15	8.0092E+05	2.4437E-14	3.2562E+03	4.7025E+05	1.6321E-10	1.1715E-14	7.7296E+03	2.2684E+07	**0.0000E+00**	9.0367E-10	3.2179E-10	6.0400E-15	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	7/0/3 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	12	4	9	11	5	3	10	13	14	7	6	2	1	1
2	Worst	1.0691E+05	1.0865E+16	6.2175E-09	5.9187E+21	4.4225E+03	6.2454E-05	1.0945E+01	5.5313E+02	8.9722E+16	1.0000E+10	**0.0000E+00**	6.3900E+02	2.8422E-14	**0.0000E+00**	**0.0000E+00**
	Best	1.0691E+05	4.4815E+11	7.3896E-13	3.9339E-06	4.7365E+00	3.4044E-10	1.6584E-10	4.2688E-09	4.0043E+15	1.0000E+10	**0.0000E+00**	3.0000E+00	0.0000E+00	**0.0000E+00**	**0.0000E+00**
	Mean	1.0691E+05	6.8824E+14	4.0198E-10	1.9093E+20	7.9661E+02	3.0610E-06	3.5306E-01	1.7845E+01	3.6297E+16	1.0000E+10	**0.0000E+00**	4.7968E+01	2.7505E-15	**0.0000E+00**	**0.0000E+00**
	SD	**0.0000E+00**	2.3728E+15	1.1583E-09	1.0630E+21	1.2915E+03	1.1359E-05	1.9658E+00	9.9344E+01	2.7228E+16	**0.0000E+00**	**0.0000E+00**	1.1421E+02	8.5418E-15	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/+/−/−	6/0/4 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	9	11	3	13	8	4	5	6	12	10	1	7	2	1	1
3	Worst	4.3356E-01	1.0548E+04	8.5265E-13	1.9506E+02	1.1421E-01	5.1620E+00	6.4707E-02	3.4828E-03	1.6797E+04	6.4095E+01	9.9398E-09	1.3475E-09	5.6843E-14	**0.0000E+00**	**0.0000E+00**
	Best	4.3356E-01	3.3404E+03	1.7053E-13	1.1369E-13	6.0635E-03	2.0467E-09	2.8781E-05	8.2284E-06	7.1117E+03	9.8503E-03	7.8969E-09	6.5654E-11	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	4.3356E-01	6.5346E+03	3.9057E-13	1.7080E+01	2.3701E-02	2.4569E-01	6.7151E-03	6.1306E-04	1.1616E+04	3.6964E+00	9.0638E-09	3.7603E-10	4.4008E-14	**0.0000E+00**	**0.0000E+00**
	SD	**0.0000E+00**	1.9704E+03	1.8838E-13	4.0194E+01	2.0945E-02	9.6942E-01	1.1553E-02	8.1415E-04	2.8472E+03	1.1332E+01	5.9420E-10	3.2546E-10	2.4160E-14	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	13	3	12	8	9	7	6	14	11	5	4	2	1	1
4	Worst	6.6449E+01	1.9076E+02	6.7897E+01	2.1084E+02	1.1940E+02	6.4117E+01	7.1889E+01	8.3681E+01	1.8914E+02	8.6848E+01	5.8562E+01	6.4206E+01	6.4117E+01	5.8562E+01	**0.0000E+00**
	Best	6.6449E+01	7.5350E+01	**2.2737E-13**	8.4596E-05	7.1870E+01	7.7147E-02	1.9684E-07	9.4751E-02	9.0723E+01	2.3302E-03	5.8562E+01	3.4106E-13	5.8562E+01	5.8562E+01	**0.0000E+00**
	Mean	6.6449E+01	1.1948E+02	8.5144E+00	8.6017E+01	9.1248E+01	4.9144E+01	1.8880E+01	4.7329E+01	1.2232E+02	2.6639E+01	5.8562E+01	1.3727E+01	5.8920E+01	5.8562E+01	**0.0000E+00**
	SD	2.8892E-14	2.1869E+01	1.9022E+01	6.2412E+01	1.1213E+01	2.2131E+01	2.8091E+01	2.7837E+01	1.7925E+01	3.1825E+01	4.2711E-14	2.2883E+01	1.3875E+00	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/+/+/−	−/−/−/−	−/−/−/−	−/+/+/−	−/+/+/−	−/+/+/−	−/−/−/−	−/+/+/−	−/+/=/−	9/0/1 (+/=/−)	5/0/5 (+/=/−)	5/0/5 (+/=/−)	10/0/0 (+/=/−)
	Rank	11	14	2	12	13	7	4	6	15	5	8	3	10	9	1
5	Worst	1.0746E+02	2.2079E+02	1.6217E+02	1.4825E+02	1.4791E+02	8.8551E+01	1.2138E+02	1.3730E+02	1.6997E+02	1.5621E+02	**5.2375E+00**	3.8803E+01	1.0199E+01	3.4824E+01	4.3524E+00
	Best	1.0746E+02	9.0203E+01	1.0945E+01	6.9647E+01	4.8976E+01	3.3829E+01	3.8803E+01	5.3728E+01	1.0894E+02	4.9748E+01	**4.8317E-12**	4.9748E+00	2.2155E+00	3.9799E+00	1.2333E+00
	Mean	1.0746E+02	1.5408E+02	7.5676E+01	1.1038E+02	9.7120E+01	5.5638E+01	7.7045E+01	8.3747E+01	1.3380E+02	9.7460E+01	**1.8318E+00**	1.6773E+01	6.8204E+00	2.0023E+01	2.7907E+00
	SD	**0.0000E+00**	3.2297E+01	6.3890E+01	1.9697E+01	2.6391E+01	1.3972E+01	2.1279E+01	1.8180E+01	1.6647E+01	2.5139E+01	1.4382E+00	7.9104E+00	1.6362E+00	8.0063E+00	8.5708E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	7	13	10	6	8	9	14	11	1	4	3	5	2
6	Worst	9.9901E-01	4.8592E+01	2.0593E-05	1.3965E+01	2.0115E+01	2.9963E-01	2.1632E-05	2.0496E-02	1.6290E+01	3.4957E+01	9.9733E-09	1.2772E+00	1.3687E-07	**2.2737E-13**	5.2653E-06
	Best	9.9901E-01	2.7435E+01	3.2699E-07	7.8560E-05	9.6752E-01	3.1983E-06	2.6026E-09	3.7089E-04	3.9410E+00	1.0722E+01	7.4575E-09	1.1369E-13	1.1369E-13	**1.1369E-13**	9.2086E-12
	Mean	9.9901E-01	3.8304E+01	9.2602E-06	4.5564E+00	5.3257E+00	2.3766E-02	2.9368E-06	3.5313E-03	7.6872E+00	1.8518E+01	9.2814E-09	1.0677E-01	5.5192E-09	**1.2102E-13**	4.4384E-07
	SD	**0.0000E+00**	6.2481E+00	5.1738E-06	3.3012E+00	4.8116E+00	6.5065E-02	4.7046E-06	4.4013E-03	2.7270E+00	5.5670E+00	7.1672E-10	3.1112E-01	2.5140E-08	2.8391E-14	1.0283E-06
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/+	6/0/4 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)

No	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	Rank	10	15	6	11	12	8	5	7	13	14	3	9	2	1	4
7	Worst	9.5540E+01	3.9186E+02	2.0048E+02	8.3724E+01	1.8229E+02	1.1533E+02	2.1715E+02	1.6568E+02	2.8714E+02	2.9166E+02	3.5177E+01	6.0781E+01	3.8753E+01	4.9023E+01	**1.4615E+01**
	Best	9.5540E+01	2.0530E+02	4.4094E+01	4.2125E+01	7.5176E+01	5.3785E+01	8.3156E+01	7.9514E+01	1.8261E+02	9.4699E+01	3.1807E+01	3.4885E+01	3.4170E+01	3.2886E+01	**1.0871E+01**
	Mean	9.5540E+01	2.6675E+02	1.7190E+02	5.5062E+01	1.2288E+02	7.9873E+01	1.3807E+02	1.1756E+02	2.3953E+02	1.9778E+02	3.3455E+01	4.9913E+01	3.6883E+01	3.9201E+01	**1.2978E+01**
	SD	**0.0000E+00**	5.0331E+01	4.3662E+01	8.6062E+00	2.3918E+01	1.4490E+01	2.9297E+01	2.3635E+01	2.8719E+01	4.4587E+01	7.8647E-01	5.7124E+00	1.1241E+00	3.6289E+00	7.3332E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	15	12	6	10	7	11	9	14	13	2	5	3	4	1
8	Worst	7.1637E+01	1.6266E+02	1.7438E+02	1.2238E+02	1.6919E+02	8.3059E+01	1.0149E+02	1.2138E+02	1.3506E+02	1.2536E+02	**4.9748E+00**	3.8803E+01	1.2145E+01	2.2884E+01	4.4584E+00
	Best	7.1637E+01	9.3545E+01	1.1940E+01	5.9697E+01	5.7406E+01	3.5818E+01	4.5404E+01	5.1738E+01	9.1716E+01	3.2842E+01	**1.8213E-10**	6.9647E+00	4.1373E+00	4.7265E+00	5.8274E-01
	Mean	7.1637E+01	1.3110E+02	7.2131E+01	8.7813E+01	1.0307E+02	5.5677E+01	7.1114E+01	8.1683E+01	1.1235E+02	8.8565E+01	**2.3916E+00**	1.5493E+01	7.1376E+00	1.2552E+01	3.1281E+00
	SD	**5.7783E-14**	1.8657E+01	6.6486E+01	1.6247E+01	2.5387E+01	1.4119E+01	1.2907E+01	1.5275E+01	1.1562E+01	1.9947E+01	1.3182E+00	6.7744E+00	1.7372E+00	4.7858E+00	8.2546E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	15	9	11	13	6	7	10	14	12	1	5	3	4	2
9	Worst	5.6511E+01	5.4033E+03	4.5432E-01	3.9945E+02	9.5971E+03	1.7636E+01	2.0079E+03	2.8992E+02	2.6907E+03	4.2232E+03	9.9658E-09	4.5432E-01	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Best	5.6511E+01	1.5915E+03	**0.0000E+00**	**0.0000E+00**	2.0263E+00	8.9528E-02	5.0817E-01	6.3565E+00	4.4829E+01	6.9009E+02	5.7507E-09	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	5.6511E+01	3.4079E+03	1.7544E-02	1.2886E+01	2.8048E+03	3.9909E+00	7.7105E+02	9.2996E+01	5.1187E+02	1.6940E+03	8.6584E-09	1.4656E-02	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	SD	**0.0000E+00**	9.3451E+02	8.2641E-02	7.1744E+01	2.8783E+03	3.8378E+00	4.5741E+02	8.1308E+01	5.3809E+02	7.6093E+02	1.0326E-09	8.1599E-02	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	7	13	4	6	12	5	10	8	9	11	2	3	1	1	1
10	Worst	2.2817E+03	5.5621E+03	7.3433E+03	4.2028E+03	3.8392E+03	4.1947E+03	3.1649E+03	2.8842E+03	4.8453E+03	4.6614E+03	1.9567E+03	2.8959E+03	1.6640E+03	2.9186E+03	**2.9264E+02**
	Best	2.2817E+03	2.6683E+03	6.0936E+03	2.1884E+03	1.9065E+03	1.7357E+03	1.2848E+03	1.4327E+03	2.2896E+03	2.8003E+03	9.5267E+02	5.0788E+02	1.0849E+03	1.0728E+03	**1.9791E+01**
	Mean	2.2817E+03	3.9886E+03	6.7873E+03	3.1372E+03	2.9500E+03	3.3130E+03	2.4630E+03	2.1958E+03	3.4763E+03	3.7032E+03	1.5317E+03	1.3873E+03	1.3845E+03	1.6378E+03	**1.3622E+02**
	SD	**1.3868E-12**	5.6802E+02	3.3317E+02	5.1423E+02	5.2670E+02	5.8388E+02	3.8949E+02	3.5279E+02	6.9713E+02	5.2625E+02	2.2640E+02	5.3939E+02	1.4654E+02	4.1530E+02	7.9744E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	7	14	15	10	9	11	8	6	12	13	4	3	2	5	1
11	Worst	1.1309E+02	3.2867E+02	6.2964E+01	1.9850E+02	3.0239E+02	1.5256E+02	7.8675E+01	1.1868E+02	1.9335E+02	1.5748E+02	7.9665E+00	7.7885E+01	6.3337E+01	6.3959E+01	3.7626E+00
	Best	1.1309E+02	1.1274E+02	1.9899E+00	5.0779E+01	5.8706E+01	1.0021E+01	1.2277E+01	2.0532E+01	7.4046E+01	1.7909E+01	2.0236E-10	**5.6843E-11**	2.8107E+00	9.9496E-01	1.2414E+00
	Mean	1.1309E+02	2.1987E+02	9.7692E+00	1.2273E+02	1.6096E+02	6.5291E+01	2.9723E+01	5.4599E+01	1.3231E+02	6.8872E+01	3.2436E+00	1.8511E+01	1.2426E+01	7.2410E+00	**2.5731E+00**
	SD	**8.6675E-14**	5.5290E+01	1.0497E+01	4.1739E+01	6.1405E+01	4.2596E+01	1.5588E+01	2.0150E+01	2.8182E+01	3.6261E+01	2.1516E+00	2.5271E+01	1.7237E+01	1.5144E+01	7.0175E-01
	BRT	−/−/−/−	−/−/−/−	+/+/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	9/0/1 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	4	12	14	9	7	8	13	10	2	6	5	3	1
12	Worst	6.0188E+04	2.9793E+07	1.9083E+04	5.3182E+05	7.1778E+06	4.6964E+04	2.2825E+04	2.7900E+05	1.9240E+07	1.0000E+10	1.1939E+03	**2.0527E+01**	1.6878E+03	5.5022E+02	2.3708E+02
	Best	6.0188E+04	1.4122E+06	9.6827E+02	2.1806E+04	1.6997E+05	2.5614E+03	1.8754E+03	1.0639E+04	5.1922E+06	1.2708E+03	7.6581E+00	**2.0859E-01**	2.7210E+02	1.1383E+01	8.1973E-03
	Mean	6.0188E+04	9.3119E+06	6.6910E+03	2.3599E+05	2.0815E+06	1.7175E+04	8.2644E+03	5.6572E+04	1.0835E+07	2.5807E+09	4.6584E+02	**4.3119E+00**	8.7528E+02	2.6106E+02	7.0973E+01
	SD	**2.2189E-11**	6.8896E+06	4.8236E+03	1.3267E+05	1.8056E+06	1.3262E+04	5.6407E+03	4.9744E+04	3.5354E+06	4.4480E+09	2.5002E+02	4.0306E+00	3.5496E+02	1.4498E+02	6.4670E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	13	6	11	12	8	7	9	14	15	4	1	5	3	2
13	Worst	1.6582E+04	3.7670E+05	1.1844E+02	4.9249E+04	6.1204E+05	6.0776E+04	1.4084E+02	1.8697E+02	1.6498E+06	1.5358E+03	2.5731E+01	2.8000E+02	2.5515E+01	**2.3169E+01**	6.2653E+00
	Best	1.6582E+04	4.9891E+04	6.8583E+00	9.0513E+03	2.3461E+04	2.9210E+01	3.0208E+01	3.2174E+01	2.6239E+05	4.6039E+01	**1.0487E+00**	1.2833E+01	2.2452E+00	1.9899E+00	3.8011E-01
	Mean	1.6582E+04	1.8666E+05	3.3254E+01	2.7447E+04	1.6101E+05	4.5204E+03	7.7373E+01	9.3128E+01	7.9364E+05	2.1364E+02	**1.4669E+01**	4.5852E+01	1.6800E+01	1.5734E+01	2.8908E+00
	SD	**7.3962E-12**	8.3338E+04	2.4492E+01	1.0482E+04	1.2049E+05	1.1274E+04	3.2118E+01	3.8227E+01	3.2854E+05	2.6202E+02	6.6516E+00	5.1506E+01	6.0063E+00	5.8070E+00	2.1296E+00
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/+	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	14	5	12	13	10	7	8	15	9	2	6	4	3	1
14	Worst	1.1209E+03	3.6545E+05	3.0832E+01	3.7084E+04	1.5536E+04	1.2149E+02	5.5559E+01	5.8800E+01	2.3880E+04	7.4086E+01	2.7001E+01	6.1816E+01	2.3432E+01	2.9062E+01	**4.7604E+00**
	Best	1.1209E+03	4.7842E+03	2.3292E+01	6.1087E+02	3.7752E+02	3.1911E+01	3.0261E+01	1.2014E+01	4.6115E+02	3.5705E+01	2.0310E+01	**4.5642E-04**	3.3028E+00	9.9496E-01	1.0475E-01
	Mean	1.1209E+03	1.0880E+05	2.6509E+01	5.2795E+03	6.7757E+03	6.6292E+01	4.2997E+01	3.5160E+01	5.4721E+03	5.4375E+01	2.2880E+01	1.6601E+01	1.8983E+01	2.1847E+01	**1.4157E+00**
	SD	**2.3113E-13**	9.3929E+04	1.9167E+00	6.8539E+03	3.5636E+03	2.7543E+01	6.5820E+00	1.0013E+01	5.5114E+03	1.1010E+01	1.4236E+00	1.3397E+01	5.9647E+00	7.3106E+00	1.2941E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	6	12	14	10	8	7	13	9	5	2	3	4	1
15	Worst	2.4238E+03	3.5357E+05	1.5555E+01	1.1890E+04	2.5673E+05	3.6544E+02	7.2298E+01	1.1712E+02	7.7479E+04	1.5828E+02	9.8203E+00	9.5017E+00	7.7485E+00	4.2948E+00	**1.3862E+00**
	Best	2.4238E+03	1.2978E+04	1.1626E+00	1.4050E+03	1.4081E+04	1.7833E+01	8.8605E+00	1.2258E+01	9.4996E+03	2.2471E+01	3.1598E-01	5.8206E+00	2.7776E-01	2.8060E-01	**2.7894E-02**
	Mean	2.4238E+03	7.7242E+04	7.4150E+00	4.7321E+03	6.3608E+04	1.2858E+02	2.6592E+01	3.4047E+01	3.5836E+04	7.1902E+01	3.8664E+00	2.5033E+01	2.5831E+00	1.5283E+00	**3.7734E-01**
	SD	**1.3868E-12**	6.8663E+04	3.7364E+00	2.7796E+03	4.6900E+04	1.0369E+02	1.2628E+01	1.9716E+01	1.8186E+04	3.7404E+01	2.3634E+00	2.6561E+01	1.6946E+00	1.2382E+00	2.7875E-01
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	5	12	14	10	7	8	13	9	4	6	3	2	1
16	Worst	2.1248E+02	1.9885E+03	1.2685E+03	1.7788E+03	1.3534E+03	1.1508E+03	8.4767E+02	7.9931E+02	1.1419E+03	1.0109E+03	1.4074E+02	7.0185E+02	1.7032E+02	1.4843E+02	**5.2691E+00**
	Best	2.1248E+02	8.6393E+02	3.3408E+00	6.7737E+02	5.6227E+01	2.6365E+02	3.0781E+01	1.4608E+01	2.3398E+02	2.5725E+02	2.7706E+00	6.9366E+00	8.2655E+00	3.0832E+00	**8.9794E-01**
	Mean	2.1248E+02	1.2782E+03	2.8432E+02	1.1848E+03	7.1316E+02	5.1464E+02	4.4323E+02	4.5707E+02	6.8482E+02	5.7206E+02	3.5253E+01	3.9912E+02	4.4886E+01	4.8955E+01	**2.4564E+00**

No	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	SD	**1.7335E-13**	2.7804E+02	3.9368E+02	2.7250E+02	2.7607E+02	1.8679E+02	2.0155E+02	1.7755E+02	2.1248E+02	1.8048E+02	4.1391E+01	1.6279E+02	3.9647E+01	4.3523E+01	9.9000E-01
	BRT	+/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	8/0/2 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	5	15	6	14	13	10	8	9	12	11	2	7	3	4	1
17	Worst	4.3145E+02	9.9572E+02	1.4195E+02	1.5725E+03	8.1480E+02	5.1016E+02	2.0508E+02	1.8304E+02	2.4105E+02	3.0237E+02	4.5583E+01	1.6263E+02	4.2601E+01	5.3961E+01	**5.8378E+00**
	Best	4.3145E+02	1.2174E+02	2.8263E+01	3.9538E+02	1.9033E+02	3.4616E+01	3.5229E+01	3.0814E+01	6.8977E+01	4.8554E+01	1.3610E+01	1.2308E+00	1.0687E+01	1.0981E+01	**1.1054E+00**
	Mean	4.3145E+02	5.3871E+02	5.0054E+01	9.7875E+02	4.4216E+02	2.0266E+02	9.3878E+01	8.5959E+01	1.4153E+02	1.4686E+02	3.2521E+01	3.7452E+01	3.3750E+01	3.0740E+01	**3.0897E+00**
	SD	**0.0000E+00**	2.3956E+02	2.1367E+01	3.1468E+02	1.3591E+02	1.3626E+02	5.7180E+01	5.3083E+01	5.8465E+01	6.7936E+01	6.6818E+00	3.6508E+01	6.2083E+00	8.4417E+00	1.1550E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	14	6	15	13	11	8	7	9	10	3	5	4	2	1
18	Worst	4.4424E+04	3.6496E+06	1.6437E+02	1.1055E+05	7.3248E+05	8.2254E+04	1.0011E+02	5.6534E+01	3.5909E+05	2.1227E+02	2.5253E+01	5.5485E+01	2.3453E+01	2.3624E+01	**2.4193E+00**
	Best	4.4424E+04	1.1209E+05	2.9118E+01	2.0997E+04	6.2582E+04	6.3487E+02	2.9451E+01	2.6058E+01	2.2615E+04	3.1070E+01	2.0272E+01	1.1349E+01	**2.2253E+00**	2.0437E+01	**1.2044E-02**
	Mean	4.4424E+04	1.2200E+06	5.9042E+01	5.8655E+04	2.5215E+05	1.4682E+04	5.3931E+01	4.0671E+01	1.2526E+05	1.1019E+02	2.1982E+01	2.1502E+01	2.0879E+01	2.1539E+01	**3.5365E-01**
	SD	**7.3962E-12**	1.0123E+06	3.5276E+01	2.2981E+04	1.8406E+05	2.1066E+04	1.7341E+01	8.9290E+00	7.4691E+04	5.1198E+01	1.1287E+00	6.5282E+00	3.5495E+00	8.9384E-01	4.7246E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	8	12	14	10	7	6	13	9	5	3	2	4	1
19	Worst	2.8907E+03	6.8653E+05	1.3792E+01	1.0375E+04	5.9479E+04	1.6520E+02	2.6029E+01	2.6869E+01	1.6363E+05	7.5021E+01	1.3859E+01	3.0322E+01	1.0351E+01	6.7400E+00	**7.1576E-01**
	Best	2.8907E+03	1.8709E+04	4.4399E+00	3.3321E+02	5.2581E+03	1.0204E+01	9.4978E+00	5.9170E+00	8.9535E+03	1.4506E+01	5.1331E+00	1.9466E+00	3.1264E+00	2.4296E+00	**2.8406E-02**
	Mean	2.8907E+03	3.4997E+05	8.2575E+00	3.9224E+03	2.6156E+04	4.8531E+01	1.8374E+01	1.3863E+01	5.3401E+04	3.8565E+01	9.4791E+00	4.7966E+00	5.9375E+00	4.2613E+00	**1.2110E-01**
	SD	**4.6226E-13**	2.1442E+05	2.0270E+00	2.5976E+03	1.5498E+04	4.0039E+01	3.7759E+00	5.5717E+00	4.3652E+04	1.6886E+01	1.9189E+00	6.1815E+00	1.8312E+00	1.0109E+00	1.2164E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	5	12	13	10	8	7	14	9	6	3	4	2	1
20	Worst	5.7178E+02	6.4189E+02	2.7823E+02	1.4026E+03	7.0276E+02	5.1980E+02	2.8135E+02	1.9752E+02	3.5308E+02	4.5589E+02	1.5069E+02	4.3338E+02	6.1517E+01	3.6545E+01	**2.0537E+00**
	Best	5.7178E+02	2.2275E+02	2.4305E+01	2.9046E+02	1.2878E+02	2.8731E+01	3.0433E+01	1.7689E+01	1.0240E+02	6.4280E+01	1.3631E+01	1.2262E+02	2.6334E+01	4.2921E+00	**4.8602E-02**
	Mean	5.7178E+02	4.3365E+02	6.3337E+01	9.0482E+02	4.0653E+02	1.7996E+02	1.3384E+02	1.1050E+02	2.2952E+02	2.4394E+02	4.0733E+01	1.9921E+02	3.5759E+01	2.5863E+01	**7.2373E-01**
	SD	**4.6226E-13**	1.1741E+02	6.0407E+01	2.4140E+02	1.6629E+02	1.2146E+02	5.6724E+01	6.4768E+01	6.5577E+01	8.8479E+01	2.3439E+01	8.7544E+01	6.4053E+00	5.8276E+00	5.6676E-01
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	6/0/4 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	14	13	5	15	12	8	7	6	10	11	4	9	3	2	1
21	Worst	2.6977E+02	4.0782E+02	3.6371E+02	4.1248E+02	3.8195E+02	2.9747E+02	3.2105E+02	2.9244E+02	3.4862E+02	3.1384E+02	2.0606E+02	2.3483E+02	2.0873E+02	2.3167E+02	**2.0563E+02**
	Best	2.6977E+02	2.7601E+02	2.0931E+02	1.0000E+02	2.6486E+02	2.3135E+02	2.3659E+02	1.0000E+02	1.0692E+02	1.0000E+02	1.0000E+02	2.0593E+02	2.0302E+02	2.1144E+02	**4.2990E+01**
	Mean	2.6977E+02	3.3113E+02	2.4778E+02	3.1040E+02	3.0191E+02	2.5703E+02	2.6049E+02	2.1339E+02	2.1024E+02	2.5776E+02	1.9945E+02	2.2026E+02	2.0629E+02	2.2110E+02	**1.3899E+02**
	SD	**0.0000E+00**	3.5163E+01	5.2796E+01	5.1812E+01	2.7536E+01	1.7586E+01	1.7210E+01	7.4621E+01	1.0503E+02	5.3643E+01	1.8506E+01	7.8463E+00	1.4954E+00	5.4188E+00	3.5004E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	+/−/+/−	−/−/−/−	+/+/+/−	10/0/2 (+/=/-)	10/0/0 (+/=/-)	8/0/2 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	8	14	13	9	11	5	4	10	2	6	3	7	1
22	Worst	3.5664E+03	1.1650E+02	**1.0000E+02**	3.9243E+03	4.5349E+03	5.1337E+03	**1.0000E+02**	1.0887E+02	1.4849E+02	1.0386E+02	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**
	Best	3.5664E+03	1.1151E+02	**1.0000E+02**	**1.0000E+02**	1.0465E+02	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	1.3135E+02	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	1.0006E+02
	Mean	3.5664E+03	1.1451E+02	**1.0000E+02**	2.2336E+02	2.1758E+03	3.2716E+03	**1.0000E+02**	1.0213E+02	1.4028E+02	1.0035E+02	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0001E+02**
	SD	2.7736E-12	1.0604E+00	8.5116E-13	6.8686E+02	1.5490E+03	1.4428E+03	3.5098E-13	2.9812E+00	3.6627E+00	1.1001E+00	**0.0000E+00**	2.3112E-13	**0.0000E+00**	**0.0000E+00**	1.2683E-02
	BRT	−/−/−/−	−/−/−/−	=/=/=/+	−/−/−/−	−/−/−/−	−/−/−/−	=/=/=/+	−/−/−/−	−/−/−/−	−/−/−/−	=/=/=/=	8/2/0 (+/=/-)	8/2/0 (+/=/-)	8/2/0 (+/=/-)	8/0/2 (+/=/−)
	Rank	9	4	1	6	7	8	1	3	5	2	1	1	1	1	1
23	Worst	4.2826E+02	6.4290E+02	3.7778E+02	7.9602E+02	4.7588E+02	4.8103E+02	4.4479E+02	4.4152E+02	5.0713E+02	5.0483E+02	3.5922E+02	4.0680E+02	3.5173E+02	3.9124E+02	**3.0594E+02**
	Best	4.2826E+02	4.6624E+02	3.4530E+02	4.1604E+02	3.9531E+02	3.8303E+02	3.8774E+02	**1.1995E+02**	4.1849E+02	4.0429E+02	3.4471E+02	3.5154E+02	3.4304E+02	3.5146E+02	3.0075E+02
	Mean	4.2826E+02	5.3888E+02	3.6081E+02	5.4772E+02	4.3632E+02	4.1528E+02	4.1497E+02	3.5754E+02	4.6048E+02	4.4819E+02	3.5132E+02	3.7497E+02	3.4739E+02	3.6707E+02	**3.0404E+02**
	SD	**2.8892E-13**	4.3149E+01	8.7083E+00	7.6428E+01	2.0022E+01	1.9881E+01	1.5837E+01	1.0601E+02	1.9331E+01	2.6304E+01	2.8415E+00	1.6029E+01	1.8118E+00	8.1658E+00	1.3453E+00
	BRT	−/−/−/−	−/−/−/−	+/−/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	−/−/−/−	−/−/−/−	+/−/+/−	8/0/2 (+/=/-)	10/0/0 (+/=/-)	8/0/2 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	14	5	15	11	9	8	4	13	12	3	7	2	6	1
24	Worst	4.8356E+02	7.4889E+02	4.5041E+02	6.1201E+02	5.7748E+02	5.4130E+02	5.1850E+02	5.8464E+02	5.8903E+02	6.2181E+02	4.2869E+02	4.6068E+02	4.2889E+02	4.5572E+02	**3.3030E+02**
	Best	4.8356E+02	5.2019E+02	4.2429E+02	**1.0000E+02**	4.6763E+02	4.4618E+02	4.5163E+02	4.5673E+02	5.0865E+02	4.7281E+02	4.2305E+02	4.1663E+02	4.2041E+02	4.2241E+02	1.0492E+02
	Mean	4.8356E+02	6.0548E+02	4.3419E+02	5.1333E+02	5.1766E+02	4.8199E+02	4.9021E+02	5.0638E+02	5.4501E+02	5.3343E+02	4.2537E+02	4.3397E+02	4.2321E+02	4.4177E+02	**2.7025E+02**
	SD	**3.4670E-13**	5.2407E+01	6.7201E+00	8.6815E+01	2.3808E+01	2.0465E+01	1.7060E+01	2.7976E+01	1.7664E+01	3.4744E+01	1.7036E+00	1.0534E+01	1.7567E+00	7.4517E+00	6.9460E+01
	BRT	−/−/−/−	−/−/−/−	−/−/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	15	5	11	12	7	9	10	14	13	3	4	2	6	1
25	Worst	4.4120E+02	4.3297E+02	3.9666E+02	4.3952E+02	3.8733E+02	3.8877E+02	3.8719E+02	4.4160E+02	4.1186E+02	3.9698E+02	3.8676E+02	3.8679E+02	3.8686E+02	3.8675E+02	4.4351E+02
	Best	4.4120E+02	3.8388E+02	3.8343E+02	3.8422E+02	3.8357E+02	3.8345E+02	3.8341E+02	3.8350E+02	3.8829E+02	3.8348E+02	3.8348E+02	3.8672E+02	3.8669E+02	3.8669E+02	3.9774E+02
	Mean	4.4120E+02	3.9950E+02	3.8728E+02	4.0193E+02	3.8694E+02	3.8667E+02	**3.8593E+02**	3.9333E+02	3.9631E+02	3.8750E+02	3.8652E+02	3.8675E+02	3.8678E+02	3.8670E+02	4.2260E+02
	SD	**2.8892E-13**	1.5298E+01	2.8276E+00	1.6362E+01	6.3895E-01	1.8190E+00	1.6268E+00	1.7390E+01	5.6812E+00	4.1896E+00	8.0854E-01	2.1324E-02	4.0624E-02	1.3684E-02	2.2742E+01
	BRT	−/−/−/−	−/−/−/+	−/−/−/+	−/−/−/+	−/−/−/+	+/+/+/+	+/+/+/+	−/−/−/+	−/−/−/+	−/−/−/+	+/+/+/+	8/0/2 (+/=/-)	8/0/2 (+/=/-)	8/0/2 (+/=/-)	1/0/9 (+/=/−)
	Rank	15	12	8	13	7	3	1	10	11	9	2	5	6	4	14
26	Worst	1.5341E+03	4.1384E+03	1.2771E+03	3.4082E+03	2.6018E+03	2.1011E+03	2.3157E+03	**3.0001E+02**	2.9216E+03	2.6970E+03	9.2852E+02	1.4168E+03	9.5670E+02	1.2894E+03	**3.0000E+02**

No	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	Best	1.5341E+03	3.0554E+02	3.0000E+02	2.0000E+02	2.2155E+02	1.3651E+03	2.0000E+02	3.0000E+02	3.8208E+02	3.0000E+02	**2.0000E+02**	2.0000E+02	8.3961E+02	9.2638E+02	3.0000E+02
	Mean	1.5341E+03	1.2196E+03	9.2647E+02	4.5285E+02	1.9615E+03	1.6864E+03	7.2268E+02	**3.0000E+02**	2.2633E+03	1.1651E+03	5.2295E+02	9.8926E+02	8.8883E+02	1.0696E+03	**3.0000E+02**
	SD	4.6226E-13	1.5147E+03	3.2126E+02	7.5423E+02	4.0280E+02	1.6898E+02	7.6653E+02	1.5666E-03	4.1980E+02	9.8476E+02	3.2260E+02	3.3901E+02	3.2568E+01	8.7463E+01	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/−/+/−	+/+/+/−	−/−/−/−	−/−/−/−	+/+/+/−	+/+/+/=	−/−/−/−	−/−/−/−	+/+/+/−	6/0/4 (+/=/-)	7/0/3 (+/=/-)	6/0/4 (+/=/-)	8/1/1 (+/=/−)
	Rank	11	10	6	2	13	12	4	1	14	9	3	7	5	8	1
27	Worst	5.2954E+02	6.7157E+02	5.2237E+02	7.5695E+02	5.3797E+02	5.3665E+02	5.2489E+02	5.2746E+02	5.0001E+02	5.7147E+02	5.1201E+02	5.2448E+02	5.0933E+02	5.0759E+02	**3.9666E+02**
	Best	5.2954E+02	5.2923E+02	4.6763E+02	5.5956E+02	4.8458E+02	4.9301E+02	4.8033E+02	4.9325E+02	5.0001E+02	5.0189E+02	4.9326E+02	5.0225E+02	4.8668E+02	4.8036E+02	**3.9156E+02**
	Mean	5.2954E+02	5.7093E+02	4.9862E+02	6.3226E+02	5.1072E+02	5.1382E+02	5.0750E+02	5.1235E+02	5.0001E+02	5.2852E+02	5.0369E+02	5.1066E+02	4.9630E+02	4.9725E+02	**3.9404E+02**
	SD	**4.6226E-13**	3.2619E+01	1.0529E+01	4.8781E+01	1.3274E+01	1.1343E+01	9.1398E+00	9.7211E+00	9.4544E-05	1.6596E+01	4.8881E+00	4.5959E+00	6.0951E+00	6.1469E+00	8.6295E-01
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	+/−/−/−	7/0/3 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	13	14	4	15	9	11	7	10	5	12	6	8	2	3	1
28	Worst	**3.0000E+02**	5.3061E+02	**3.0000E+02**	4.6019E+02	5.1155E+02	4.8329E+02	4.6011E+02	4.6011E+02	4.9997E+02	4.6011E+02	4.1398E+02	4.1398E+02	4.1398E+02	4.1398E+02	**3.0000E+02**
	Best	**3.0000E+02**	4.0998E+02	**3.0000E+02**	**3.0000E+02**	3.0135E+02	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	4.9800E+02	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**	**3.0000E+02**
	Mean	3.0000E+02	4.5270E+02	**3.0000E+02**	3.2063E+02	4.2702E+02	3.8812E+02	3.1516E+02	3.1635E+02	4.9952E+02	3.4148E+02	3.1366E+02	3.2034E+02	3.1769E+02	3.2470E+02	**3.0000E+02**
	SD	1.1557E-13	2.6168E+01	1.3170E-12	4.8071E+01	4.6988E+01	7.3860E+01	4.1034E+01	4.1507E+01	4.8236E-01	5.3471E+01	3.6121E+01	4.2234E+01	4.1070E+01	4.6565E+01	**8.3025E-14**
	BRT	+/+/+/=	−/−/−/−	+/+/+/=	−/−/+/−	−/−/−/−	−/−/−/−	+/+/+/−	+/+/+/−	−/−/−/−	−/−/−/−	+/+/+/−	6/0/4 (+/=/-)	6/0/4 (+/=/-)	5/0/5 (+/=/-)	8/2/0 (+/=/−)
	Rank	1	12	1	7	11	10	3	4	13	9	2	6	5	8	1
29	Worst	6.9533E+02	1.6136E+03	6.4762E+02	1.6612E+03	1.1409E+03	9.8311E+02	7.7216E+02	5.9360E+02	9.1979E+02	9.9073E+02	4.5173E+02	6.7430E+02	4.4207E+02	4.5556E+02	**2.7117E+02**
	Best	6.9533E+02	8.9051E+02	3.5952E+02	6.9866E+02	5.0941E+02	3.5611E+02	3.5827E+02	3.5920E+02	4.6840E+02	5.2883E+02	4.2547E+02	4.1657E+02	4.1776E+02	3.4992E+02	**2.3740E+02**
	Mean	6.9533E+02	1.2733E+03	4.6202E+02	1.1030E+03	7.4571E+02	6.1312E+02	5.2396E+02	4.7388E+02	6.3584E+02	6.9336E+02	4.3543E+02	4.6234E+02	4.3093E+02	4.3133E+02	**2.5094E+02**
	SD	**4.6226E-13**	2.2293E+02	4.3589E+01	2.1980E+02	1.6293E+02	1.3814E+02	8.9120E+01	4.8265E+01	1.0789E+02	1.2503E+02	7.1916E+00	5.9424E+01	6.9022E+00	1.8589E+01	6.6273E+00
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	5	14	13	9	8	7	10	11	4	6	2	3	1
30	Worst	3.8103E+03	6.6627E+06	2.6118E+03	5.1721E+04	3.5367E+05	5.8377E+03	2.5591E+03	3.3718E+03	1.5271E+06	2.7585E+03	2.0864E+03	2.2665E+03	2.1584E+03	1.9891E+03	**5.4460E+02**
	Best	3.8103E+03	7.3343E+05	1.9504E+03	7.6357E+03	3.3087E+04	2.0228E+03	1.9549E+03	1.9569E+03	1.4720E+05	1.9798E+03	1.9418E+03	2.0038E+03	1.9552E+03	1.9549E+03	**3.9452E+02**
	Mean	3.8103E+03	2.8161E+06	2.0920E+03	2.5397E+04	1.2384E+05	2.7216E+03	2.1397E+03	2.3250E+03	5.3347E+05	2.2327E+03	1.9866E+03	2.0780E+03	1.9823E+03	1.9688E+03	**4.0709E+02**
	SD	**1.8491E-12**	1.3842E+06	1.3488E+02	1.1439E+04	8.5358E+04	8.0706E+02	1.2062E+02	3.4032E+02	2.7109E+05	1.9207E+02	3.7186E+01	6.6133E+01	3.5999E+01	1.0023E+01	2.8341E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	6	12	13	10	7	9	14	8	4	5	3	2	1
+/=/−		2/0/28 1/0/29 1/0/29 1/0/29 0/1/29	0/0/30 0/0/30 0/0/30 0/0/30 1/0/29	15/1/14 3/1/26 5/1/24 2/1/27	1/0/29 1/0/29 2/0/28 1/0/29	0/0/30 0/0/30 0/0/30 1/0/29	5/0/25 2/0/28 2/0/28 1/0/29	8/1/21 4/1/25 4/1/25 2/0/28	7/0/23 3/0/27 3/0/27 1/1/28	2/0/28 0/0/30 1/0/29 1/0/29	0/0/30 1/0/29 1/0/29 1/0/29	21/1/8 14/1/15 14/2/14 5/1/24	266/3/61	298/3/29	293/4/33	310/3/17

Table S3 The computational results on benchmark functions with 50 variables

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
1	Worst	5.9132E+02	1.7466E+07	4.4016E+03	1.3217E+04	1.3665E+07	2.9184E+02	5.2429E+00	2.9761E+04	7.1335E+08	1.0000E+10	9.9645E-09	2.0858E-08	7.1054E-14	2.8422E-14	**0.0000E+00**
	Best	5.9132E+02	6.7782E+06	1.1511E-12	5.7189E+00	1.0323E+06	3.7774E-02	4.3327E-07	1.5242E+02	3.4155E+08	1.0000E+10	8.0777E-09	4.9837E-11	2.8422E-14	1.4211E-14	**0.0000E+00**
	Mean	5.9132E+02	9.8875E+06	6.0995E+02	2.2344E+03	6.4441E+06	2.3570E+01	7.8411E-01	5.3488E+03	5.1797E+08	1.0000E+10	9.5722E-09	2.6393E-09	4.0799E-14	1.6045E-14	**0.0000E+00**
	SD	**0.0000E+00**	2.3937E+06	1.1382E+03	3.3604E+03	2.7882E+06	5.7583E+01	1.3100E+00	7.2063E+03	9.8548E+07	**0.0000E+00**	4.4344E-10	5.1693E-09	1.2573E-14	4.8427E-15	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	13	9	10	12	7	6	11	14	15	5	4	3	2	1
2	Worst	2.3191E+14	2.2434E+28	5.2757E+01	3.3132E+12	1.8601E+10	5.2625E+19	1.8536E+07	1.0154E+12	1.2276E+37	1.0000E+10	8.4000E+01	1.0340E+43	**6.8781E-12**	1.0000E+00	**0.0000E+00**
	Best	2.3191E+14	6.0539E+19	2.3893E-08	1.7022E+01	2.7781E+04	6.2155E-06	5.2849E+01	1.7613E+02	1.6655E+31	1.0000E+10	**0.0000E+00**	1.3200E+02	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	2.3191E+14	8.9648E+26	6.7646E+00	1.1708E+11	1.7713E+09	1.7000E+18	6.0008E+05	3.2979E+10	1.6073E+36	1.0000E+10	2.7419E+00	3.3355E+41	**2.7872E-13**	3.2258E-02	**0.0000E+00**
	SD	1.5883E-01	4.1148E+27	1.5451E+01	5.9588E+11	4.3007E+09	9.4514E+18	3.3287E+06	1.8234E+11	3.2041E+36	**0.0000E+00**	1.5082E+01	1.8571E+42	1.2280E-12	1.7961E-01	**0.0000E+00**
	BRT	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	0/0/10 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	13	5	10	7	12	6	9	14	8	4	15	2	3	1
3	Worst	8.9506E+02	7.2787E+04	1.1832E-05	3.7329E+03	9.9318E-02	1.4507E+03	1.7168E+03	7.9913E+00	6.9234E+04	4.0870E+03	9.9951E-09	1.6076E-08	6.2528E-13	1.1369E-13	**0.0000E+00**
	Best	8.9506E+02	4.2684E+04	1.9617E-08	2.2324E+01	1.0373E-02	5.5139E-04	1.6721E+02	3.6501E-02	1.8638E+04	3.9094E+02	8.9790E-09	1.0408E-10	1.7053E-13	5.6843E-14	**0.0000E+00**
	Mean	8.9506E+02	5.6429E+04	1.8810E-06	1.1044E+03	3.5225E-02	8.6933E+01	6.6691E+02	1.7613E+00	3.3643E+04	1.3943E+03	9.8033E-09	1.9115E-09	3.8690E-13	5.8677E-14	**0.0000E+00**
	SD	3.4670E-13	7.8953E+03	2.7053E-06	1.0185E+03	2.3644E-02	3.1233E+02	3.1502E+02	2.2250E+00	9.3314E+03	7.7219E+02	2.0945E-10	3.2795E-09	1.1314E-13	1.0209E-14	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	6	12	7	9	10	8	14	13	5	4	3	2	1

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
4	Worst	2.8513E+01	4.1599E+02	1.1401E+02	2.8645E+02	2.2667E+02	1.4911E+02	1.2270E+02	2.2295E+02	3.4715E+02	2.0577E+02	1.4231E+02	1.1402E+02	1.2270E+02	1.4231E+02	**1.1369E-13**
	Best	2.8513E+01	1.2632E+02	1.7916E-08	2.5606E+00	5.0413E+01	2.8513E+01	2.6151E-05	2.5558E+01	1.7555E+02	7.3900E-01	2.7393E-10	2.8513E+01	2.3291E-02	8.0507E+00	**0.0000E+00**
	Mean	2.8513E+01	2.2131E+02	2.1589E+01	1.3956E+02	1.4486E+02	9.1601E+01	2.3839E+01	9.0510E+01	2.5123E+02	8.4842E+01	3.8467E+01	1.0799E+02	7.3723E+01	4.6499E+01	**5.5010E-15**
	SD	**0.0000E+00**	5.6802E+01	3.3091E+01	6.7481E+01	3.9965E+01	4.4293E+01	2.7284E+01	5.4203E+01	4.4928E+01	5.1098E+01	3.0274E+01	2.1392E+01	4.4373E+01	4.0554E+01	2.2522E-14
	BRT	+/+/+/−	−/−/−/−	+/+/+/−	−/−/−/−	−/−/−/−	+/−/−/−	+/+/+/−	+/−/−/−	−/−/−/−	+/−/−/−	+/+/+/−	4/0/6 (+/=/-)	7/0/3 (+/=/-)	7/0/3 (+/=/-)	10/0/0 (+/=/−)
	Rank	4	14	2	12	13	10	3	9	15	8	5	11	7	6	1
5	Worst	2.9053E+02	3.9235E+02	6.7657E+01	3.2535E+02	3.4344E+02	2.1193E+02	2.4774E+02	3.0545E+02	3.6214E+02	3.4425E+02	1.2934E+01	4.9748E+00	1.8428E+01	4.5768E+01	**4.4090E+00**
	Best	2.9053E+02	2.2773E+02	3.1839E+01	1.5621E+02	1.3898E+02	7.7635E+01	1.4228E+02	1.6815E+02	2.6451E+02	1.9103E+02	2.9849E+00	**1.6689E-10**	9.8652E+00	6.9647E+00	5.6550E-01
	Mean	2.9053E+02	2.9964E+02	4.4099E+01	2.3725E+02	2.2145E+02	1.3199E+02	1.9759E+02	2.1703E+02	3.2086E+02	2.5363E+02	6.9104E+00	**1.1233E+00**	1.3881E+01	1.5458E+01	2.9527E+00
	SD	**5.7783E-14**	4.2806E+01	9.4787E+00	3.8381E+01	4.7023E+01	3.1541E+01	2.8254E+01	3.4463E+01	2.4634E+01	4.0425E+01	2.4812E+00	1.2518E+00	1.9975E+00	7.3776E+00	8.8707E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	13	14	6	11	10	7	8	9	15	12	3	1	4	5	2
6	Worst	5.8976E+00	6.7426E+01	3.3834E-02	2.3456E+01	5.2106E+01	2.0102E+00	1.1515E-01	1.1488E+00	3.2257E+01	5.5000E+01	5.8730E-07	7.5329E-04	4.7673E-06	**4.7943E-08**	1.0250E-06
	Best	5.8976E+00	3.8247E+01	7.1067E-06	1.2498E+00	3.1899E+00	6.7283E-03	4.6907E-06	3.9758E-02	9.5233E+00	2.4534E+01	8.5506E-09	1.6179E-08	**0.0000E+00**	1.1369E-13	6.9267E-08
	Mean	5.8976E+00	5.2379E+01	1.6560E-03	1.1826E+01	2.5787E+01	3.2056E-01	1.0035E-02	3.4405E-01	1.7942E+01	3.7520E+01	1.0967E-07	1.2084E-04	8.5700E-07	**1.5467E-09**	4.2819E-07
	SD	**0.0000E+00**	7.3688E+00	6.5415E-03	4.8264E+00	1.3743E+01	3.8704E-01	2.7937E-02	2.5884E-01	5.4511E+00	6.8183E+00	1.3442E-07	2.1823E-04	1.3310E-06	8.6107E-09	2.7789E-07
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/−/+	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	15	6	11	13	8	7	9	12	14	2	5	4	1	3
7	Worst	2.7648E+02	6.9198E+02	4.0078E+02	1.2871E+02	4.3114E+02	2.7800E+02	4.3880E+02	4.0343E+02	5.7560E+02	7.0794E+02	6.0810E+01	5.7779E+01	6.5234E+01	7.6933E+01	**1.6659E+01**
	Best	2.7648E+02	4.0302E+02	7.6658E+01	8.1372E+01	2.0456E+02	1.1108E+02	2.6620E+02	2.4593E+02	4.2353E+02	3.4177E+02	5.4778E+01	5.4021E+01	5.9285E+01	5.7125E+01	**1.2461E+01**
	Mean	2.7648E+02	5.3492E+02	1.6851E+02	9.9406E+01	3.0224E+02	1.7621E+02	3.4930E+02	3.0753E+02	5.0302E+02	5.1413E+02	5.8243E+01	5.5461E+01	6.2097E+01	6.1240E+01	**1.3840E+01**
	SD	**1.1557E-13**	7.9178E+01	1.1988E+02	1.2086E+01	5.4080E+01	3.6637E+01	5.1615E+01	3.9486E+01	3.8310E+01	8.7632E+01	1.5143E+00	8.5916E-01	1.3146E+00	4.0152E+00	8.8333E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	9	15	7	6	10	8	12	11	13	14	3	2	5	4	1
8	Worst	1.5024E+02	3.9305E+02	7.4622E+01	2.9550E+02	3.2163E+02	2.5637E+02	2.6246E+02	3.2137E+02	3.5929E+02	3.1739E+02	1.3929E+01	**3.9798E+00**	1.8065E+01	3.1839E+01	4.8824E+00
	Best	1.5024E+02	2.1956E+02	3.3829E+01	1.9302E+02	1.2538E+02	7.5617E+01	1.5520E+02	1.8904E+02	2.7151E+02	1.6118E+02	2.9849E+00	**3.7357E-10**	9.5643E+00	1.9899E+00	2.2546E+00
	Mean	1.5024E+02	3.0926E+02	4.5126E+01	2.3872E+02	2.2059E+02	1.2251E+02	2.0144E+02	2.3686E+02	3.1504E+02	2.3850E+02	7.7029E+00	**1.7332E+00**	1.4078E+01	1.6392E+01	3.3039E+00
	SD	**2.8892E-14**	4.2805E+01	1.0386E+01	2.8602E+01	5.0860E+01	3.5695E+01	2.6435E+01	3.5371E+01	2.4301E+01	4.2445E+01	2.9734E+00	1.2041E+00	2.4802E+00	6.8191E+00	7.5897E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	8	14	6	13	10	7	9	11	15	12	3	1	4	5	2
9	Worst	1.2791E+03	2.2717E+04	4.4537E+00	2.4047E+03	2.9532E+04	5.7991E+02	9.5194E+03	2.9429E+03	1.5776E+04	1.5429E+04	9.8291E-09	1.2904E+01	1.1369E-13	**0.0000E+00**	**0.0000E+00**
	Best	1.2791E+03	8.9362E+03	6.8212E-13	1.1369E-13	2.5990E+03	1.6539E+01	2.4423E+03	1.6711E+02	4.6993E+03	4.7365E+03	6.1890E-09	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**	**0.0000E+00**
	Mean	1.2791E+03	1.3186E+04	7.8700E-01	7.2757E+02	1.5330E+04	1.4200E+02	6.1304E+03	8.4485E+02	8.2122E+03	8.1233E+03	8.6657E-09	1.2609E+00	1.1002E-13	**0.0000E+00**	**0.0000E+00**
	SD	6.9340E-13	3.1141E+03	9.4947E-01	6.8377E+02	7.5446E+03	1.4072E+02	1.8482E+03	6.1540E+02	2.5506E+03	2.0692E+03	8.3310E-10	2.6086E+00	2.0419E-14	**0.0000E+00**	**0.0000E+00**
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	9	13	4	7	14	6	10	8	12	11	3	5	2	1	1
10	Worst	6.2363E+03	7.3919E+03	1.3357E+04	6.9469E+03	7.3091E+03	8.5245E+03	6.0302E+03	5.3103E+03	8.9732E+03	7.0558E+03	3.8522E+03	5.5959E+02	3.6602E+03	5.3106E+03	3.4056E+02
	Best	6.2363E+03	4.5900E+03	1.1932E+04	3.9480E+03	4.0432E+03	5.1635E+03	4.2434E+03	2.9948E+03	5.4560E+03	3.8934E+03	1.8254E+03	**1.2473E+02**	2.6823E+03	2.8321E+03	**3.9383E+01**
	Mean	6.2363E+03	6.3664E+03	1.2922E+04	5.1222E+03	5.1864E+03	6.5712E+03	4.9233E+03	4.3196E+03	7.0086E+03	5.6491E+03	3.0164E+03	2.2201E+02	3.2244E+03	3.7154E+03	**1.7016E+02**
	SD	**1.8491E-12**	6.5855E+02	3.0992E+02	7.3121E+02	7.5529E+02	1.0135E+03	4.8448E+02	5.9557E+02	8.3426E+02	8.0586E+02	5.1942E+02	1.5904E+02	2.3632E+02	5.9160E+02	9.0233E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	12	15	8	9	13	7	6	14	10	3	2	4	5	1
11	Worst	1.9114E+02	5.0685E+02	4.1149E+01	2.6650E+02	4.6074E+02	3.3153E+02	1.4960E+02	2.4345E+02	5.1025E+02	3.1470E+02	3.2137E+01	2.7163E+01	7.0003E+01	3.7112E+01	3.4605E+00
	Best	1.9114E+02	2.1855E+02	2.0576E+01	1.1693E+02	1.8099E+02	5.9001E+01	5.2094E+01	9.1914E+01	3.2879E+02	1.0857E+02	2.1250E+01	**1.2708E-07**	3.0204E+01	1.9260E+01	**8.1397E-01**
	Mean	1.9114E+02	3.2931E+02	3.0626E+01	1.7056E+02	2.9999E+02	1.6036E+02	9.0863E+01	1.5872E+02	4.1801E+02	1.8236E+02	2.6018E+01	2.2268E+01	4.6749E+01	2.6331E+01	**2.4924E+00**
	SD	**0.0000E+00**	7.5293E+01	4.2334E+00	3.0909E+01	7.0682E+01	6.5652E+01	2.3124E+01	3.6650E+01	5.1968E+01	5.2648E+01	3.3926E+00	4.5238E+00	1.0171E+01	4.3783E+00	6.0479E-01
	BRT	−/−/−/−	−/−/−/−	−/+/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	14	5	10	13	9	7	8	15	11	3	2	6	4	1
12	Worst	4.0275E+05	7.6017E+07	3.0606E+04	5.5551E+07	5.0076E+07	2.5091E+05	2.3194E+05	7.2713E+06	1.1005E+08	1.0000E+10	3.0571E+03	3.9962E+02	3.2751E+03	2.3730E+03	1.2142E+02
	Best	4.0275E+05	5.9073E+06	2.0912E+03	2.3106E+05	6.5030E+05	2.1018E+04	1.9171E+04	1.6319E+05	3.9293E+07	1.0000E+10	1.0112E+03	2.4469E+00	6.8580E+02	5.9173E+02	**5.2493E-01**
	Mean	4.0275E+05	3.1672E+07	9.1904E+03	2.7402E+06	1.1922E+07	1.1139E+05	7.8374E+04	2.0134E+06	6.8092E+07	1.0000E+10	1.9036E+03	8.6095E+01	2.0700E+03	1.4543E+03	**5.7053E+01**
	SD	2.9585E-10	1.8031E+07	6.2426E+03	9.8191E+06	1.0559E+07	5.3088E+04	5.2125E+04	1.6827E+06	1.8838E+07	**0.0000E+00**	5.1330E+02	1.1135E+02	5.5505E+02	4.1175E+02	5.3551E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	9	13	6	11	12	8	7	10	14	15	4	2	5	3	1
13	Worst	4.8584E+03	1.2742E+06	2.0648E+04	4.7133E+04	8.7899E+05	3.8098E+04	1.3096E+03	3.1579E+04	9.7298E+06	1.0000E+10	1.2734E+02	8.7302E+01	1.8480E+02	1.2158E+02	**9.7969E+00**
	Best	4.8584E+03	1.5127E+05	6.1270E+01	1.0433E+04	8.0957E+04	6.3831E+02	2.6048E+02	3.2785E+02	2.1903E+06	1.0000E+10	7.9597E+00	1.2657E+00	1.5764E+01	4.2311E+00	**1.7227E-01**
	Mean	4.8584E+03	4.5789E+05	4.9330E+03	2.1414E+04	2.9439E+05	1.5441E+04	5.7850E+02	5.7439E+03	6.0254E+06	1.0000E+10	3.8020E+01	5.4115E+01	7.0923E+01	3.4582E+01	**3.9945E+00**

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
	SD	**0.0000E+00**	2.1451E+05	5.9740E+03	8.4879E+03	2.0503E+05	1.2357E+04	2.9098E+02	7.6768E+03	1.7194E+06	**0.0000E+00**	2.6622E+01	1.8318E+01	4.1457E+01	2.3659E+01	2.8366E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	7	13	8	11	12	10	6	9	14	15	3	4	5	2	1
14	Worst	6.8205E+04	1.2666E+06	1.5353E+02	6.0380E+04	2.1910E+05	4.3913E+03	1.8314E+02	1.6916E+02	6.1136E+05	3.2134E+02	4.5890E+01	2.2412E+01	3.3425E+01	3.8411E+01	**4.9478E+00**
	Best	6.8205E+04	8.5028E+04	3.0117E+01	7.9899E+03	3.5093E+03	2.6117E+02	7.0927E+01	4.4305E+01	1.6396E+04	1.3864E+02	2.3981E+01	**2.5827E-03**	2.2812E+01	2.3045E+01	4.4824E-01
	Mean	6.8205E+04	4.8014E+05	6.3227E+01	2.6983E+04	6.7614E+04	1.9580E+03	1.1146E+02	1.0375E+02	1.4258E+05	2.0317E+02	3.1947E+01	1.8534E+01	2.7779E+01	3.0098E+01	**2.3803E+00**
	SD	**2.9585E-11**	2.6783E+05	2.9334E+01	1.5464E+04	5.4089E+04	1.1661E+03	2.6056E+01	2.6060E+01	1.2845E+05	4.3822E+01	4.3817E+00	6.3023E+00	2.6520E+00	3.8942E+00	1.4310E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	13	15	6	11	12	10	8	7	14	9	5	2	3	4	1
15	Worst	1.8545E+04	3.5178E+05	1.7619E+02	1.3586E+04	4.1771E+05	3.1203E+04	2.2486E+02	2.8482E+02	1.9821E+06	8.4264E+02	4.2541E+01	1.8418E+01	5.1174E+01	3.1038E+01	**8.9633E-01**
	Best	1.8545E+04	4.8890E+04	2.1502E+01	5.5512E+02	1.0294E+04	5.1990E+01	5.7560E+01	8.3252E+01	1.4304E+05	1.3189E+02	2.2851E+01	1.7266E+01	2.4997E+01	1.9393E+01	**5.9185E-02**
	Mean	1.8545E+04	1.3701E+05	6.9335E+01	8.5696E+03	1.3461E+05	9.5831E+03	1.3333E+02	1.6580E+02	6.2930E+05	4.1051E+02	3.1086E+01	1.7620E+01	3.3732E+01	2.3283E+01	**3.7375E-01**
	SD	**1.1094E-11**	6.9029E+04	3.2951E+01	4.1693E+03	9.9481E+04	9.3788E+03	4.2595E+01	5.3170E+01	4.0785E+05	1.5589E+02	4.8736E+00	4.4267E-01	6.3096E+00	2.5455E+00	2.0601E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	14	6	10	13	11	7	8	15	9	4	2	5	3	1
16	Worst	1.2944E+03	3.4672E+03	8.7040E+02	2.6398E+03	2.4500E+03	2.3280E+03	1.5713E+03	1.4086E+03	1.9380E+03	1.9008E+03	8.0130E+02	9.4242E+02	5.5937E+02	8.7418E+02	**5.5188E+00**
	Best	1.2944E+03	1.3851E+03	5.9600E+00	9.3255E+02	5.1635E+02	4.1968E+02	6.8430E+02	6.5293E+02	5.9132E+02	5.0041E+02	1.3122E+02	1.2598E+02	1.4728E+02	1.2874E+02	**1.0472E+00**
	Mean	1.2944E+03	2.1526E+03	4.4441E+02	1.9544E+03	1.4449E+03	1.1099E+03	1.0780E+03	1.0022E+03	1.2525E+03	1.1137E+03	3.8462E+02	5.5543E+02	3.5222E+02	4.2923E+02	**2.6401E+00**
	SD	**2.3113E-13**	4.7706E+02	2.2391E+02	4.9678E+02	3.7771E+02	4.2706E+02	1.9377E+02	1.9063E+02	3.4012E+02	2.7322E+02	1.5292E+02	2.0875E+02	1.2068E+02	2.0487E+02	1.0932E+00
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/+/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	5	14	13	9	8	7	11	10	3	6	2	4	1
17	Worst	1.0684E+03	2.3929E+03	1.5933E+03	2.3239E+03	1.8538E+03	1.9219E+03	1.0624E+03	9.1384E+02	1.2581E+03	1.6697E+03	4.8126E+02	1.0654E+03	3.9682E+02	5.8260E+02	**7.3732E+00**
	Best	1.0684E+03	1.1028E+03	1.6354E+02	1.2607E+03	3.7036E+02	2.4488E+02	3.5491E+02	2.5912E+02	4.6401E+02	6.3572E+02	1.0180E+02	1.4782E+02	1.1761E+02	5.3871E+01	**1.8948E+00**
	Mean	1.0684E+03	1.6838E+03	5.1746E+02	1.7653E+03	1.2741E+03	8.5487E+02	7.3948E+02	6.4546E+02	8.5811E+02	9.6486E+02	2.9399E+02	5.2709E+02	2.7568E+02	2.4524E+02	**4.4163E+00**
	SD	**2.3113E-13**	3.8724E+02	2.6993E+02	3.1035E+02	3.2082E+02	3.4411E+02	1.8933E+02	1.6829E+02	2.2583E+02	2.2312E+02	1.0708E+02	2.3285E+02	6.5463E+01	1.2898E+02	1.5658E+00
	BRT	−/−/−/−	−/−/−/−	+/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	14	5	15	13	9	8	7	10	11	4	6	3	2	1
18	Worst	4.3412E+04	8.6735E+06	2.3994E+03	8.5900E+07	1.3385E+06	9.6553E+04	1.6512E+04	1.7332E+04	7.6091E+06	2.6757E+04	5.7335E+01	2.1130E+01	5.3321E+01	2.6780E+01	**5.0249E-01**
	Best	4.3412E+04	1.0767E+06	2.3731E+02	3.6962E+04	1.7608E+05	4.9987E+03	8.8157E+02	8.0956E+02	4.2623E+05	1.3390E+03	2.4273E+01	2.0834E+01	2.2661E+01	2.1605E+01	**1.9224E-02**
	Mean	4.3412E+04	3.5807E+06	9.2881E+02	4.2862E+06	4.2687E+05	4.0410E+04	4.3107E+03	5.4558E+03	1.2717E+06	7.6729E+03	3.0899E+01	2.0966E+01	3.3279E+01	2.3591E+01	**2.8793E-01**
	SD	**2.9585E-11**	1.9419E+06	4.9571E+02	1.5711E+07	2.7229E+05	2.6509E+04	3.5682E+03	3.7939E+03	1.3046E+06	6.2027E+03	6.3401E+00	7.4223E-02	6.3797E+00	1.4742E+00	1.5779E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	14	6	15	12	10	7	8	13	9	4	2	5	3	1
19	Worst	2.1851E+04	1.5306E+06	1.6990E+02	3.1805E+04	2.8844E+05	3.9863E+04	8.9091E+01	1.1693E+03	6.6078E+05	2.8469E+02	3.1016E+01	2.8819E+01	2.9058E+01	1.7897E+01	**1.2592E+00**
	Best	2.1851E+04	5.3332E+04	2.1306E+01	7.6032E+03	3.1968E+04	7.5583E+01	3.4896E+01	2.8901E+01	1.4706E+05	7.2114E+01	1.5752E+01	3.7637E+00	1.4231E+01	1.0549E+01	**6.2812E-02**
	Mean	2.1851E+04	6.1942E+05	4.7864E+01	1.6318E+04	9.9837E+04	5.5626E+03	5.6063E+01	1.2878E+02	3.3829E+05	1.5788E+02	2.4924E+01	1.0498E+01	1.9865E+01	1.4484E+01	**2.8575E-01**
	SD	**1.4792E-11**	3.9843E+05	2.7862E+01	6.6402E+03	5.6662E+04	1.0375E+04	1.4089E+01	2.0901E+02	1.3815E+05	4.7438E+01	3.8121E+00	6.1961E+00	3.5504E+00	2.3672E+00	2.6083E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	6	11	13	10	7	8	14	9	5	2	4	3	1
20	Worst	7.6109E+02	1.6535E+03	1.5480E+03	1.9866E+03	1.5815E+03	1.4552E+03	8.1142E+02	8.7050E+02	1.2883E+03	9.9023E+02	3.1005E+02	2.3784E+02	3.8833E+02	2.6671E+02	**3.7560E+00**
	Best	7.6109E+02	7.6201E+02	1.0052E+02	4.9843E+02	2.7254E+02	2.2887E+02	1.7641E+02	1.0706E+02	3.8376E+02	5.3105E+02	5.7606E+01	2.3053E+01	8.4876E+01	3.9307E+01	**2.1730E-01**
	Mean	7.6109E+02	1.1042E+03	6.7578E+02	1.2966E+03	8.9243E+02	7.7594E+02	4.6199E+02	4.7133E+02	6.8819E+02	7.2245E+02	1.4907E+02	3.3428E+01	1.7093E+02	1.0053E+02	**1.7239E+00**
	SD	**3.4670E-13**	2.2653E+02	4.5657E+02	3.5435E+02	2.8849E+02	2.9819E+02	1.8350E+02	1.7153E+02	2.0160E+02	1.1209E+02	7.3798E+01	3.8141E+01	7.4092E+01	7.1755E+01	9.1189E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/−/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	14	8	15	13	12	6	7	9	10	4	2	5	3	1
21	Worst	3.5643E+02	6.5226E+02	2.5392E+02	5.5931E+02	5.4788E+02	4.2058E+02	4.1397E+02	4.1501E+02	5.5296E+02	4.8619E+02	2.2111E+02	2.0698E+02	2.1706E+02	2.6392E+02	**2.0573E+02**
	Best	3.5643E+02	4.3244E+02	2.2931E+02	3.6841E+02	3.3118E+02	2.7530E+02	3.0021E+02	**1.0002E+02**	4.2961E+02	3.2923E+02	2.0300E+02	2.0000E+02	2.0991E+02	2.2094E+02	1.1034E+02
	Mean	3.5643E+02	5.2407E+02	2.4100E+02	4.4573E+02	4.1581E+02	3.2601E+02	3.5166E+02	3.4883E+02	5.0189E+02	3.9774E+02	2.1131E+02	2.0490E+02	2.1300E+02	2.3841E+02	**1.4556E+02**
	SD	**2.3113E-13**	5.2767E+01	6.3669E+00	4.2010E+01	5.7932E+01	3.1191E+01	2.7183E+01	5.1100E+01	2.9868E+01	3.4950E+01	4.5855E+00	1.2545E+00	2.2542E+00	9.0746E+00	3.0229E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	15	6	13	12	7	9	8	14	11	3	2	4	5	1
22	Worst	5.8306E+03	9.4136E+03	1.3778E+04	8.5575E+03	8.8496E+03	8.2594E+03	7.0081E+03	6.2107E+03	2.7387E+02	7.7665E+03	3.5940E+03	**1.0000E+02**	4.0285E+03	4.2597E+03	**1.0007E+02**
	Best	5.8306E+03	1.2335E+02	5.3429E+03	5.5029E+03	1.2348E+02	5.2312E+03	**1.0000E+02**	**1.0000E+02**	2.2107E+02	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**	**1.0000E+02**
	Mean	5.8306E+03	6.8278E+03	1.2685E+04	6.9049E+03	5.6095E+03	6.7457E+03	5.2056E+03	3.4763E+03	2.4482E+02	5.9036E+03	2.1312E+02	**1.0000E+02**	1.8298E+03	1.1035E+03	1.0001E+02
	SD	**2.7736E-12**	1.5554E+03	1.4595E+03	7.4621E+02	1.8023E+03	8.3108E+02	1.5283E+03	2.5946E+03	1.3751E+01	2.0195E+03	6.2747E+02	3.7031E-08	1.7343E+03	1.7332E+03	1.6816E-02
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/−)
	Rank	10	13	15	14	9	12	8	7	4	11	3	1	6	5	2

No.	Algorithms	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	EBCM	HSES	ED-EB	LS-SPA	NLSHADE
23	Worst	5.4363E+02	1.2168E+03	4.8240E+02	1.3747E+03	7.7817E+02	6.8162E+02	6.6639E+02	6.0930E+02	8.2239E+02	8.9854E+02	4.4921E+02	4.4837E+02	4.3819E+02	4.9592E+02	**3.0829E+02**
	Best	5.4363E+02	7.4732E+02	4.3278E+02	7.6902E+02	5.6499E+02	4.9507E+02	5.2648E+02	5.0106E+02	6.7966E+02	6.2920E+02	4.2736E+02	4.0855E+02	4.1857E+02	4.3260E+02	**3.0015E+02**
	Mean	5.4363E+02	9.0058E+02	4.5339E+02	9.9534E+02	6.4470E+02	5.6933E+02	5.9731E+02	5.5613E+02	7.5097E+02	7.2877E+02	4.3699E+02	4.2492E+02	4.2796E+02	4.6201E+02	**3.0391E+02**
	SD	**2.3113E-13**	1.0511E+02	1.1550E+01	1.6019E+02	4.5326E+01	4.1741E+01	3.1471E+01	2.4868E+01	3.7430E+01	6.8634E+01	5.5444E+00	8.5212E+00	4.8736E+00	1.3496E+01	1.9247E+00
	BRT	−/−/−/−	−/−/−/−	−/−/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/−)
	Rank	7	14	5	15	11	9	10	8	13	12	4	2	3	6	1
24	Worst	5.7029E+02	1.1047E+03	5.5721E+02	1.0033E+03	8.3395E+02	7.4216E+02	7.5663E+02	8.0561E+02	9.4708E+02	**1.0036E+03**	5.1503E+02	4.9651E+02	5.1347E+02	5.5071E+02	3.3407E+02
	Best	5.7029E+02	7.8877E+02	5.0690E+02	7.1932E+02	6.3372E+02	5.8118E+02	6.0540E+02	6.2091E+02	7.7698E+02	7.1641E+02	5.0182E+02	4.8628E+02	4.9819E+02	5.1285E+02	**1.4320E+02**
	Mean	5.7029E+02	9.2688E+02	5.2888E+02	8.8067E+02	7.0109E+02	6.2739E+02	6.8087E+02	7.0600E+02	8.3538E+02	8.3790E+02	5.0916E+02	4.8988E+02	5.0461E+02	5.3165E+02	**2.7570E+02**
	SD	**4.6226E-13**	8.8383E+01	1.1809E+01	7.0289E+01	4.8784E+01	3.3759E+01	3.8391E+01	4.4095E+01	4.2836E+01	7.1472E+01	2.9749E+00	2.2723E+00	3.4979E+00	1.0551E+01	5.8522E+01
	BRT	−/−/−/−	−/−/−/−	−/−/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/−)
	Rank	7	15	5	14	10	8	9	11	12	13	4	2	3	6	1
25	Worst	5.5298E+02	6.6410E+02	6.1507E+02	7.0039E+02	5.7888E+02	5.7368E+02	6.1165E+02	6.1660E+02	7.5780E+02	6.1116E+02	5.1889E+02	5.6258E+02	5.6273E+02	4.9184E+02	**4.4580E+02**
	Best	5.5298E+02	5.2305E+02	4.6089E+02	5.6839E+02	4.8062E+02	4.6047E+02	4.6105E+02	4.6265E+02	5.9905E+02	4.6013E+02	4.8024E+02	4.8023E+02	4.7738E+02	4.7736E+02	**3.9774E+02**
	Mean	5.5298E+02	5.8672E+02	5.6852E+02	6.1808E+02	5.3337E+02	5.2923E+02	5.4501E+02	5.4915E+02	6.8656E+02	5.5116E+02	4.8305E+02	5.5142E+02	5.1336E+02	4.8127E+02	**4.2135E+02**
	SD	**4.6226E-13**	3.2092E+01	3.2159E+01	3.3937E+01	2.7166E+01	3.7756E+01	4.1487E+01	3.9286E+01	4.0090E+01	4.8927E+01	7.7253E+00	2.7215E+01	2.5090E+01	3.5545E+00	2.3053E+01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	−/−/−/−	+/−/−/−	+/+/−/−	5/0/5 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	13	12	14	6	5	7	8	15	9	3	10	4	2	1
26	Worst	**3.0000E+02**	9.1066E+03	1.6130E+03	**3.0000E+02**	4.3294E+03	3.1211E+03	4.7576E+03	3.7443E+03	6.1363E+03	7.4009E+03	1.1787E+03	8.4124E+02	1.1974E+03	1.5638E+03	**3.0000E+02**
	Best	**3.0000E+02**	3.1277E+02	**3.0000E+02**	**3.0000E+02**	2.5097E+03	2.0365E+03	**3.0000E+02**	**3.0000E+02**	5.4345E+02	**3.0000E+02**	**3.0000E+02**	4.0000E+02	9.6205E+02	1.0932E+03	**3.0000E+02**
	Mean	**3.0000E+02**	1.3587E+03	1.1064E+03	**3.0000E+02**	3.3302E+03	2.5715E+03	1.8038E+03	4.7348E+02	3.9298E+03	2.2910E+03	7.5380E+02	6.3291E+02	1.1003E+03	1.3412E+03	**3.0000E+02**
	SD	**0.0000E+00**	2.5638E+03	5.3094E+02	2.4117E-13	4.9620E+02	2.9467E+02	1.8323E+03	6.9923E+02	1.8908E+03	2.6239E+03	3.9450E+02	1.5655E+02	5.0786E+01	1.2700E+02	**0.0000E+00**
	BRT	+/+/+/=	−/−/−/−	−/−/+/−	+/+/+/=	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	−/−/−/−	−/−/−/−	−/+/+/−	7/0/3 (+/=/-)	7/0/3 (+/=/-)	6/0/4 (+/=/-)	8/2/0 (+/=/−)
	Rank	1	8	6	1	12	11	9	2	13	10	4	10	5	7	1
27	Worst	6.2780E+02	1.2428E+03	1.0345E+03	2.0519E+03	6.7859E+02	7.6837E+02	7.5313E+02	8.2290E+02	5.0001E+02	1.0672E+03	5.5609E+02	5.9757E+02	5.4255E+02	6.0853E+02	**3.9536E+02**
	Best	6.2780E+02	7.2298E+02	5.1906E+02	1.0401E+03	5.1865E+02	5.5648E+02	5.3332E+02	5.3251E+02	5.0001E+02	6.0152E+02	5.0386E+02	5.3211E+02	4.9193E+02	4.9318E+02	**3.9139E+02**
	Mean	6.2780E+02	9.2748E+02	6.9228E+02	1.4082E+03	5.7286E+02	6.5206E+02	6.0323E+02	6.4638E+02	5.0001E+02	8.3982E+02	5.2396E+02	5.5182E+02	5.1944E+02	5.0939E+02	**3.9386E+02**
	SD	**0.0000E+00**	1.3089E+02	1.4767E+02	2.4582E+02	3.8363E+01	5.1532E+01	5.0124E+01	8.5017E+01	1.4940E-04	1.3776E+02	9.7509E+00	1.3955E+01	1.0273E+01	1.9889E+01	5.7955E-01
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	+/+/+/−	−/−/−/−	+/−/−/−	9/0/1 (+/=/-)	9/0/1 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/−)
	Rank	9	14	12	15	7	11	8	10	2	13	5	6	4	3	1
28	Worst	4.6962E+02	6.4720E+02	5.8882E+02	7.2498E+02	5.3851E+02	5.3339E+02	5.1445E+02	5.9213E+02	5.0001E+02	5.9349E+02	5.0769E+02	5.0770E+02	5.0769E+02	4.5885E+02	**3.0192E+02**
	Best	4.6962E+02	4.8551E+02	4.5493E+02	4.6839E+02	4.6036E+02	4.5414E+02	4.5885E+02	4.5385E+02	4.9951E+02	4.5885E+02	4.5885E+02	4.5885E+02	4.5885E+02	4.5885E+02	**3.0000E+02**
	Mean	4.6962E+02	5.4477E+02	4.9222E+02	5.5913E+02	4.8317E+02	4.8816E+02	4.8058E+02	4.9982E+02	4.9994E+02	4.9049E+02	4.6673E+02	5.0454E+02	4.8046E+02	4.5885E+02	**3.0006E+02**
	SD	**0.0000E+00**	3.4395E+01	3.0565E+01	5.1377E+01	2.4491E+01	2.2435E+01	2.0769E+01	3.5409E+01	9.9750E-02	3.2705E+01	1.8262E+01	1.2198E+01	2.4333E+01	3.4670E-13	3.4502E-01
	BRT	+/+/−/−	−/−/−/−	+/−/−/−	−/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/−/−/−	+/+/−/−	2/0/8 (+/=/-)	9/0/1 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	4	14	10	15	7	8	6	11	12	9	3	13	5	2	1
29	Worst	1.1616E+03	3.1051E+03	7.6190E+02	2.7349E+03	1.8138E+03	1.6262E+03	1.1100E+03	1.2197E+03	1.8036E+03	1.6021E+03	4.1327E+02	3.3982E+02	3.7160E+02	4.2067E+02	**2.8053E+02**
	Best	1.1616E+03	1.4800E+03	3.6949E+02	1.1458E+03	6.9447E+02	4.8926E+02	4.8008E+02	4.1632E+02	6.8210E+02	8.9933E+02	3.3118E+02	3.1055E+02	3.3154E+02	3.2588E+02	**2.4658E+02**
	Mean	1.1616E+03	2.2752E+03	4.9900E+02	1.8766E+03	1.1522E+03	8.5011E+02	7.9762E+02	7.0694E+02	1.1597E+03	1.2102E+03	3.5868E+02	3.2646E+02	3.5450E+02	3.6663E+02	**2.5622E+02**
	SD	**2.3113E-13**	4.4111E+02	1.0782E+02	3.6857E+02	3.0242E+02	2.5197E+02	1.5662E+02	1.6727E+02	2.9044E+02	1.7032E+02	2.3173E+01	7.0689E+00	1.0066E+01	2.2312E+01	7.2847E+00
	BRT	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/+/−	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/-)	10/0/0 (+/=/−)
	Rank	12	15	6	14	10	9	8	7	11	13	4	2	3	5	1
30	Worst	8.4260E+05	3.3030E+07	6.6544E+05	6.9926E+06	7.4694E+06	1.3963E+06	7.9646E+05	1.0296E+06	1.5665E+07	1.0575E+06	7.3316E+05	6.4796E+05	7.3397E+05	6.8056E+05	**4.6436E+02**
	Best	8.4260E+05	1.4326E+07	5.7941E+05	2.5133E+06	3.4910E+06	5.8028E+05	5.7942E+05	5.7986E+05	2.0627E+06	5.7945E+05	5.7941E+05	5.8304E+05	5.7941E+05	5.7941E+05	**3.9453E+02**
	Mean	8.4260E+05	2.3094E+07	5.9983E+05	4.8078E+06	5.0668E+06	7.3343E+05	6.1475E+05	6.5969E+05	8.5683E+06	7.0672E+05	6.1121E+05	5.9933E+05	6.1459E+05	6.1601E+05	**4.0289E+02**
	SD	**1.1834E-10**	4.7030E+06	2.7564E+04	1.0858E+06	1.1145E+06	1.6549E+05	4.6300E+04	8.5484E+04	3.3293E+06	1.2663E+05	3.6169E+04	1.3080E+04	4.1274E+04	2.9292E+04	1.8451E+01
	BRT	−/−/−/−	−/−/−/−	−/+/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/−/+/−	−/−/−/−	−/−/−/−	−/−/−/−	−/+/+/−	10/0/0 (+/=/-)	9/0/1 (+/=/-)	8/0/2 (+/=/-)	10/0/0 (+/=/−)
	Rank	11	15	3	12	13	10	6	8	14	9	4	2	5	7	1
+/=/−		4/0/26 3/0/27 2/0/28 0/1/29	1/0/29 0/0/30 0/0/30 0/0/30	6/0/24 3/0/27 5/0/25 0/0/30	2/0/28 1/0/29 1/0/29 0/1/29	3/0/27 0/0/30 0/0/30 0/0/30	4/0/26 0/0/30 0/0/30 0/0/30	4/0/26 1/0/29 2/0/28 0/0/30	5/0/25 1/0/29 1/0/29 0/0/30	3/0/27 2/0/28 2/0/28 0/0/30	4/0/26 0/0/30 0/0/30 0/0/30	10/0/20 18/0/12 14/0/16 1/0/29	312/0/18	301/0/29	303/0/27	327/2/1

Table S4 Friedman test results of algorithms on the CEC2017 functions

Algorithms	Average ranking on functions with 10 variables	Average ranking on functions with 30 variables	Average ranking on functions with 50 variables
EO	11.0333 (12)	8.1167 (10)	7.95 (7)
MPA	3.85 (1)	7.55 (9)	7.95 (7)
GSK	7.75 (9)	7.3667 (4)	7.95 (7)
MSCA	10.4333 (11)	9.55 (14)	7.95 (7)
IMFO	8.7667 (10)	7.5 (8)	7.95 (7)
MFLA	5.5667 (5)	7.3667 (4)	7.95 (7)
HGSA	12 (13)	8.5333 (12)	7.95 (7)
IGOA	12.4667 (14)	9.0833 (13)	7.95 (7)
SDCS	7.65 (8)	8.25 (11)	7.95 (7)
AO	13.8667 (15)	9.85 (15)	8.1667 (14)
NLSHADE	5.7 (6)	7.3667 (4)	7.95 (7)
EBCM	4.1833 (2)	7.3667 (4)	7.95 (7)
HSES	7.4333 (7)	7.3667 (4)	8.2333 (15)
LS-SPA	4.75 (4)	7.3667 (4)	7.95 (7)
ED-EB	4.55 (3)	7.3667 (4)	7.95 (7)

In Tables S5-S7, the black **bold** numbers indicate p value is less than 0.05.

Table S5 Holm post-hoc non-parametric tests with control algorithm MPA in 10 variables

Algorithm	z	p	Holm
AO	8.674688	**0**	0.003571
IGOA	7.462252	**0**	0.003846
HGSA	7.058107	**0**	0.004167
EO	6.220949	**0**	0.004545
MSCA	5.701334	**0**	0.005
IMFO	6.220949	**0.000021**	0.005556
GSK	3.377499	**0.000731**	0.00625
SDCS	3.290897	**0.000999**	0.007143
HSES	3.103258	**0.001914**	0.008333
NLSHADE	1.602147	0.109123	0.01
MFLA	1.486677	0.1371	0.0125
LS-SPA	0.779423	0.435731	0.016667
ED-EB	0.606218	0.54437	0.025
EBCM	0.288675	0.77283	0.05

Table S6 Holm post-hoc non-parametric tests with control algorithm GSK in 30 variables

Algorithm	z	p	Holm
AO	2.15063	0.031505	0.003571
MSCA	1.890822	0.058648	0.003846

IGOA	1.486677	0.1371	0.004167
HGSA	1.010363	0.312321	0.004545
SDCS	0.764989	0.444278	0.005
EO	0.649519	0.516003	0.005556
MPA	0.158771	0.873849	0.00625
IMFO	0.11547	0.908073	0.007143
MFLA	0	1	0.008333
HSES	0	1	0.01
EBCM	0	1	0.0125
ED-EB	0	1	0.016667
LS-SPA	0	1	0.025
NLSHADE	0	1	0.05

Table S7 Holm post-hoc non-parametric tests with control algorithm EO in 50 variables

Algorithm	z	p	Holm
HSES	0.245374	0.806167	0.003571
MSCA	0.216506	0.828593	0.003846
AO	0.187639	0.85116	0.004167
GSK	0	1	0.004545
HGSA	0	1	0.005
IGOA	0	1	0.005556
IMFO	0	1	0.00625
MFLA	0	1	0.007143
MPA	0	1	0.008333
SDCS	0	1	0.01
EBCM	0	1	0.0125
ED-EB	0	1	0.016667
LS-SPA	0	1	0.025
NLSHADE	0	1	0.05

In Tables S8-S22, R^+ denotes the sum of ranks for the problem in which the first algorithm outperformed the second algorithm, and R^- is the sum of ranks for the opposite condition. In the p-value column, black **bold** numbers indicate p value is less than 0.05, while red **bold** numbers indicate p value is greater than 0.05 and less than 1. If the p-value is less than or equal to 0.05, the null hypothesis is rejected, which means the median of solutions produced by the two algorithms is significantly different.

Table S8 Wilcoxon signed-rank test results for HSES in 10 variables

HSES versus	R^+	R^-	p-value
EO	396.0	69.0	**0.000743**
AO	412.0	53.0	**0.000214**
GSK	216.0	219.0	1
HGSA	384.0	81.0	**0.00177**
IGOA	387.0	78.0	**0.001432**

IMFO	267.0	198.0	**0.471592**
MFLA	144.0	321.0	1
MPA	80.0	385.0	1
MSCA	320.0	145.0	**0.070294**
SDCS	256.0	209.0	**0.62156**
EBCM	53.0	412.0	1
ED-EB	89.0	346.0	1
LS-SPA	100.0	335.0	1
NLSHADE	110.0	325.0	1

Table S9 Wilcoxon signed-rank test results for EBCM in 10 variables

EBCM versus	R^{+}	R^{-}	*p*-value
EO	444.0	21.0	**0.000013**
AO	465.0	0.0	**0.000002**
GSK	388.0	77.0	**0.001334**
HGSA	462.0	3.0	**0.000002**
IGOA	458.0	7.0	**0.000003**
IMFO	436.0	29.0	**0.000027**
MFLA	286.0	179.0	**0.266702**
MPA	171.0	264.0	1
MSCA	416.0	49.0	**0.000154**
SDCS	307.0	158.0	**0.122922**
HSES	412.0	53.0	**0.000214**
ED-EB	282.0	153.0	**0.15987**
LS-SPA	251.0	184.0	**0.462224**
NLSHADE	314.0	121.0	**0.035954**

Table S10 Wilcoxon signed-rank test results for ED-EB in 10 variables

ED-EB versus	R^{+}	R^{-}	*p*-value
EO	447.0	18.0	**0.000009**
AO	465.0	0.0	**0.000002**
GSK	356.0	79.0	**0.00265**
HGSA	440.0	25.0	**0.000019**
IGOA	455.0	10.0	**0.000005**
IMFO	445.5	19.5	**0.000011**
MFLA	279.5	185.5	**0.328571**
MPA	172.0	263.0	1
MSCA	353.0	112.0	**0.012819**
SDCS	287.0	148.0	**0.130121**
HSES	346.0	89.0	**0.005281**
EBCM	153.0	282.0	1
LS-SPA	256.5	178.5	**0.39304**
NLSHADE	293.5	171.5	**0.205888**

Table S11 Wilcoxon signed-rank test results for LS-SPA in 10 variables

LS-SPA versus	R^+	R^-	p-value
EO	454.0	11.0	**0.000005**
AO	465.0	0.0	**0.000002**
GSK	354.0	81.0	**0.003053**
HGSA	440.0	25.0	**0.000019**
IGOA	453.0	12.0	**0.000005**
IMFO	445.5	19.5	**0.000011**
MFLA	290.5	174.5	**0.22888**
MPA	170.0	265.0	1
MSCA	376.0	89.0	**0.003058**
SDCS	296.0	139.0	**0.087593**
HSES	335.0	100.0	**0.010725**
EBCM	184.0	251.0	1
ED-EB	178.5	256.5	1
NLSHADE	295.5	169.5	**0.191522**

Table S12 Wilcoxon signed-rank test results for NLSHADE in 10 variables

NLSHADE versus	R^+	R^-	p-value
EO	439.0	26.0	**0.000021**
AO	465.0	0.0	**0.000002**
GSK	353.0	82.0	**0.003274**
HGSA	440.0	25.0	**0.000019**
IGOA	458.0	7.0	**0.000003**
IMFO	377.5	58.0	**0.000541**
MFLA	189.5	245.5	1
MPA	112.0	323.0	1
MSCA	392.0	73.0	**0.000999**
SDCS	272.0	163.0	**0.234331**
HSES	325.0	110.0	**0.019527**
EBCM	121.0	314.0	1
ED-EB	171.5	293.5	1
LS-SPA	169.5	295.5	1

Table S13 Wilcoxon signed-rank test results for HSES in 30 variables

HSES versus	R^+	R^-	p-value
EO	444.0	21.0	**0.000013**
AO	465.0	0.0	**0.000002**
GSK	230.0	205.0	**0.778632**
HGSA	449.0	16.0	**0.000008**
IGOA	465.0	0.0	**0.000002**
IMFO	436.0	29.0	**0.000027**
MFLA	346.0	89.0	**0.005281**
MPA	375.0	90.0	**0.003269**

MSCA	458.0	7.0	**0.000003**
SDCS	465.0	0.0	**0.000002**
EBCM	100.0	335.0	1
ED-EB	71.0	364.0	1
LS-SPA	160.0	275.0	1
NLSHADE	39.0	426.0	1

Table S14 Wilcoxon signed-rank test results for EBCM in 30 variables

EBCM versus	R^+	R^-	p-value
EO	460.0	5.0	**0.000003**
AO	465.0	0.0	**0.000002**
GSK	378.0	57.0	**0.000499**
HGSA	457.0	8.0	**0.000004**
IGOA	465.0	0.0	**0.000002**
IMFO	457.0	8.0	**0.000004**
MFLA	416.0	19.0	**0.000017**
MPA	431.0	34.0	**0.000043**
MSCA	464.0	1.0	**0.000002**
SDCS	456.0	9.0	**0.000004**
HSES	335.0	100.0	**0.010725**
ED-EB	237.0	198.0	**0.665404**
LS-SPA	256.5	178.5	**0.39304**
NLSHADE	42.0	393.0	1

Table S15 Wilcoxon signed-rank test results for ED-EB in 30 variables

ED-EB versus	R^+	R^-	p-value
EO	460.0	5.0	**0.000003**
AO	465.0	0.0	**0.000002**
GSK	388.0	47.0	**0.000218**
HGSA	449.0	16.0	**0.000008**
IGOA	465.0	0.0	**0.000002**
IMFO	454.0	11.0	**0.000005**
MFLA	386.0	49.0	**0.000258**
MPA	426.0	39.0	**0.000066**
MSCA	465.0	0.0	**0.000002**
SDCS	458.0	7.0	**0.000003**
HSES	364.0	71.0	**0.00148**
EBCM	198.0	237.0	1
LS-SPA	279.5	185.5	**0.328571**
NLSHADE	27.0	408.0	1

Table S16 Wilcoxon signed-rank test results for LS-SPA in 30 variables

LS-SPA versus	R^+	R^-	p-value
EO	460.0	5.0	**0.000003**

AO	465.0	0.0	**0.000002**
GSK	347.0	88.0	**0.004939**
HGSA	448.0	17.0	**0.000009**
IGOA	465.0	0.0	**0.000002**
IMFO	454.0	11.0	**0.000005**
MFLA	385.0	50.0	**0.00028**
MPA	410.0	55.0	**0.000251**
MSCA	461.0	4.0	**0.000002**
SDCS	458.0	7.0	**0.000003**
HSES	275.0	160.0	**0.209789**
EBCM	178.5	256.5	1
ED-EB	185.5	279.5	1
NLSHADE	35.0	430.0	1

Table S17 Wilcoxon signed-rank test results for NLSHADE in 30 variables

NLSHADE versus	R^+	R^-	p-value
EO	435.0	0.0	**0.000002**
AO	463.0	2.0	**0.000002**
GSK	417.0	18.0	**0.000015**
HGSA	460.0	5.0	**0.000003**
IGOA	462.0	3.0	**0.000002**
IMFO	459.0	6.0	**0.000003**
MFLA	450.0	15.0	**0.000007**
MPA	428.0	7.0	**0.000005**
MSCA	463.0	2.0	**0.000002**
SDCS	460.0	5.0	**0.000003**
HSES	426.0	39.0	**0.000066**
EBCM	393.0	42.0	**0.000141**
ED-EB	408.0	27.0	**0.000036**
LS-SPA	430.0	35.0	**0.000047**

Table S18 Wilcoxon signed-rank test results for HSES in 50 variables

HSES versus	R^+	R^-	p-value
EO	414.0	51.0	**0.000182**
AO	435.0	30.0	**0.00003**
GSK	388.0	77.0	**0.001334**
HGSA	425.0	40.0	**0.000072**
IGOA	429.0	36.0	**0.000051**
IMFO	426.0	39.0	**0.000066**
MFLA	420.0	45.0	**0.00011**
MPA	409.0	56.0	**0.000272**
MSCA	431.0	34.0	**0.000043**
SDCS	429.0	36.0	**0.000051**
EBCM	285.0	180.0	**0.275659**

ED-EB	302.0	163.0	0.149929
LS-SPA	286.0	179.0	0.266702
NLSHADE	17.0	448.0	1

Table S19 Wilcoxon signed-rank test results for EBCM in 50 variables

EBCM versus	R^+	R^-	p-value
EO	449.0	16.0	**0.000008**
AO	465.0	0.0	**0.000002**
GSK	429.0	36.0	**0.000051**
HGSA	454.0	11.0	**0.000005**
IGOA	465.0	0.0	**0.000002**
IMFO	465.0	0.0	**0.000002**
MFLA	461.0	4.0	**0.000002**
MPA	448.0	17.0	**0.000009**
MSCA	463.0	2.0	**0.000002**
SDCS	465.0	0.0	**0.000002**
HSES	180.0	285.0	1
ED-EB	332.0	133.0	**0.039702**
LS-SPA	276.0	189.0	0.365462
NLSHADE	4.0	461.0	1

Table S20 Wilcoxon signed-rank test results for ED-EB in 50 variables

ED-EB versus	R^+	R^-	p-value
EO	443.0	22.0	**0.000014**
AO	465.0	0.0	**0.000002**
GSK	412.0	53.0	**0.000214**
HGSA	452.0	13.0	**0.000006**
IGOA	465.0	0.0	**0.000002**
IMFO	465.0	0.0	**0.000002**
MFLA	458.0	7.0	**0.000003**
MPA	445.0	20.0	**0.000012**
MSCA	446.0	19.0	**0.000011**
SDCS	465.0	0.0	**0.000002**
HSES	163.0	302.0	1
EBCM	133.0	332.0	1
LS-SPA	208.0	257.0	1
NLSHADE	0.0	465.0	1

Table S21 Wilcoxon signed-rank test results for LS-SPA in 50 variables

LS-SPA versus	R^+	R^-	p-value
EO	443.0	22.0	**0.000014**
AO	465.0	0.0	**0.000002**
GSK	391.0	74.0	**0.001074**
HGSA	451.0	14.0	**0.000007**

IGOA	465.0	0.0	**0.000002**
IMFO	465.0	0.0	**0.000002**
MFLA	436.0	29.0	**0.000027**
MPA	442.0	23.0	**0.000016**
MSCA	447.0	18.0	**0.00001**
SDCS	465.0	0.0	**0.000002**
HSES	179.0	286.0	1
EBCM	189.0	276.0	1
ED-EB	257.0	208.0	**0.607106**
NLSHADE	3.0	432.0	1

Table S22 Wilcoxon signed-rank test results for NLSHADE in 50 variables

NLSHADE versus	R^{+}	R^{-}	p-value
EO	435.0	0.0	**0.000002**
AO	465.0	0.0	**0.000002**
GSK	465.0	0.0	**0.000002**
HGSA	435.0	0.0	**0.000002**
IGOA	465.0	0.0	**0.000002**
IMFO	465.0	0.0	**0.000002**
MFLA	465.0	0.0	**0.000002**
MPA	465.0	0.0	**0.000002**
MSCA	465.0	0.0	**0.000002**
SDCS	465.0	0.0	**0.000002**
HSES	448.0	7.0	**0.000009**
EBCM	461.0	4.0	**0.000002**
ED-EB	465.0	0.0	**0.000002**
LS-SPA	432.0	3.0	**0.000003**

In Table S23-S24, the numbers without and with brackets are the results of 15 algorithms on the shifted and non-shifted functions, respectively. The **bold** numbers are the better results between any two numbers in the same cell.

Table S23 The mean results of the experiment on the shifted and non-shifted functions with 10 variables

No.	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	HSES	EBCM	ED-EB	LS-SPA	NLSHADE
1	2.3923E+03 **(6.6013E-07)**	1.7606E+05 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	8.9940E+02 **(5.0540E+02)**	6.0933E+03 **(1.3512E-07)**	1.0973E-11 (6.3647E-11)	4.5841E-16 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	2.0705E+06 **(0.0000E+00)**	3.0321E-06 **(0.0000E+00)**	6.2343E-11 (9.3248E-11)	8.0218E-09 **(7.9338E-09)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
2	8.5703E-06 **(8.2948E-07)**	1.5449E+03 **(1.7307E-09)**	9.1683E-16 (9.1683E-16)	1.6683E-05 (1.6999E-05)	1.8111E-04 **(5.1458E-09)**	1.1679E-09 **(1.1662E-09)**	2.2004E-14 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	9.5497E+02 **(8.2857E-10)**	9.9438E+08 **(0.0000E+00)**	3.7922E+05 **(2.7516E+01)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
3	5.6843E-14 **(0.0000E+00)**	1.8254E+00 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	1.2836E-14 (1.6503E-14)	3.4719E-03 **(5.6843E-13)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	1.9589E+01 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	2.3177E-11 **(1.1257E-11)**	8.3224E-09 **(7.4255E-09)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
4	3.2414E+00 **(0.0000E+00)**	6.2187E+00 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	6.3787E-01 **(2.1682E-01)**	2.3489E+00 (3.7512E+00)	9.0496E-03 (1.9448E+00)	8.6771E-11 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	5.5235E+00 **(0.0000E+00)**	2.1454E-13 **(0.0000E+00)**	1.5637E-11 (2.4377E-11)	7.5029E-09 (8.2571E-09)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
5	7.9597E+00 **(0.0000E+00)**	2.3998E+01 **(0.0000E+00)**	1.7740E+01 (1.8540E+01)	1.7075E+01 **(4.9748E+00)**	1.3711E+01 **(2.8238E-13)**	7.5382E+00 **(6.9647E+00)**	6.2882E+00 **(0.0000E+00)**	5.2316E+00 **(1.7011E+00)**	1.6071E+01 **(0.0000E+00)**	7.4698E+00 **(0.0000E+00)**	1.9578E+00 **(1.7652E+00)**	3.3593E-12 (5.2388E-12)	2.5047E+00 **(2.1526E+00)**	3.1157E+00 **(3.8583E-01)**	3.2070E+00 (2.6466E+00)
6	1.1369E-13 **(0.0000E+00)**	1.2006E+01 **(8.9006E-06)**	7.3346E-14 (8.8016E-14)	3.1023E-02 **(4.8264E-05)**	3.8274E-01 **(3.0607E-07)**	0.0000E+00 (3.6673E-15)	7.5278E-09 **(0.0000E+00)**	6.2711E-05 **(0.0000E+00)**	1.1957E+00 **(0.0000E+00)**	8.0336E-02 **(0.0000E+00)**	4.9157E-11 **(3.1568E-11)**	8.6065E-09 **(8.5933E-09)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	6.1987E-09 (4.4010E-09)
7	2.1777E+01 **(1.4497E+01)**	4.6087E+01 **(1.6206E-06)**	2.9837E+01 **(2.9067E+01)**	1.6612E+01 **(6.9334E+00)**	2.2504E+01 **(1.4364E+01)**	1.6078E+01 **(1.5958E+01)**	1.8486E+01 **(0.0000E+00)**	1.6300E+01 **(9.2812E-01)**	2.9538E+01 **(0.0000E+00)**	2.0689E+01 **(0.0000E+00)**	1.3447E+01 (1.4355E+01)	1.0533E+01 (1.0567E+01)	1.2316E+01 **(1.1892E+01)**	1.2530E+01 **(7.5676E+00)**	1.3194E+01 (1.2807E+01)
8	6.9647E+00 **(1.9899E+00)**	2.2854E+01 **(0.0000E+00)**	1.9845E+01 **(1.7921E+01)**	1.0046E+01 **(5.2637E+00)**	1.7502E+01 **(2.2737E-13)**	7.2536E+00 **(7.2215E+00)**	4.6572E+00 **(0.0000E+00)**	5.5525E+00 **(1.0271E+00)**	1.4182E+01 **(0.0000E+00)**	9.2057E+00 **(0.0000E+00)**	8.9867E-01 (1.3159E+00)	9.7551E-13 (1.9627E-11)	2.4412E+00 **(2.1532E+00)**	3.5987E+00 **(6.0982E-01)**	2.8743E+00 (2.4296E+00)
9	1.1369E-13 (1.1369E-13)	5.6851E+01 **(5.9482E-03)**	0.0000E+00 (0.0000E+00)	3.6673E-15 **(0.0000E+00)**	1.5039E-03 (1.7574E-03)	1.4656E-02 **(0.0000E+00)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	7.8557E-01 **(1.2458E-02)**	8.5094E-02 **(0.0000E+00)**	1.9693E-12 (2.2774E-12)	7.1489E-09 (7.8470E-09)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
10	4.5752E+02 **(1.2491E-01)**	7.5558E+02 **(0.0000E+00)**	1.0345E+03 (1.0417E+03)	8.7332E+02 **(2.0344E+02)**	5.0039E+02 **(3.0866E+02)**	2.6865E+02 **(2.4271E+02)**	2.0492E+02 **(0.0000E+00)**	2.5467E+02 **(2.3962E+01)**	3.6643E+02 **(0.0000E+00)**	4.2997E+02 **(0.0000E+00)**	1.2459E+02 **(7.6513E+00)**	4.0516E+01 **(5.1468E+00)**	3.0363E+01 **(9.9925E+00)**	2.1481E+01 **(3.4071E-01)**	1.4771E+02 **(3.5260E+01)**
11	3.0271E+00 **(0.0000E+00)**	5.2549E+01 **(0.0000E+00)**	3.2095E-02 (3.2095E-02)	3.9475E+01 **(7.0068E+00)**	1.0018E+01 **(4.5258E+00)**	1.5868E+00 (1.8988E+00)	9.1498E-01 **(0.0000E+00)**	5.1641E-01 **(0.0000E+00)**	9.3527E+00 **(0.0000E+00)**	9.6741E-01 **(0.0000E+00)**	2.5676E-01 (3.5305E-01)	4.0987E-09 (7.1726E-09)	4.9077E-01 (5.3249E-01)	6.1651E-02 **(0.0000E+00)**	2.5439E+00 (2.2682E+00)

12	4.0160E+03 (2.0692E+04)	2.2284E+06 **(0.0000E+00)**	8.5575E+01 **(6.1919E+01)**	7.7122E+03 **(1.2807E+03)**	2.0835E+04 **(3.8836E+02)**	3.6795E+02 **(3.2969E+02)**	4.6132E+01 **(0.0000E+00)**	2.2771E-02 (5.3797E-02)	2.9872E+05 **(0.0000E+00)**	4.2142E+01 **(1.2002E-10)**	9.7574E+00 (3.8828E+01)	9.3855E+01 **(5.6185E-01)**	2.3348E+01 **(6.3570E-01)**	3.6233E+01 **(3.4243E-01)**	6.2862E+01 **(1.1526E+00)**
13	1.1736E+03 **(3.0700E+00)**	1.5350E+04 **(0.0000E+00)**	5.1682E+00 **(4.6342E+00)**	8.3347E+03 **(4.1322E+02)**	8.5808E+03 **(1.2188E+02)**	5.3955E+00 **(5.0948E+00)**	5.5236E+00 **(0.0000E+00)**	1.5987E+00 **(7.5697E-01)**	1.6794E+03 **(0.0000E+00)**	4.8897E+00 **(7.2864E-06)**	3.4590E+00 (4.6322E+00)	3.2820E+00 **(2.6385E+00)**	3.1584E+00 (4.3793E+00)	2.3989E+00 (4.1453E+00)	2.9995E+00 (4.7396E+00)
14	4.2902E+01 **(2.0970E+00)**	3.0332E+02 **(2.2605E-02)**	2.9449E-01 (9.5066E-01)	5.7309E+02 **(2.5721E+01)**	5.5855E+01 **(6.0229E-07)**	4.9942E+00 **(4.7375E+00)**	1.1071E+00 **(0.0000E+00)**	6.0981E-01 **(2.7353E-01)**	3.9884E+01 **(0.0000E+00)**	1.8622E+00 **(3.3006E-13)**	3.8535E+00 (2.6443E+01)	1.6001E-02 **(8.6571E-03)**	3.0671E-01 **(1.9467E-01)**	1.2838E-01 **(9.6286E-02)**	1.5018E+00 **(9.8091E-01)**
15	1.2048E+02 **(1.1590E+00)**	1.8090E+03 **(8.7862E-02)**	2.0539E-01 (2.8647E-01)	5.9161E+02 **(2.3242E+01)**	3.6295E+01 **(2.4883E+01)**	5.2509E-01 (5.5995E-01)	2.9237E-01 **(1.2640E-04)**	6.0971E-02 **(5.7807E-02)**	4.0530E+01 **(2.0372E-05)**	4.2284E-01 **(1.1337E-04)**	5.9480E-01 **(3.8118E-01)**	2.2551E-01 **(1.9924E-01)**	1.8367E-01 **(1.4697E-01)**	2.4901E-01 (3.1594E-01)	3.2229E-01 (7.1043E-01)
16	3.8612E+01 **(1.9801E-02)**	1.0979E+02 **(3.9261E-06)**	4.4518E+00 (6.2951E+00)	3.5519E+02 **(3.0431E+01)**	2.4299E+02 **(6.5786E+01)**	2.0742E+01 **(4.2854E+00)**	7.0398E-01 **(2.9605E-03)**	6.0838E-01 **(3.0222E-02)**	7.7596E+00 **(3.4099E-06)**	8.2432E+00 **(2.6431E-07)**	7.0804E-01 (7.9798E-01)	4.4826E-01 **(3.4273E-01)**	3.9235E-01 (6.2932E-01)	5.9265E-01 **(3.1218E-01)**	1.9189E+00 (1.6851E+00)
17	3.8846E+01 **(1.3071E+00)**	6.0829E+01 **(0.0000E+00)**	3.1645E+01 **(2.8214E+01)**	1.0201E+02 **(3.2596E+01)**	7.6443E+01 **(3.5691E+01)**	1.4550E+01 **(4.1758E+00)**	5.0576E+00 **(3.6673E-14)**	5.3226E+00 **(6.0750E-02)**	3.1830E+01 **(4.6122E-08)**	3.0617E+01 **(0.0000E+00)**	1.7948E+01 **(3.4987E+00)**	1.5410E-01 **(5.6728E-02)**	1.6366E-01 **(1.2479E-01)**	1.1968E-01 **(1.2877E-02)**	3.0719E+00 (1.7767E+00)
18	3.0419E+03 (5.5050E+03)	2.3639E+04 **(0.0000E+00)**	4.2599E+00 **(2.3206E+00)**	4.9069E+03 **(1.5064E+03)**	1.1628E+04 **(2.5017E+01)**	9.6130E+00 (1.1886E+01)	4.2702E-01 **(3.9721E-04)**	2.0609E-01 **(5.0357E-02)**	6.8867E+03 **(5.4160E-06)**	1.1203E+00 **(5.8444E-05)**	4.8643E-01 (1.0826E+00)	1.0239E+00 **(2.3389E-01)**	2.6178E-01 (2.7311E-01)	9.7625E-01 **(3.7089E-01)**	3.8614E-01 (3.4985E-01)
19	1.0848E+02 **(3.4838E+00)**	4.0988E+03 **(2.2981E-01)**	9.9150E-02 **(7.2070E-02)**	7.4148E+02 **(1.4931E+01)**	1.9878E+01 **(8.4294E-01)**	8.9291E-01 **(5.2821E-01)**	2.1643E-01 **(0.0000E+00)**	5.5260E-02 **(4.7815E-02)**	3.6505E+01 **(0.0000E+00)**	8.7369E-01 **(1.4669E-14)**	3.3298E-01 (2.0653E+00)	1.9350E-02 **(1.7773E-02)**	7.5198E-03 **(3.6067E-03)**	1.7676E-02 (3.2664E-02)	1.1144E-01 (1.0131E-01)
20	1.8029E+01 **(3.1217E-01)**	1.1733E+02 **(0.0000E+00)**	6.5643E+00 **(9.9622E-01)**	1.5701E+02 **(1.8603E+01)**	4.6205E+01 **(1.4986E+01)**	4.7709E+00 (6.2778E+00)	2.3873E-01 **(0.0000E+00)**	3.0317E+00 **(0.0000E+00)**	2.3986E+01 **(0.0000E+00)**	2.1945E+01 **(0.0000E+00)**	1.7278E+01 **(3.0152E+00)**	1.2084E-01 **(8.4047E-09)**	0.0000E+00 (0.0000E+00)	1.3091E-01 **(0.0000E+00)**	9.0668E-01 (5.8422E-01)
21	1.0000E+02 (1.0000E+02)	2.1532E+02 **(1.0000E+02)**	1.7641E+02 **(1.0000E+02)**	2.0863E+02 **(1.0000E+02)**	1.8483E+02 **(1.0000E+02)**	1.6158E+02 **(1.0000E+02)**	1.2102E+02 **(1.0000E+02)**	1.0000E+02 (1.0000E+02)	1.0067E+02 **(1.0000E+02)**	1.0000E+02 (1.0000E+02)	1.9695E+02 **(1.0000E+02)**	1.2969E+02 **(1.0000E+02)**	1.5381E+02 **(1.0000E+02)**	1.0712E+02 **(1.0000E+02)**	1.3913E+02 (1.0000E+02)
22	1.0035E+02 **(1.0000E+02)**	1.0651E+02 **(1.0000E+02)**	1.0017E+02 (1.0877E+02)	1.0057E+02 (1.0853E+02)	1.5509E+02 (3.1295E+02)	9.3890E+01 (3.2674E+02)	9.3848E+01 (1.0000E+02)	8.1629E+01 (1.0000E+02)	1.0831E+02 **(1.0000E+02)**	5.9591E+01 (1.0000E+02)	1.0000E+02 (1.0000E+02)	9.8113E+01 (1.0000E+02)	1.0001E+02 (1.0121E+02)	1.0002E+02 **(1.0000E+02)**	**9.7568E+01** (1.0545E+02)
23	3.1989E+02 (6.1129E+02)	3.3804E+02 **(1.5000E+02)**	3.0854E+02 (6.0755E+02)	3.2892E+02 **(1.5774E+02)**	3.1662E+02 (3.9397E+02)	3.1307E+02 (6.0651E+02)	3.0790E+02 **(1.5154E+02)**	2.9827E+02 (3.3556E+02)	3.1511E+02 **(1.5000E+02)**	3.0953E+02 **(1.5000E+02)**	3.0457E+02 **(1.5000E+02)**	3.0037E+02 (3.7823E+02)	3.0276E+02 (4.1826E+02)	3.0431E+02 **(1.5754E+02)**	3.0393E+02 (4.2117E+02)
24	3.4642E+02 **(1.5000E+02)**	3.2725E+02 **(1.5000E+02)**	3.1601E+02 **(1.5000E+02)**	2.2236E+02 **(1.5000E+02)**	3.2742E+02 **(1.5000E+02)**	3.3615E+02 **(1.5000E+02)**	2.5891E+02 **(1.5000E+02)**	1.0971E+02 (1.5000E+02)	1.4644E+02 (1.5000E+02)	9.6774E+01 (1.5000E+02)	3.2126E+02 **(1.5000E+02)**	1.6042E+02 **(1.5000E+02)**	2.7910E+02 **(1.5000E+02)**	2.9597E+02 **(1.5000E+02)**	2.7286E+02 (1.5000E+02)

25	4.4369E+02 **(3.1377E+02)**	4.2751E+02 (2.0000E+02)	4.1945E+02 **(3.3172E+02)**	4.3636E+02 **(2.9171E+02)**	4.0449E+02 **(2.6207E+02)**	4.2083E+02 **(3.2694E+02)**	4.0098E+02 **(2.0000E+02)**	3.6902E+02 **(2.0000E+02)**	4.0093E+02 **(2.0000E+02)**	3.8324E+02 **(2.0000E+02)**	4.4519E+02 **(3.3952E+02)**	4.1409E+02 **(3.2576E+02)**	4.1718E+02 **(3.3200E+02)**	4.2012E+02 **(2.4264E+02)**	4.1152E+02 (3.3192E+02)
26	4.0118E+02 **(2.0000E+02)**	3.3587E+02 (2.0000E+02)	3.0000E+02 **(2.0000E+02)**	2.8551E+02 **(2.0436E+02)**	4.9759E+02 **(3.1876E+02)**	3.4956E+02 **(2.7721E+02)**	2.8390E+02 **(2.0000E+02)**	2.1613E+02 **(2.0000E+02)**	2.7355E+02 **(2.0000E+02)**	2.5810E+02 **(2.0000E+02)**	3.0000E+02 **(2.0000E+02)**	2.8437E+02 **(2.0000E+02)**	3.0000E+02 **(2.0000E+02)**	3.0000E+02 **(2.0000E+02)**	3.0000E+02 (2.0006E+02)
27	3.9236E+02 (5.4257E+02)	3.9776E+02 **(2.5000E+02)**	3.8948E+02 (5.1025E+02)	4.1877E+02 (4.3537E+02)	3.9969E+02 (5.0342E+02)	3.9002E+02 (5.3140E+02)	3.8938E+02 (4.3563E+02)	3.8893E+02 **(3.8489E+02)**	3.8296E+02 **(2.5733E+02)**	3.8949E+02 **(2.5000E+02)**	3.9773E+02 (5.6593E+02)	3.9066E+02 (4.9336E+02)	3.8943E+02 (5.1993E+02)	3.8940E+02 (4.0324E+02)	3.9401E+02 (5.1965E+02)
28	6.1182E+02 **(2.5000E+02)**	5.3761E+02 (2.5000E+02)	3.0312E+02 **(2.6962E+02)**	5.6565E+02 **(2.5000E+02)**	4.7140E+02 **(3.4307E+02)**	4.4625E+02 **(4.0540E+02)**	3.0000E+02 **(2.5000E+02)**	2.9032E+02 **(2.5000E+02)**	3.4817E+02 **(2.5000E+02)**	3.9053E+02 **(2.5000E+02)**	5.9299E+02 **(2.5000E+02)**	3.1289E+02 **(2.5000E+02)**	3.5673E+02 **(3.3043E+02)**	3.1006E+02 **(2.5000E+02)**	3.0000E+02 (2.5000E+02)
29	4.1337E+02 **(3.1095E+02)**	3.0548E+02 **(1.0004E+02)**	2.4658E+02 (3.3692E+02)	3.3425E+02 (5.0104E+02)	3.1441E+02 (3.7522E+02)	2.4146E+02 (3.1719E+02)	2.4778E+02 (2.9796E+02)	2.3669E+02 (2.7139E+02)	2.6802E+02 **(1.3346E+02)**	2.5937E+02 **(2.0070E+02)**	2.5752E+02 (3.5647E+02)	2.3355E+02 (2.6968E+02)	2.3327E+02 (2.7238E+02)	2.3070E+02 (2.7101E+02)	2.5586E+02 (2.8876E+02)
30	8.1758E+05 **(6.3358E+03)**	2.1092E+05 **(1.0000E+02)**	4.4025E+02 **(3.4667E+02)**	4.1658E+05 **(1.5770E+03)**	3.0903E+05 **(6.8452E+03)**	1.0597E+05 **(2.4030E+03)**	4.0990E+02 **(1.9084E+02)**	3.9689E+02 **(1.3919E+02)**	2.7729E+03 **(1.0338E+02)**	4.0705E+02 **(1.1085E+02)**	4.1301E+02 **(1.1661E+02)**	4.0574E+02 **(2.3786E+02)**	2.6758E+04 **(2.5815E+02)**	5.3122E+04 **(3.4816E+02)**	4.0446E+02 (3.3561E+02)

Table S24 The mean results of the experiment on the shifted and non-shifted functions with 30 variables

No.	EO	AO	GSK	HGSA	IGOA	IMFO	MFLA	MPA	MSCA	SDCS	HSES	EBCM	ED-EB	LS-SPA	NLSHADE
1	1.1285E+01 **(0.0000E+00)**	2.8983E+06 **(0.0000E+00)**	5.5468E-14 (1.1506E-13)	3.2012E+03 **(6.2560E+02)**	8.1083E+05 **(1.7817E-07)**	5.0255E-11 (6.2404E-11)	3.2547E-14 **(0.0000E+00)**	6.6689E+03 **(0.0000E+00)**	9.0374E+07 **(0.0000E+00)**	1.0000E+10 **(0.0000E+00)**	3.2484E-10 (3.2784E-10)	9.1231E-09 **(8.9512E-09)**	3.2089E-15 **(2.2921E-15)**	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
2	1.0691E+05 **(3.5142E-07)**	6.8824E+14 **(9.4739E-16)**	4.0198E-10 (4.4152E-10)	1.9093E+20 **(4.5594E-05)**	7.9661E+02 **(8.7842E-09)**	3.0610E-06 (4.1786E-06)	3.5306E-01 **(3.6673E-15)**	1.7845E+01 **(0.0000E+00)**	3.6297E+16 **(9.9773E-10)**	1.0000E+10 **(0.0000E+00)**	4.7968E+01 **(4.2710E+01)**	0.0000E+00 (0.0000E+00)	2.7505E-15 (2.7505E-15)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
3	4.3356E-01 **(0.0000E+00)**	6.5346E+03 **(0.0000E+00)**	3.9057E-13 (3.9790E-13)	1.7080E+01 **(2.3104E-13)**	2.3701E-02 **(2.8367E-12)**	2.4569E-01 (3.9461E-01)	6.7151E-03 **(0.0000E+00)**	6.1306E-04 **(0.0000E+00)**	1.1616E+04 **(0.0000E+00)**	3.6964E+00 **(0.0000E+00)**	3.7603E-10 **(3.3095E-10)**	9.0638E-09 **(8.9682E-09)**	4.4008E-14 (4.4008E-14)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
4	6.6449E+01 **(0.0000E+00)**	1.1948E+02 **(0.0000E+00)**	8.5144E+00 **(9.1838E-02)**	8.6017E+01 **(8.1588E-01)**	9.1248E+01 **(5.4638E+00)**	4.9144E+01 **(1.6739E+01)**	1.8880E+01 **(0.0000E+00)**	4.7329E+01 **(0.0000E+00)**	1.2232E+02 **(0.0000E+00)**	2.6639E+01 **(0.0000E+00)**	1.3727E+01 **(9.4228E-01)**	5.8562E+01 **(3.2750E-09)**	5.8920E+01 **(2.4084E-03)**	5.8562E+01 **(1.6808E-05)**	0.0000E+00 (0.0000E+00)
5	1.0746E+02 **(1.5919E+01)**	1.5408E+02 **(0.0000E+00)**	7.5676E+01 **(6.3275E+01)**	1.1038E+02 **(1.9835E+01)**	9.7120E+01 **(1.9804E-13)**	5.5638E+01 **(4.9973E+01)**	7.7045E+01 **(0.0000E+00)**	8.3747E+01 **(0.0000E+00)**	1.3380E+02 **(0.0000E+00)**	9.7460E+01 **(0.0000E+00)**	1.6773E+01 **(1.4496E+01)**	1.8318E+00 **(9.5439E-01)**	6.8204E+00 **(5.1290E+00)**	2.0023E+01 **(4.4614E+00)**	2.7907E+00 (3.0238E+00)
6	9.9901E-01	3.8304E+01	9.2602E-06	4.5564E+00	5.3257E+00	2.3766E-02	2.9368E-06	3.5313E-03	7.6872E+00	1.8518E+01	1.0677E-01	9.2814E-09	5.5192E-09	1.2102E-13	4.4384E-07

	(1.1369E-13)	**(0.0000E+00)**	**(5.9273E-06)**	**(5.2999E-04)**	**(2.2231E-07)**	**(4.9009E-03)**	**(0.0000E+00)**	**(0.0000E+00)**	**(0.0000E+00)**	**(0.0000E+00)**	**(1.0635E-13)**	(1.4081E-08)	**(1.1369E-13)**	**(1.1369E-13)**	(1.8707E-07)
7	9.5540E+01 **(1.2491E+01)**	2.6675E+02 **(0.0000E+00)**	1.7190E+02 **(1.2168E+02)**	5.5062E+01 **(2.4752E+01)**	1.2288E+02 **(1.7446E+01)**	7.9873E+01 (8.0349E+01)	1.3807E+02 **(0.0000E+00)**	1.1756E+02 **(0.0000E+00)**	2.3953E+02 **(0.0000E+00)**	1.9778E+02 **(0.0000E+00)**	4.9913E+01 **(2.2132E+01)**	3.3455E+01 **(3.2312E+01)**	3.6883E+01 **(3.6649E+01)**	3.9201E+01 **(7.3648E+00)**	1.2978E+01 (1.3203E+01)
8	7.1637E+01 **(0.0000E+00)**	1.3110E+02 **(0.0000E+00)**	7.2131E+01 **(6.3510E+01)**	8.7813E+01 **(1.8166E+01)**	1.0307E+02 **(3.3739E-13)**	5.5677E+01 **(4.8881E+01)**	7.1114E+01 **(0.0000E+00)**	8.1683E+01 **(0.0000E+00)**	1.1235E+02 **(0.0000E+00)**	8.8565E+01 **(0.0000E+00)**	1.5493E+01 **(1.3191E+01)**	2.3916E+00 **(9.9496E-01)**	7.1376E+00 **(5.6887E+00)**	1.2552E+01 **(4.2687E+00)**	3.1281E+00 (3.0068E+00)
9	5.6511E+01 **(8.9528E-02)**	3.4079E+03 **(2.8966E-01)**	1.7544E-02 **(2.8880E-03)**	1.2886E+01 **(1.1002E-13)**	2.8048E+03 **(5.6553E-03)**	3.9909E+00 (5.1492E+00)	7.7105E+02 **(6.9312E-02)**	9.2996E+01 **(2.6284E-01)**	5.1187E+02 **(6.3684E-01)**	1.6940E+03 **(2.6858E-01)**	1.4656E-02 (2.9311E-02)	8.6584E-09 (8.7967E-09)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)	0.0000E+00 (0.0000E+00)
10	2.2817E+03 **(0.0000E+00)**	3.9886E+03 **(0.0000E+00)**	6.7873E+03 **(6.3815E+03)**	3.1372E+03 **(1.1429E+03)**	2.9500E+03 **(3.1205E+02)**	3.3130E+03 (3.3320E+03)	2.4630E+03 **(0.0000E+00)**	2.1958E+03 **(1.6582E+02)**	3.4763E+03 **(0.0000E+00)**	3.7032E+03 **(0.0000E+00)**	1.3873E+03 **(3.8121E+02)**	1.5317E+03 **(6.9146E+02)**	1.3845E+03 **(1.1574E+03)**	1.6378E+03 **(6.7103E+01)**	1.3622E+02 **(3.2311E+01)**
11	1.1309E+02 **(5.9698E+00)**	2.1987E+02 **(0.0000E+00)**	9.7692E+00 **(5.4241E+00)**	1.2273E+02 **(1.3718E+01)**	1.6096E+02 **(3.7506E+00)**	6.5291E+01 **(4.1929E+01)**	2.9723E+01 **(0.0000E+00)**	5.4599E+01 **(0.0000E+00)**	1.3231E+02 **(0.0000E+00)**	6.8872E+01 **(0.0000E+00)**	1.8511E+01 **(7.2857E+00)**	3.2436E+00 **(1.8294E+00)**	1.2426E+01 **(8.6615E+00)**	7.2410E+00 **(8.6658E-01)**	2.5731E+00 (1.9772E+00)
12	6.0188E+04 **(0.0000E+00)**	9.3119E+06 **(0.0000E+00)**	6.6910E+03 **(1.1215E+03)**	2.3599E+05 **(2.9703E+04)**	2.0815E+06 **(3.9151E+02)**	1.7175E+04 **(1.2693E+04)**	8.2644E+03 **(0.0000E+00)**	5.6572E+04 **(3.7982E-08)**	1.0835E+07 **(0.0000E+00)**	2.5807E+09 **(0.0000E+00)**	4.3119E+00 (1.0630E+02)	4.6584E+02 **(4.4660E+02)**	8.7528E+02 **(4.8997E+02)**	2.6106E+02 (3.7533E+02)	7.0973E+01 **(4.3375E-01)**
13	1.6582E+04 **(1.2846E+01)**	1.8666E+05 **(0.0000E+00)**	3.3254E+01 (5.9187E+01)	2.7447E+04 **(2.3111E+03)**	1.6101E+05 **(6.4500E+02)**	4.5204E+03 (1.3067E+04)	7.7373E+01 **(0.0000E+00)**	9.3128E+01 **(2.0287E+00)**	7.9364E+05 **(0.0000E+00)**	2.1364E+02 **(0.0000E+00)**	4.5852E+01 (5.1840E+01)	1.4669E+01 **(8.7612E+00)**	1.6800E+01 **(1.2328E+01)**	1.5734E+01 **(1.2785E+01)**	2.8908E+00 (5.1572E+00)
14	1.1209E+03 **(1.0977E+02)**	1.0880E+05 **(0.0000E+00)**	2.6509E+01 **(2.2802E+01)**	5.2795E+03 **(1.0372E+03)**	6.7757E+03 **(4.6499E-07)**	6.6292E+01 (6.7035E+01)	4.2997E+01 **(0.0000E+00)**	3.5160E+01 **(8.3063E+00)**	5.4721E+03 **(0.0000E+00)**	5.4375E+01 **(0.0000E+00)**	1.6601E+01 **(8.8364E+00)**	2.2880E+01 **(7.3651E+00)**	1.8983E+01 **(3.6266E+00)**	2.1847E+01 **(1.7678E+00)**	1.4157E+00 **(8.6023E-01)**
15	2.4238E+03 **(3.2810E-03)**	7.7242E+04 **(1.1245E-08)**	7.4150E+00 (8.2856E+00)	4.7321E+03 **(8.4026E+02)**	6.3608E+04 **(1.5921E+01)**	1.2858E+02 **(9.9285E+01)**	2.6592E+01 **(4.2309E-05)**	3.4047E+01 **(7.8230E+00)**	3.5836E+04 **(3.5947E-06)**	7.1902E+01 **(1.5556E-08)**	2.5033E+01 **(1.5809E+01)**	3.8664E+00 **(3.0472E+00)**	2.5831E+00 (2.6108E+00)	1.5283E+00 **(1.3770E+00)**	**3.7734E-01** (5.7461E-01)
16	2.1248E+02 **(2.5822E-01)**	1.2782E+03 **(3.2972E-04)**	2.8432E+02 **(8.5279E+01)**	1.1848E+03 **(6.1179E+02)**	7.1316E+02 **(6.7271E+01)**	5.1464E+02 **(4.4310E+02)**	4.4323E+02 **(9.0653E-03)**	4.5707E+02 **(7.7993E+00)**	6.8482E+02 **(7.8624E-06)**	5.7206E+02 **(5.8533E-10)**	3.9912E+02 **(3.1649E+01)**	3.5253E+01 **(1.0118E+01)**	4.4886E+01 **(1.7626E+01)**	4.8955E+01 **(7.2156E+00)**	2.4564E+00 (1.7171E+00)
17	4.3145E+02 **(3.7197E+01)**	5.3871E+02 **(0.0000E+00)**	5.0054E+01 **(3.3308E+01)**	9.7875E+02 **(2.2500E+02)**	4.4216E+02 **(3.1522E+01)**	2.0266E+02 **(1.6483E+02)**	9.3878E+01 **(4.6942E-13)**	8.5959E+01 **(5.5475E-02)**	1.4153E+02 **(0.0000E+00)**	1.4686E+02 **(0.0000E+00)**	3.7452E+01 **(1.5560E+01)**	3.2521E+01 **(1.4668E+01)**	3.3750E+01 **(2.0756E+01)**	3.0740E+01 **(1.4315E+01)**	3.0897E+00 (2.0713E+00)
18	4.4424E+04 **(2.7606E+03)**	1.2200E+06 **(5.9069E-08)**	5.9042E+01 **(4.4629E+01)**	5.8655E+04 **(8.0990E+03)**	2.5215E+05 **(6.1861E+01)**	1.4682E+04 (1.9388E+04)	5.3931E+01 **(4.0132E-06)**	4.0671E+01 **(2.3347E+01)**	1.2526E+05 **(1.7317E-05)**	1.1019E+02 **(1.4669E-13)**	2.1502E+01 **(3.6643E+00)**	2.1982E+01 **(1.4900E+01)**	2.0879E+01 **(8.0457E+00)**	2.1539E+01 **(7.8479E+00)**	3.5365E-01 (3.2167E-01)
19	2.8907E+03	3.4997E+05	8.2575E+00	3.9224E+03	2.6156E+04	4.8531E+01	1.8374E+01	1.3863E+01	5.3401E+04	3.8565E+01	4.7966E+00	9.4791E+00	5.9375E+00	4.2613E+00	1.2110E-01

	(1.6845E+01)	**(0.0000E+00)**	(8.6084E+00)	**(4.7538E+02)**	**(1.5011E+00)**	(4.9551E+01)	**(0.0000E+00)**	**(4.7954E+00)**	**(0.0000E+00)**	**(0.0000E+00)**	(9.4159E+00)	**(6.1708E+00)**	**(3.4877E+00)**	**(2.7297E+00)**	**(9.9884E-02)**
20	5.7178E+02	4.3365E+02	6.3337E+01	9.0482E+02	4.0653E+02	1.7996E+02	1.3384E+02	1.1050E+02	2.2952E+02	2.4394E+02	1.9921E+02	4.0733E+01	3.5759E+01	2.5863E+01	7.2373E-01
	(3.0146E+01)	**(1.5073E-10)**	**(4.4279E+01)**	**(1.5915E+02)**	**(2.1754E+01)**	**(1.1139E+02)**	**(0.0000E+00)**	**(4.7323E+00)**	**(2.5021E-10)**	**(0.0000E+00)**	**(1.8563E+01)**	**(2.0054E+01)**	**(3.5562E+01)**	**(2.4033E+00)**	(5.0227E-01)
21	2.6977E+02	3.3113E+02	2.4778E+02	3.1040E+02	3.0191E+02	2.5703E+02	2.6049E+02	2.1339E+02	2.1024E+02	2.5776E+02	2.2026E+02	1.9945E+02	2.0629E+02	2.2110E+02	1.3899E+02
	(1.0000E+02)	**(1.0000E+02)**	**(1.8636E+02)**	**(1.0000E+02)**	**(1.0000E+02)**	(2.9972E+02)	**(1.0000E+02)**	**(1.0000E+02)**	**(1.0000E+02)**	**(1.0000E+02)**	**(2.0998E+02)**	**(1.2441E+02)**	**(1.7073E+02)**	**(1.3753E+02)**	(1.0000E+02)
22	3.5664E+03	1.1451E+02	1.0000E+02	2.2336E+02	2.1758E+03	3.2716E+03	1.0000E+02	1.0213E+02	1.4028E+02	1.0035E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0000E+02	1.0001E+02
	(1.0000E+02)	**(1.0000E+02)**	(1.8658E+02)	(3.3379E+02)	**(3.9161E+02)**	**(3.1967E+03)**	(1.0000E+02)	**(1.0000E+02)**	**(1.0000E+02)**	**(1.0000E+02)**	(1.2470E+02)	(1.1732E+02)	(1.1852E+02)	(1.2504E+02)	(1.0221E+02)
23	4.2826E+02	5.3888E+02	3.6081E+02	5.4772E+02	4.3632E+02	4.1528E+02	4.1497E+02	3.5754E+02	4.6048E+02	4.4819E+02	3.7497E+02	3.5132E+02	3.4739E+02	3.6707E+02	3.0404E+02
	(1.6777E+03)	**(1.5000E+02)**	(1.7607E+03)	**(4.9275E+02)**	**(4.0874E+02)**	(1.6197E+03)	**(2.8272E+02)**	(8.9332E+02)	**(1.5000E+02)**	**(1.5000E+02)**	**(2.9044E+02)**	(9.2818E+02)	(1.1025E+03)	(6.7972E+02)	(4.3029E+02)
24	4.8356E+02	6.0548E+02	4.3419E+02	5.1333E+02	5.1766E+02	4.8199E+02	4.9021E+02	5.0638E+02	5.4501E+02	5.3343E+02	4.3397E+02	4.2537E+02	4.2321E+02	4.4177E+02	2.7025E+02
	(1.5000E+02)	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	**(1.5000E+02)**	(1.5000E+02)
25	4.4120E+02	3.9950E+02	3.8728E+02	4.0193E+02	3.8694E+02	3.8667E+02	3.8593E+02	3.9333E+02	3.9631E+02	3.8750E+02	3.8675E+02	3.8652E+02	3.8678E+02	3.8670E+02	4.2260E+02
	(3.8973E+02)	**(2.0000E+02)**	**(3.6606E+02)**	**(3.6398E+02)**	**(2.7948E+02)**	**(3.7796E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(3.7196E+02)**	**(3.6957E+02)**	**(3.7129E+02)**	**(3.7089E+02)**	(3.2708E+02)
26	1.5341E+03	1.2196E+03	9.2647E+02	4.5285E+02	1.9615E+03	1.6864E+03	7.2268E+02	3.0000E+02	2.2633E+03	1.1651E+03	9.8926E+02	5.2295E+02	8.8883E+02	1.0696E+03	3.0000E+02
	(2.0000E+02)	**(2.0000E+02)**	**(2.3439E+02)**	**(3.9518E+02)**	**(4.2989E+02)**	**(1.4943E+03)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	**(2.0000E+02)**	(2.0026E+02)
27	5.2954E+02	5.7093E+02	4.9862E+02	6.3226E+02	5.1072E+02	5.1382E+02	5.0750E+02	5.1235E+02	5.0001E+02	5.2852E+02	5.1066E+02	5.0369E+02	4.9630E+02	4.9725E+02	3.9404E+02
	(8.4499E+02)	**(2.5000E+02)**	(8.4670E+02)	(1.1294E+03)	(5.2320E+02)	(8.4458E+02)	(7.3865E+02)	(7.9122E+02)	**(3.1452E+02)**	**(2.5000E+02)**	(8.9761E+02)	(8.4400E+02)	(7.6882E+02)	(8.3163E+02)	(5.2933E+02)
28	3.0000E+02	4.5270E+02	3.0000E+02	3.2063E+02	4.2702E+02	3.8812E+02	3.1516E+02	3.1635E+02	4.9952E+02	3.4148E+02	3.2034E+02	3.1366E+02	3.1769E+02	3.2470E+02	3.0000E+02
	(2.5000E+02)	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5001E+02)**	**(3.3475E+02)**	(5.1745E+02)	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	**(2.5000E+02)**	(2.5000E+02)
29	6.9533E+02	1.2733E+03	4.6202E+02	1.1030E+03	7.4571E+02	6.1312E+02	5.2396E+02	4.7388E+02	6.3584E+02	6.9336E+02	4.6234E+02	4.3543E+02	4.3093E+02	4.3133E+02	2.5094E+02
	(1.0819E+03)	**(2.2312E+02)**	(7.2403E+02)	(1.5576E+03)	**(3.5392E+02)**	(8.0465E+02)	(8.3642E+02)	(7.4149E+02)	**(3.1084E+02)**	(8.1844E+02)	(9.1338E+02)	(6.4144E+02)	(6.5517E+02)	(6.4784E+02)	(2.8669E+02)
30	3.8103E+03	2.8161E+06	2.0920E+03	2.5397E+04	1.2384E+05	2.7216E+03	2.1397E+03	2.3250E+03	5.3347E+05	2.2327E+03	2.0780E+03	1.9866E+03	1.9823E+03	1.9688E+03	4.0709E+02
	(3.5256E+02)	**(1.0000E+02)**	**(5.6416E+02)**	**(6.8734E+03)**	**(4.0020E+03)**	(1.0408E+04)	**(1.0000E+02)**	**(1.2512E+02)**	**(1.1044E+02)**	**(1.0000E+02)**	**(2.7250E+02)**	**(3.7443E+02)**	**(4.0864E+02)**	**(4.0405E+02)**	(2.6007E+02)

Convergence plots of 15 algorithms on functions F1, F3, F4, F10, F11, F19, F21, and F24

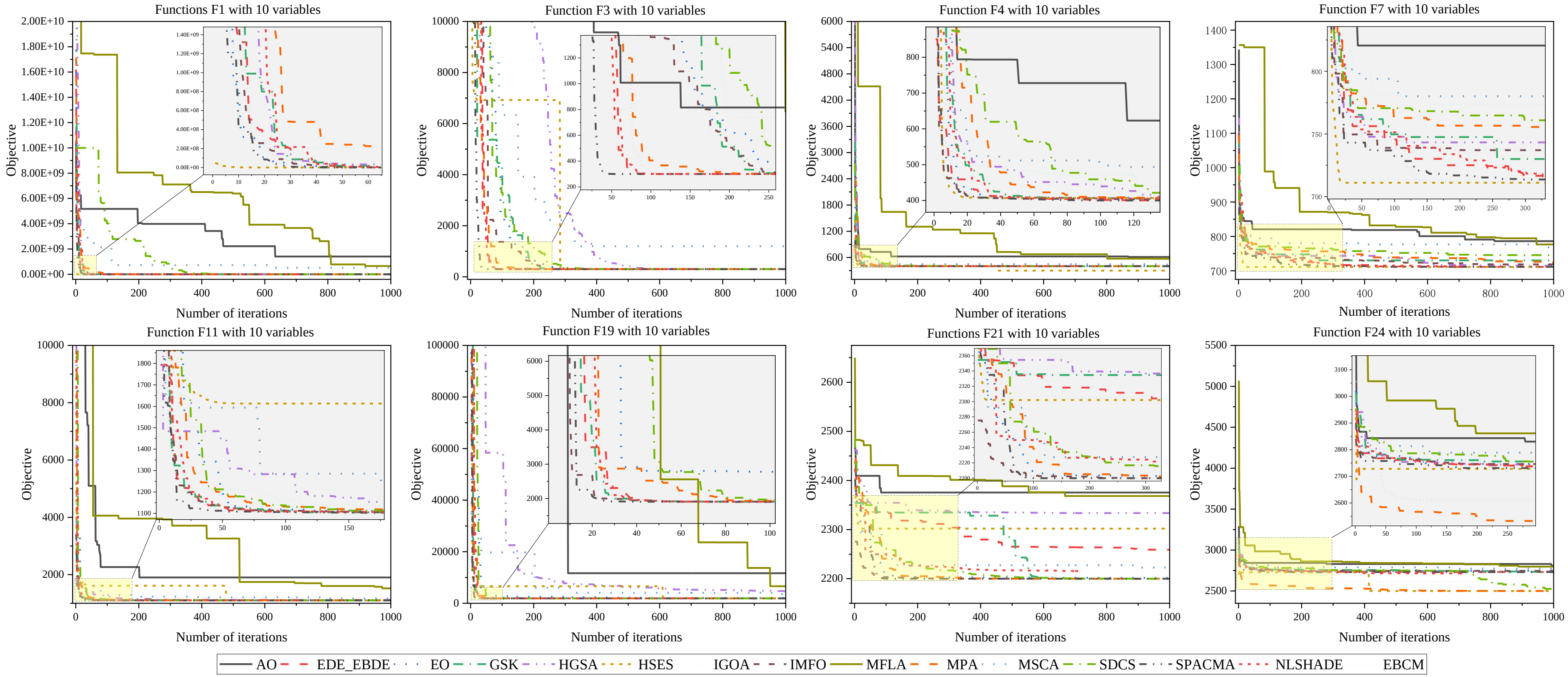


Fig.S4 Convergence plots on functions with 10 variables

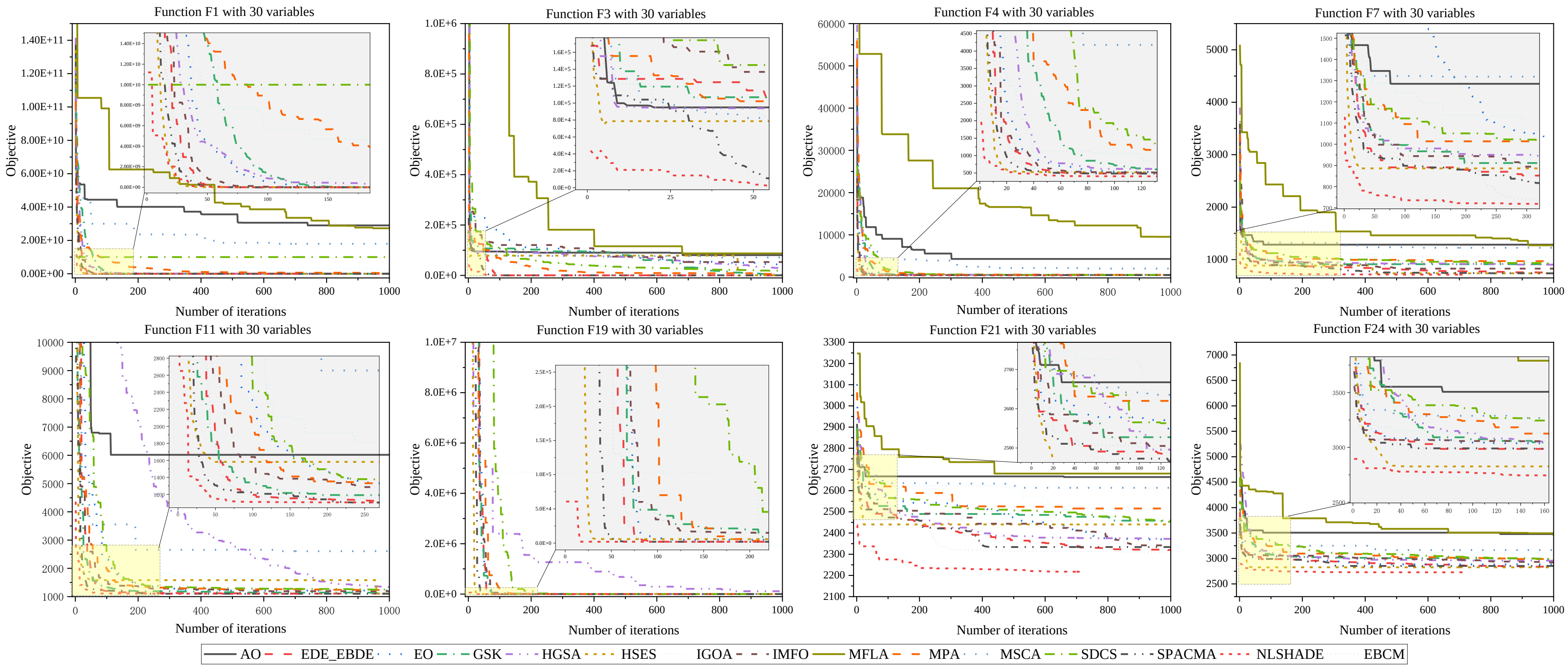


Fig.S5 Convergence plots on functions with 30 variables

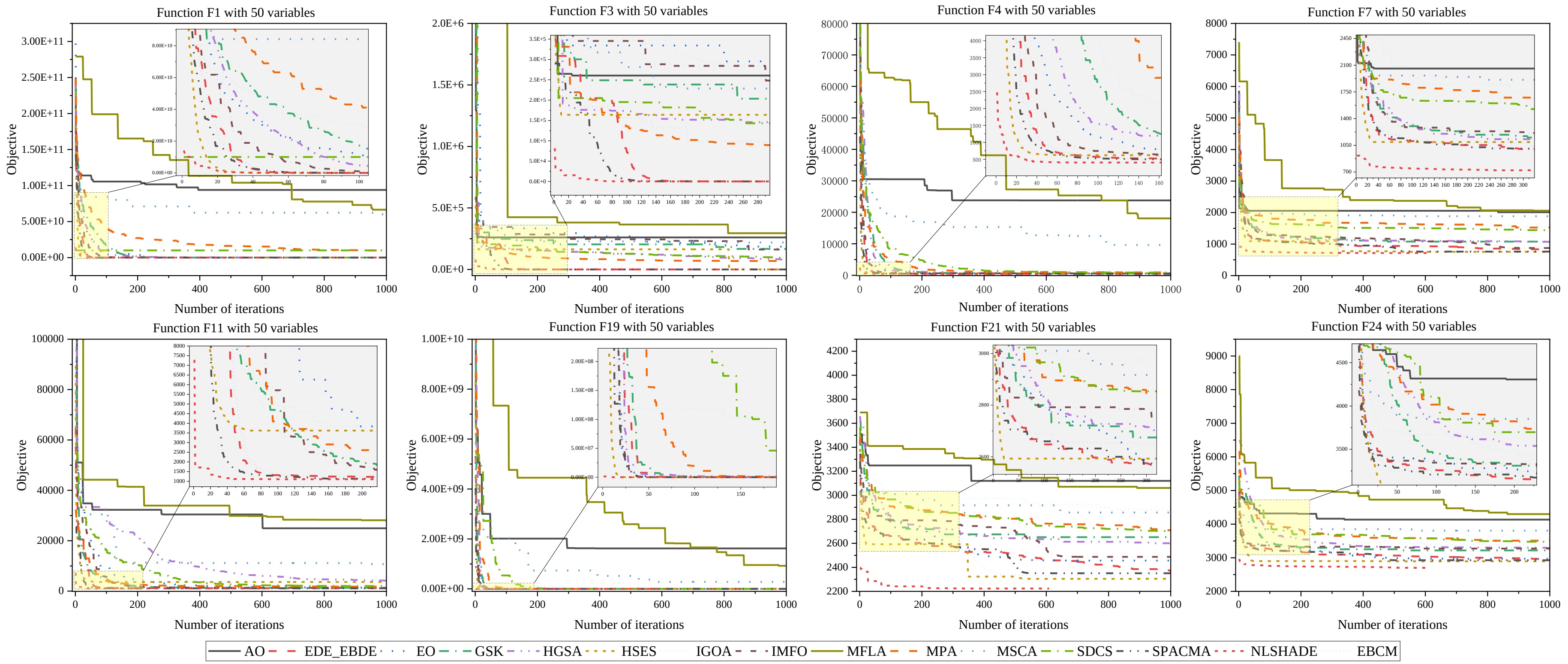
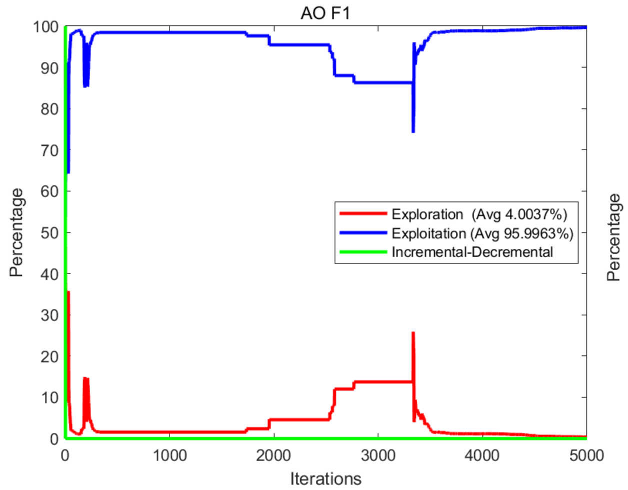
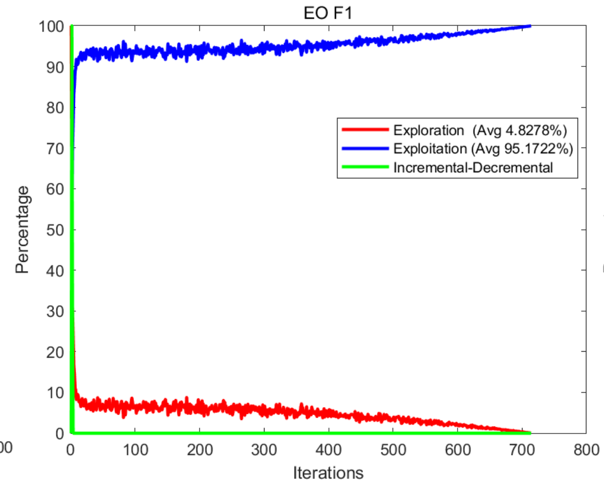


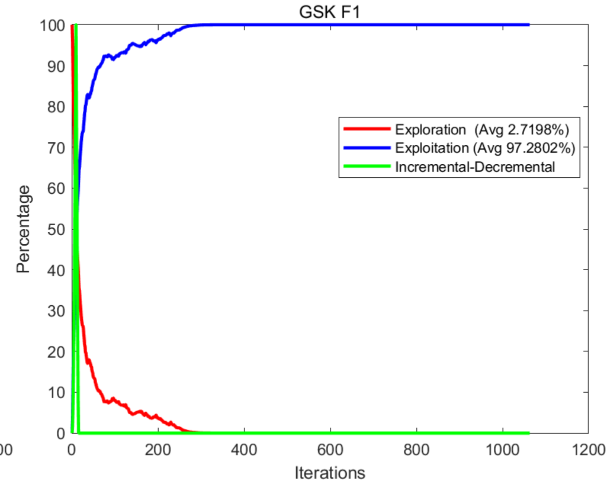
Fig.S6 Convergence plots on functions with 50 variables

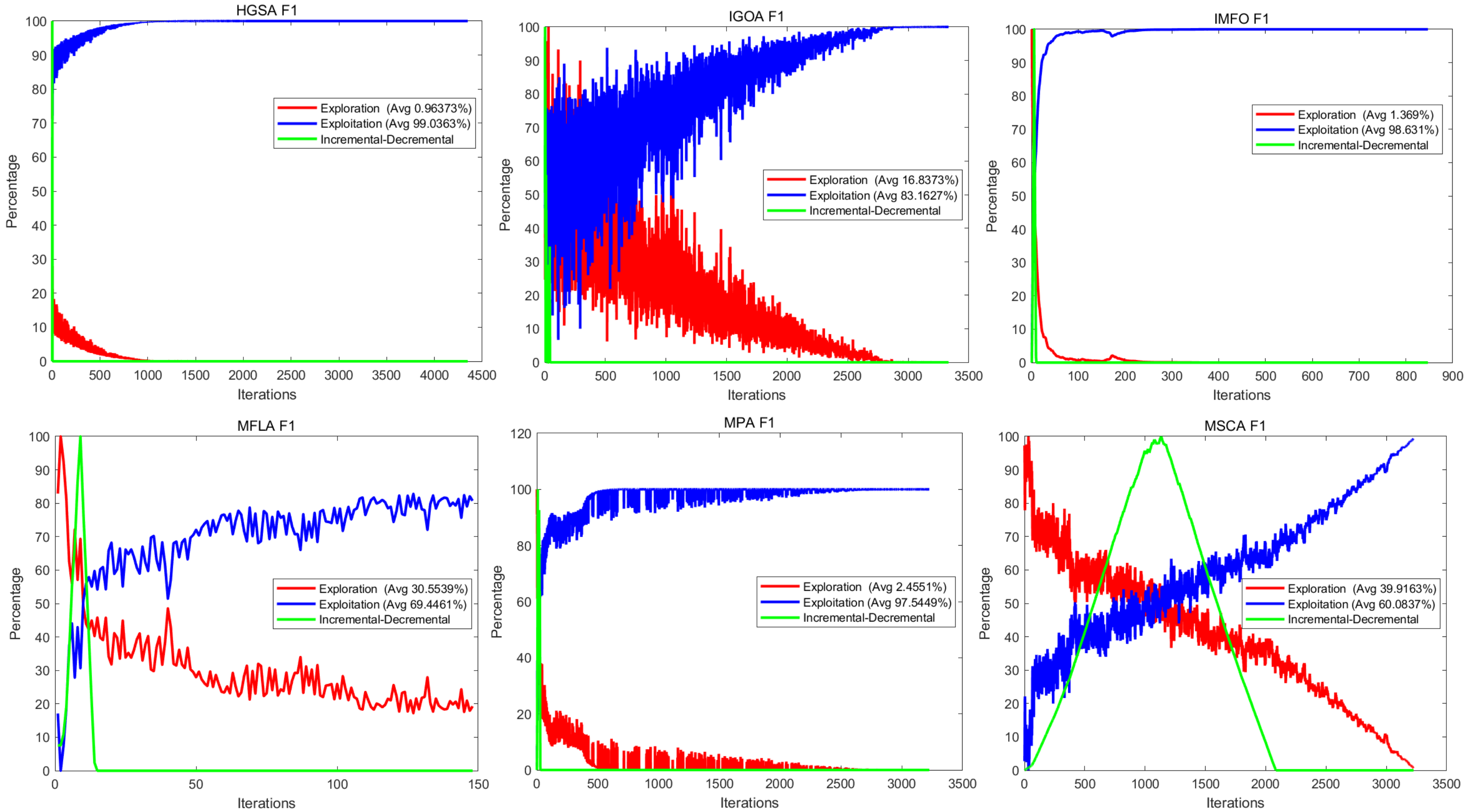
Fig.S7 Evolution of the exploration and the exploitation of 15 algorithms on functions with 10 variables

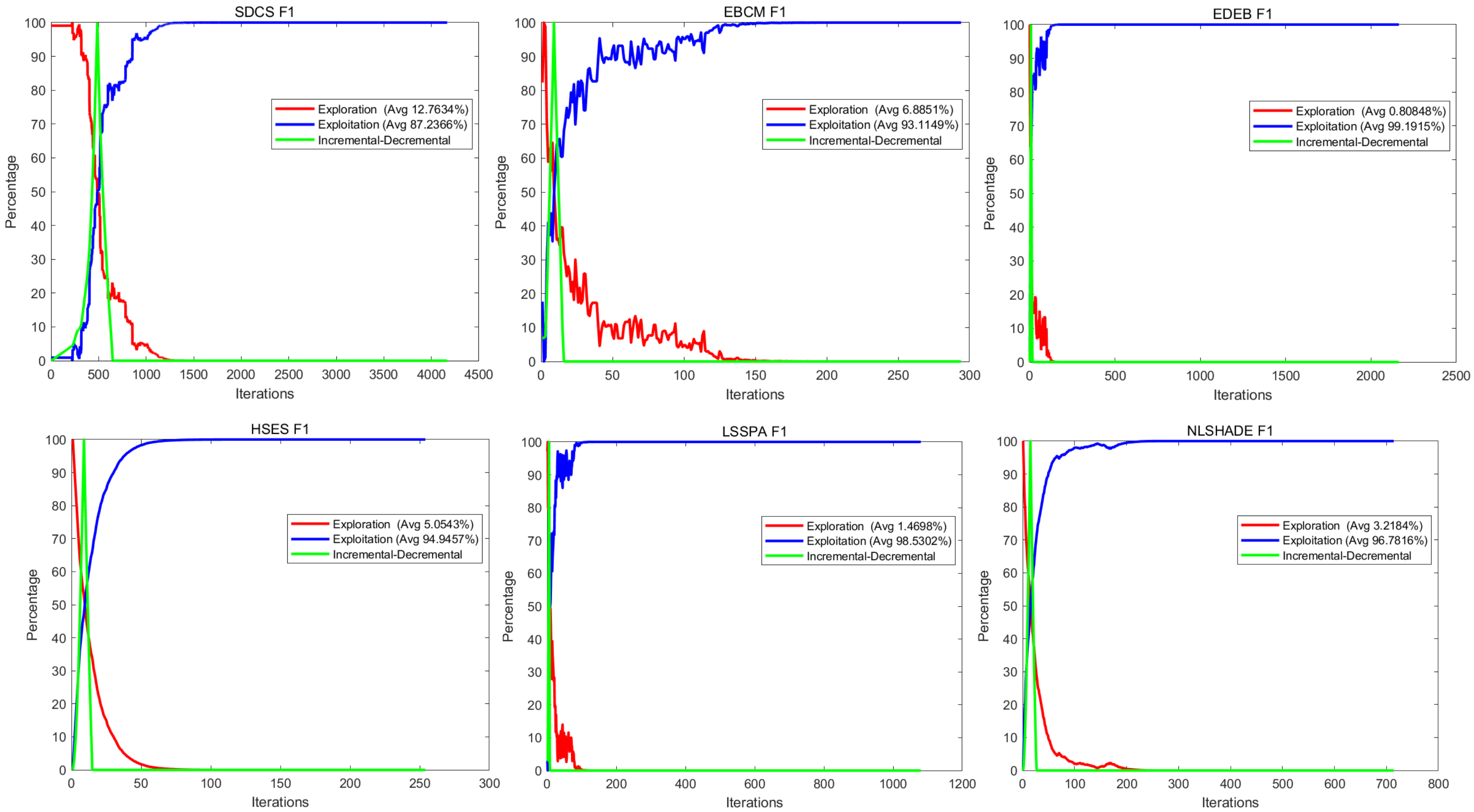
Function F1 with 10 variables



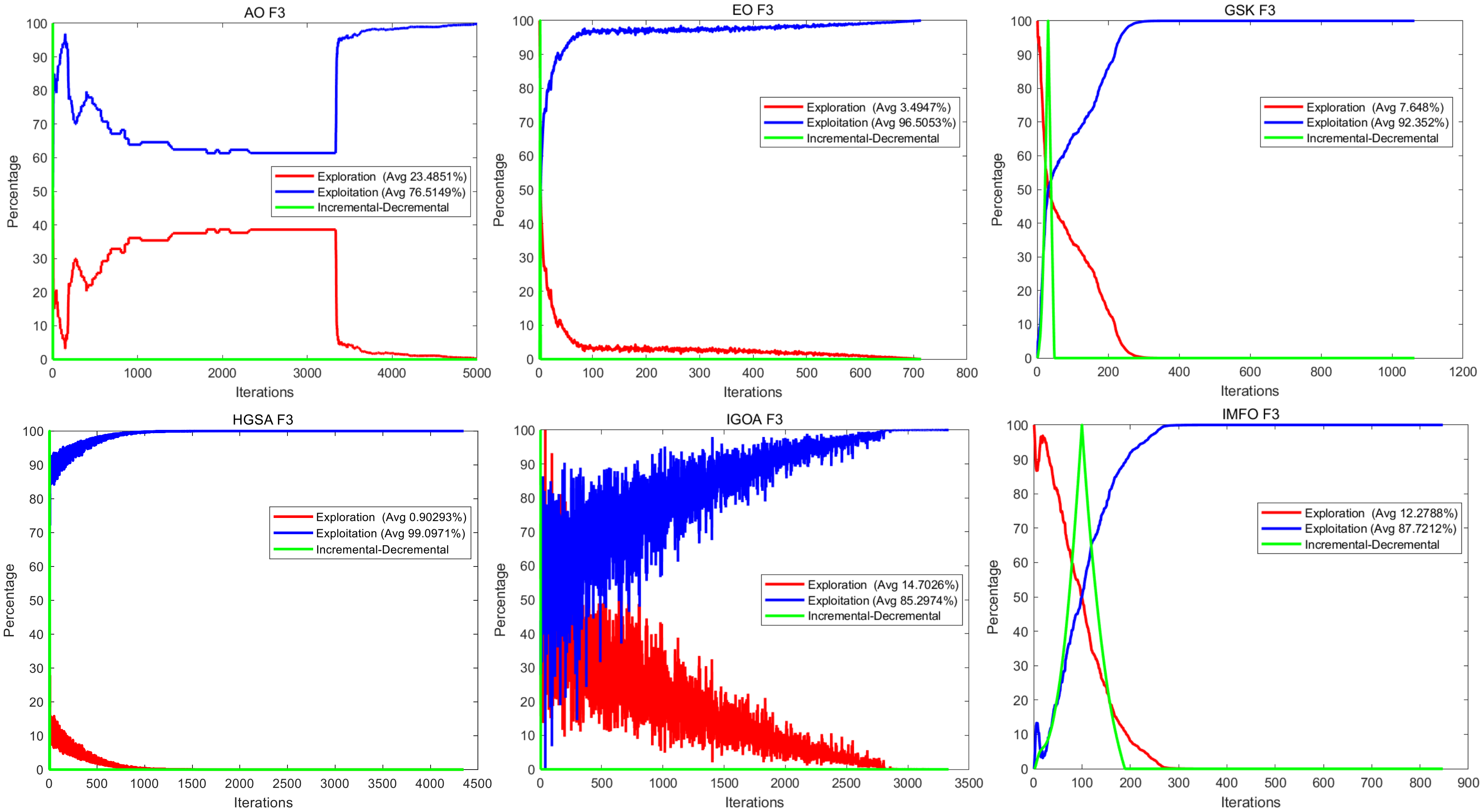


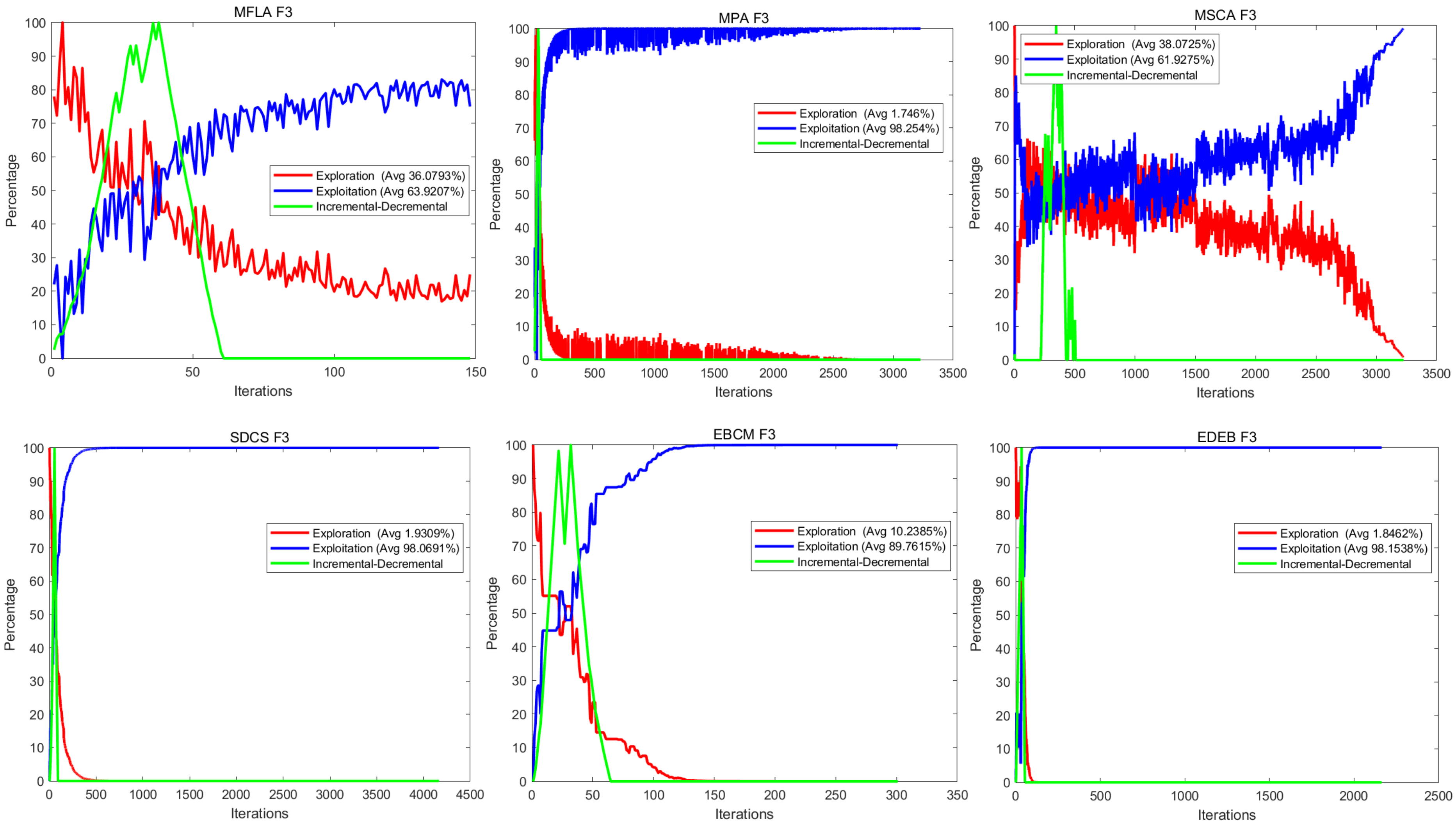


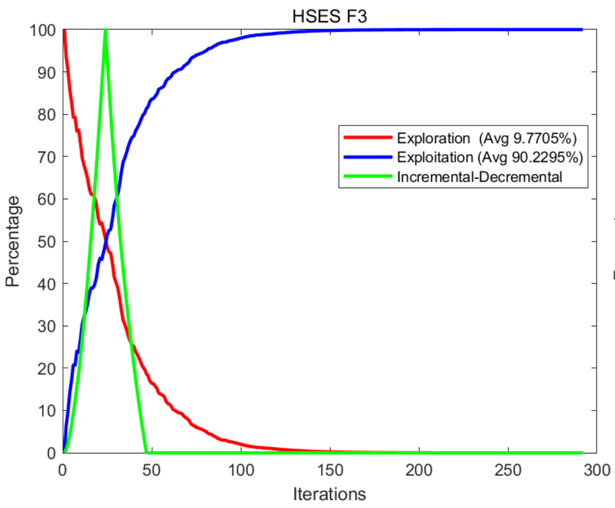

HGSA F1
Exploration (Avg 0.96373%)
Exploitation (Avg 99.0363%)
Incremental-Decremental
Percentage
Iterations
IGOA F1
Exploration (Avg 16.8373%)
Exploitation (Avg 83.1627%)
Incremental-Decremental
Percentage
Iterations
IMFO F1
Exploration (Avg 1.369%)
Exploitation (Avg 98.631%)
Incremental-Decremental
Percentage
Iterations
MFLA F1
Exploration (Avg 30.5539%)
Exploitation (Avg 69.4461%)
Incremental-Decremental
Percentage
Iterations
MPA F1
Exploration (Avg 2.4551%)
Exploitation (Avg 97.5449%)
Incremental-Decremental
Percentage
Iterations
MSCA F1
Exploration (Avg 39.9163%)
Exploitation (Avg 60.0837%)
Incremental-Decremental
Percentage
Iterations

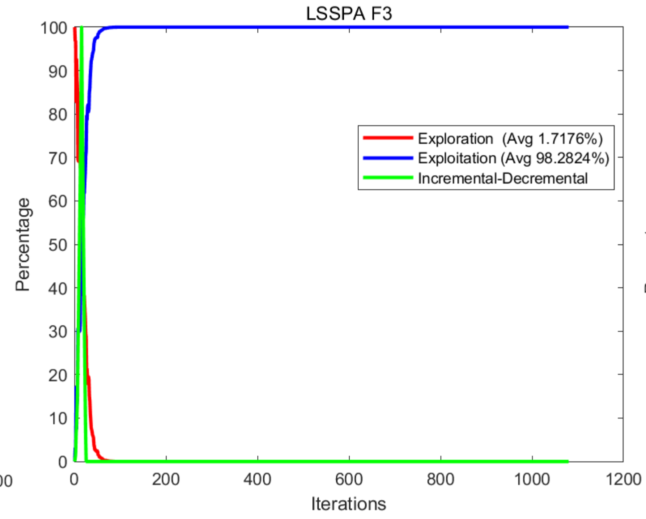


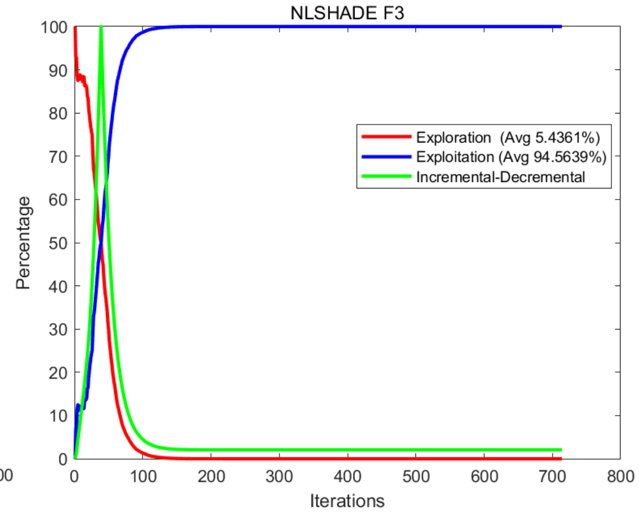
Function F3 with 10 variables


AO F3
Exploration (Avg 23.4851%)
Exploitation (Avg 76.5149%)
Incremental-Decremental
Percentage
Iterations
EO F3
Exploration (Avg 3.4947%)
Exploitation (Avg 96.5053%)
Incremental-Decremental
Percentage
Iterations
GSK F3
Exploration (Avg 7.648%)
Exploitation (Avg 92.352%)
Incremental-Decremental
Percentage
Iterations
HGSA F3
Exploration (Avg 0.90293%)
Exploitation (Avg 99.0971%)
Incremental-Decremental
Percentage
Iterations
IGOA F3
Exploration (Avg 14.7026%)
Exploitation (Avg 85.2974%)
Incremental-Decremental
Percentage
Iterations
IMFO F3
Exploration (Avg 12.2788%)
Exploitation (Avg 87.7212%)
Incremental-Decremental
Percentage
Iterations

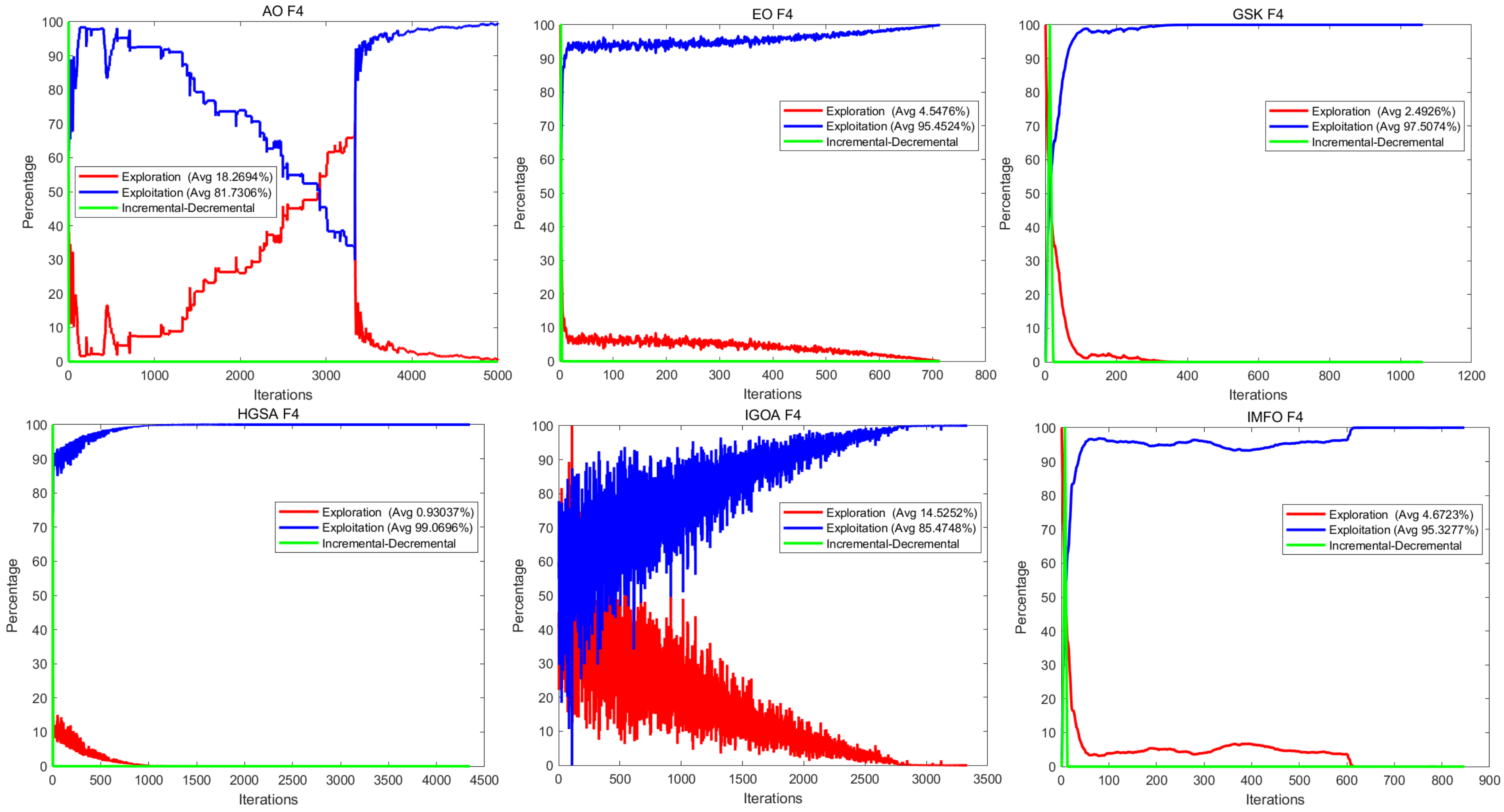

MFLA F3
Exploration (Avg 36.0793%)
Exploitation (Avg 63.9207%)
Incremental-Decremental
MPA F3
Exploration (Avg 1.746%)
Exploitation (Avg 98.254%)
Incremental-Decremental
MSCA F3
Exploration (Avg 38.0725%)
Exploitation (Avg 61.9275%)
Incremental-Decremental
SDCS F3
Exploration (Avg 1.9309%)
Exploitation (Avg 98.0691%)
Incremental-Decremental
EBCM F3
Exploration (Avg 10.2385%)
Exploitation (Avg 89.7615%)
Incremental-Decremental
EDEB F3
Exploration (Avg 1.8462%)
Exploitation (Avg 98.1538%)
Incremental-Decremental
Percentage
Iterations

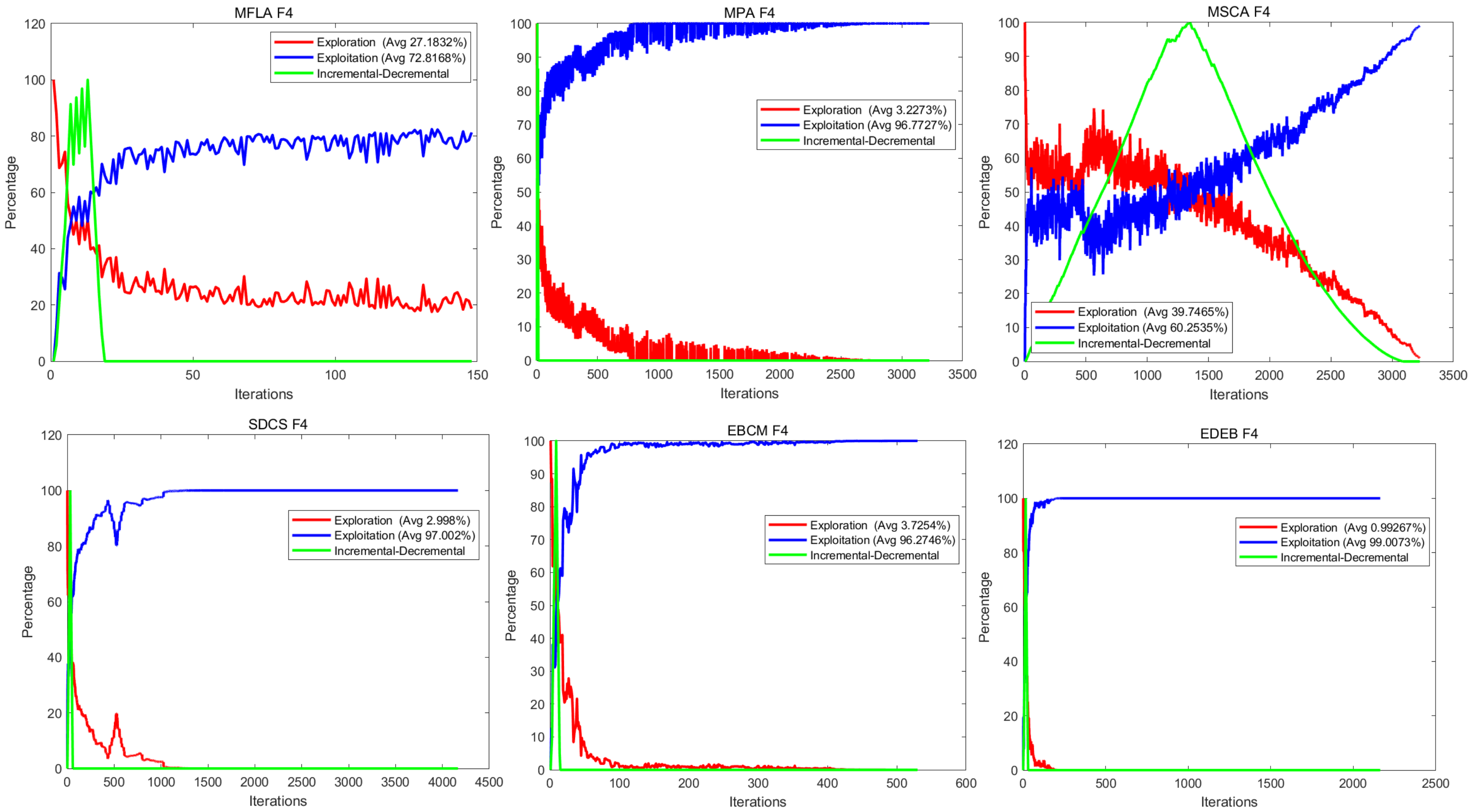


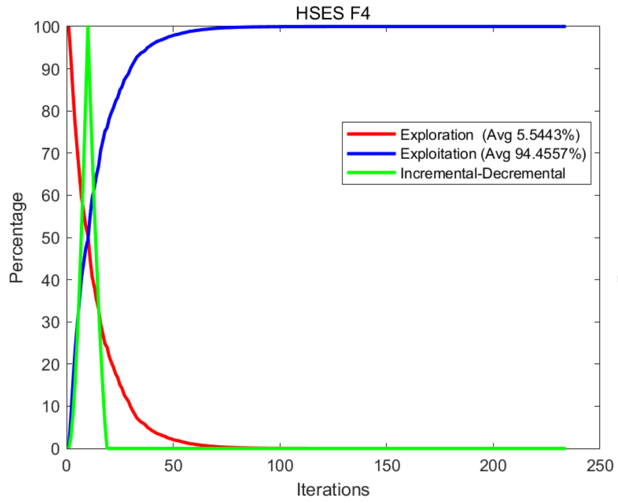


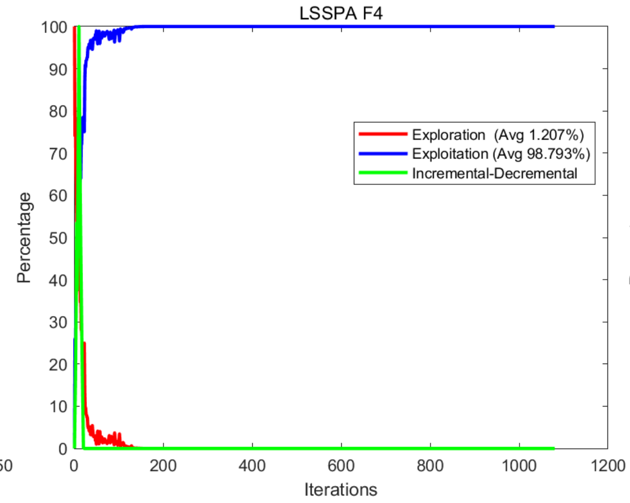


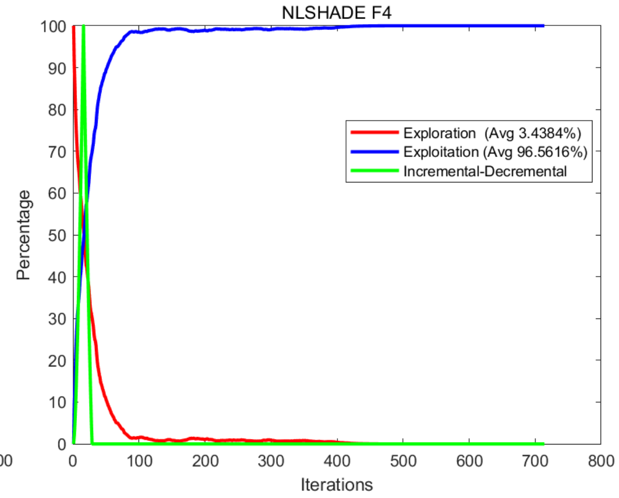
Function F4 with 10 variables


AO F4
Exploration (Avg 18.2694%)
Exploitation (Avg 81.7306%)
Incremental-Decremental
EO F4
Exploration (Avg 4.5476%)
Exploitation (Avg 95.4524%)
Incremental-Decremental
GSK F4
Exploration (Avg 2.4926%)
Exploitation (Avg 97.5074%)
Incremental-Decremental
HGSA F4
Exploration (Avg 0.93037%)
Exploitation (Avg 99.0696%)
Incremental-Decremental
IGOA F4
Exploration (Avg 14.5252%)
Exploitation (Avg 85.4748%)
Incremental-Decremental
IMFO F4
Exploration (Avg 4.6723%)
Exploitation (Avg 95.3277%)
Incremental-Decremental
Percentage
Iterations

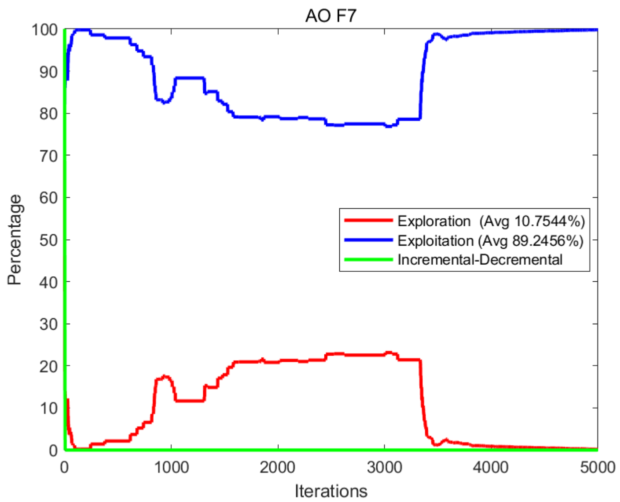

MFLA F4
Exploration (Avg 27.1832%)
Exploitation (Avg 72.8168%)
Incremental-Decremental
MPA F4
Exploration (Avg 3.2273%)
Exploitation (Avg 96.7727%)
Incremental-Decremental
MSCA F4
Exploration (Avg 39.7465%)
Exploitation (Avg 60.2535%)
Incremental-Decremental
SDCS F4
Exploration (Avg 2.998%)
Exploitation (Avg 97.002%)
Incremental-Decremental
EBCM F4
Exploration (Avg 3.7254%)
Exploitation (Avg 96.2746%)
Incremental-Decremental
EDEB F4
Exploration (Avg 0.99267%)
Exploitation (Avg 99.0073%)
Incremental-Decremental
Percentage
Iterations

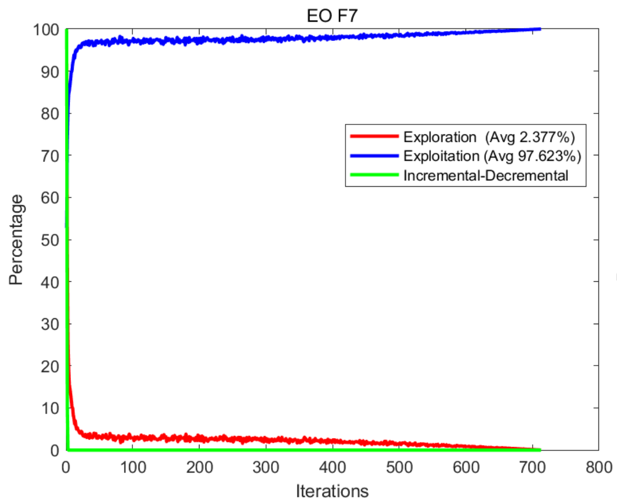


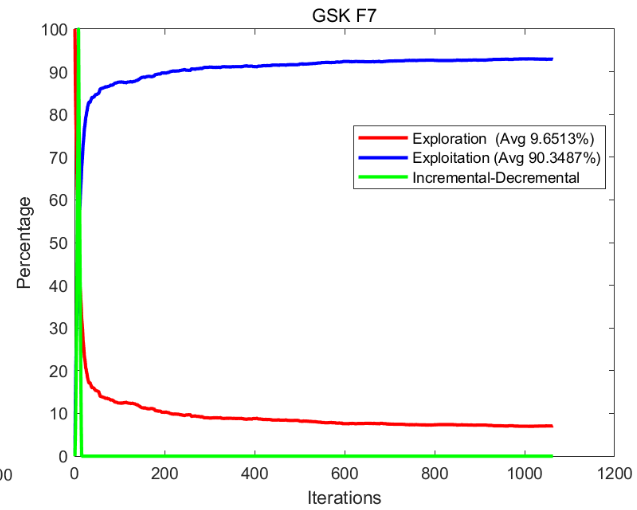


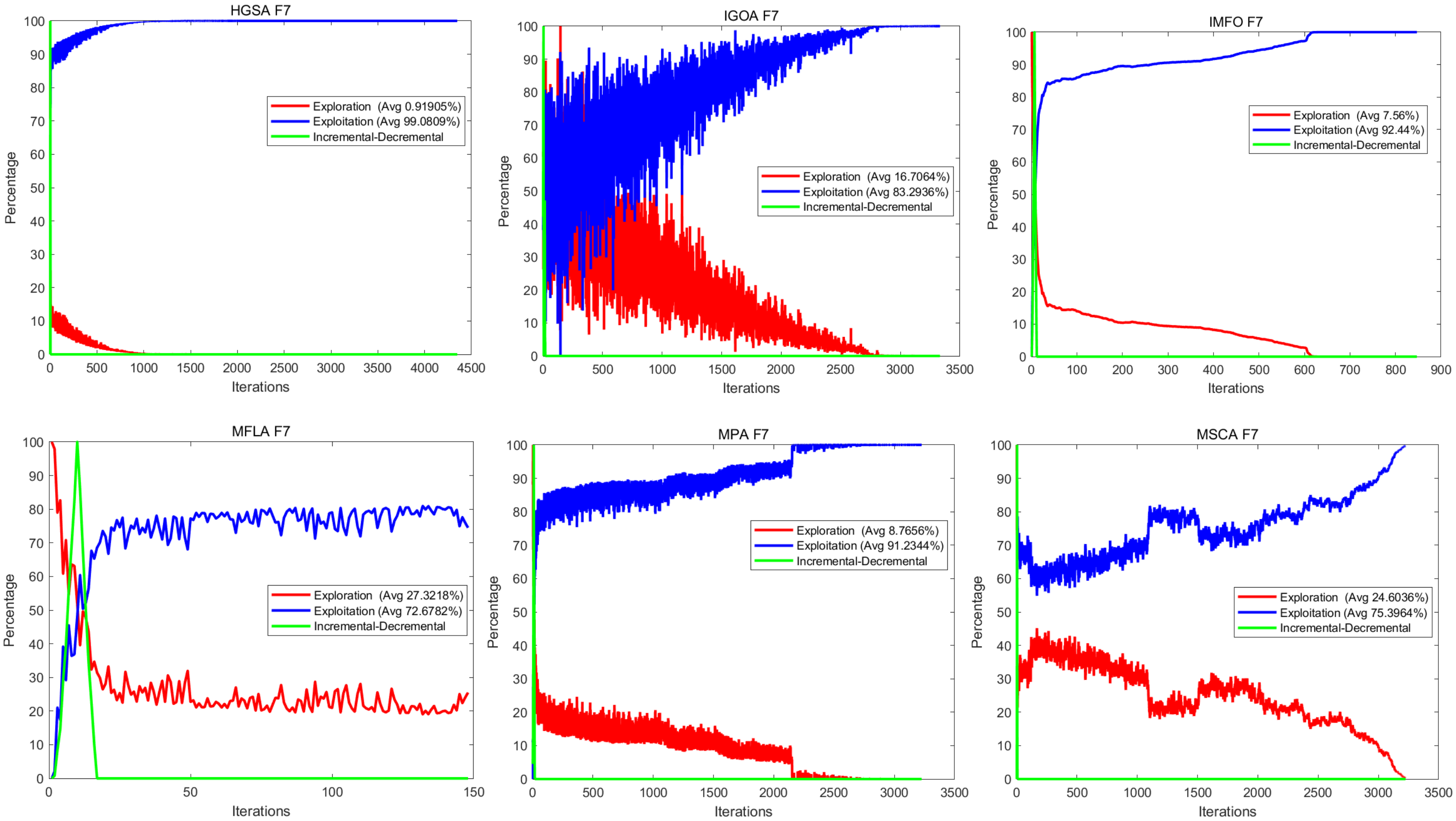


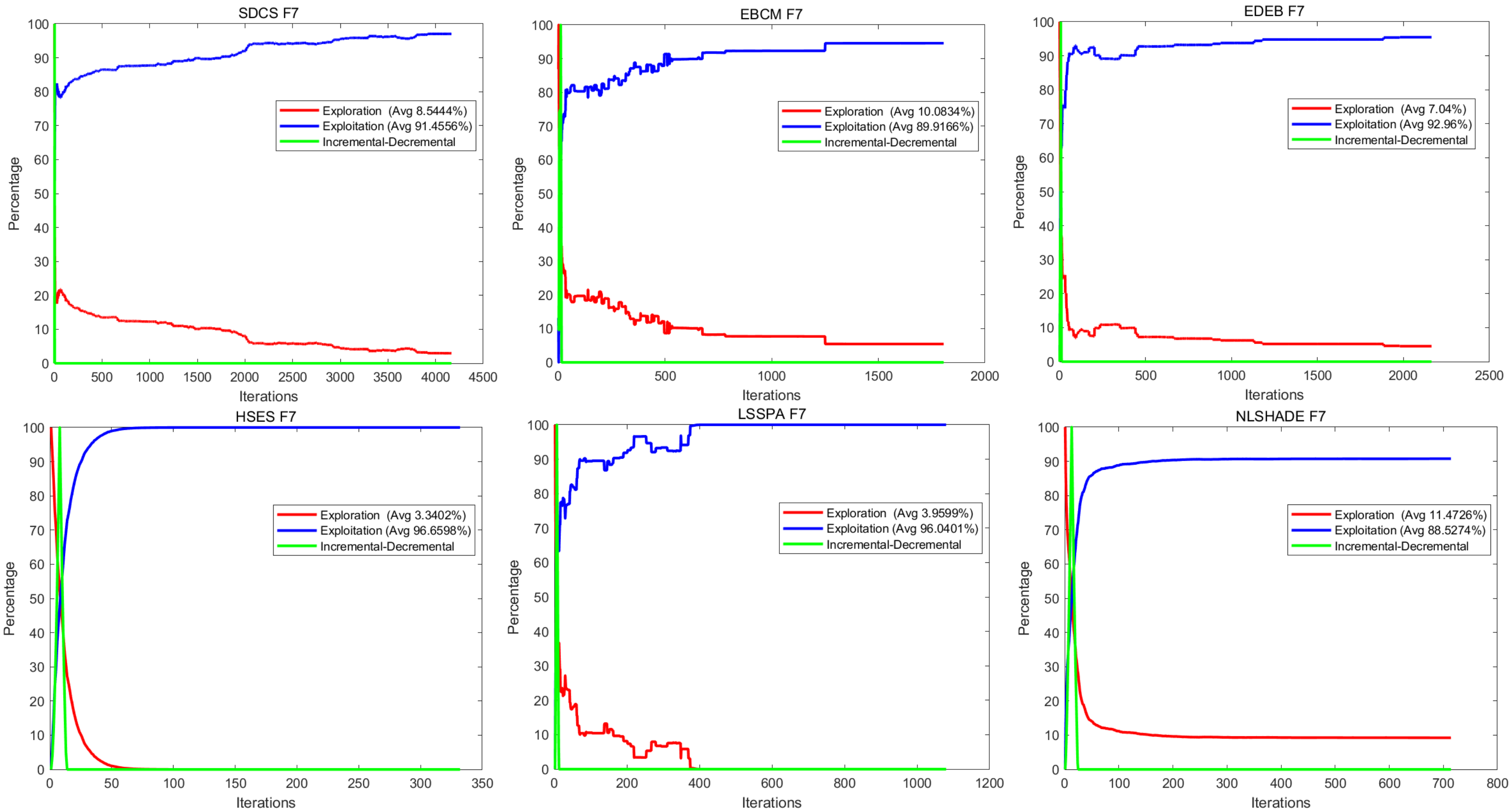
Function F7 with 10 variables



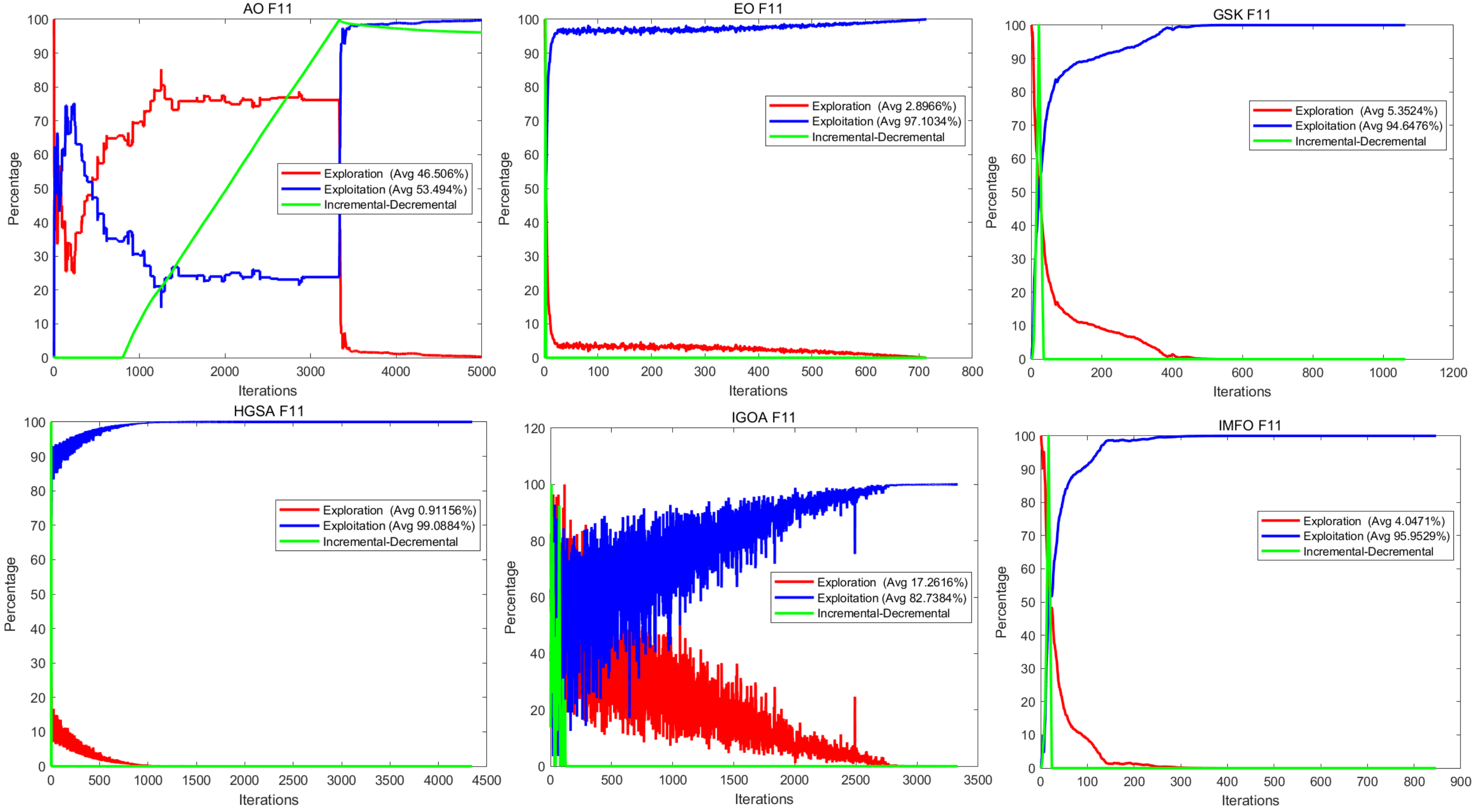




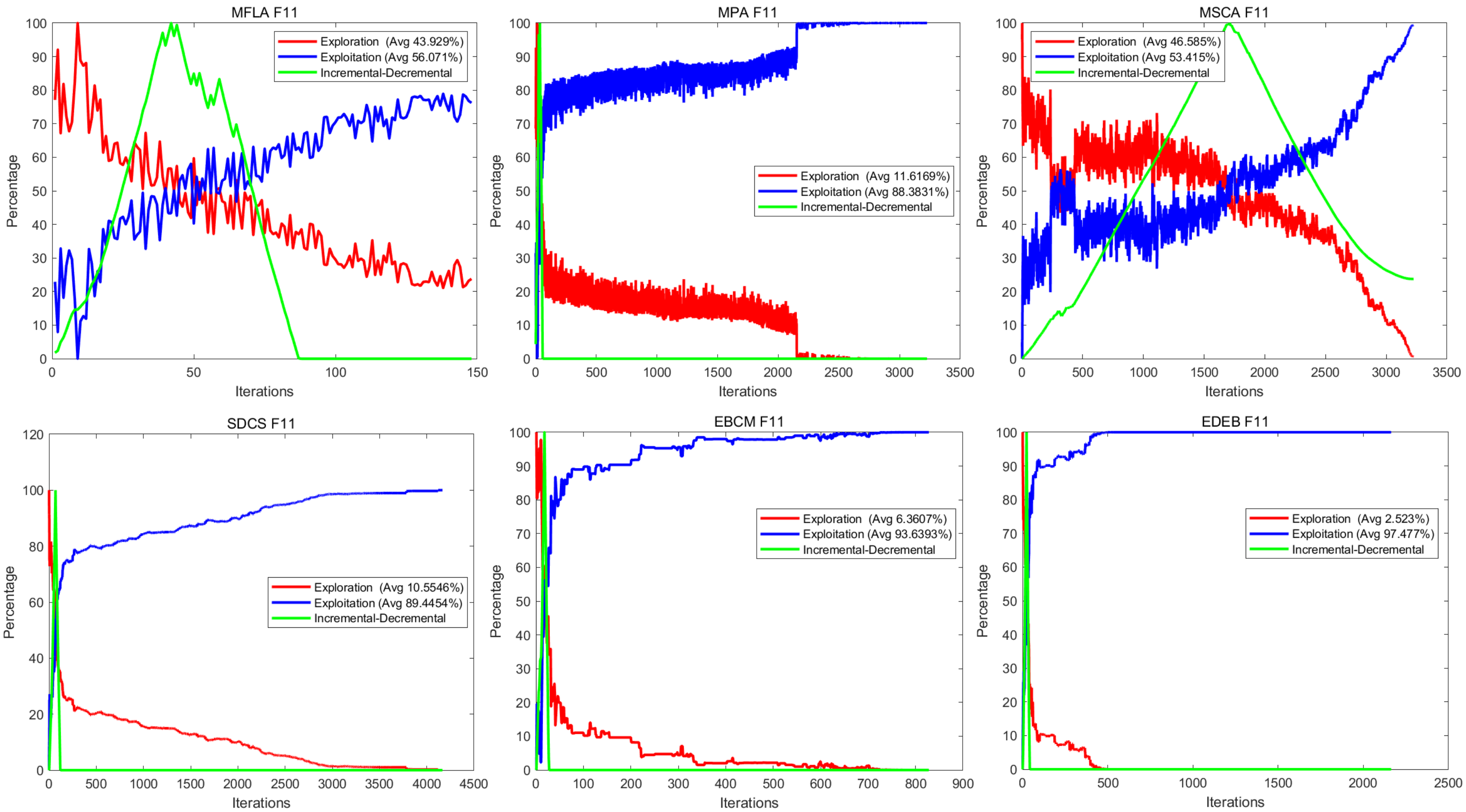

HGSA F7
Exploration (Avg 0.91905%)
Exploitation (Avg 99.0809%)
Incremental-Decremental
Percentage
Iterations
IGOA F7
Exploration (Avg 16.7064%)
Exploitation (Avg 83.2936%)
Incremental-Decremental
Percentage
Iterations
IMFO F7
Exploration (Avg 7.56%)
Exploitation (Avg 92.44%)
Incremental-Decremental
Percentage
Iterations
MFLA F7
Exploration (Avg 27.3218%)
Exploitation (Avg 72.6782%)
Incremental-Decremental
Percentage
Iterations
MPA F7
Exploration (Avg 8.7656%)
Exploitation (Avg 91.2344%)
Incremental-Decremental
Percentage
Iterations
MSCA F7
Exploration (Avg 24.6036%)
Exploitation (Avg 75.3964%)
Incremental-Decremental
Percentage
Iterations

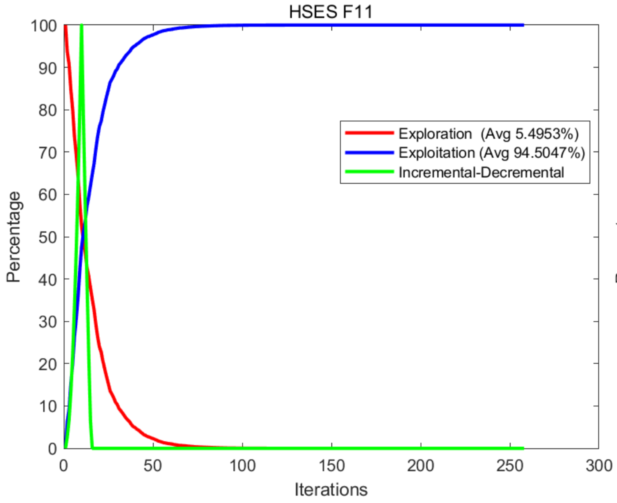


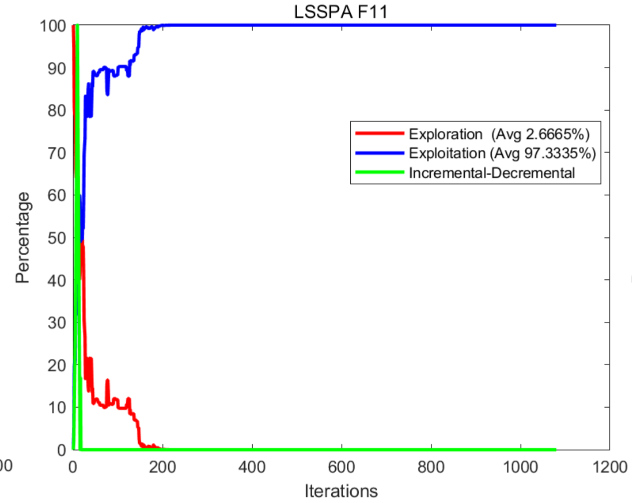
Function F11 with 10 variables

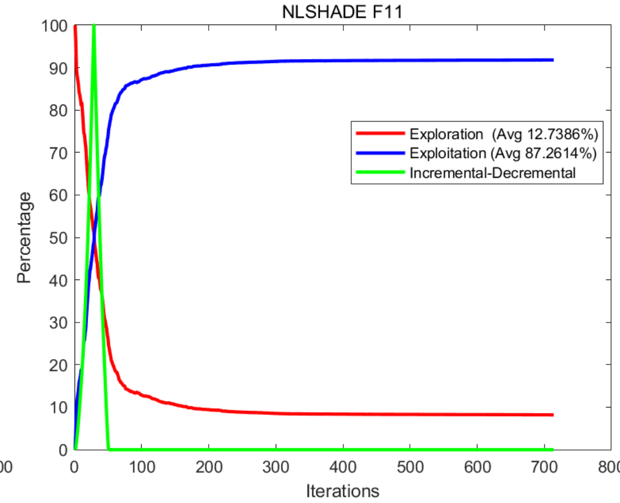


AO F11
Exploration (Avg 46.506%)
Exploitation (Avg 53.494%)
Incremental-Decremental
EO F11
Exploration (Avg 2.8966%)
Exploitation (Avg 97.1034%)
Incremental-Decremental
GSK F11
Exploration (Avg 5.3524%)
Exploitation (Avg 94.6476%)
Incremental-Decremental
HGSA F11
Exploration (Avg 0.91156%)
Exploitation (Avg 99.0884%)
Incremental-Decremental
IGOA F11
Exploration (Avg 17.2616%)
Exploitation (Avg 82.7384%)
Incremental-Decremental
IMFO F11
Exploration (Avg 4.0471%)
Exploitation (Avg 95.9529%)
Incremental-Decremental
Percentage
Iterations

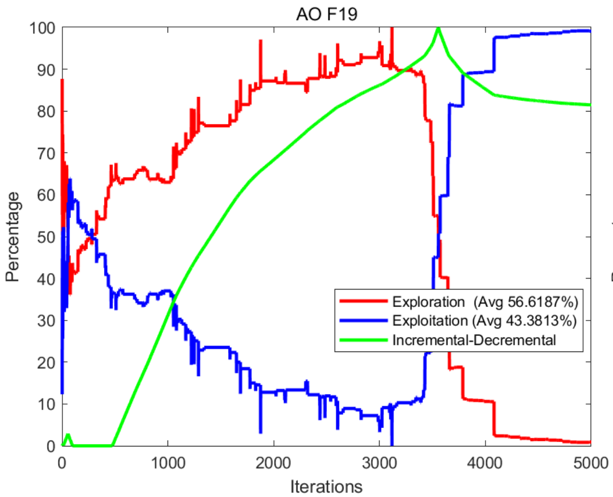

MFLA F11
Exploration (Avg 43.929%)
Exploitation (Avg 56.071%)
Incremental-Decremental
Percentage
Iterations
MPA F11
Exploration (Avg 11.6169%)
Exploitation (Avg 88.3831%)
Incremental-Decremental
Percentage
Iterations
MSCA F11
Exploration (Avg 46.585%)
Exploitation (Avg 53.415%)
Incremental-Decremental
Percentage
Iterations
SDCS F11
Exploration (Avg 10.5546%)
Exploitation (Avg 89.4454%)
Incremental-Decremental
Percentage
Iterations
EBCM F11
Exploration (Avg 6.3607%)
Exploitation (Avg 93.6393%)
Incremental-Decremental
Percentage
Iterations
EDEB F11
Exploration (Avg 2.523%)
Exploitation (Avg 97.477%)
Incremental-Decremental
Percentage
Iterations

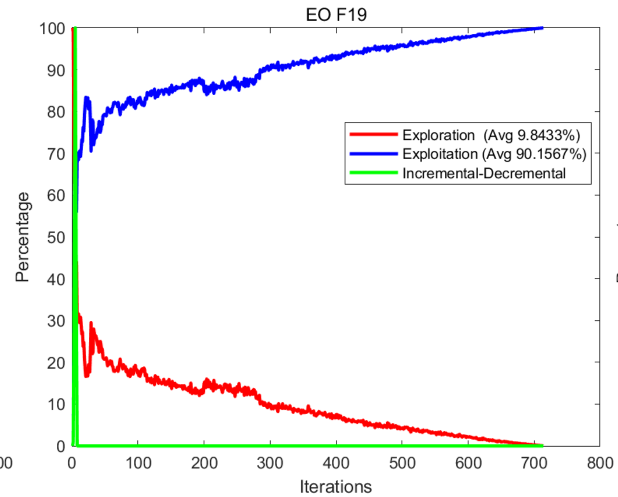


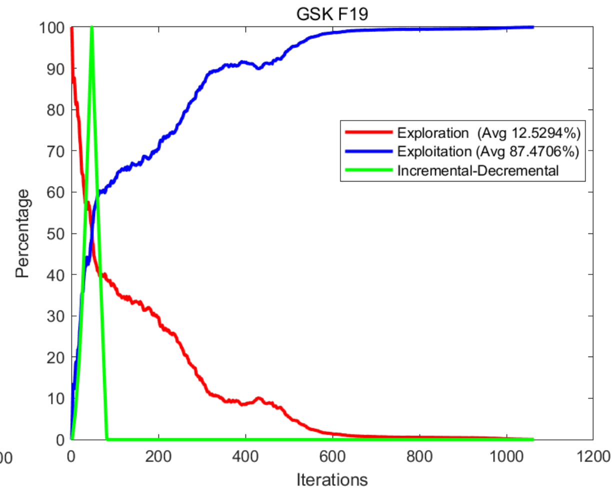


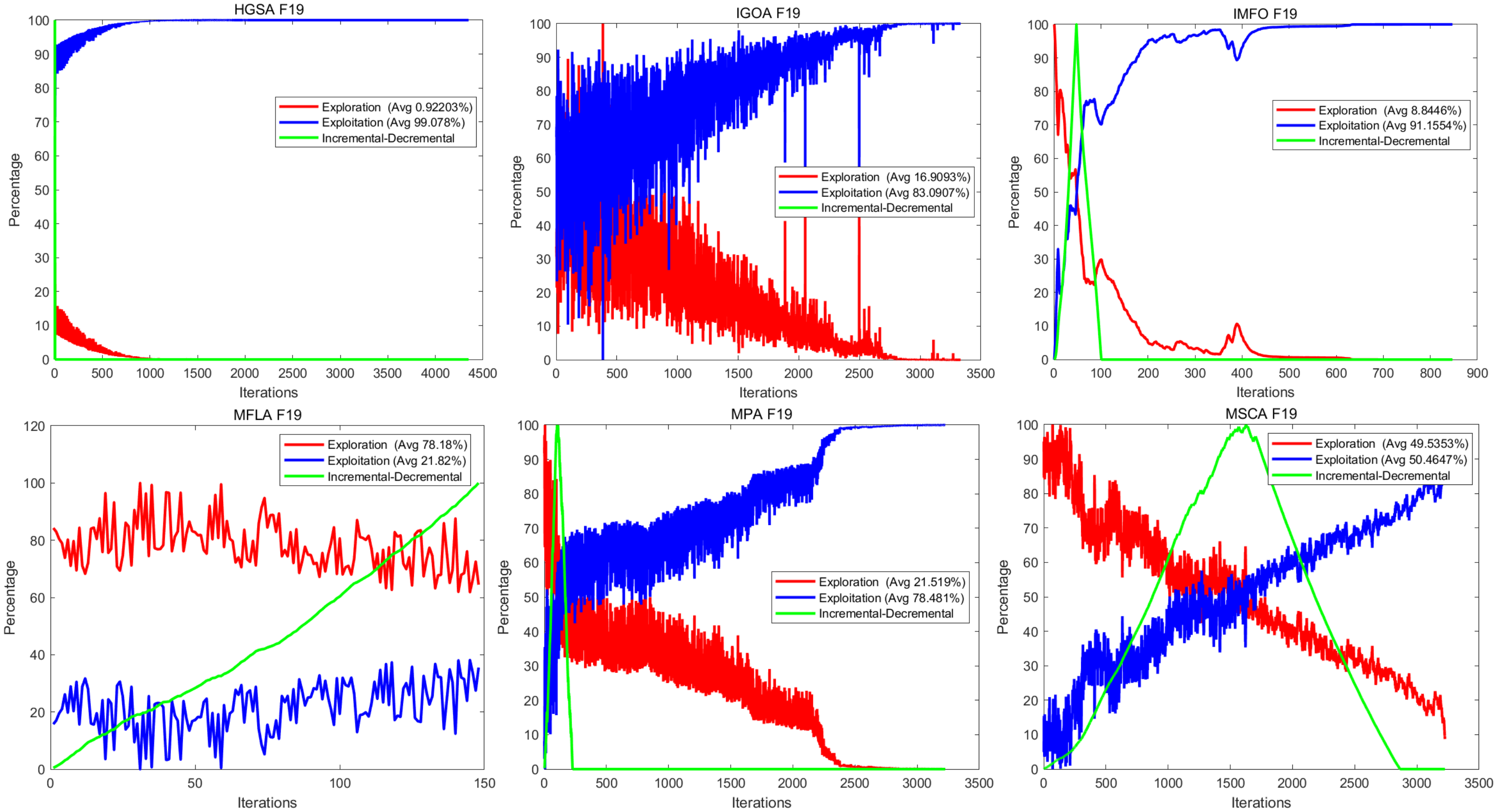


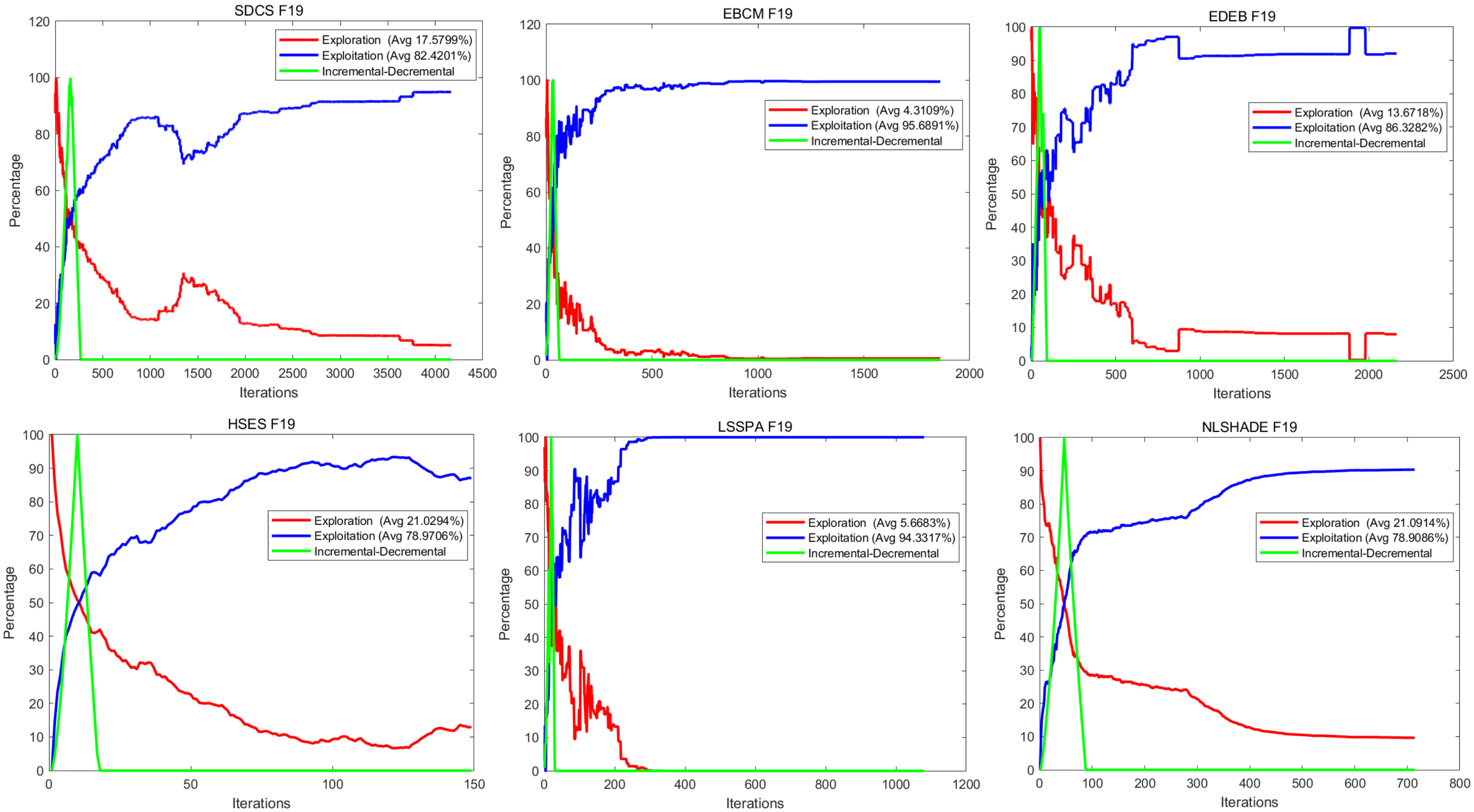
Function F19 with 10 variables



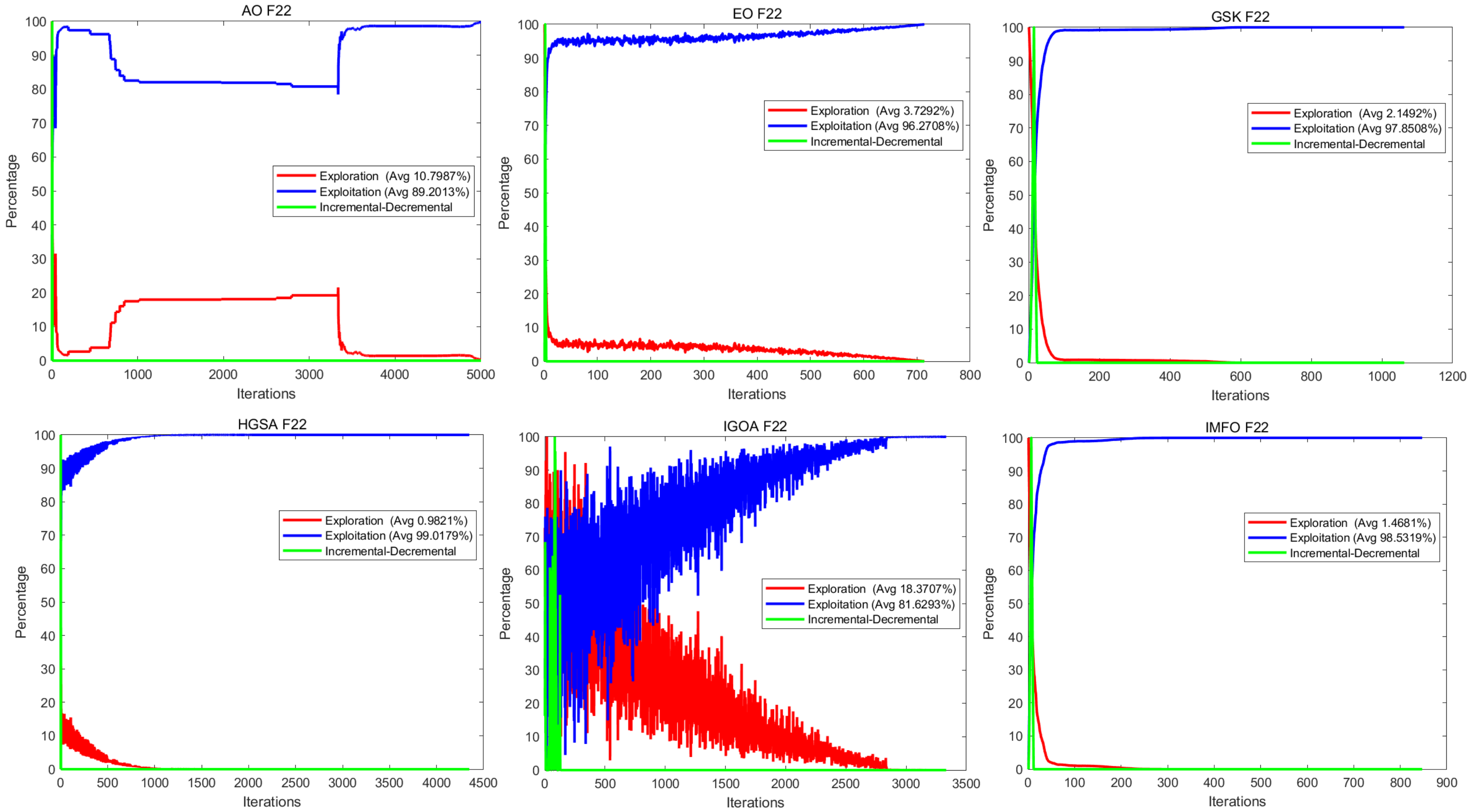


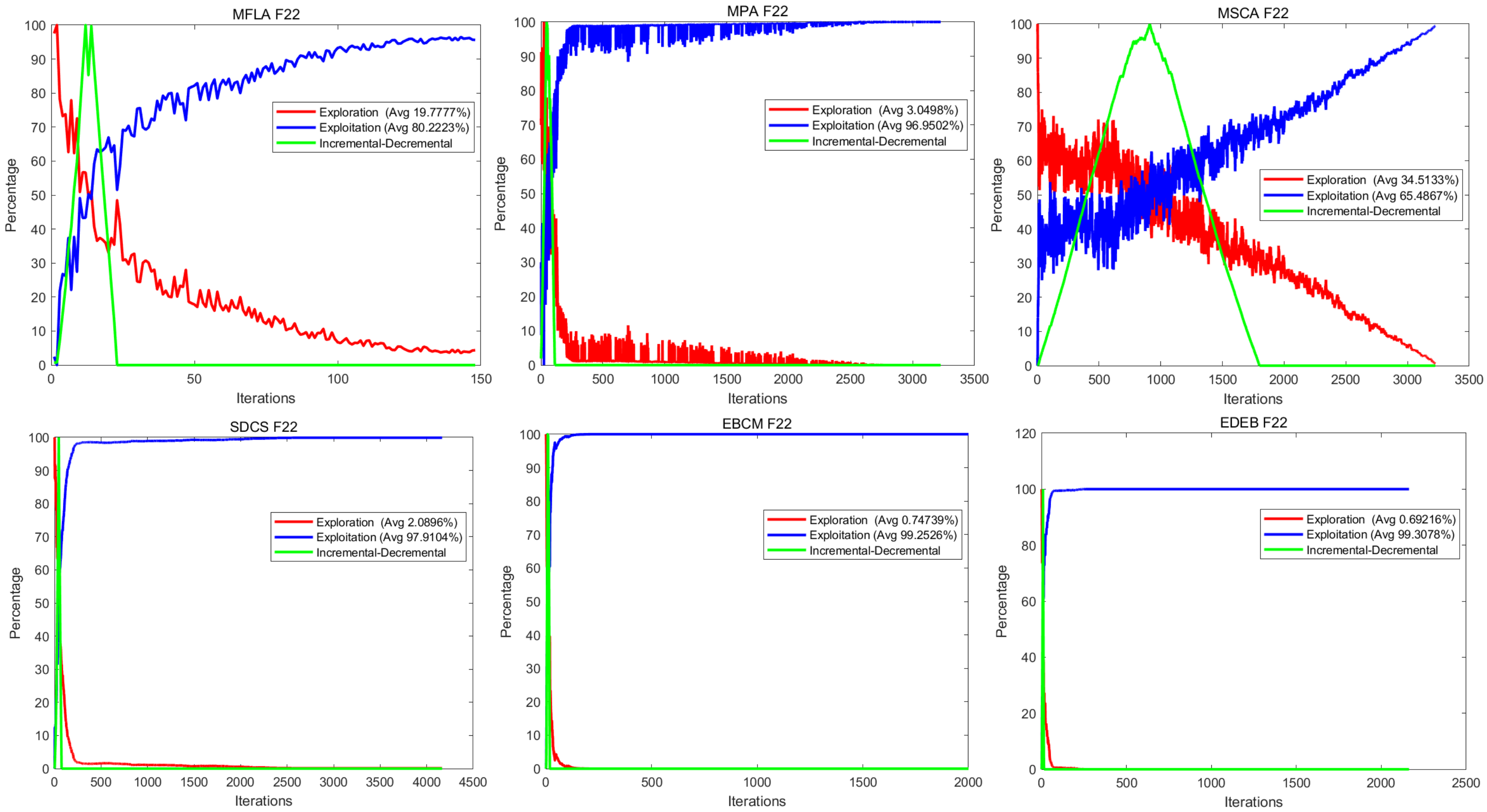


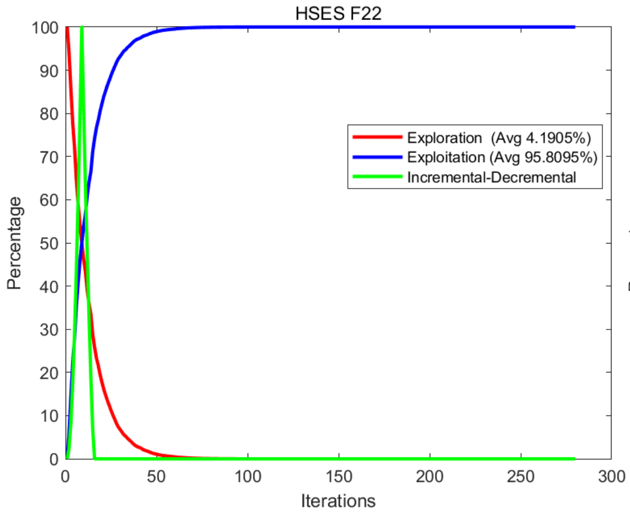

HGSA F19
Exploration (Avg 0.92203%)
Exploitation (Avg 99.078%)
Incremental-Decremental
IGOA F19
Exploration (Avg 16.9093%)
Exploitation (Avg 83.0907%)
Incremental-Decremental
IMFO F19
Exploration (Avg 8.8446%)
Exploitation (Avg 91.1554%)
Incremental-Decremental
MFLA F19
Exploration (Avg 78.18%)
Exploitation (Avg 21.82%)
Incremental-Decremental
MPA F19
Exploration (Avg 21.519%)
Exploitation (Avg 78.481%)
Incremental-Decremental
MSCA F19
Exploration (Avg 49.5353%)
Exploitation (Avg 50.4647%)
Incremental-Decremental
Percentage
Iterations

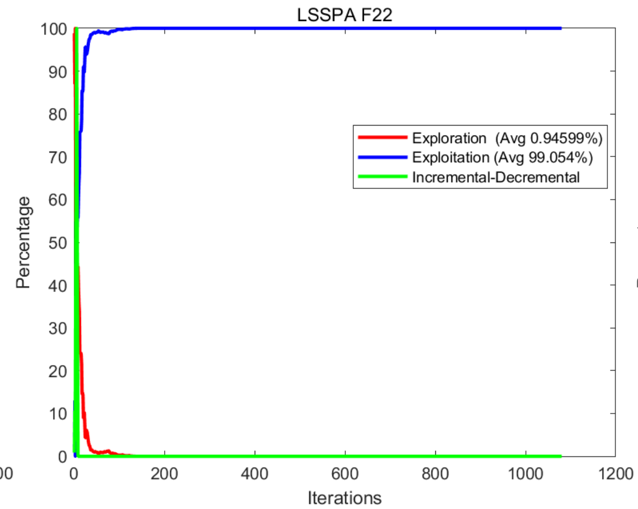


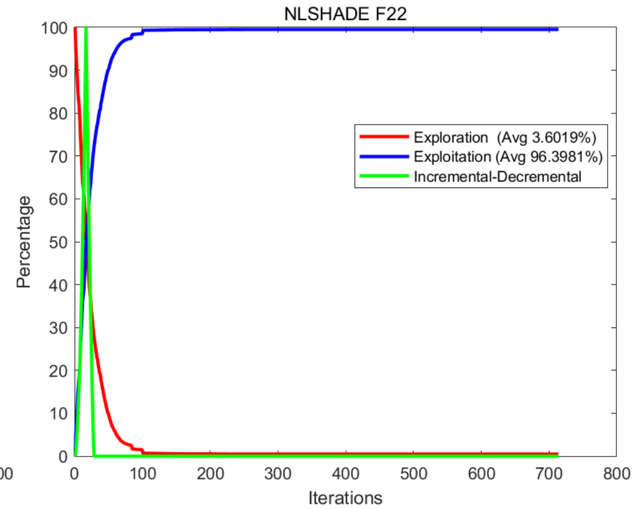
Function F22 with 10 variables


AO F22
Exploration (Avg 10.7987%)
Exploitation (Avg 89.2013%)
Incremental-Decremental
EO F22
Exploration (Avg 3.7292%)
Exploitation (Avg 96.2708%)
Incremental-Decremental
GSK F22
Exploration (Avg 2.1492%)
Exploitation (Avg 97.8508%)
Incremental-Decremental
HGSA F22
Exploration (Avg 0.9821%)
Exploitation (Avg 99.0179%)
Incremental-Decremental
IGOA F22
Exploration (Avg 18.3707%)
Exploitation (Avg 81.6293%)
Incremental-Decremental
IMFO F22
Exploration (Avg 1.4681%)
Exploitation (Avg 98.5319%)
Incremental-Decremental
Percentage
Iterations

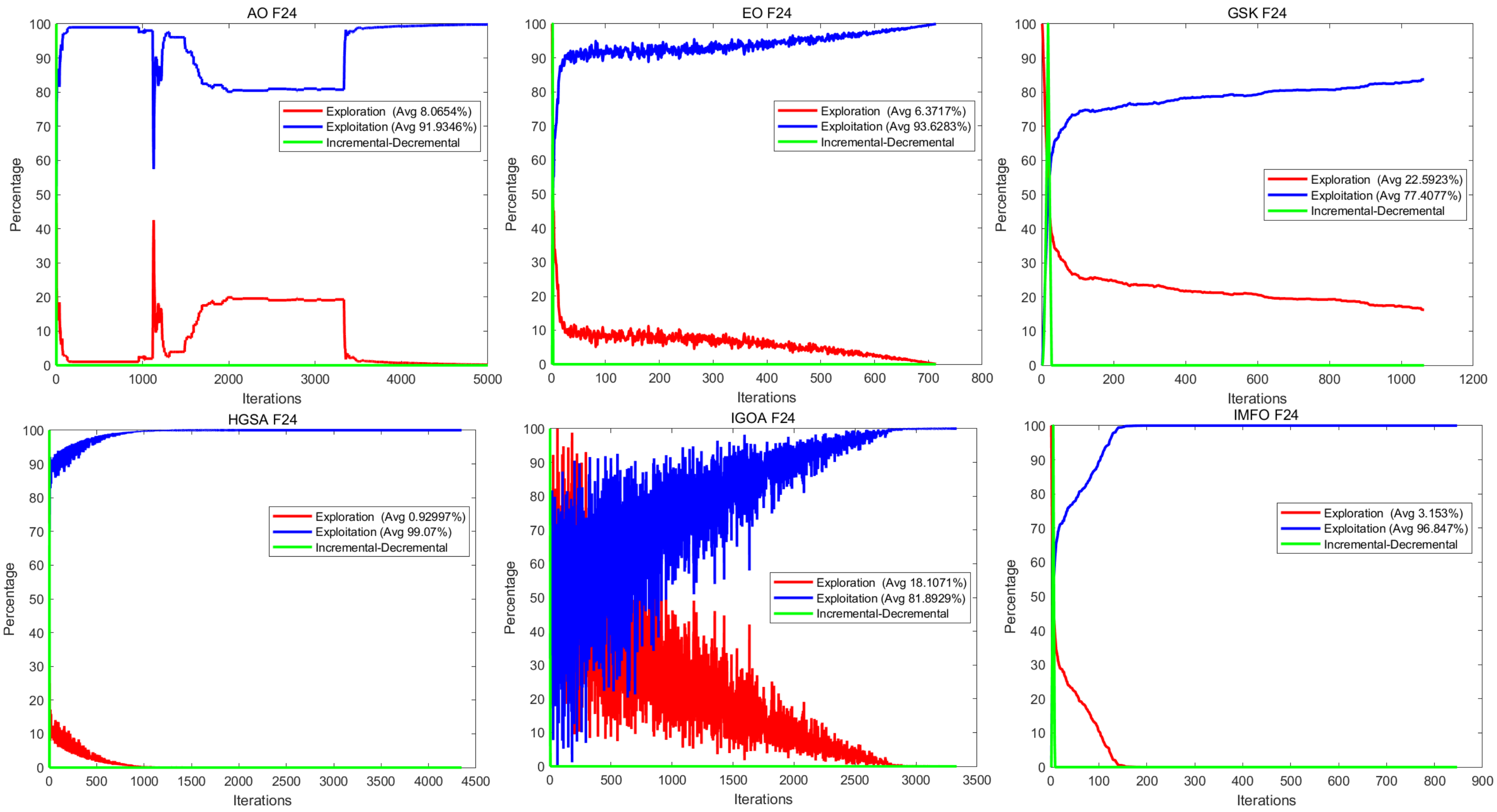

MFLA F22
Exploration (Avg 19.7777%)
Exploitation (Avg 80.2223%)
Incremental-Decremental
MPA F22
Exploration (Avg 3.0498%)
Exploitation (Avg 96.9502%)
Incremental-Decremental
MSCA F22
Exploration (Avg 34.5133%)
Exploitation (Avg 65.4867%)
Incremental-Decremental
SDCS F22
Exploration (Avg 2.0896%)
Exploitation (Avg 97.9104%)
Incremental-Decremental
EBCM F22
Exploration (Avg 0.74739%)
Exploitation (Avg 99.2526%)
Incremental-Decremental
EDEB F22
Exploration (Avg 0.69216%)
Exploitation (Avg 99.3078%)
Incremental-Decremental
Percentage
Iterations



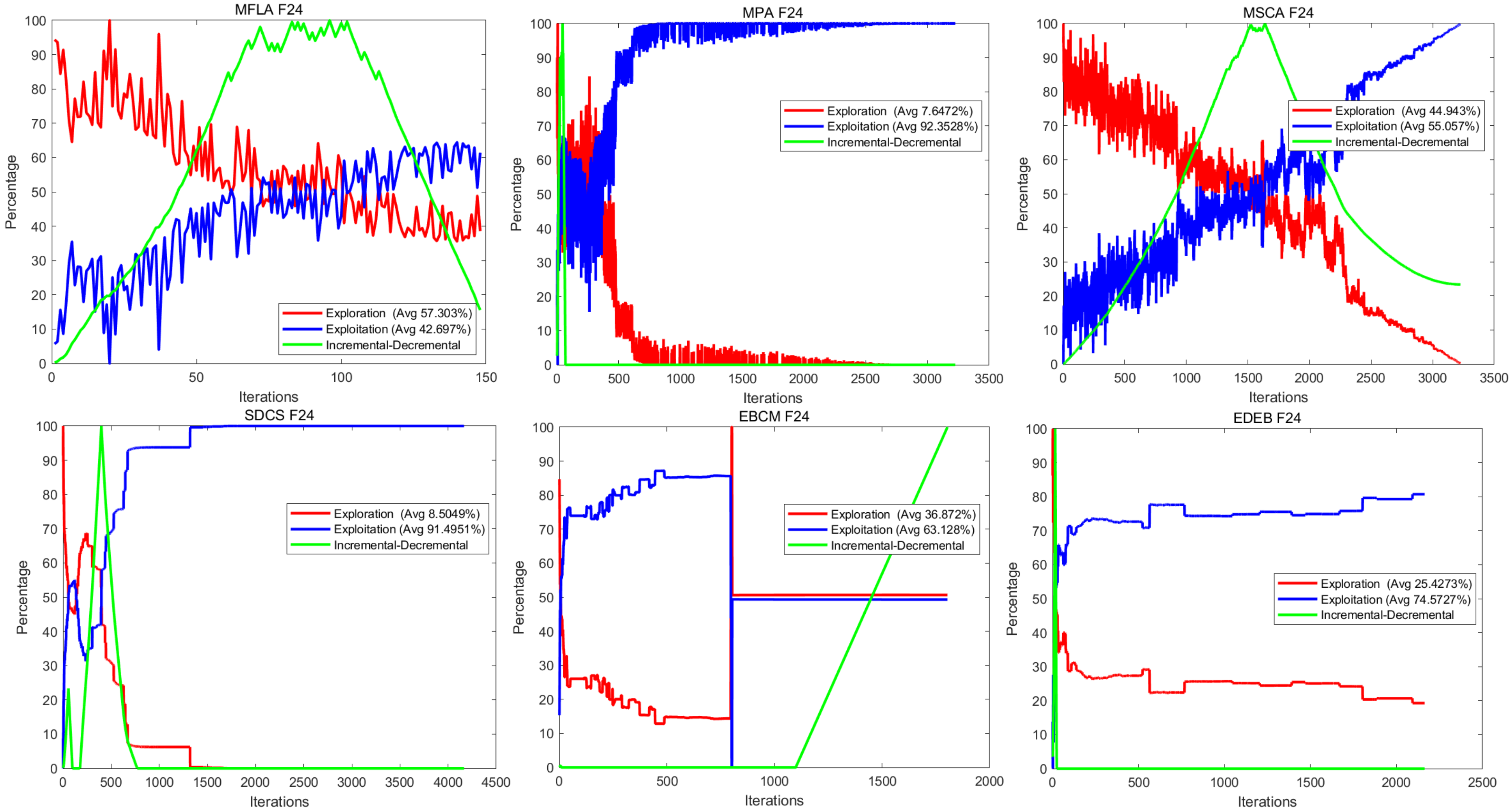




Function F24 with 10 variables



AO F24
Exploration (Avg 8.0654%)
Exploitation (Avg 91.9346%)
Incremental-Decremental
Percentage
Iterations
EO F24
Exploration (Avg 6.3717%)
Exploitation (Avg 93.6283%)
Incremental-Decremental
Percentage
Iterations
GSK F24
Exploration (Avg 22.5923%)
Exploitation (Avg 77.4077%)
Incremental-Decremental
Percentage
Iterations
HGSA F24
Exploration (Avg 0.92997%)
Exploitation (Avg 99.07%)
Incremental-Decremental
Percentage
Iterations
IGOA F24
Exploration (Avg 18.1071%)
Exploitation (Avg 81.8929%)
Incremental-Decremental
Percentage
Iterations
IMFO F24
Exploration (Avg 3.153%)
Exploitation (Avg 96.847%)
Incremental-Decremental
Percentage
Iterations


MFLA F24
Exploration (Avg 57.303%)
Exploitation (Avg 42.697%)
Incremental-Decremental
MPA F24
Exploration (Avg 7.6472%)
Exploitation (Avg 92.3528%)
Incremental-Decremental
MSCA F24
Exploration (Avg 44.943%)
Exploitation (Avg 55.057%)
Incremental-Decremental
SDCS F24
Exploration (Avg 8.5049%)
Exploitation (Avg 91.4951%)
Incremental-Decremental
EBCM F24
Exploration (Avg 36.872%)
Exploitation (Avg 63.128%)
Incremental-Decremental
EDEB F24
Exploration (Avg 25.4273%)
Exploitation (Avg 74.5727%)
Incremental-Decremental
Percentage
Iterations

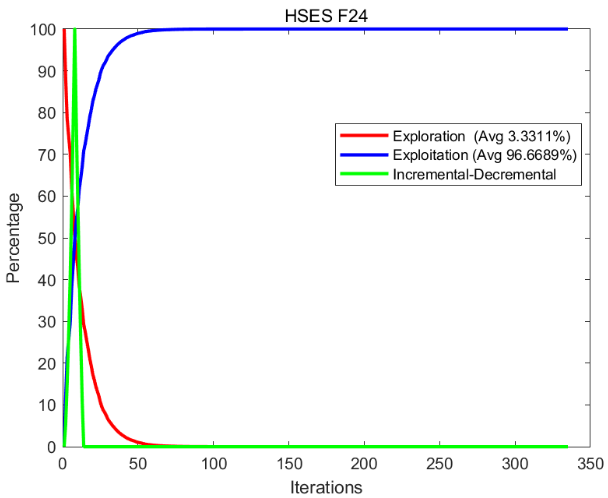
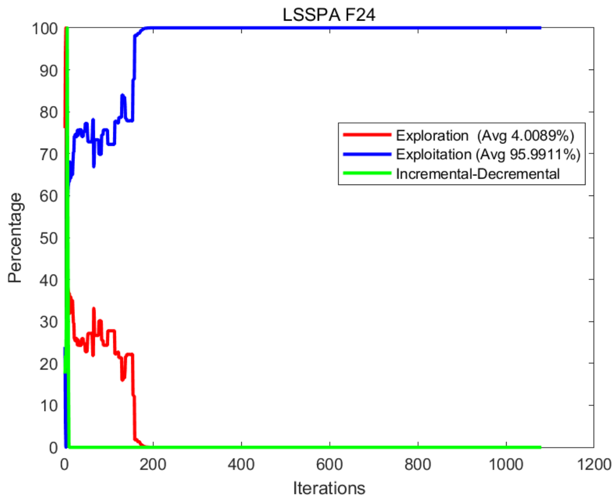
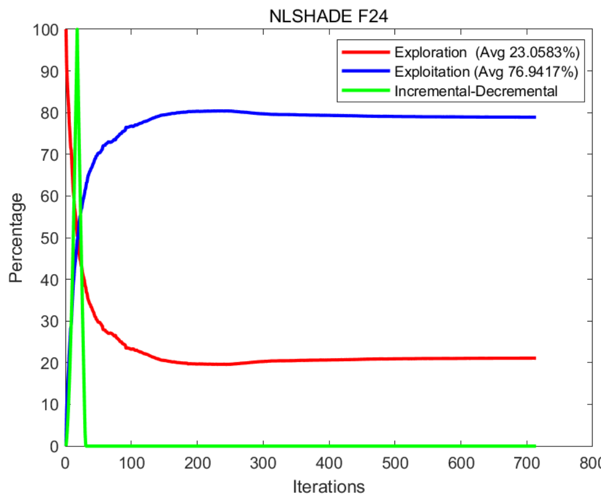
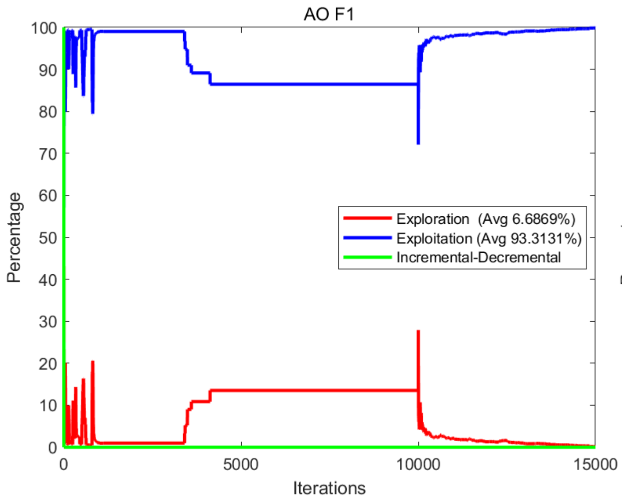
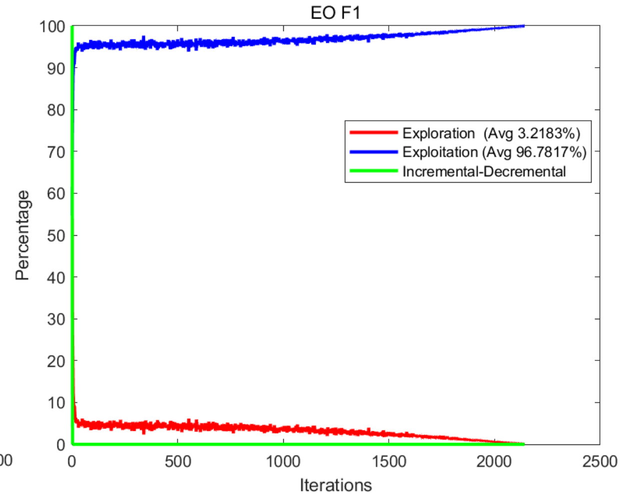
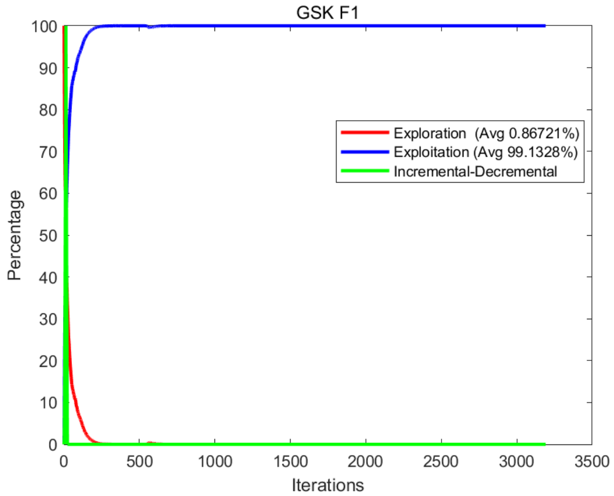

HSES F24
Exploration (Avg 3.3311%)
Exploitation (Avg 96.6689%)
Incremental-Decremental
Percentage
Iterations

LSSPA F24
Exploration (Avg 4.0089%)
Exploitation (Avg 95.9911%)
Incremental-Decremental
Percentage
Iterations

NLSHADE F24
Exploration (Avg 23.0583%)
Exploitation (Avg 76.9417%)
Incremental-Decremental
Percentage
Iterations

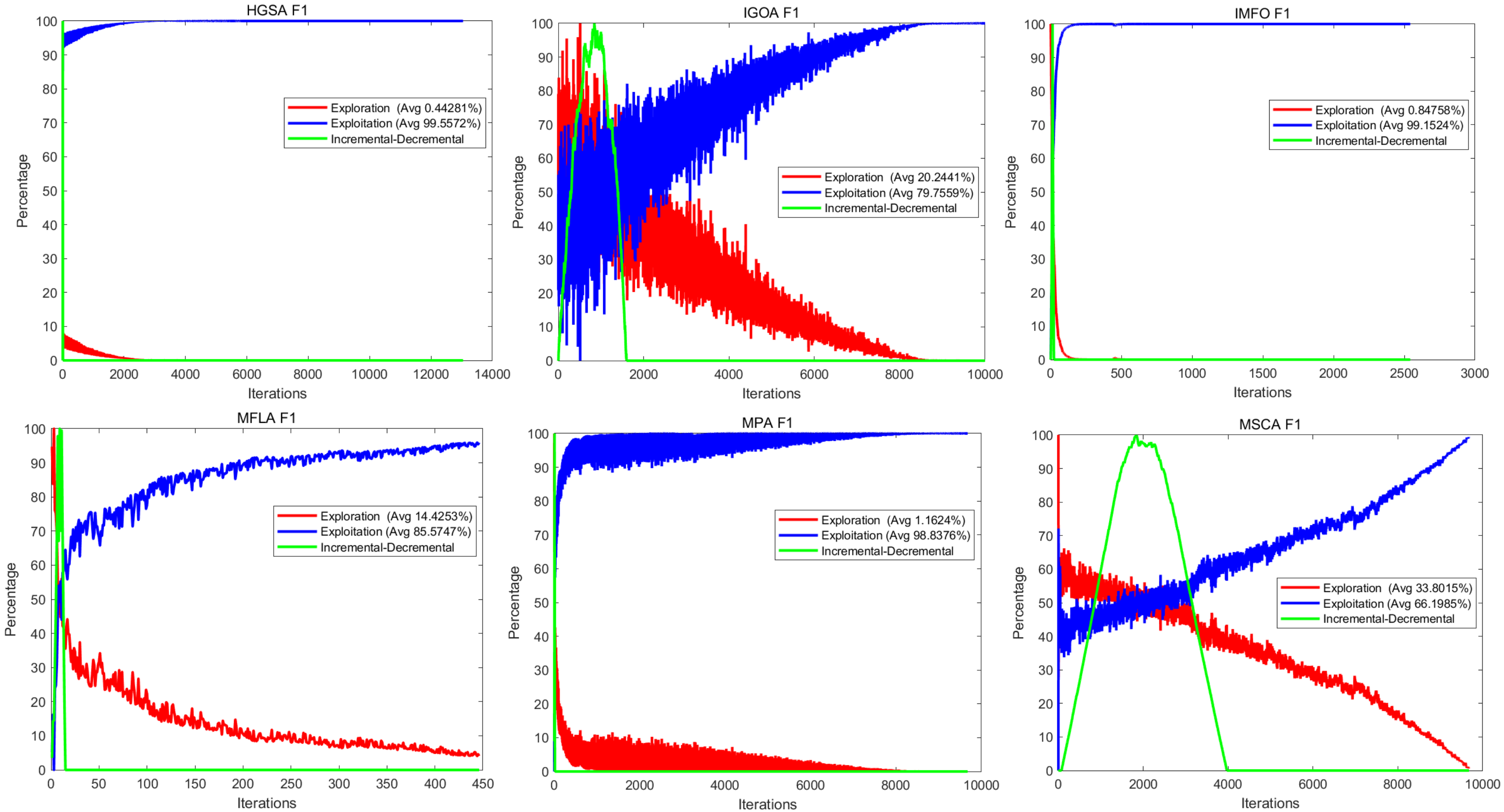
Fig.S8 Evolution of the exploration and the exploitation of 15 algorithms on functions with 30 variables

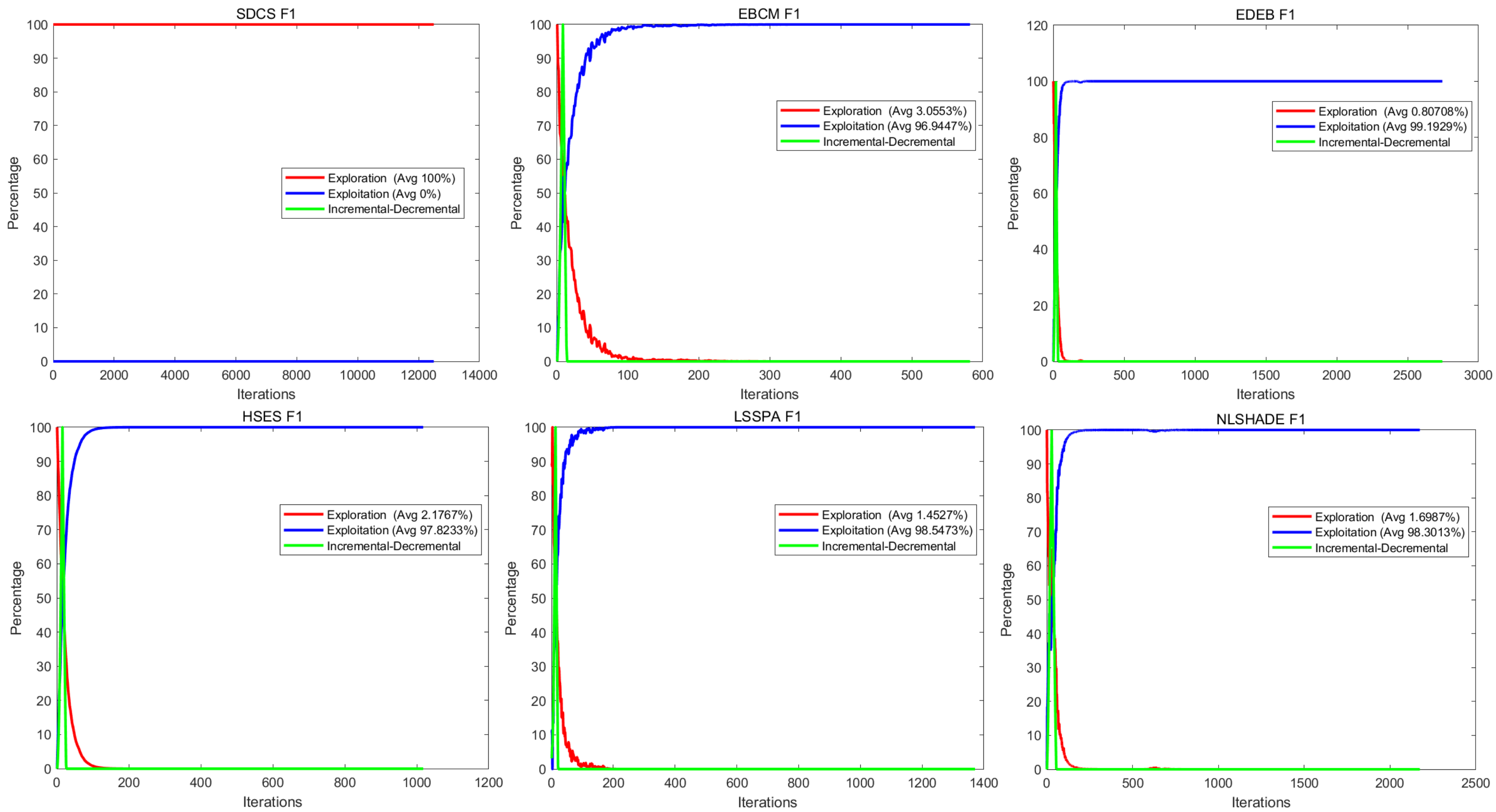
Function F1 with 30 variables



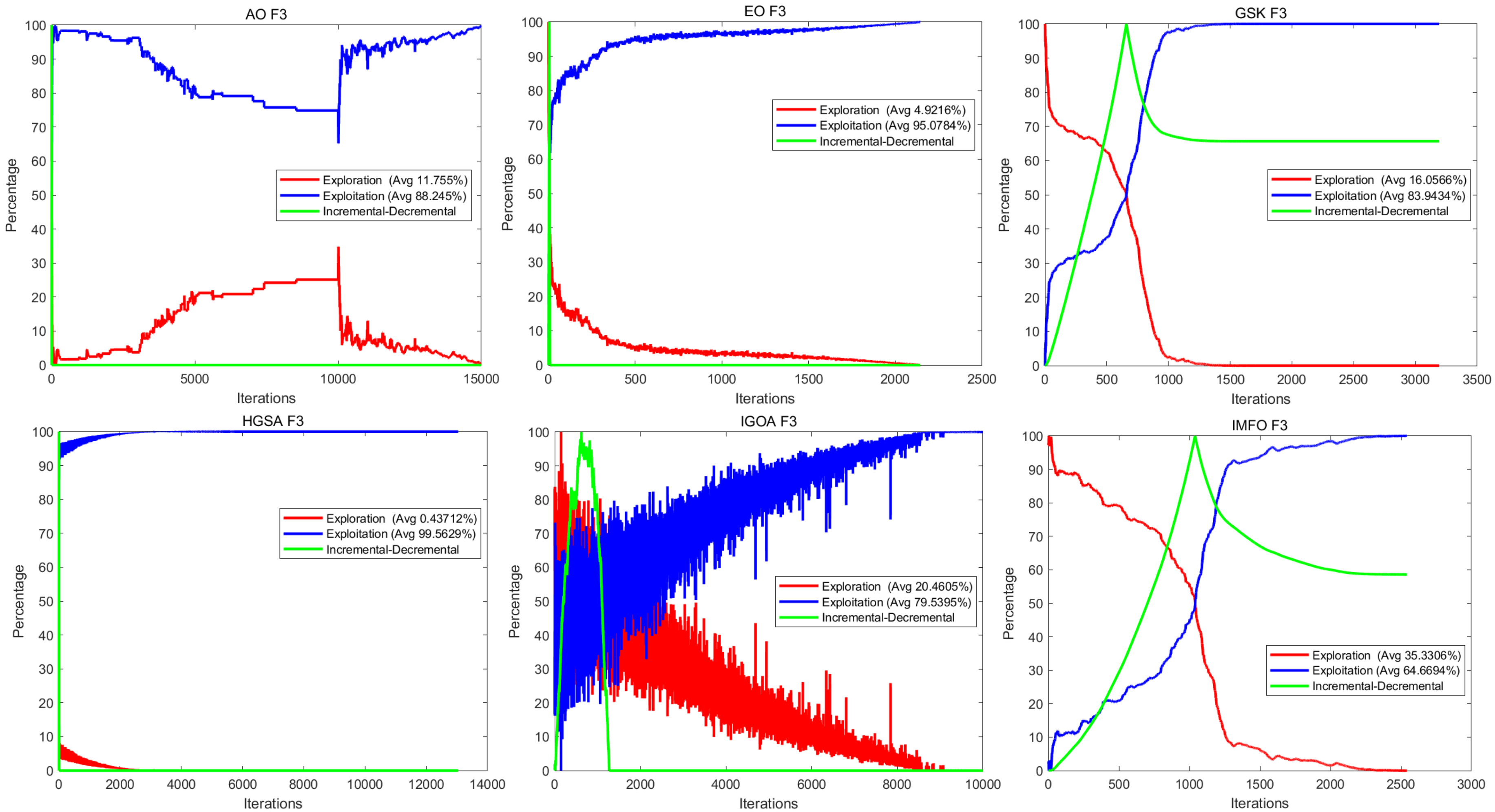


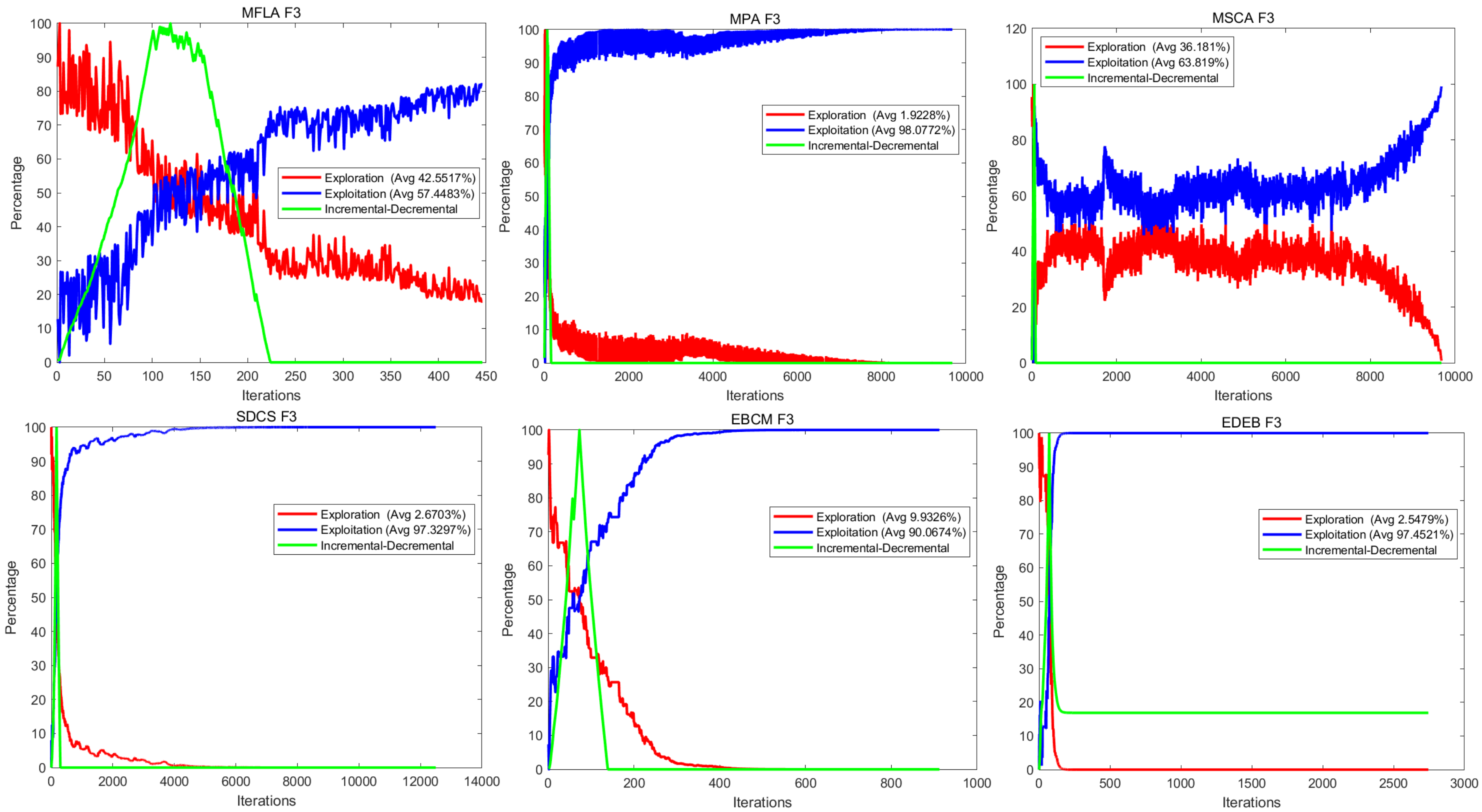


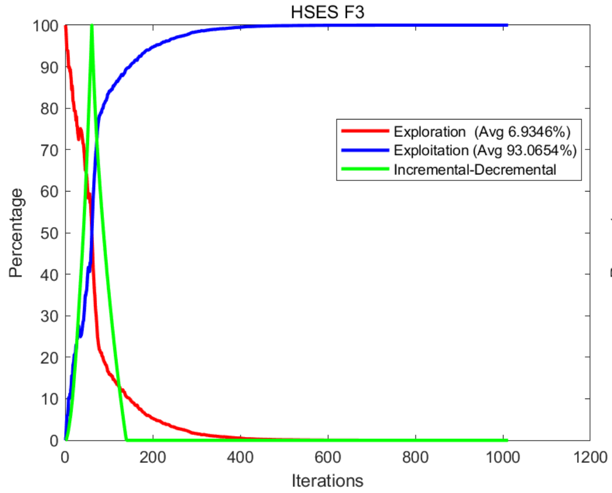

HGSA F1
Exploration (Avg 0.44281%)
Exploitation (Avg 99.5572%)
Incremental-Decremental
IGOA F1
Exploration (Avg 20.2441%)
Exploitation (Avg 79.7559%)
Incremental-Decremental
IMFO F1
Exploration (Avg 0.84758%)
Exploitation (Avg 99.1524%)
Incremental-Decremental
MFLA F1
Exploration (Avg 14.4253%)
Exploitation (Avg 85.5747%)
Incremental-Decremental
MPA F1
Exploration (Avg 1.1624%)
Exploitation (Avg 98.8376%)
Incremental-Decremental
MSCA F1
Exploration (Avg 33.8015%)
Exploitation (Avg 66.1985%)
Incremental-Decremental
Percentage
Iterations

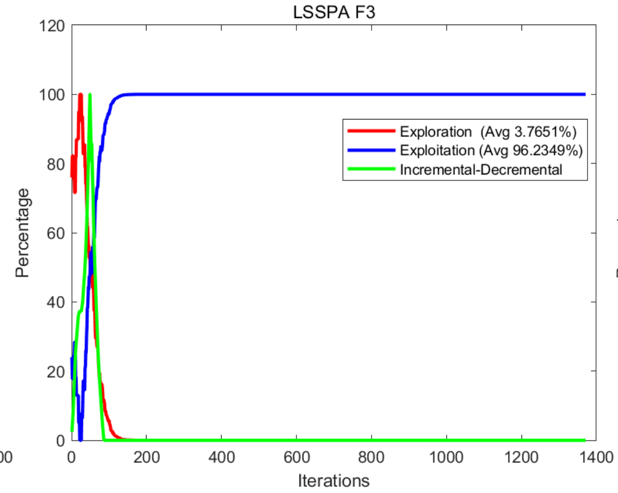


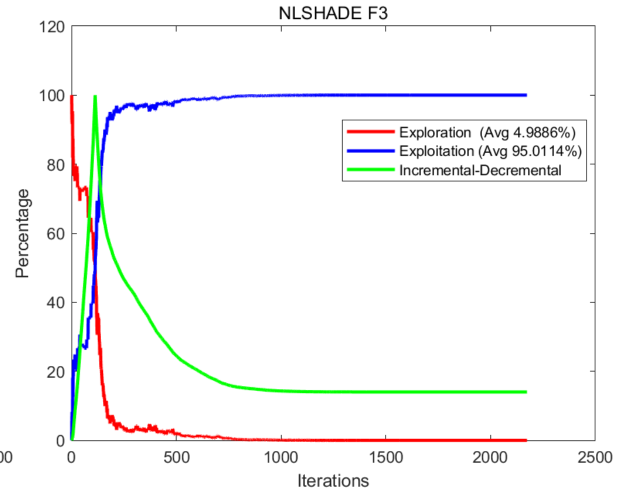
Function F3 with 30 variables


AO F3
Exploration (Avg 11.755%)
Exploitation (Avg 88.245%)
Incremental-Decremental
EO F3
Exploration (Avg 4.9216%)
Exploitation (Avg 95.0784%)
Incremental-Decremental
GSK F3
Exploration (Avg 16.0566%)
Exploitation (Avg 83.9434%)
Incremental-Decremental
HGSA F3
Exploration (Avg 0.43712%)
Exploitation (Avg 99.5629%)
Incremental-Decremental
IGOA F3
Exploration (Avg 20.4605%)
Exploitation (Avg 79.5395%)
Incremental-Decremental
IMFO F3
Exploration (Avg 35.3306%)
Exploitation (Avg 64.6694%)
Incremental-Decremental
Percentage
Iterations

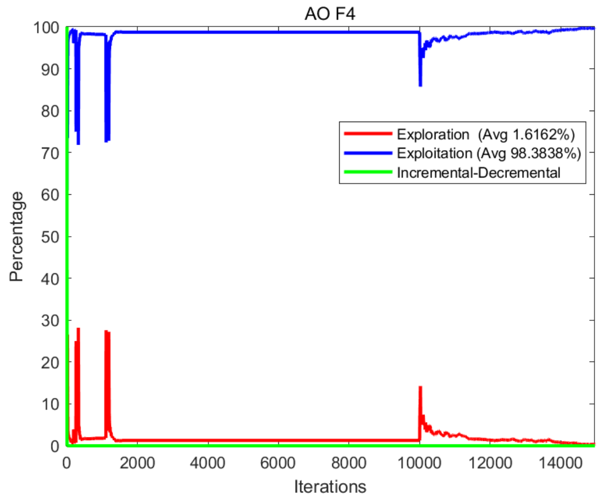

MFLA F3
Exploration (Avg 42.5517%)
Exploitation (Avg 57.4483%)
Incremental-Decremental
MPA F3
Exploration (Avg 1.9228%)
Exploitation (Avg 98.0772%)
Incremental-Decremental
MSCA F3
Exploration (Avg 36.181%)
Exploitation (Avg 63.819%)
Incremental-Decremental
SDCS F3
Exploration (Avg 2.6703%)
Exploitation (Avg 97.3297%)
Incremental-Decremental
EBCM F3
Exploration (Avg 9.9326%)
Exploitation (Avg 90.0674%)
Incremental-Decremental
EDEB F3
Exploration (Avg 2.5479%)
Exploitation (Avg 97.4521%)
Incremental-Decremental
Percentage
Iterations

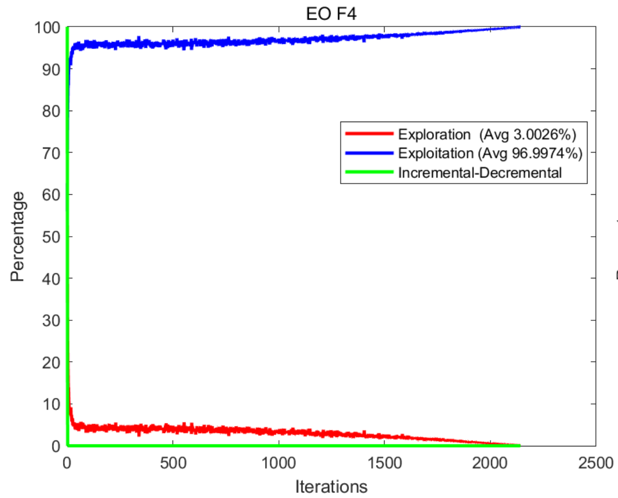


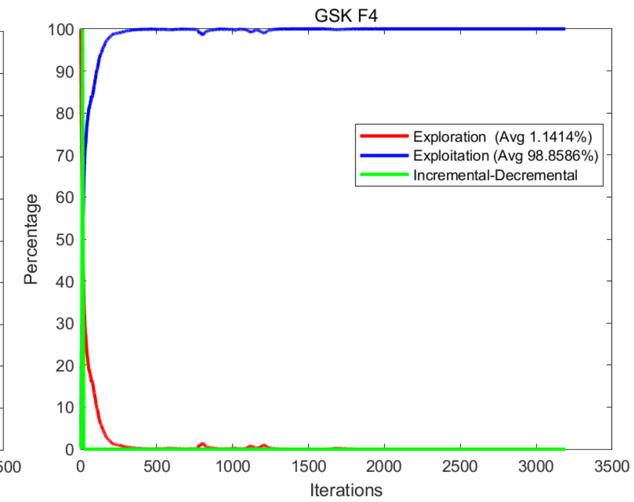


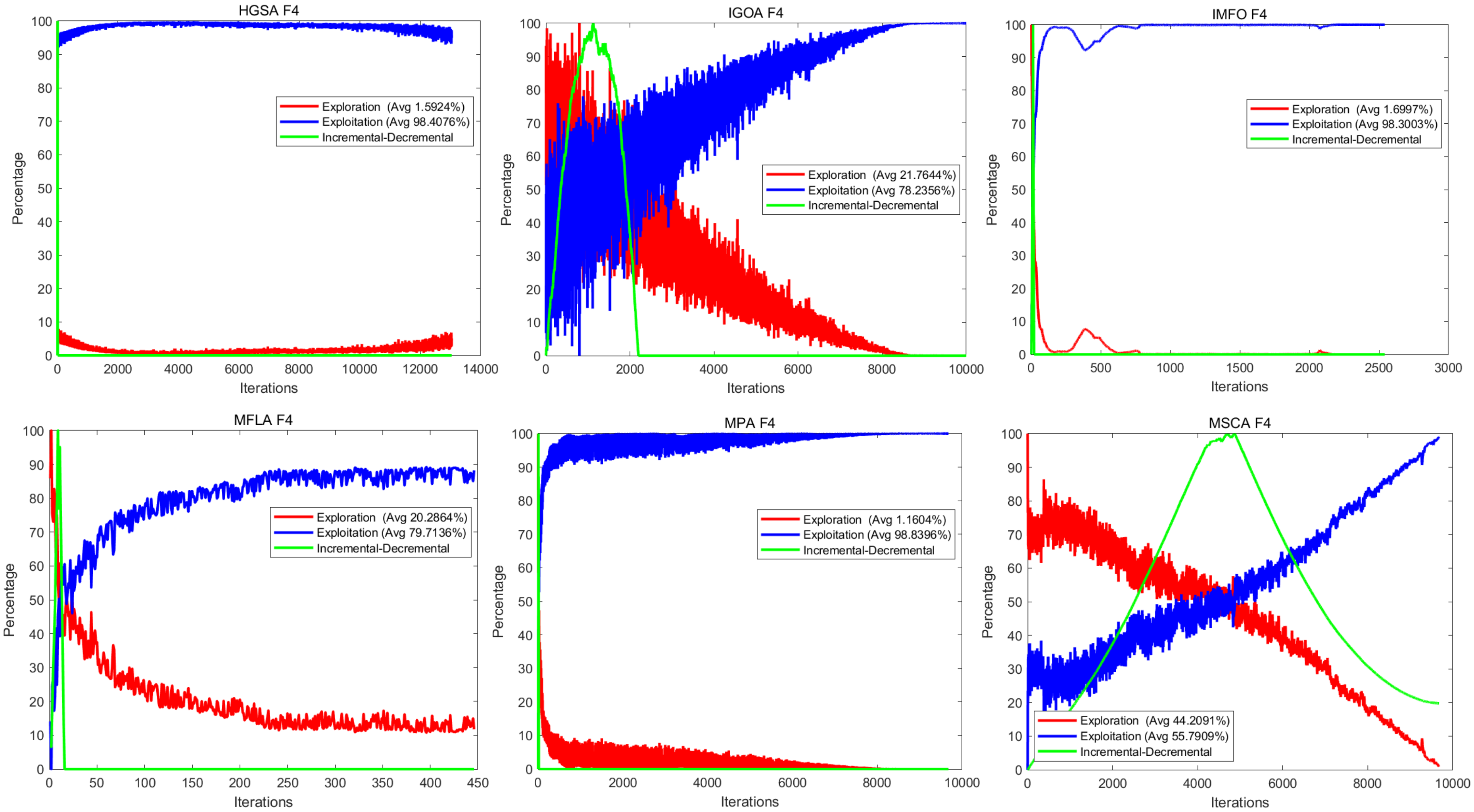


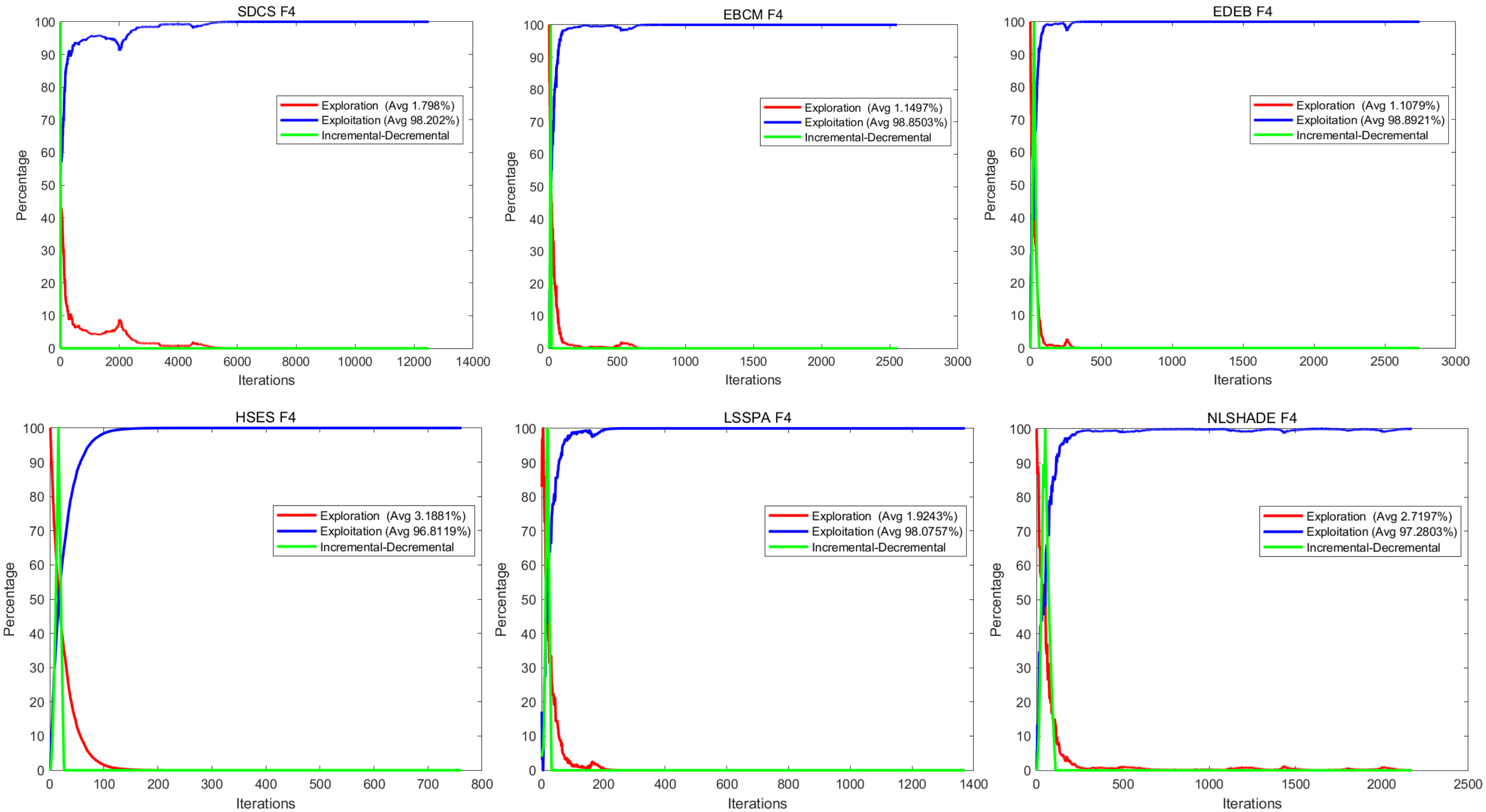
Function F4 with 30 variables



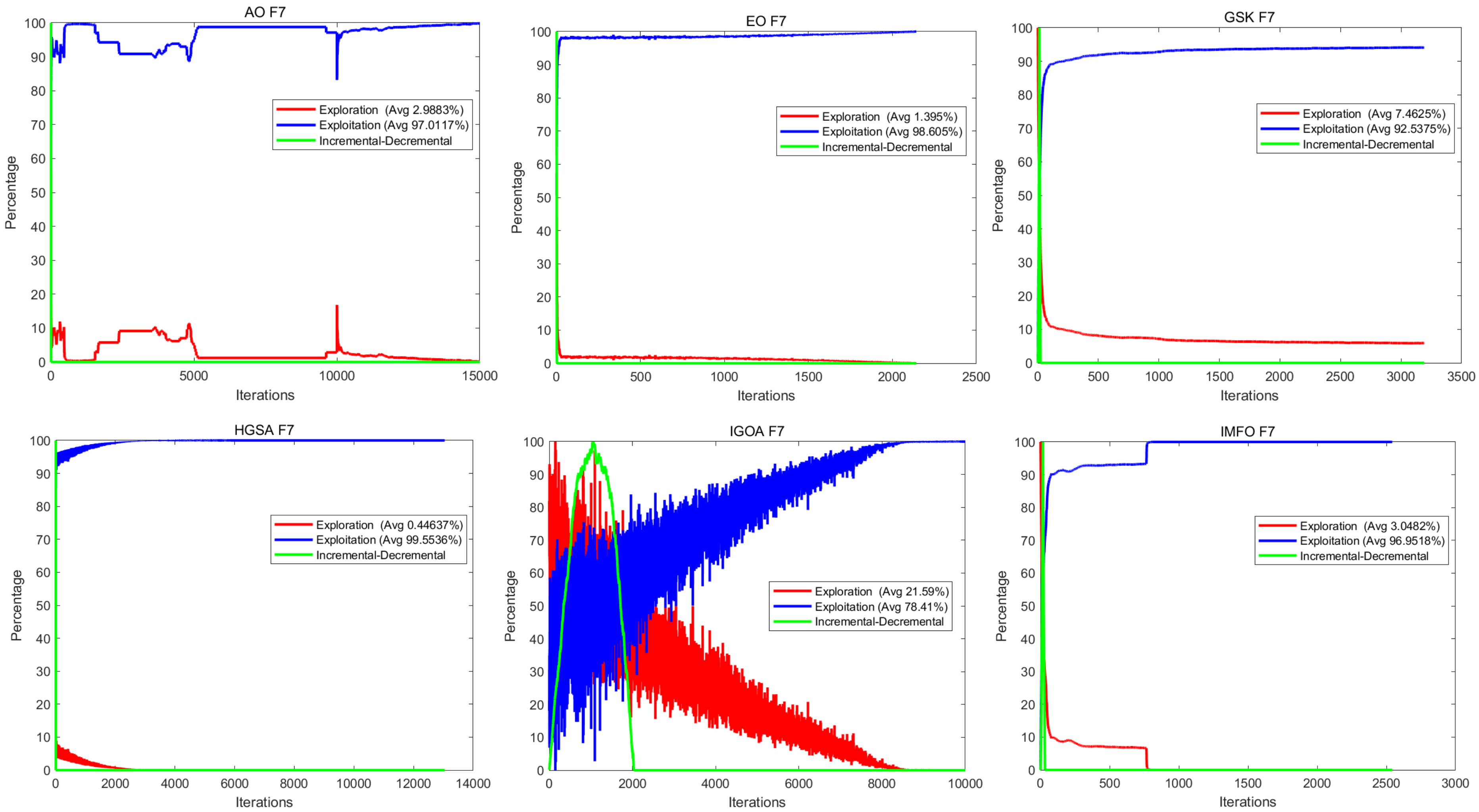


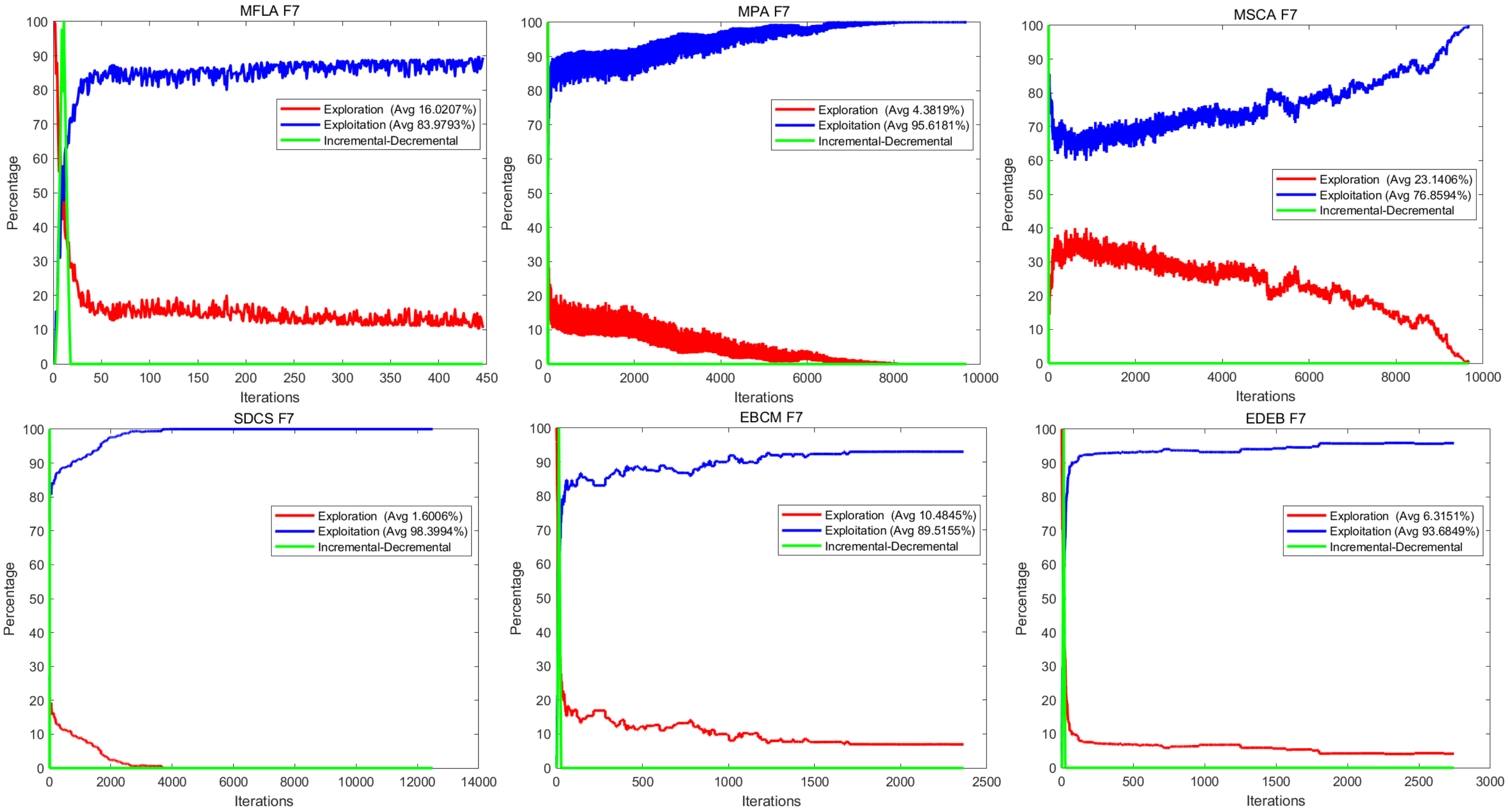


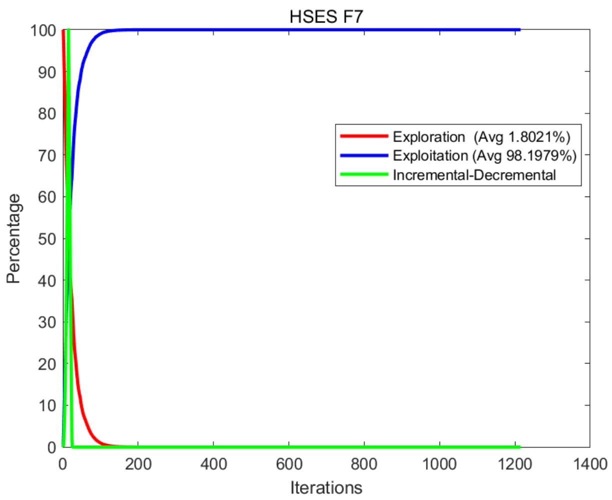

HGSA F4
Exploration (Avg 1.5924%)
Exploitation (Avg 98.4076%)
Incremental-Decremental
IGOA F4
Exploration (Avg 21.7644%)
Exploitation (Avg 78.2356%)
Incremental-Decremental
IMFO F4
Exploration (Avg 1.6997%)
Exploitation (Avg 98.3003%)
Incremental-Decremental
MFLA F4
Exploration (Avg 20.2864%)
Exploitation (Avg 79.7136%)
Incremental-Decremental
MPA F4
Exploration (Avg 1.1604%)
Exploitation (Avg 98.8396%)
Incremental-Decremental
MSCA F4
Exploration (Avg 44.2091%)
Exploitation (Avg 55.7909%)
Incremental-Decremental
Percentage
Iterations

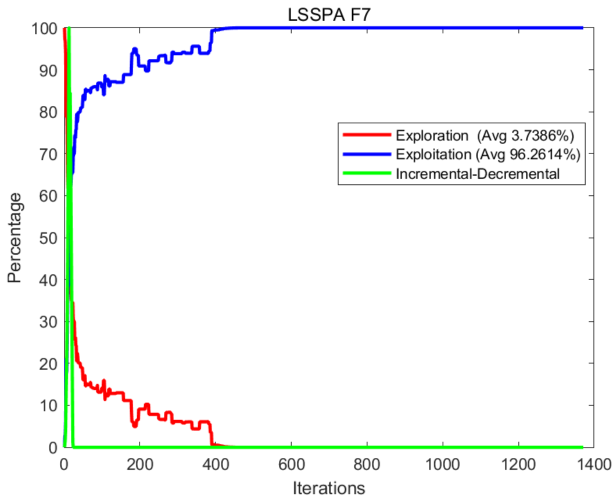


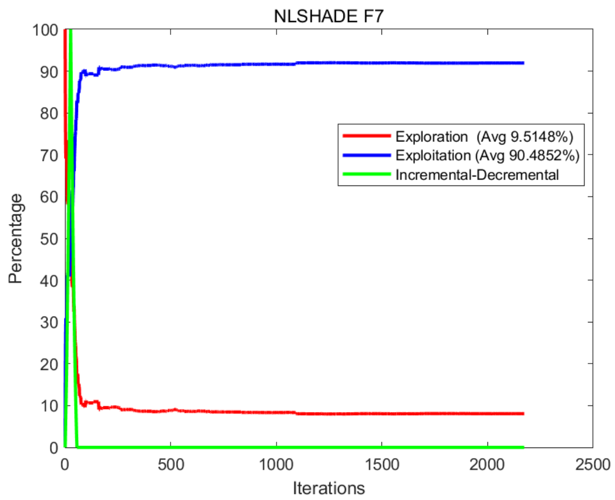
Function F7 with 30 variables


AO F7
Exploration (Avg 2.9883%)
Exploitation (Avg 97.0117%)
Incremental-Decremental
Percentage
Iterations
EO F7
Exploration (Avg 1.395%)
Exploitation (Avg 98.605%)
Incremental-Decremental
Percentage
Iterations
GSK F7
Exploration (Avg 7.4625%)
Exploitation (Avg 92.5375%)
Incremental-Decremental
Percentage
Iterations
HGSA F7
Exploration (Avg 0.44637%)
Exploitation (Avg 99.5536%)
Incremental-Decremental
Percentage
Iterations
IGOA F7
Exploration (Avg 21.59%)
Exploitation (Avg 78.41%)
Incremental-Decremental
Percentage
Iterations
IMFO F7
Exploration (Avg 3.0482%)
Exploitation (Avg 96.9518%)
Incremental-Decremental
Percentage
Iterations

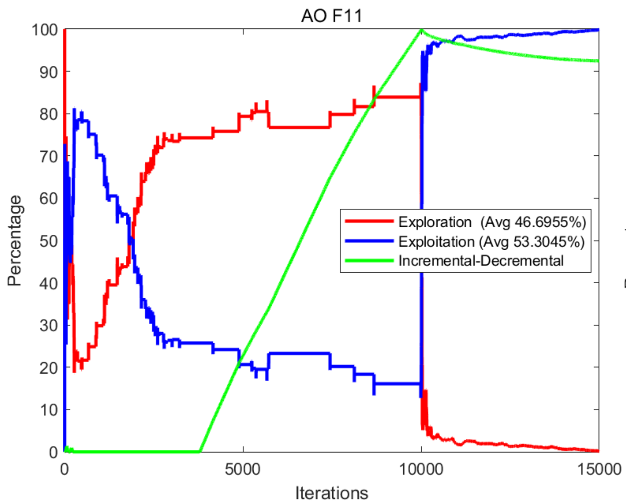

MFLA F7
Exploration (Avg 16.0207%)
Exploitation (Avg 83.9793%)
Incremental-Decremental
MPA F7
Exploration (Avg 4.3819%)
Exploitation (Avg 95.6181%)
Incremental-Decremental
MSCA F7
Exploration (Avg 23.1406%)
Exploitation (Avg 76.8594%)
Incremental-Decremental
SDCS F7
Exploration (Avg 1.6006%)
Exploitation (Avg 98.3994%)
Incremental-Decremental
EBCM F7
Exploration (Avg 10.4845%)
Exploitation (Avg 89.5155%)
Incremental-Decremental
EDEB F7
Exploration (Avg 6.3151%)
Exploitation (Avg 93.6849%)
Incremental-Decremental
Percentage
Iterations

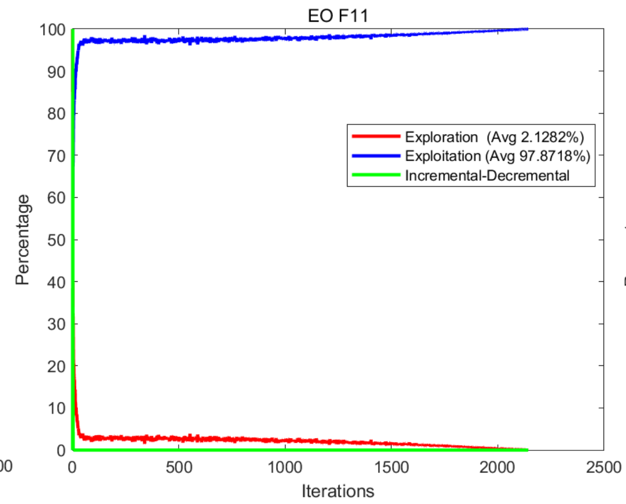


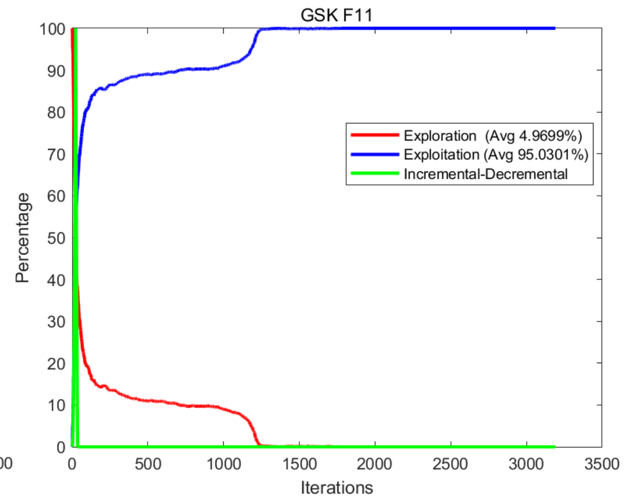


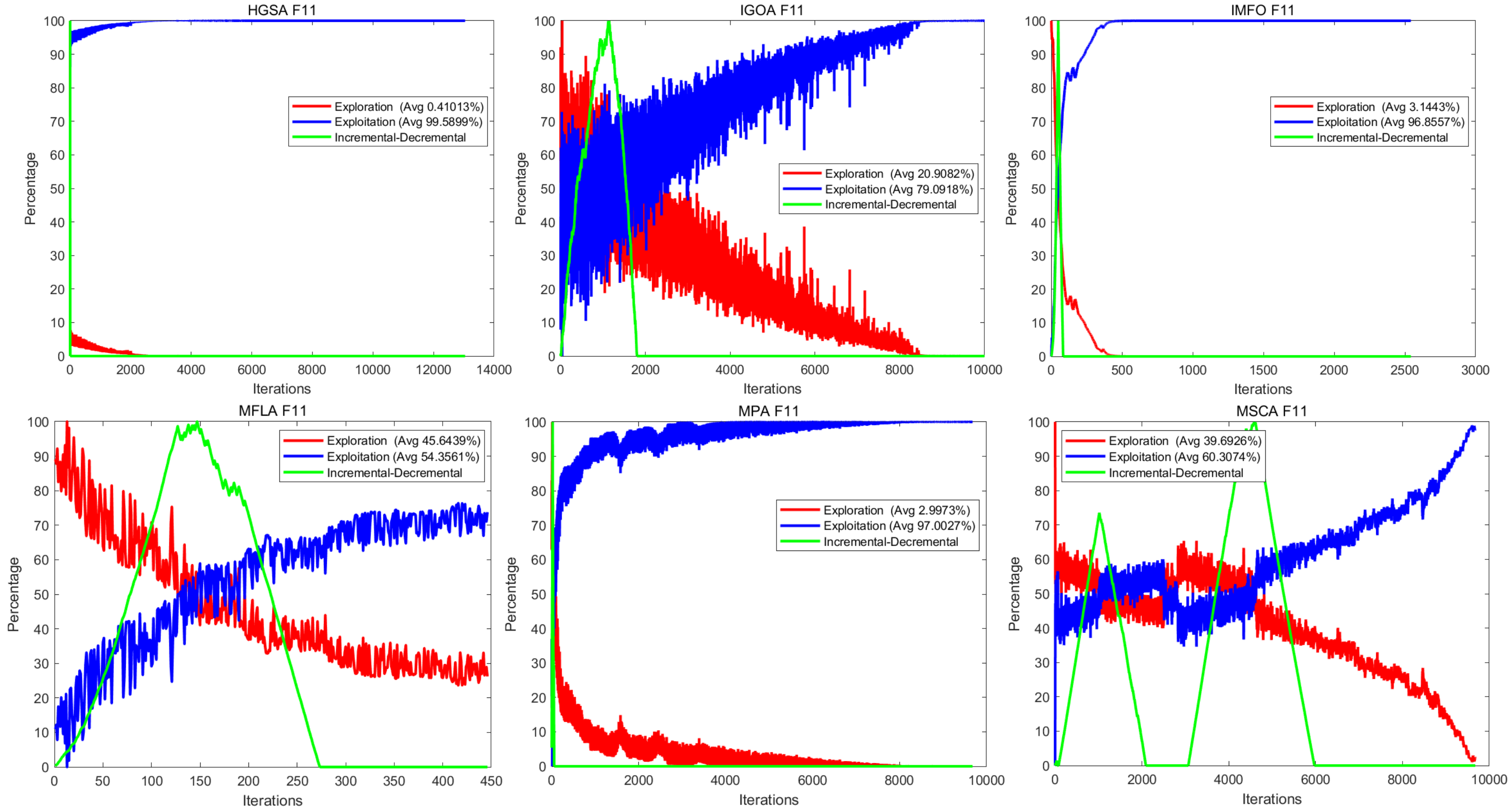


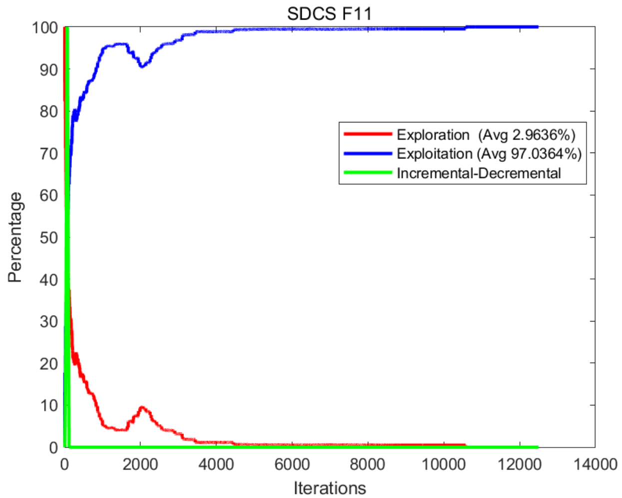
Function F11 with 30 variables

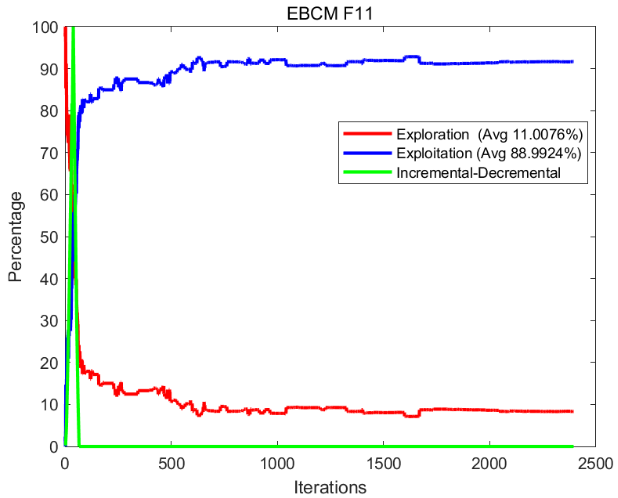


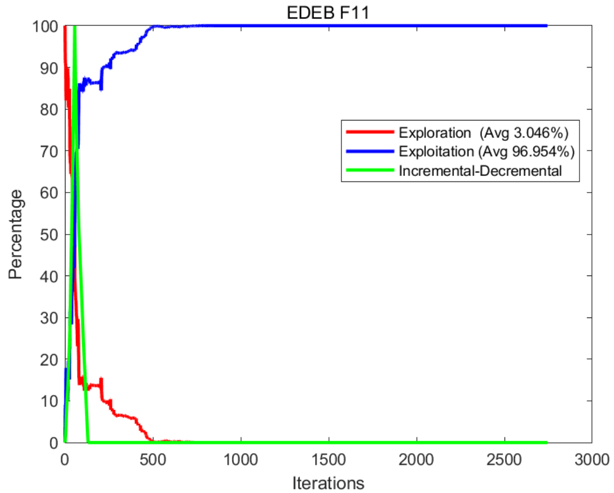


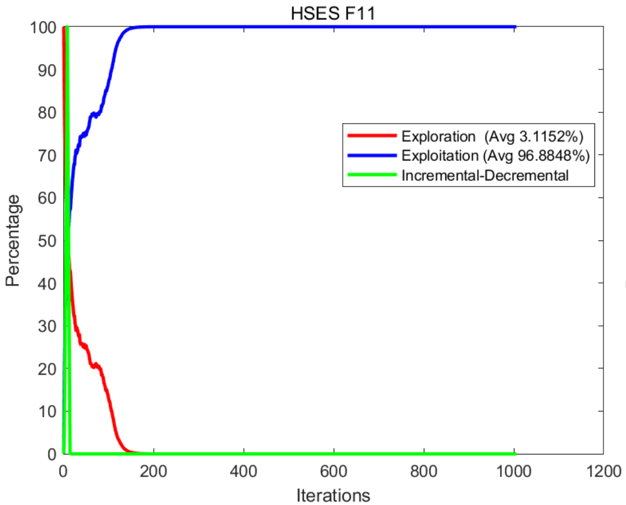


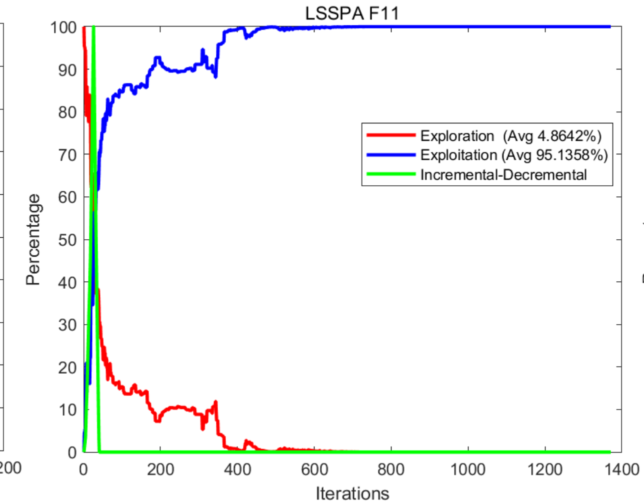

HGSA F11
Exploration (Avg 0.41013%)
Exploitation (Avg 99.5899%)
Incremental-Decremental
IGOA F11
Exploration (Avg 20.9082%)
Exploitation (Avg 79.0918%)
Incremental-Decremental
IMFO F11
Exploration (Avg 3.1443%)
Exploitation (Avg 96.8557%)
Incremental-Decremental
MFLA F11
Exploration (Avg 45.6439%)
Exploitation (Avg 54.3561%)
Incremental-Decremental
MPA F11
Exploration (Avg 2.9973%)
Exploitation (Avg 97.0027%)
Incremental-Decremental
MSCA F11
Exploration (Avg 39.6926%)
Exploitation (Avg 60.3074%)
Incremental-Decremental
Percentage
Iterations

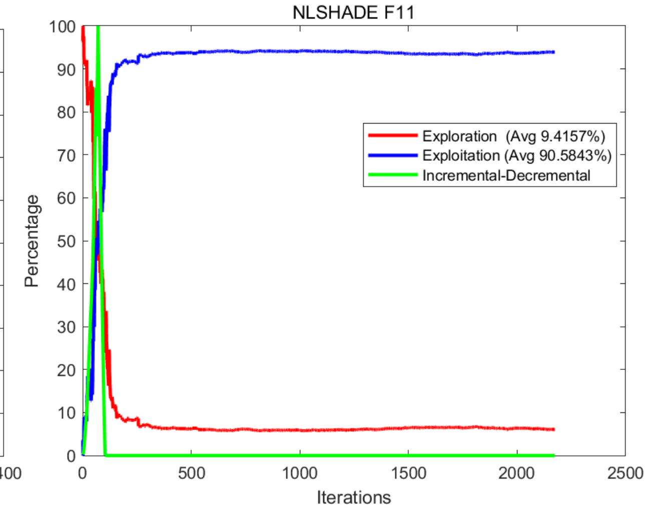




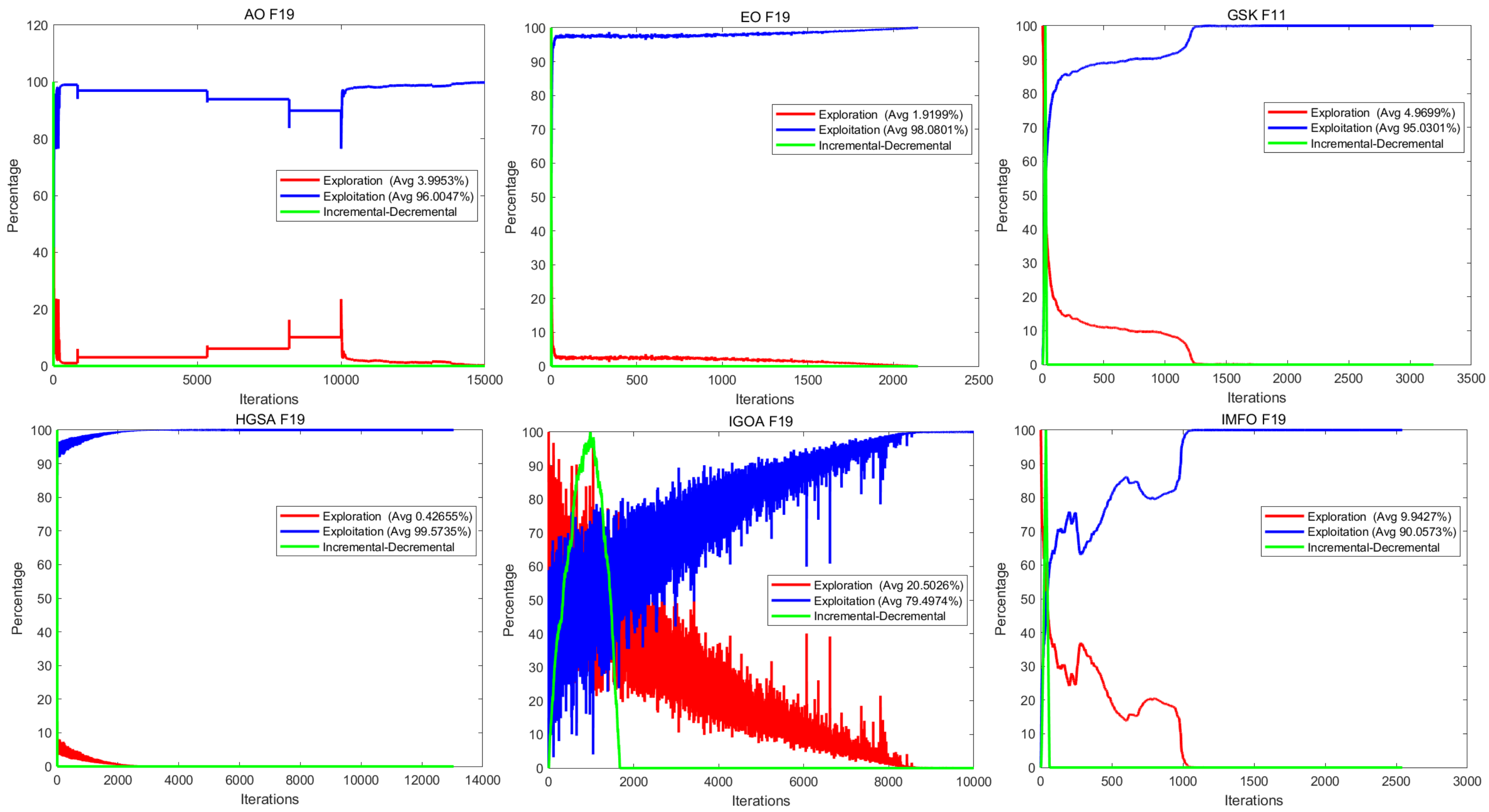




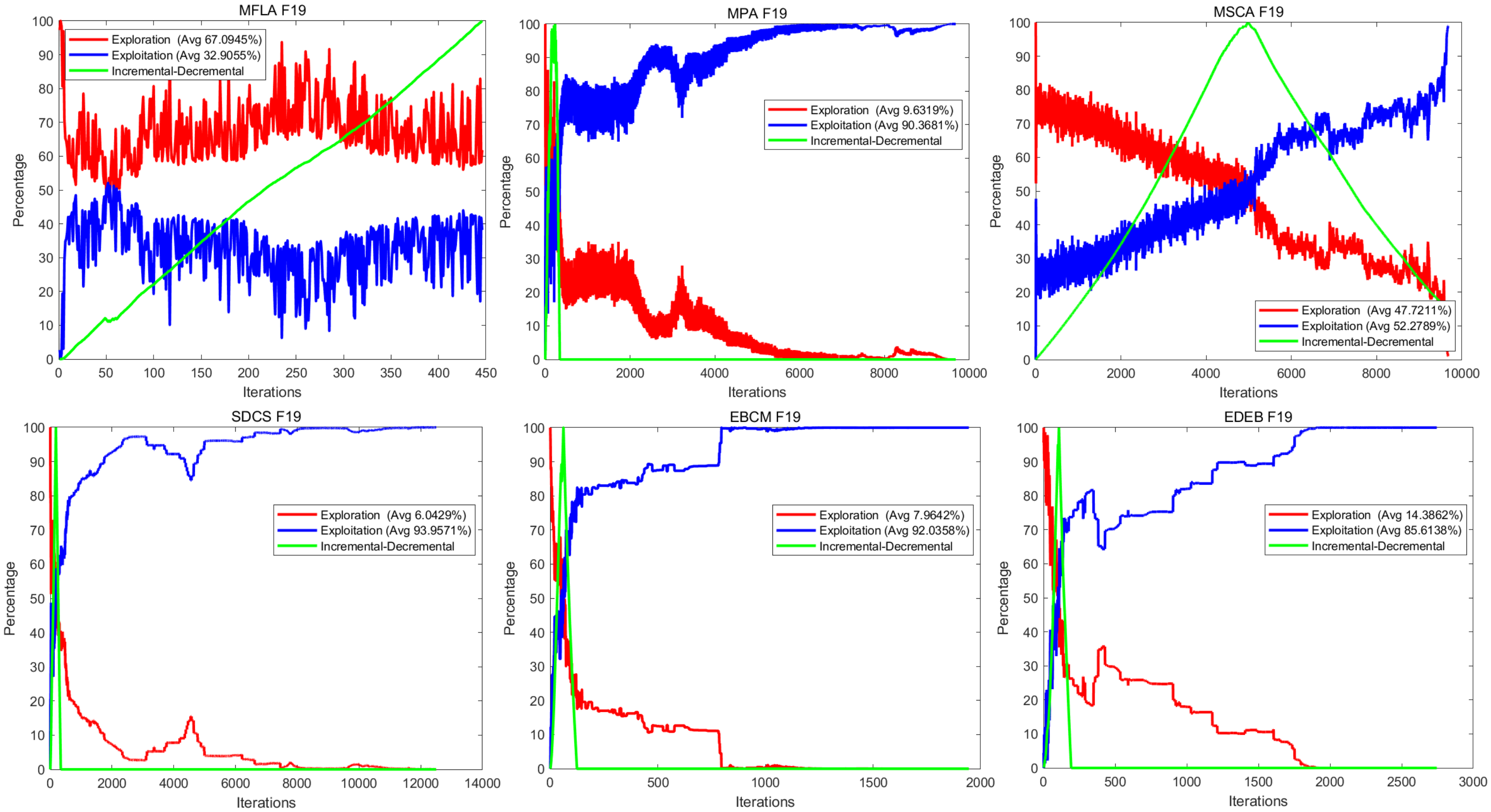


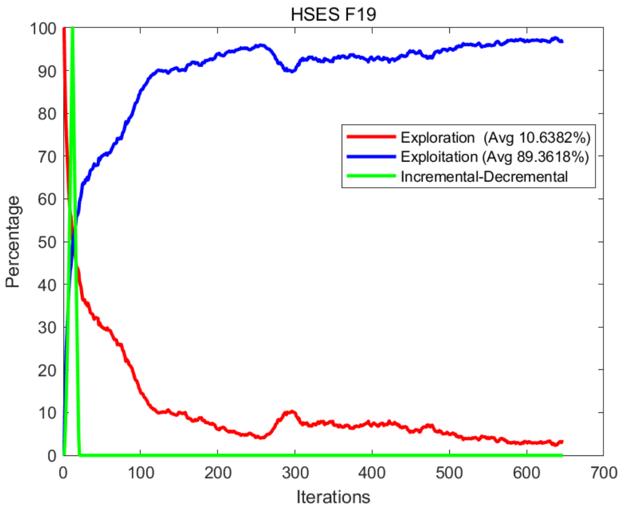


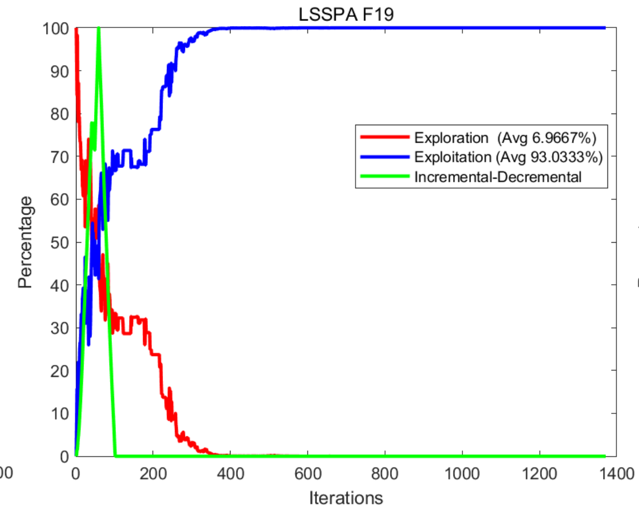
Function F19 with 30 variables

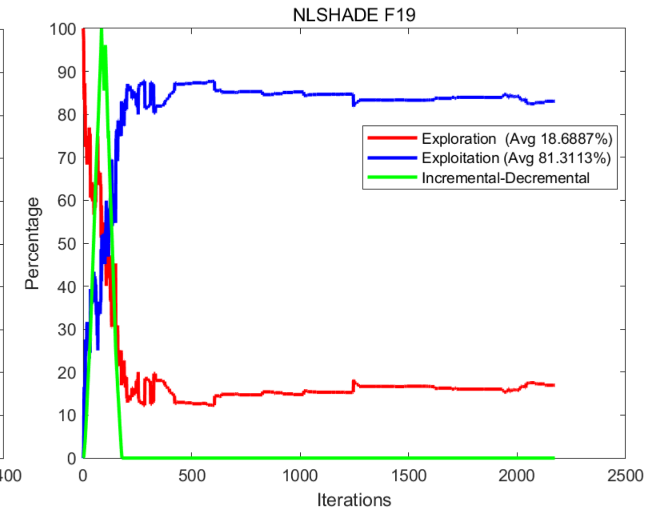


AO F19
Exploration (Avg 3.9953%)
Exploitation (Avg 96.0047%)
Incremental-Decremental
Percentage
Iterations
EO F19
Exploration (Avg 1.9199%)
Exploitation (Avg 98.0801%)
Incremental-Decremental
Percentage
Iterations
GSK F11
Exploration (Avg 4.9699%)
Exploitation (Avg 95.0301%)
Incremental-Decremental
Percentage
Iterations
HGSA F19
Exploration (Avg 0.42655%)
Exploitation (Avg 99.5735%)
Incremental-Decremental
Percentage
Iterations
IGOA F19
Exploration (Avg 20.5026%)
Exploitation (Avg 79.4974%)
Incremental-Decremental
Percentage
Iterations
IMFO F19
Exploration (Avg 9.9427%)
Exploitation (Avg 90.0573%)
Incremental-Decremental
Percentage
Iterations

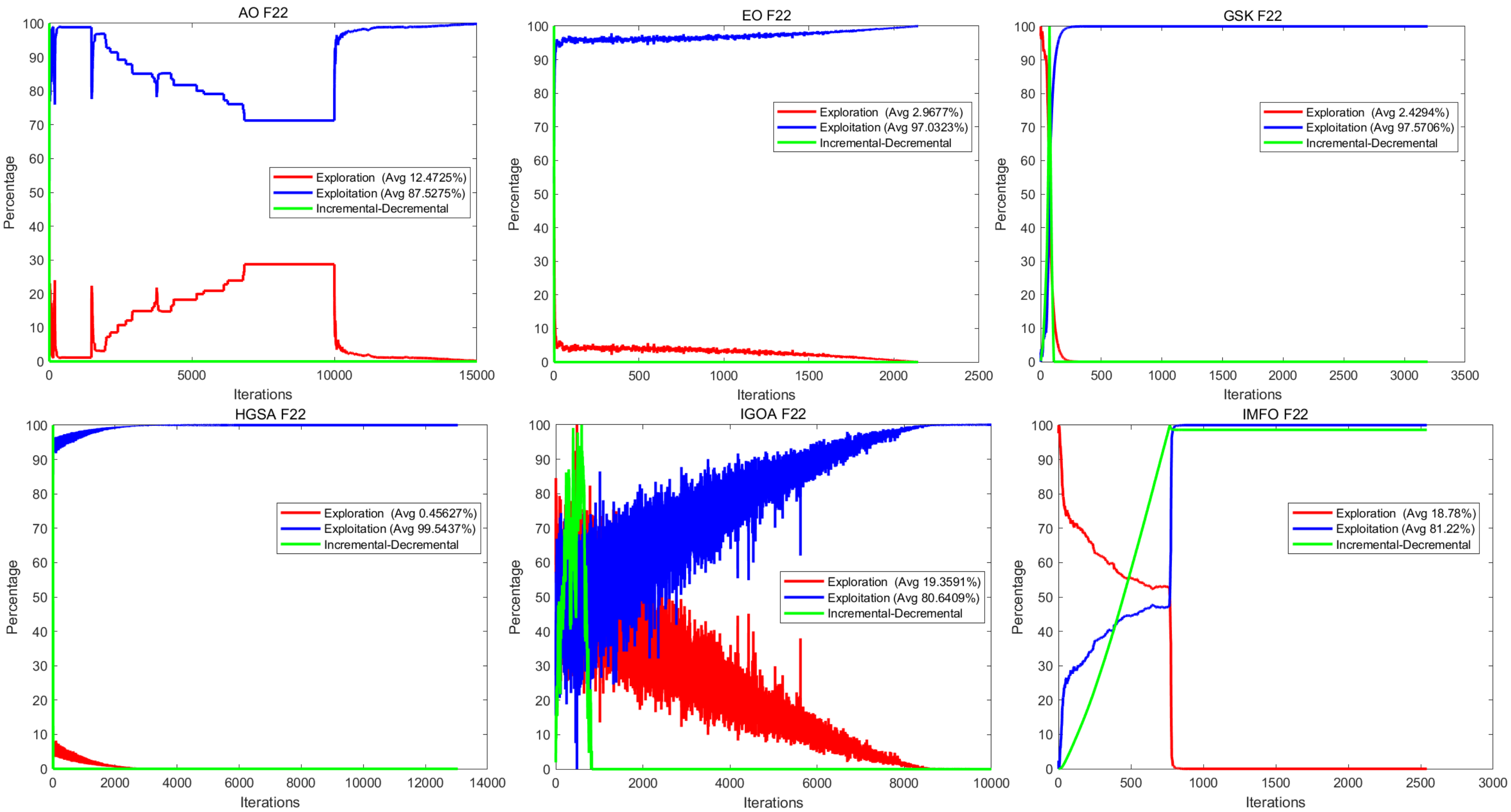

MFLA F19
Exploration (Avg 67.0945%)
Exploitation (Avg 32.9055%)
Incremental-Decremental
MPA F19
Exploration (Avg 9.6319%)
Exploitation (Avg 90.3681%)
Incremental-Decremental
MSCA F19
Exploration (Avg 47.7211%)
Exploitation (Avg 52.2789%)
Incremental-Decremental
SDCS F19
Exploration (Avg 6.0429%)
Exploitation (Avg 93.9571%)
Incremental-Decremental
EBCM F19
Exploration (Avg 7.9642%)
Exploitation (Avg 92.0358%)
Incremental-Decremental
EDEB F19
Exploration (Avg 14.3862%)
Exploitation (Avg 85.6138%)
Incremental-Decremental
Percentage
Iterations

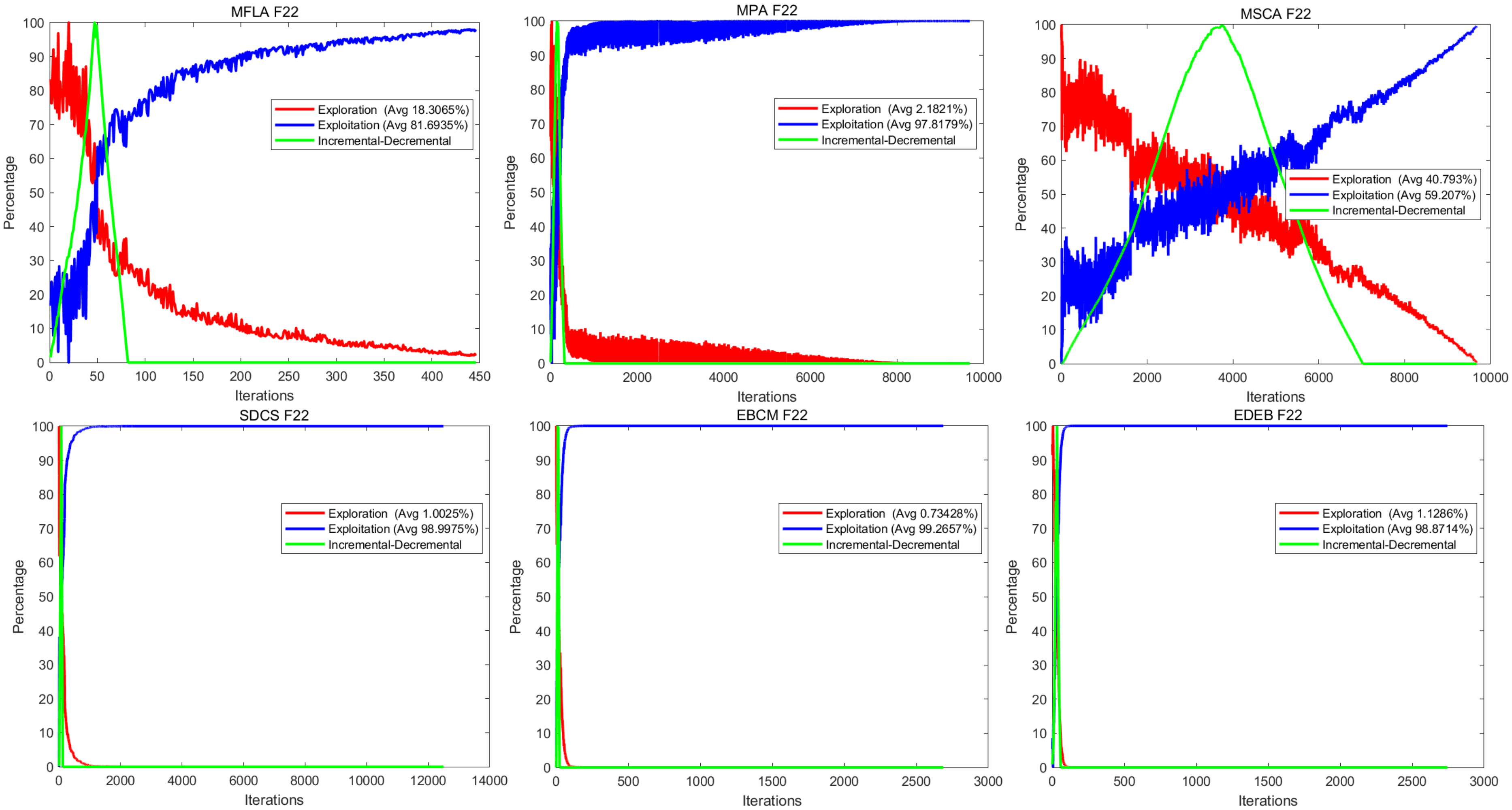


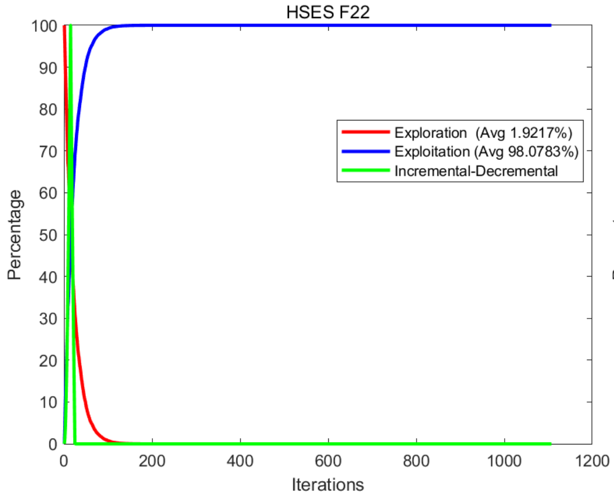


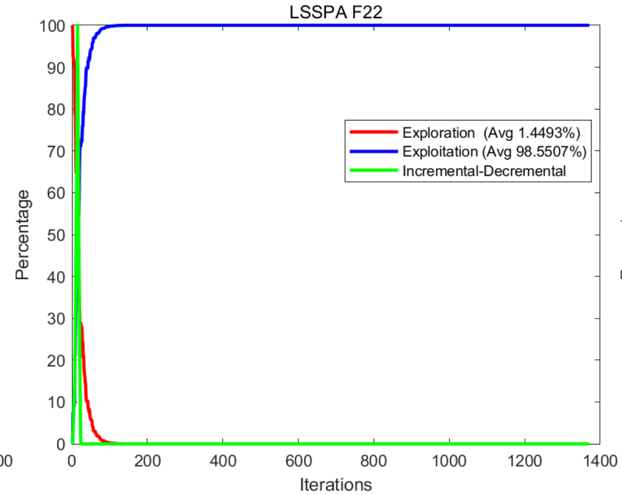


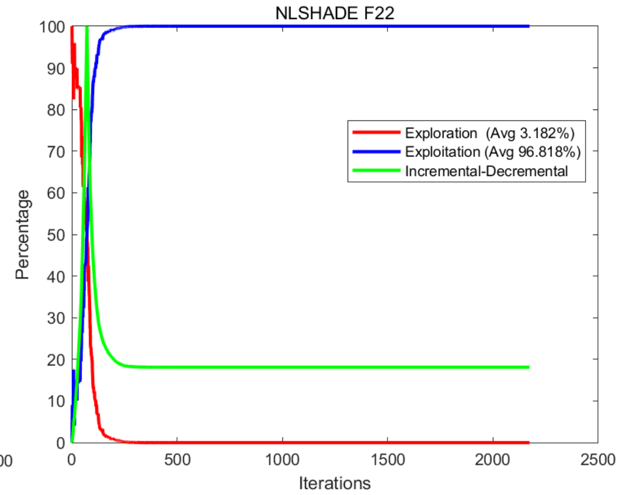
Function F22 with 30 variables


AO F22
Exploration (Avg 12.4725%)
Exploitation (Avg 87.5275%)
Incremental-Decremental
EO F22
Exploration (Avg 2.9677%)
Exploitation (Avg 97.0323%)
Incremental-Decremental
GSK F22
Exploration (Avg 2.4294%)
Exploitation (Avg 97.5706%)
Incremental-Decremental
HGSA F22
Exploration (Avg 0.45627%)
Exploitation (Avg 99.5437%)
Incremental-Decremental
IGOA F22
Exploration (Avg 19.3591%)
Exploitation (Avg 80.6409%)
Incremental-Decremental
IMFO F22
Exploration (Avg 18.78%)
Exploitation (Avg 81.22%)
Incremental-Decremental
Percentage
Iterations

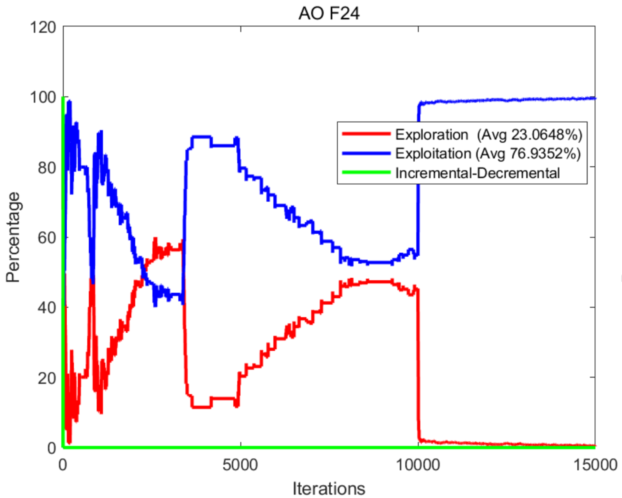

MFLA F22
Exploration (Avg 18.3065%)
Exploitation (Avg 81.6935%)
Incremental-Decremental
MPA F22
Exploration (Avg 2.1821%)
Exploitation (Avg 97.8179%)
Incremental-Decremental
MSCA F22
Exploration (Avg 40.793%)
Exploitation (Avg 59.207%)
Incremental-Decremental
SDCS F22
Exploration (Avg 1.0025%)
Exploitation (Avg 98.9975%)
Incremental-Decremental
EBCM F22
Exploration (Avg 0.73428%)
Exploitation (Avg 99.2657%)
Incremental-Decremental
EDEB F22
Exploration (Avg 1.1286%)
Exploitation (Avg 98.8714%)
Incremental-Decremental
Percentage
Iterations

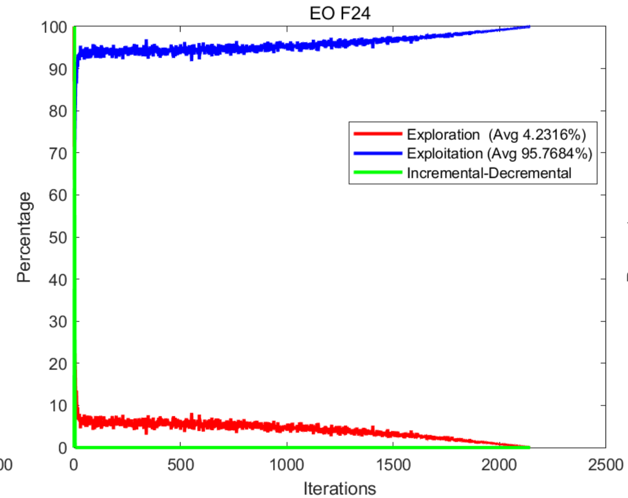


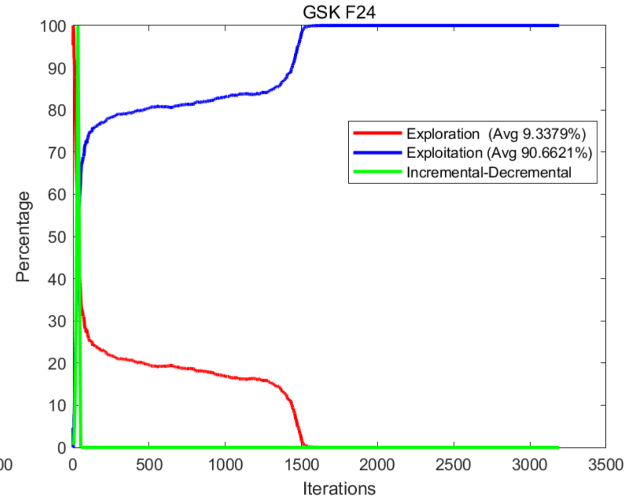


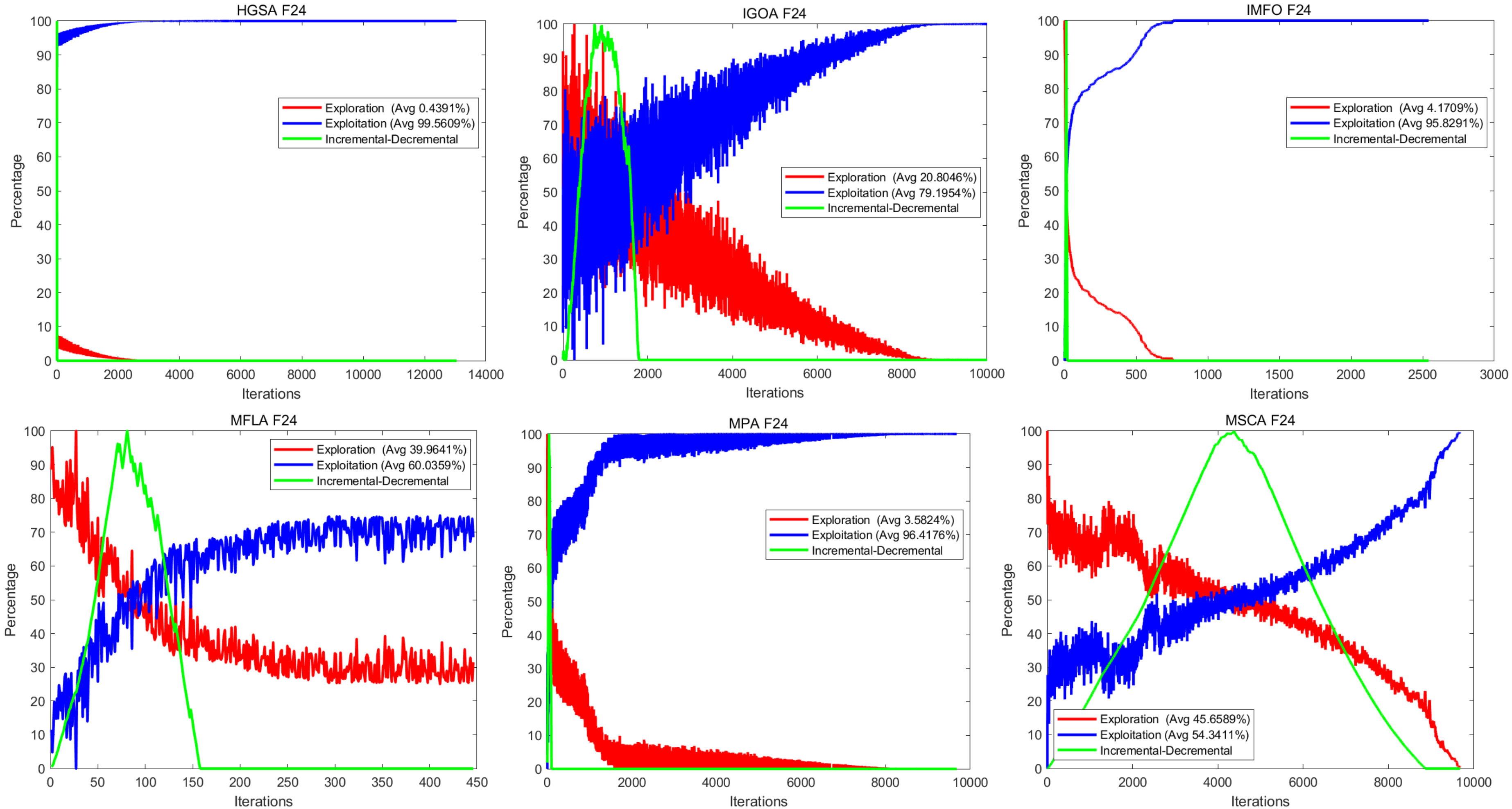


Function F24 with 30 variables








HGSA F24
Exploration (Avg 0.4391%)
Exploitation (Avg 99.5609%)
Incremental-Decremental
IGOA F24
Exploration (Avg 20.8046%)
Exploitation (Avg 79.1954%)
Incremental-Decremental
IMFO F24
Exploration (Avg 4.1709%)
Exploitation (Avg 95.8291%)
Incremental-Decremental
MFLA F24
Exploration (Avg 39.9641%)
Exploitation (Avg 60.0359%)
Incremental-Decremental
MPA F24
Exploration (Avg 3.5824%)
Exploitation (Avg 96.4176%)
Incremental-Decremental
MSCA F24
Exploration (Avg 45.6589%)
Exploitation (Avg 54.3411%)
Incremental-Decremental
Percentage
Iterations

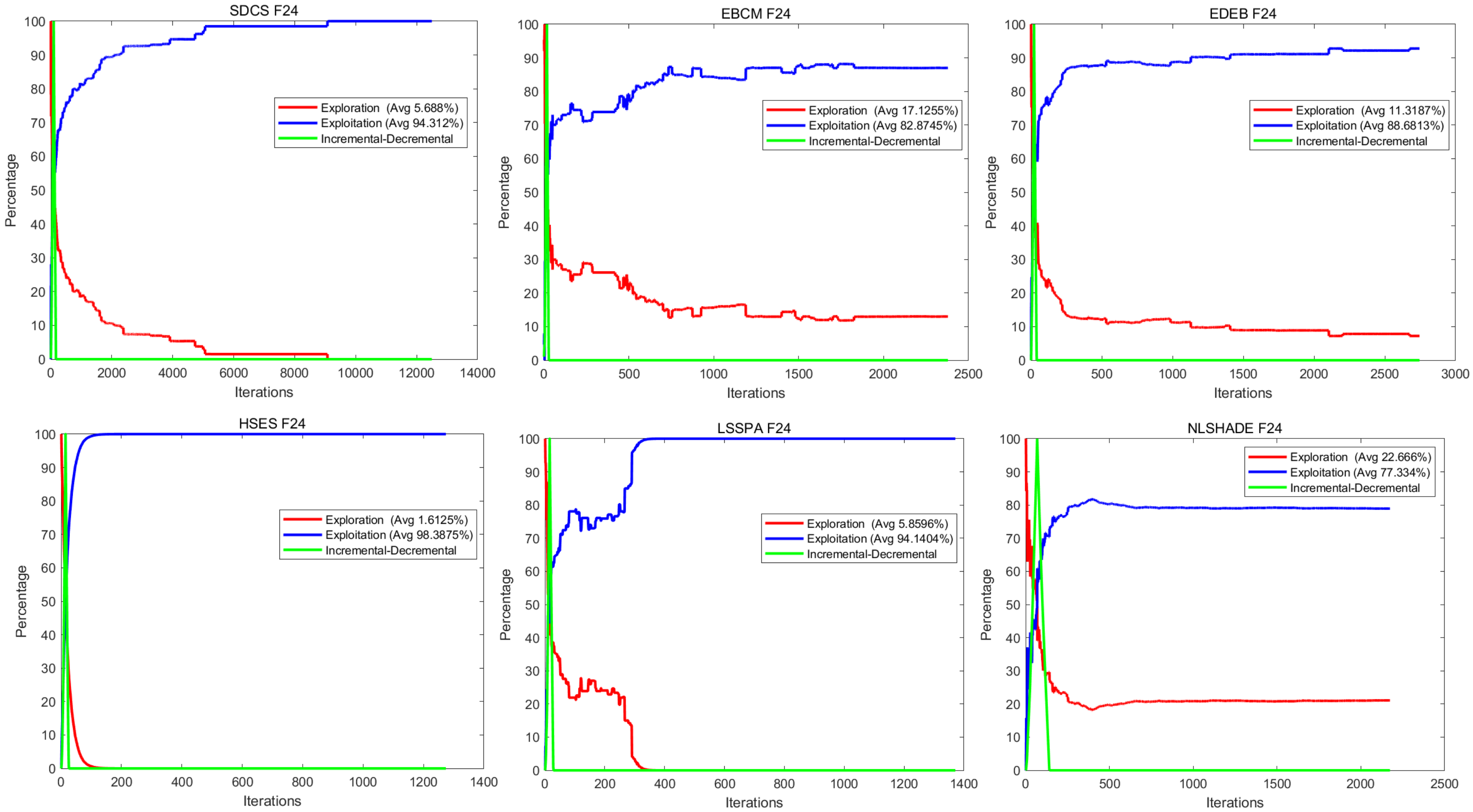
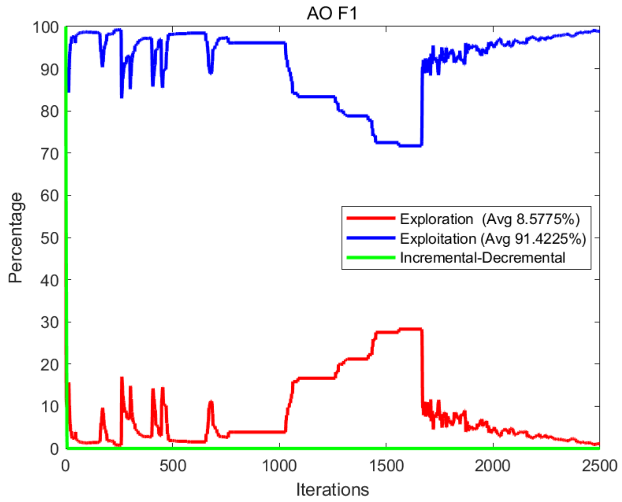
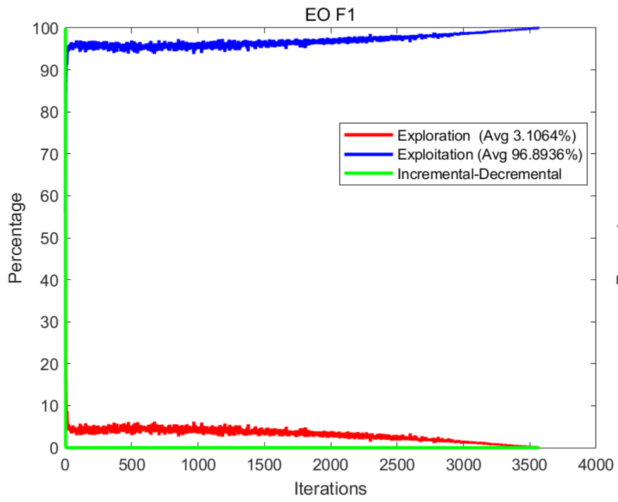
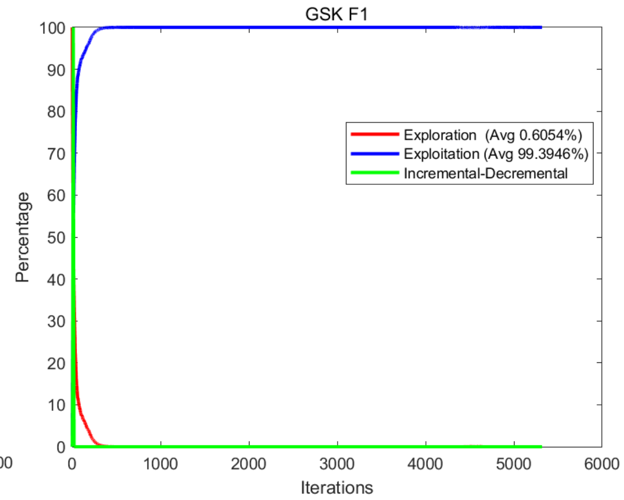

SDCS F24
Exploration (Avg 5.688%)
Exploitation (Avg 94.312%)
Incremental-Decremental
Percentage
Iterations
EBCM F24
Exploration (Avg 17.1255%)
Exploitation (Avg 82.8745%)
Incremental-Decremental
Percentage
Iterations
EDEB F24
Exploration (Avg 11.3187%)
Exploitation (Avg 88.6813%)
Incremental-Decremental
Percentage
Iterations
HSES F24
Exploration (Avg 1.6125%)
Exploitation (Avg 98.3875%)
Incremental-Decremental
Percentage
Iterations
LSSPA F24
Exploration (Avg 5.8596%)
Exploitation (Avg 94.1404%)
Incremental-Decremental
Percentage
Iterations
NLSHADE F24
Exploration (Avg 22.666%)
Exploitation (Avg 77.334%)
Incremental-Decremental
Percentage
Iterations

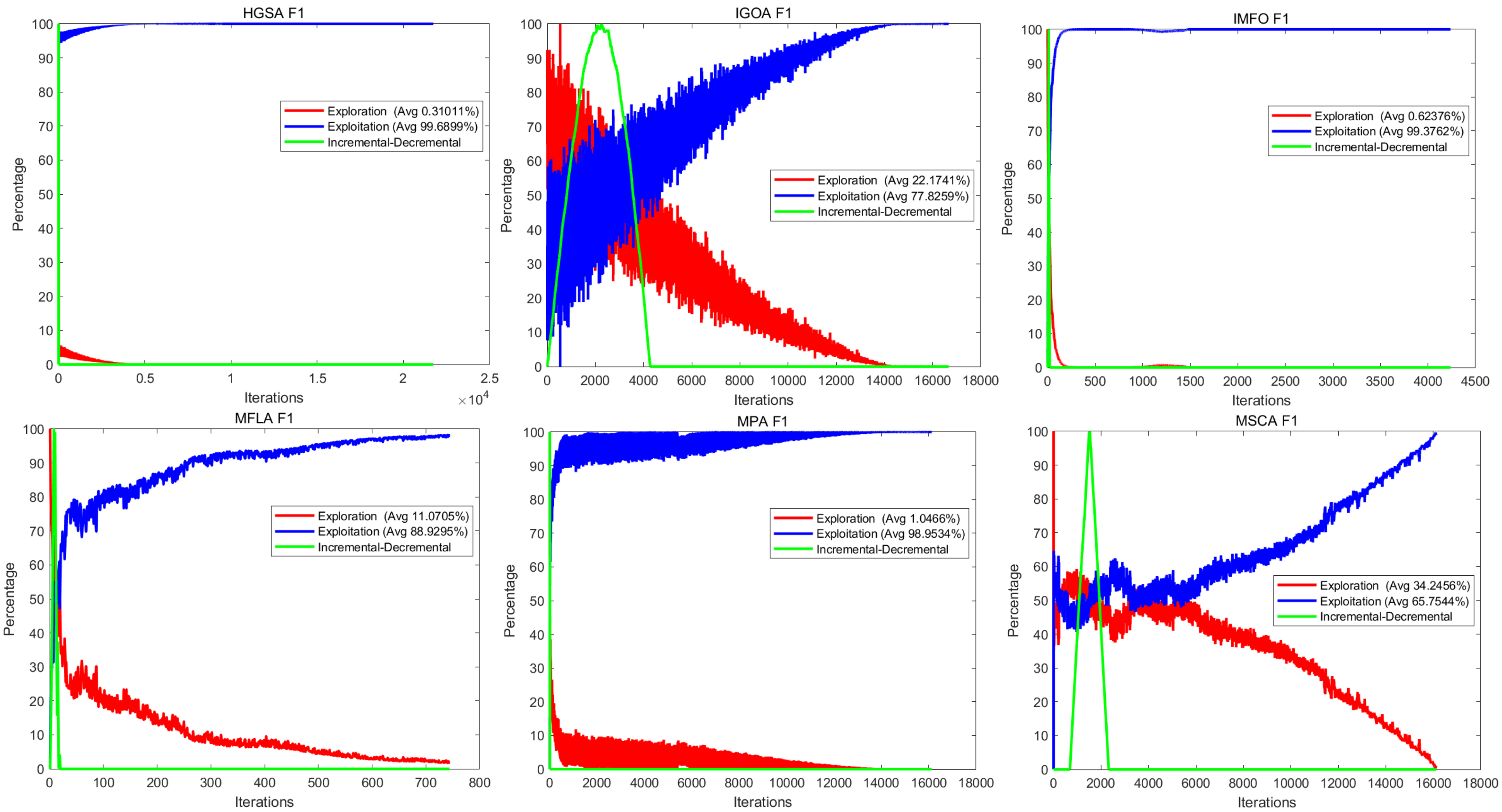
Fig.S9 Evolution of the exploration and the exploitation of 15 algorithms on functions with 50 variables

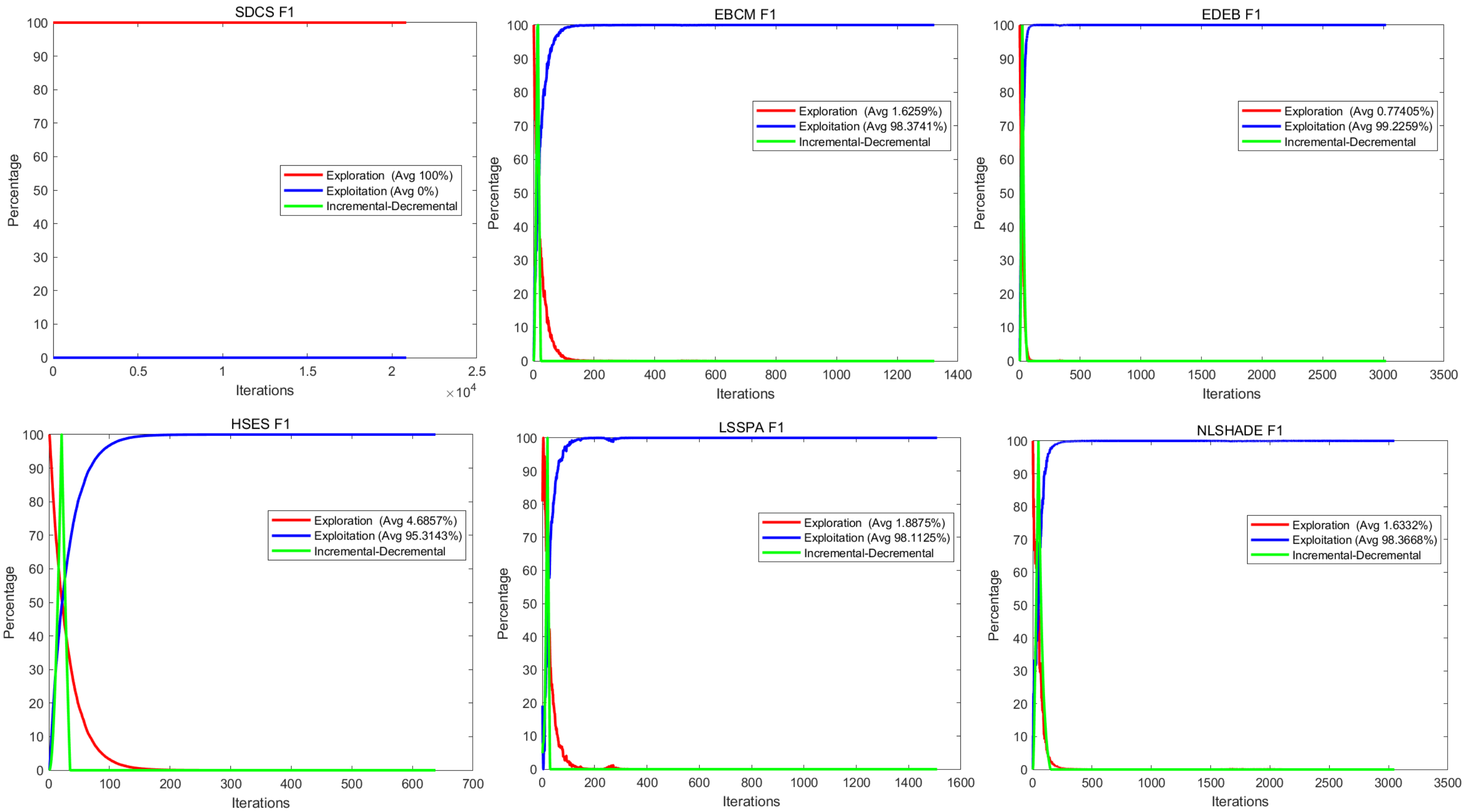
Function F1 with 50 variables



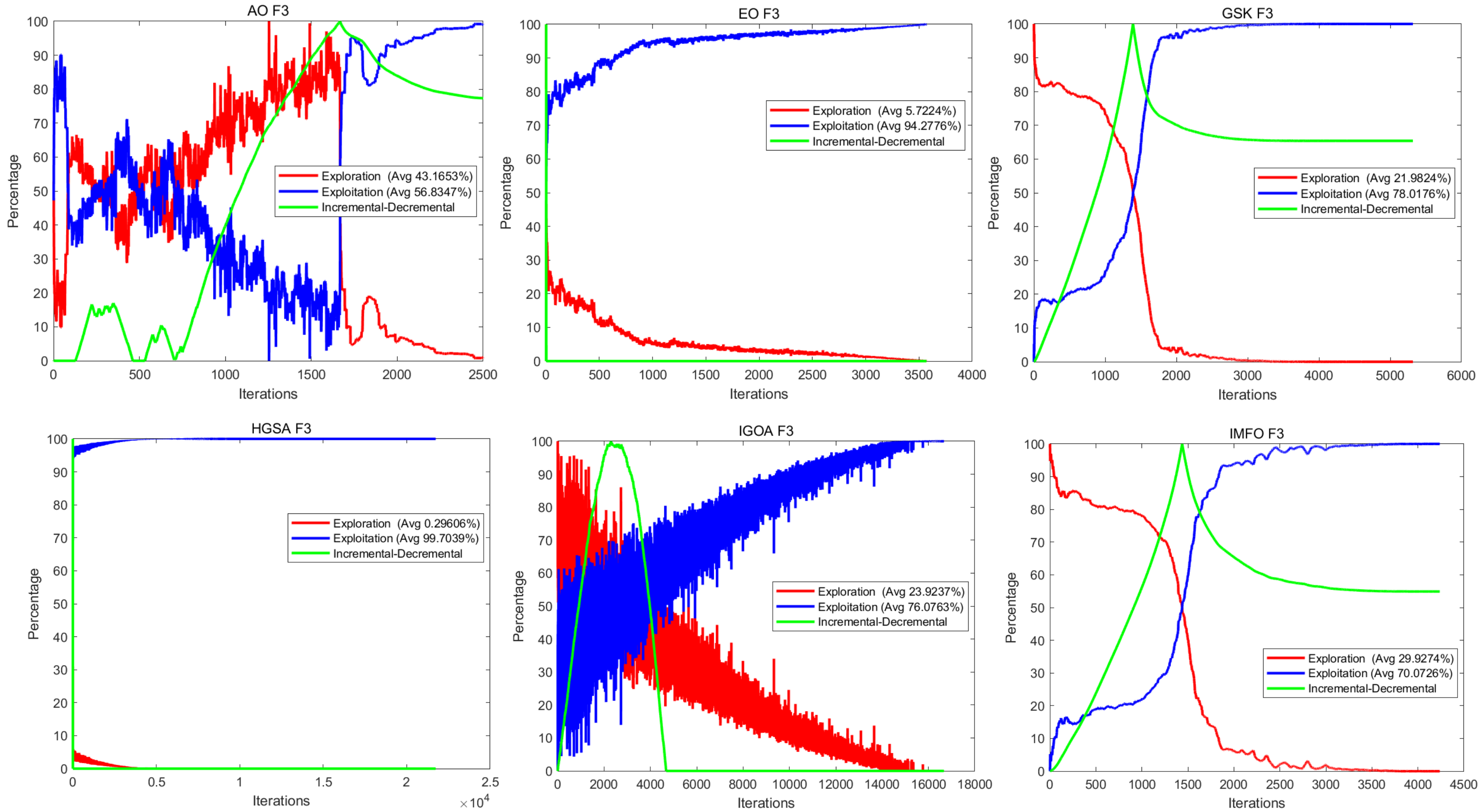


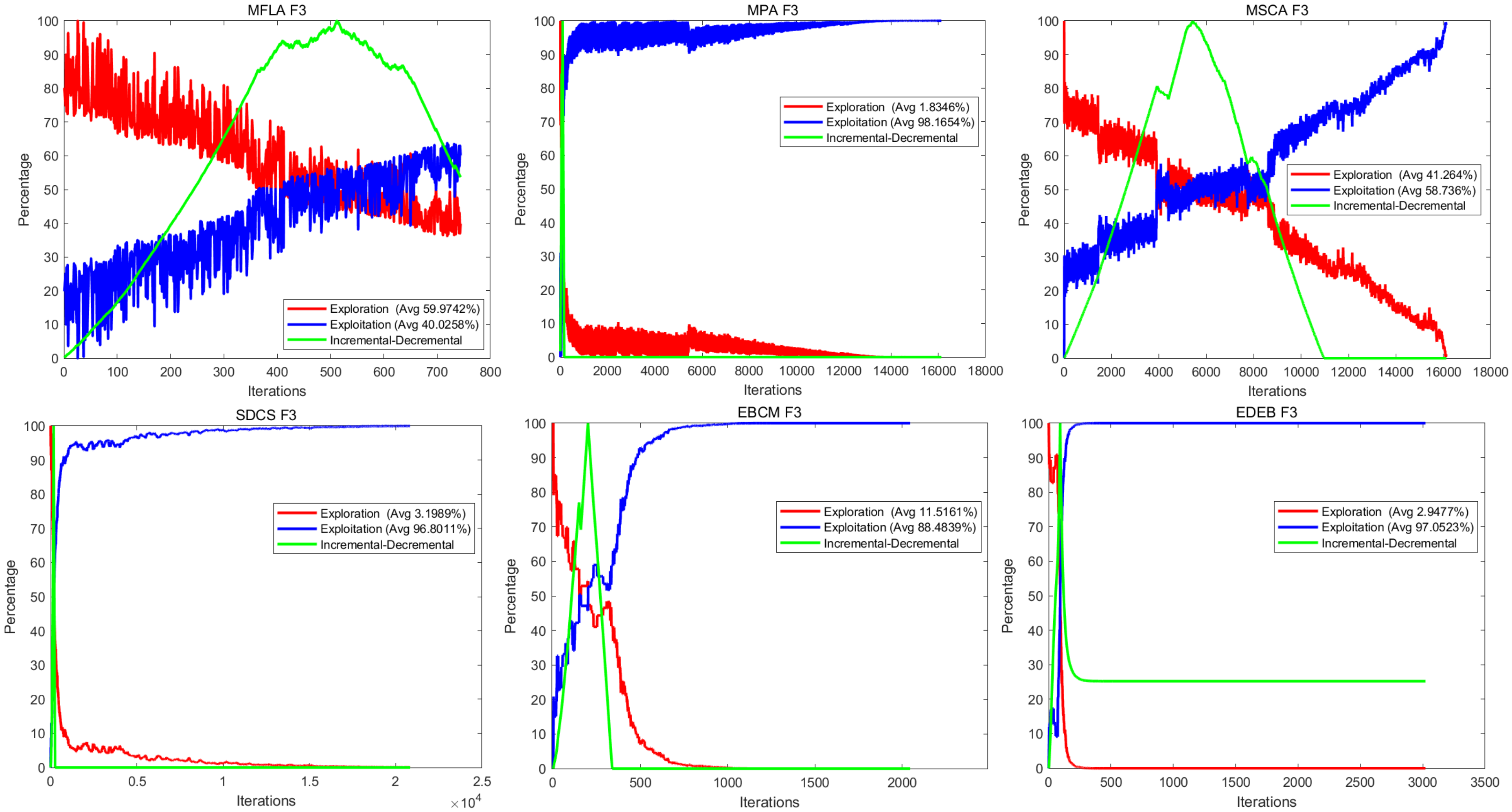


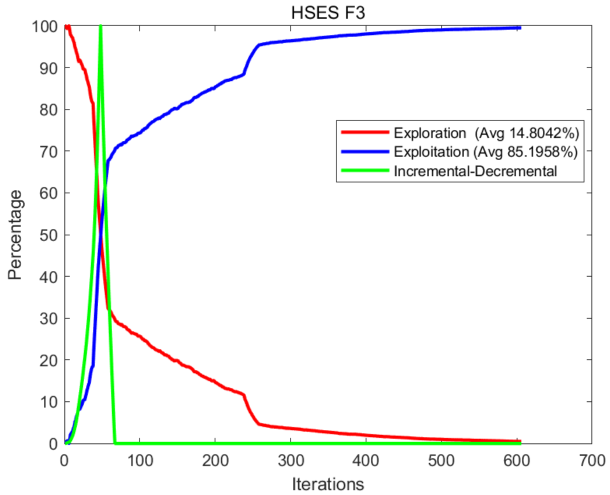

HGSA F1
Exploration (Avg 0.31011%)
Exploitation (Avg 99.6899%)
Incremental-Decremental
Percentage
Iterations
IGOA F1
Exploration (Avg 22.1741%)
Exploitation (Avg 77.8259%)
Incremental-Decremental
IMFO F1
Exploration (Avg 0.62376%)
Exploitation (Avg 99.3762%)
Incremental-Decremental
MFLA F1
Exploration (Avg 11.0705%)
Exploitation (Avg 88.9295%)
Incremental-Decremental
MPA F1
Exploration (Avg 1.0466%)
Exploitation (Avg 98.9534%)
Incremental-Decremental
MSCA F1
Exploration (Avg 34.2456%)
Exploitation (Avg 65.7544%)
Incremental-Decremental

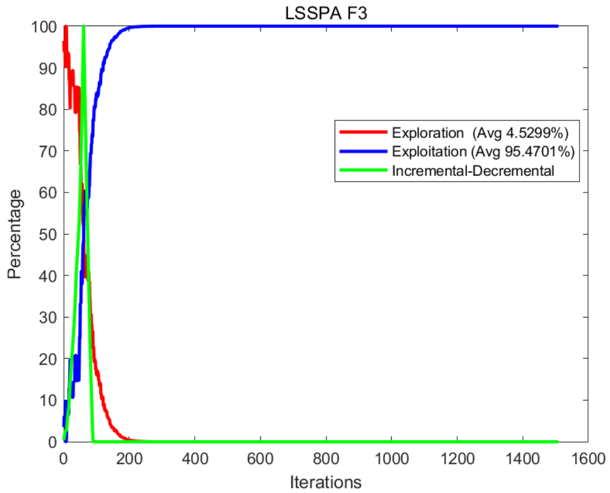


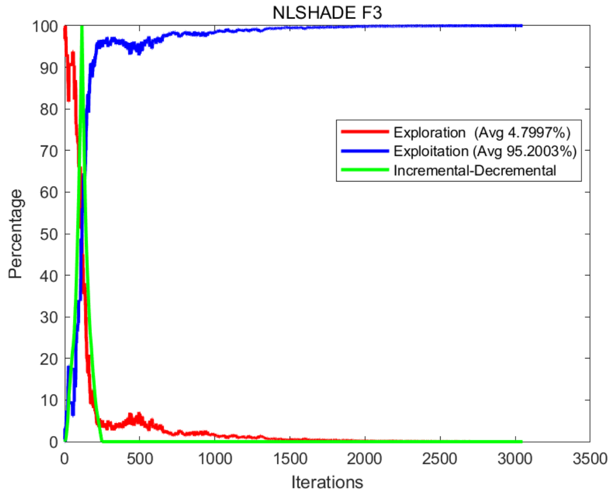
Function F3 with 50 variables


AO F3
Exploration (Avg 43.1653%)
Exploitation (Avg 56.8347%)
Incremental-Decremental
EO F3
Exploration (Avg 5.7224%)
Exploitation (Avg 94.2776%)
Incremental-Decremental
GSK F3
Exploration (Avg 21.9824%)
Exploitation (Avg 78.0176%)
Incremental-Decremental
HGSA F3
Exploration (Avg 0.29606%)
Exploitation (Avg 99.7039%)
Incremental-Decremental
IGOA F3
Exploration (Avg 23.9237%)
Exploitation (Avg 76.0763%)
Incremental-Decremental
IMFO F3
Exploration (Avg 29.9274%)
Exploitation (Avg 70.0726%)
Incremental-Decremental
Percentage
Iterations

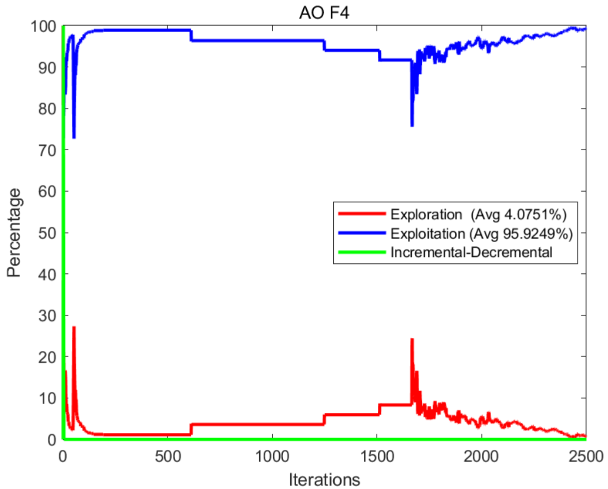

MFLA F3
Exploration (Avg 59.9742%)
Exploitation (Avg 40.0258%)
Incremental-Decremental
MPA F3
Exploration (Avg 1.8346%)
Exploitation (Avg 98.1654%)
Incremental-Decremental
MSCA F3
Exploration (Avg 41.264%)
Exploitation (Avg 58.736%)
Incremental-Decremental
SDCS F3
Exploration (Avg 3.1989%)
Exploitation (Avg 96.8011%)
Incremental-Decremental
EBCM F3
Exploration (Avg 11.5161%)
Exploitation (Avg 88.4839%)
Incremental-Decremental
EDEB F3
Exploration (Avg 2.9477%)
Exploitation (Avg 97.0523%)
Incremental-Decremental
Percentage
Iterations
$\times 10^4$

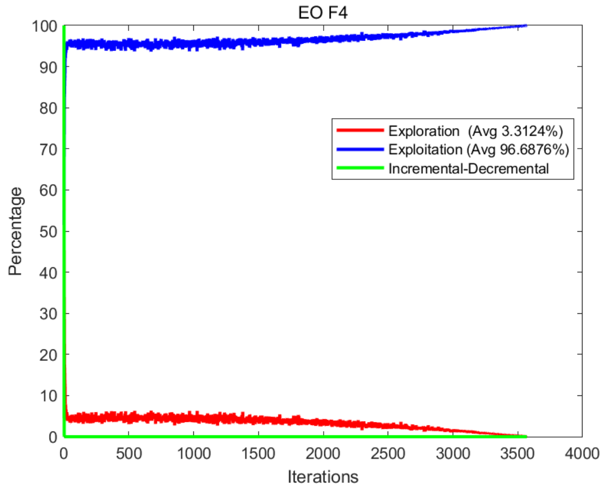


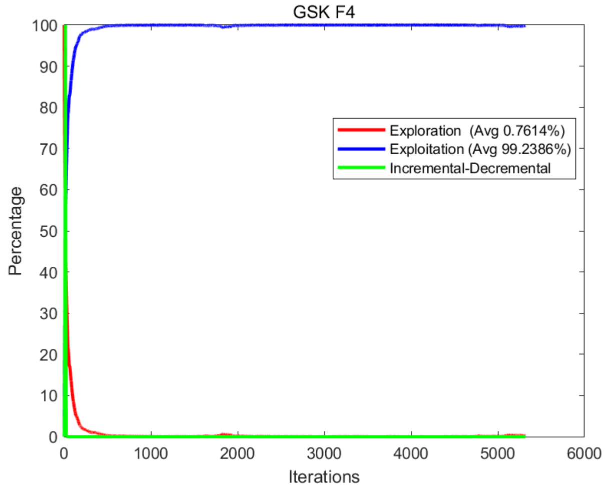


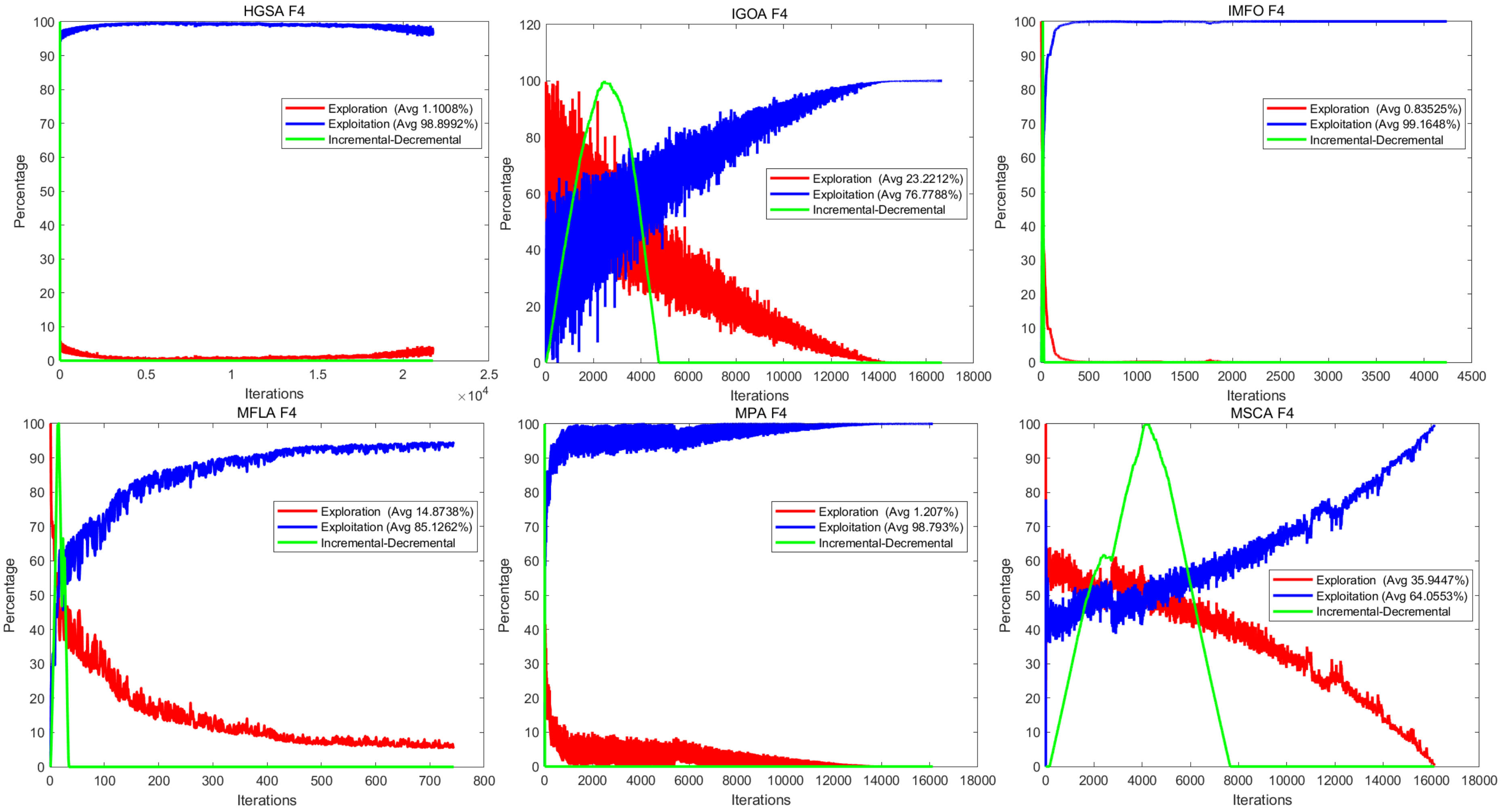


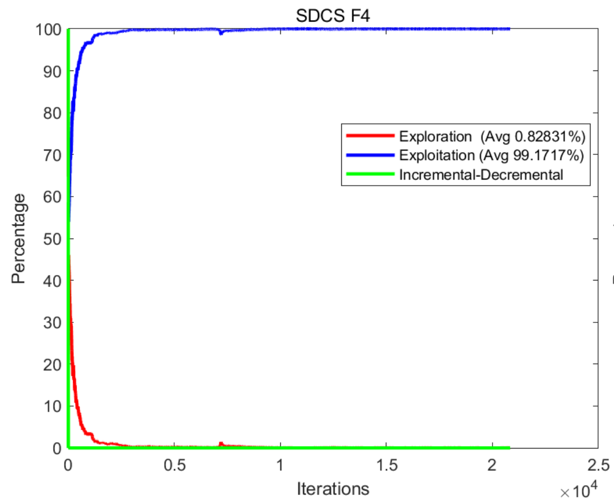
Function F4 with 50 variables

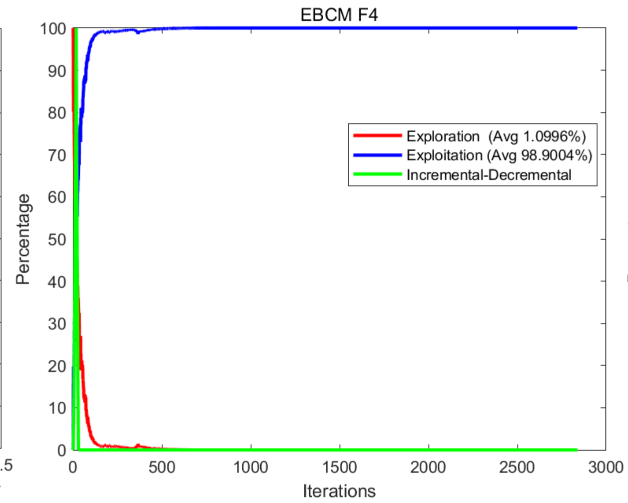


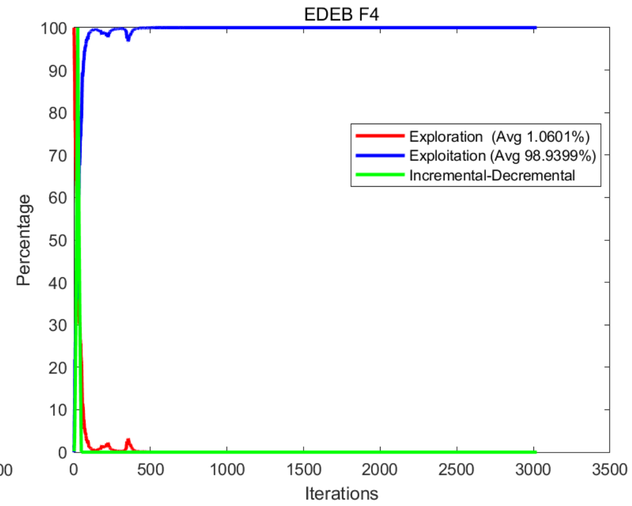


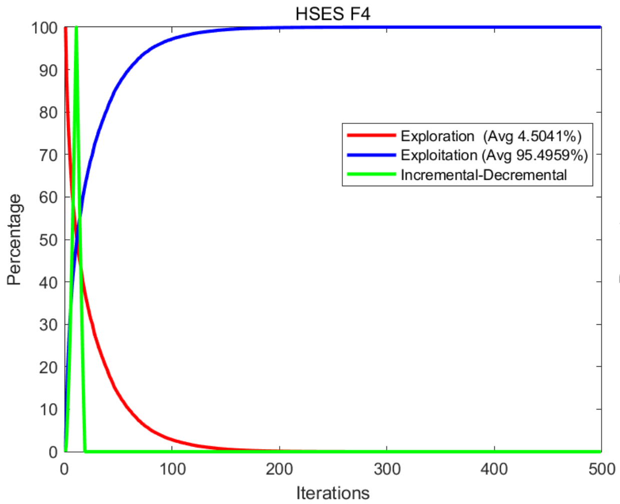


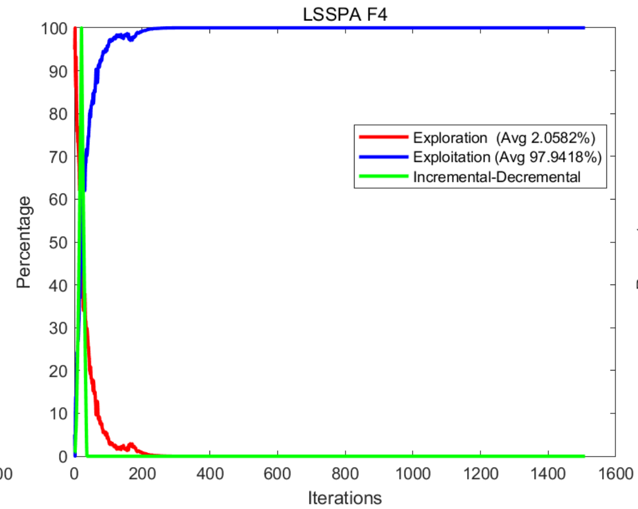

HGSA F4
Exploration (Avg 1.1008%)
Exploitation (Avg 98.8992%)
Incremental-Decremental
Percentage
Iterations
×10^4
IGOA F4
Exploration (Avg 23.2212%)
Exploitation (Avg 76.7788%)
Incremental-Decremental
Percentage
Iterations
IMFO F4
Exploration (Avg 0.83525%)
Exploitation (Avg 99.1648%)
Incremental-Decremental
Percentage
Iterations
MFLA F4
Exploration (Avg 14.8738%)
Exploitation (Avg 85.1262%)
Incremental-Decremental
Percentage
Iterations
MPA F4
Exploration (Avg 1.207%)
Exploitation (Avg 98.793%)
Incremental-Decremental
Percentage
Iterations
MSCA F4
Exploration (Avg 35.9447%)
Exploitation (Avg 64.0553%)
Incremental-Decremental
Percentage
Iterations

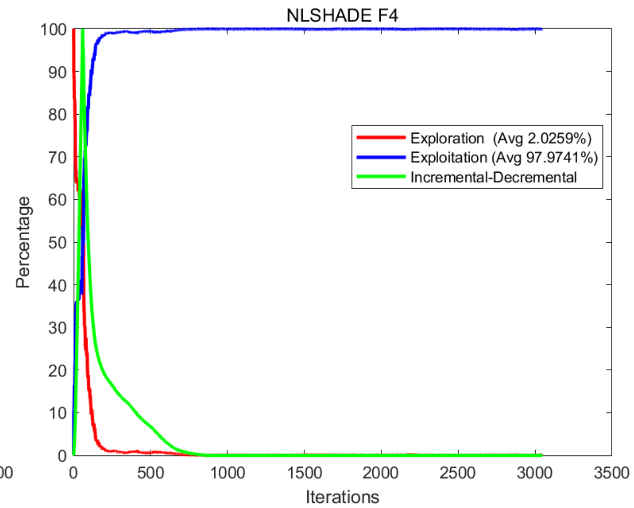




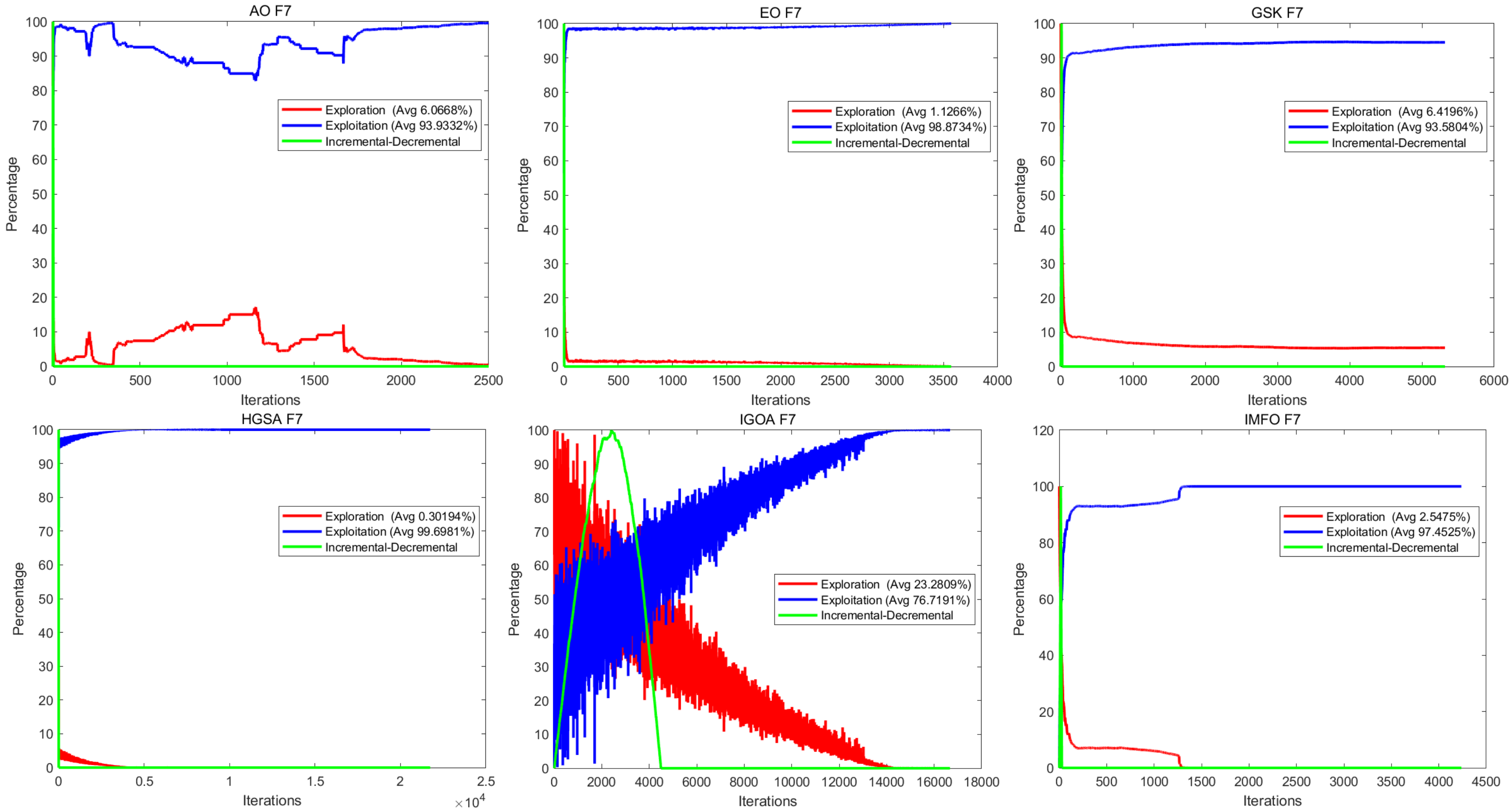


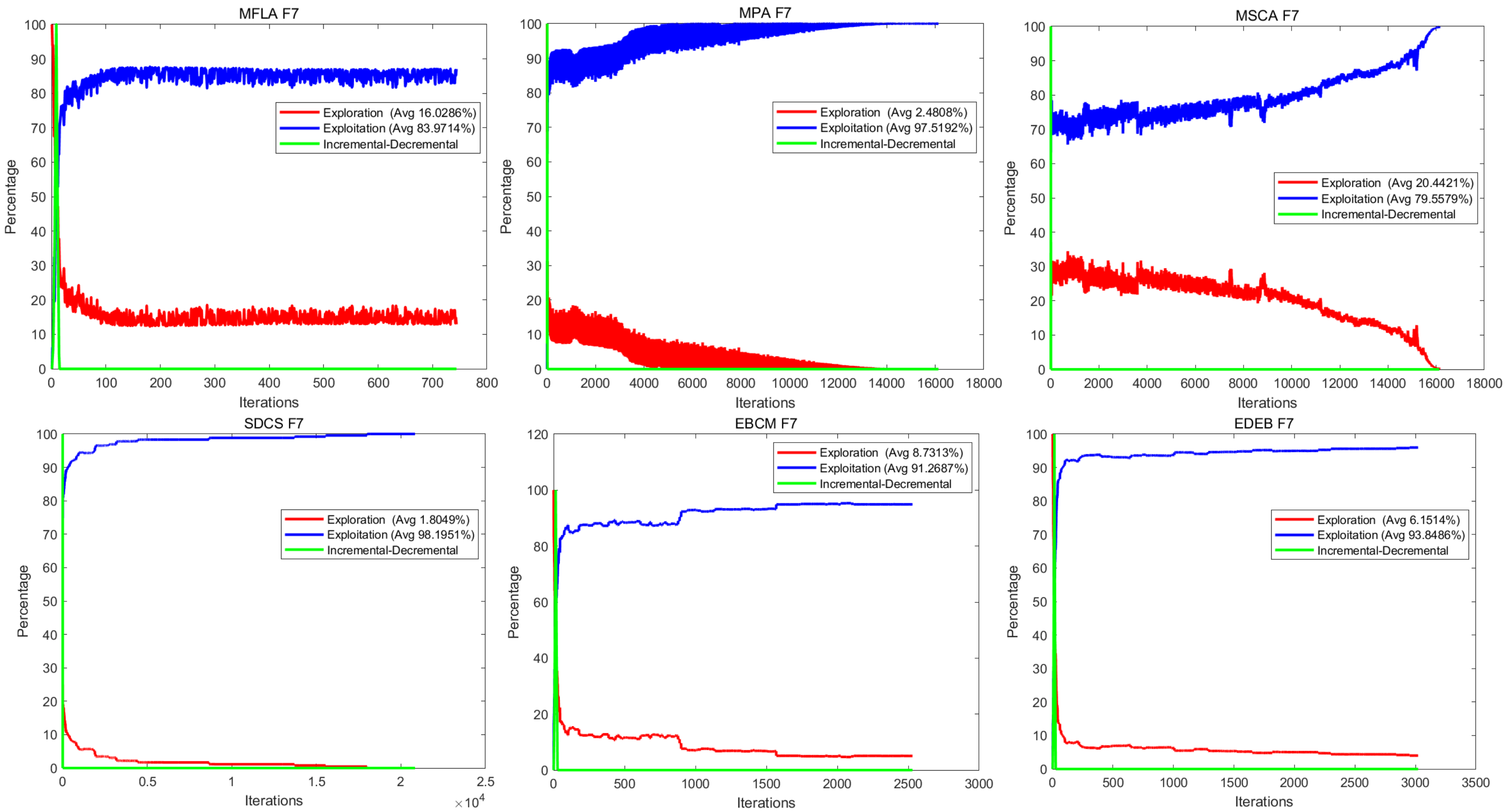


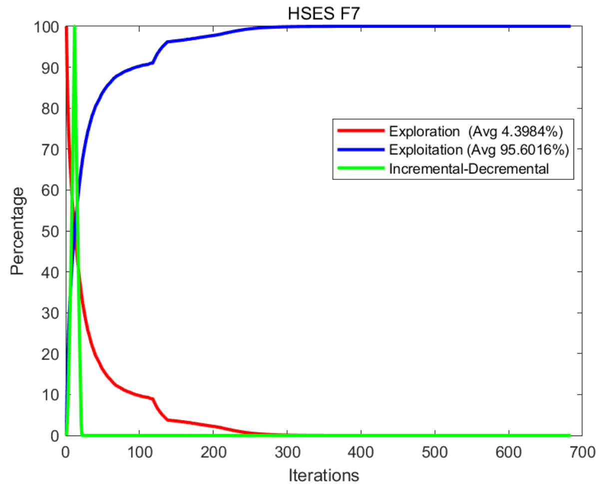


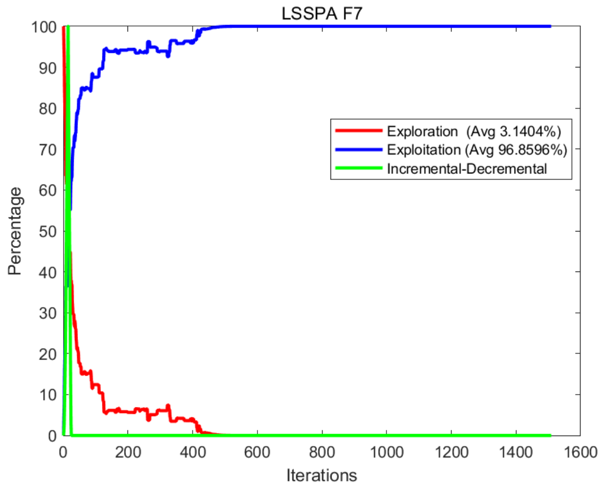


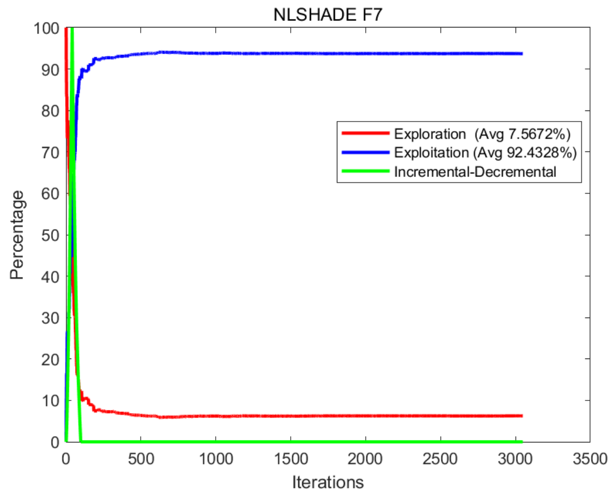
Function F7 with 50 variables


AO F7
Exploration (Avg 6.0668%)
Exploitation (Avg 93.9332%)
Incremental-Decremental
EO F7
Exploration (Avg 1.1266%)
Exploitation (Avg 98.8734%)
Incremental-Decremental
GSK F7
Exploration (Avg 6.4196%)
Exploitation (Avg 93.5804%)
Incremental-Decremental
HGSA F7
Exploration (Avg 0.30194%)
Exploitation (Avg 99.6981%)
Incremental-Decremental
IGOA F7
Exploration (Avg 23.2809%)
Exploitation (Avg 76.7191%)
Incremental-Decremental
IMFO F7
Exploration (Avg 2.5475%)
Exploitation (Avg 97.4525%)
Incremental-Decremental
Percentage
Iterations

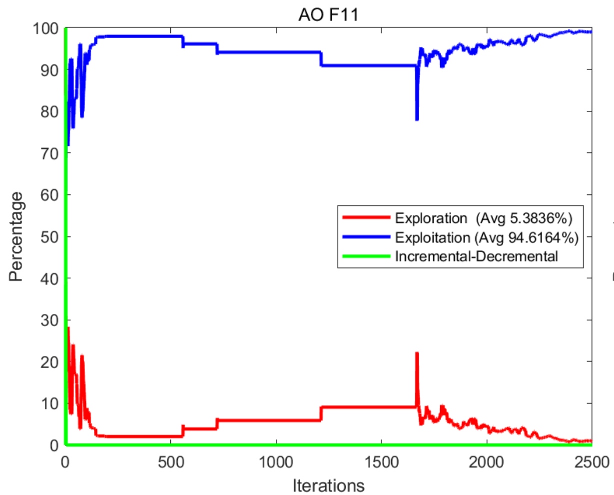

MFLA F7
Exploration (Avg 16.0286%)
Exploitation (Avg 83.9714%)
Incremental-Decremental
Percentage
Iterations
MPA F7
Exploration (Avg 2.4808%)
Exploitation (Avg 97.5192%)
Incremental-Decremental
Percentage
Iterations
MSCA F7
Exploration (Avg 20.4421%)
Exploitation (Avg 79.5579%)
Incremental-Decremental
Percentage
Iterations
SDCS F7
Exploration (Avg 1.8049%)
Exploitation (Avg 98.1951%)
Incremental-Decremental
Percentage
Iterations
$\times 10^4$
EBCM F7
Exploration (Avg 8.7313%)
Exploitation (Avg 91.2687%)
Incremental-Decremental
Percentage
Iterations
EDEB F7
Exploration (Avg 6.1514%)
Exploitation (Avg 93.8486%)
Incremental-Decremental
Percentage
Iterations

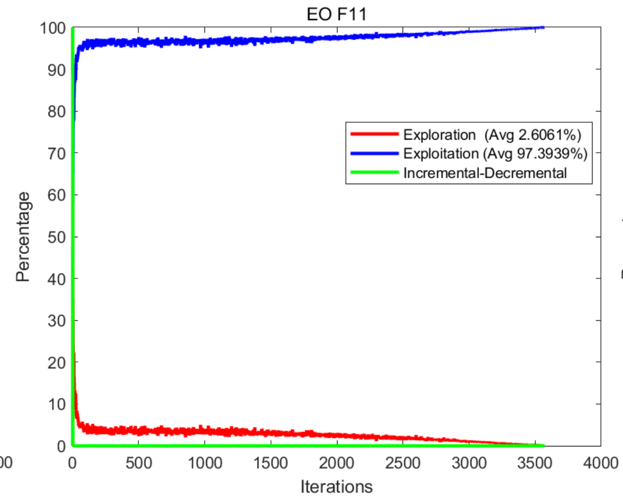


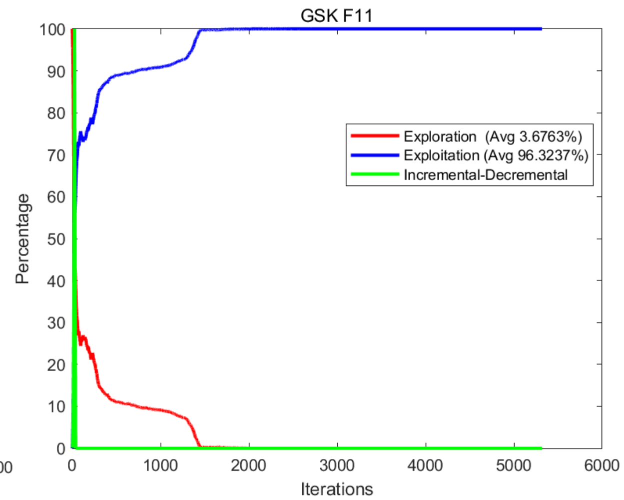


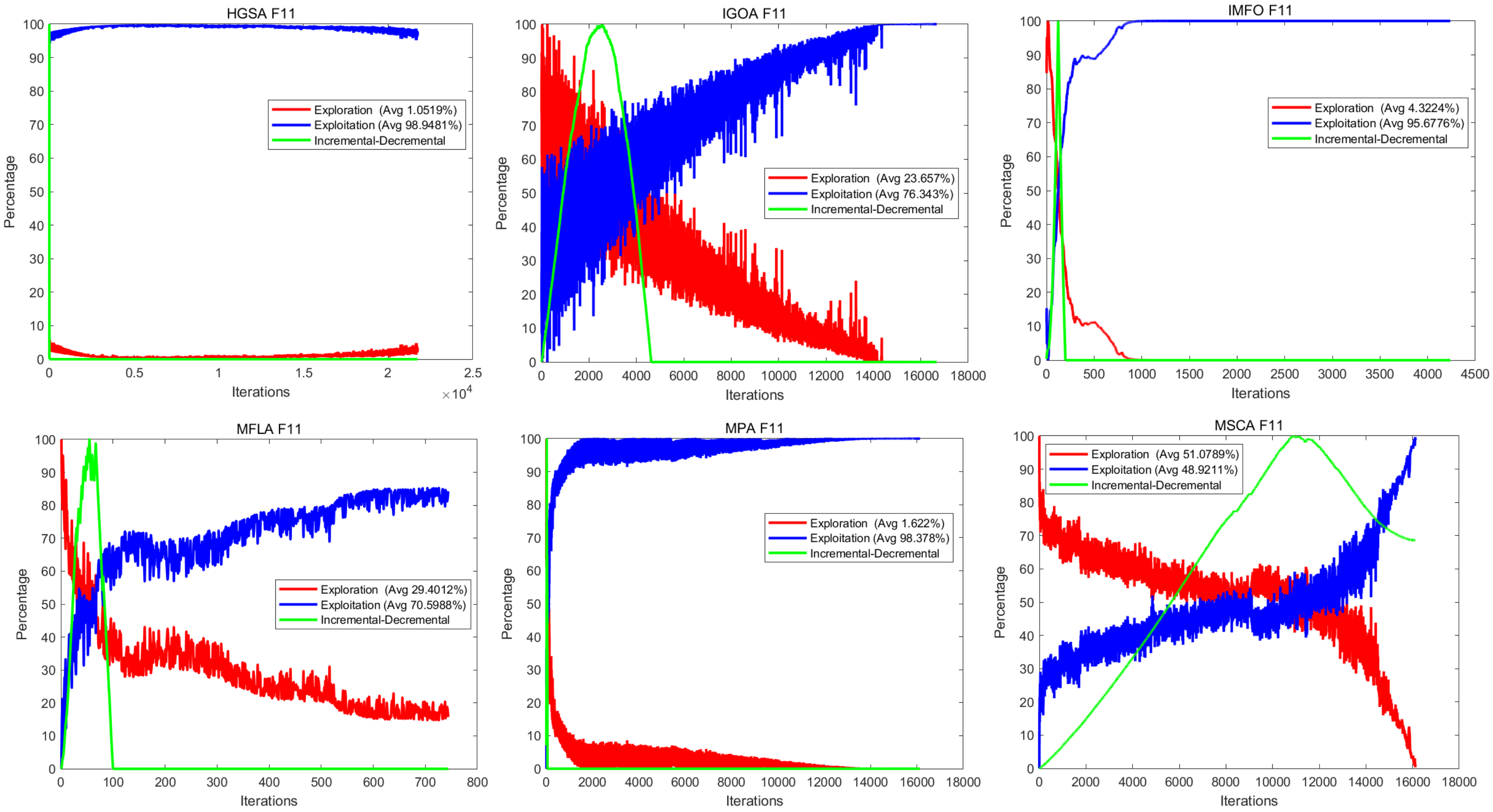


Function F11 with 50 variables

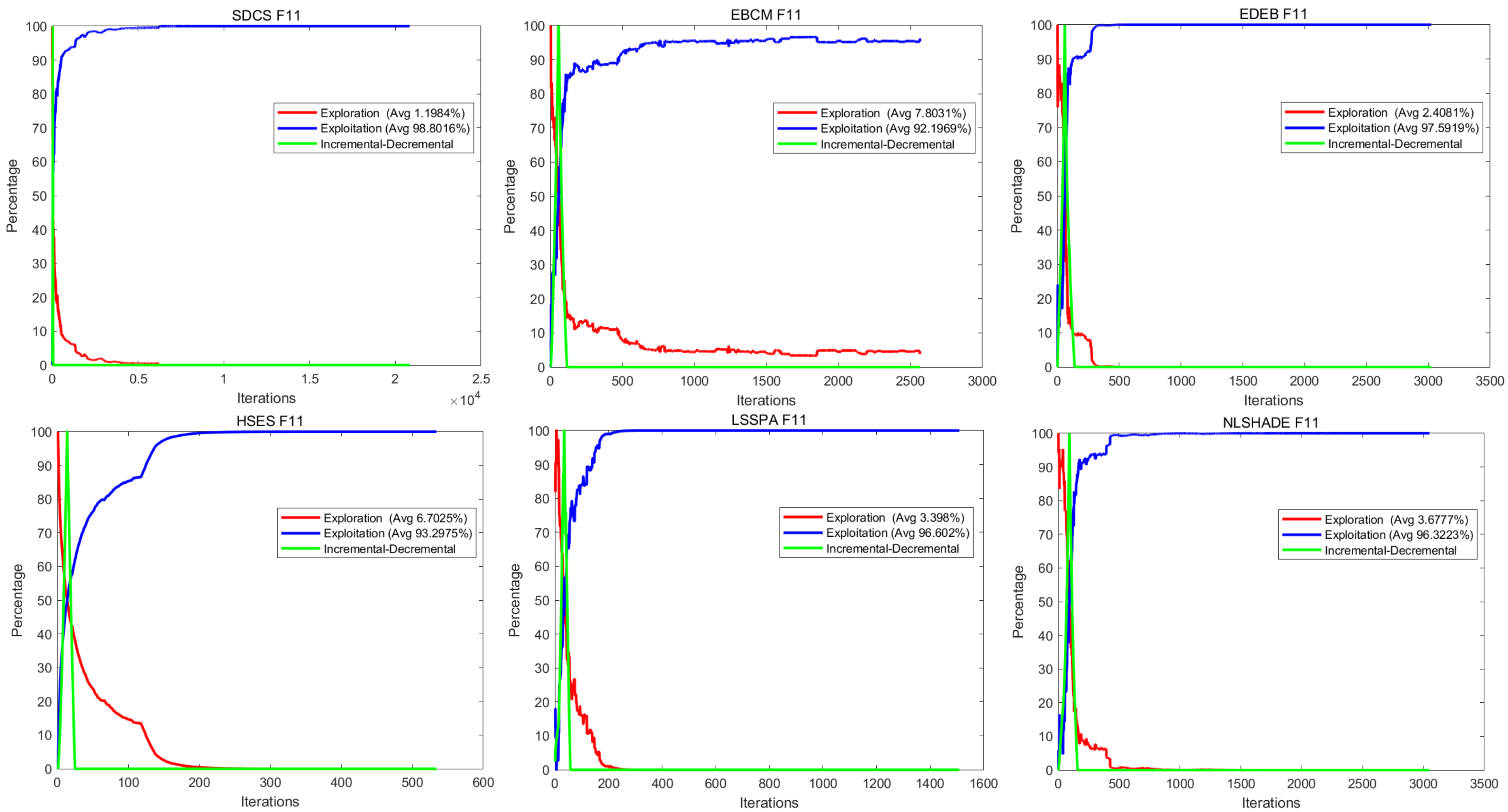




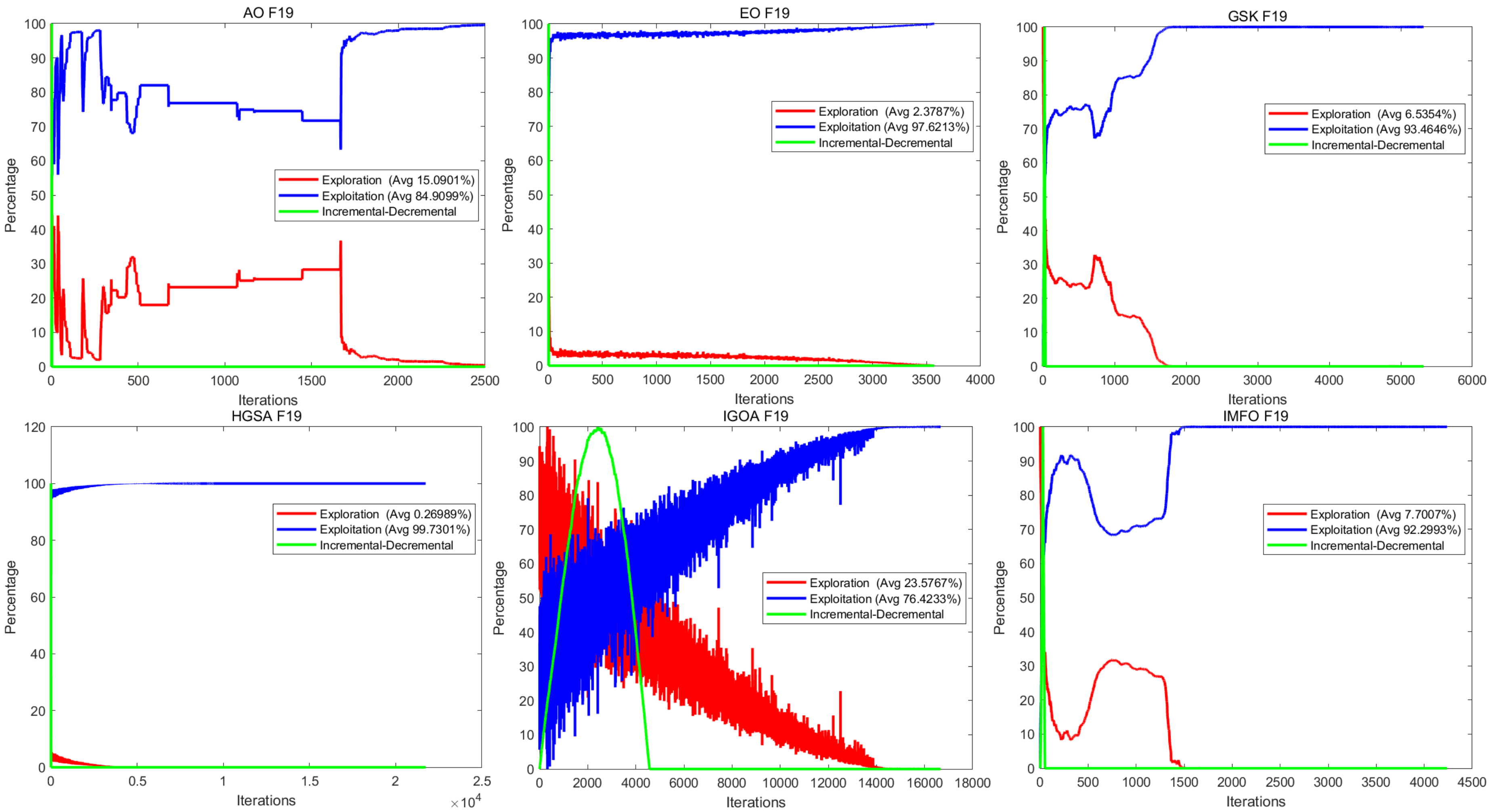


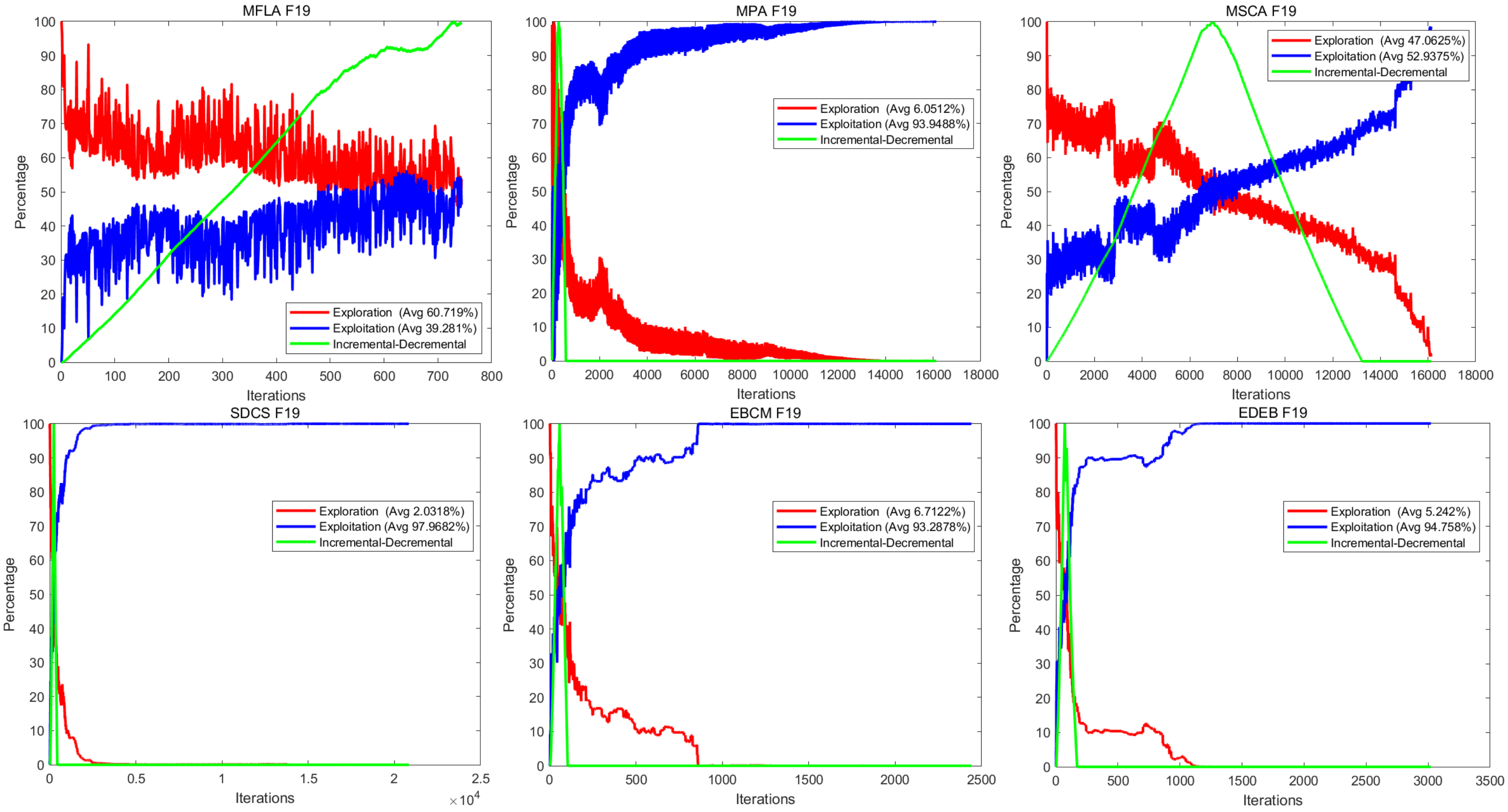


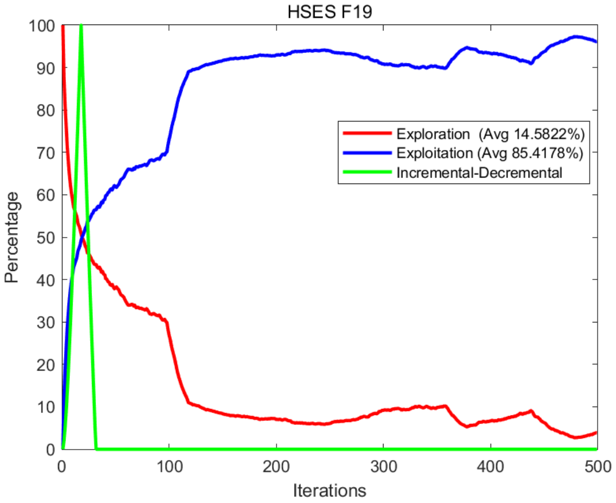
HGSA F11
Exploration (Avg 1.0519%)
Exploitation (Avg 98.9481%)
Incremental-Decremental
Percentage
Iterations
$\times 10^4$
IGOA F11
Exploration (Avg 23.657%)
Exploitation (Avg 76.343%)
Incremental-Decremental
Percentage
Iterations
IMFO F11
Exploration (Avg 4.3224%)
Exploitation (Avg 95.6776%)
Incremental-Decremental
Percentage
Iterations
MFLA F11
Exploration (Avg 29.4012%)
Exploitation (Avg 70.5988%)
Incremental-Decremental
Percentage
Iterations
MPA F11
Exploration (Avg 1.622%)
Exploitation (Avg 98.378%)
Incremental-Decremental
Percentage
Iterations
MSCA F11
Exploration (Avg 51.0789%)
Exploitation (Avg 48.9211%)
Incremental-Decremental
Percentage
Iterations

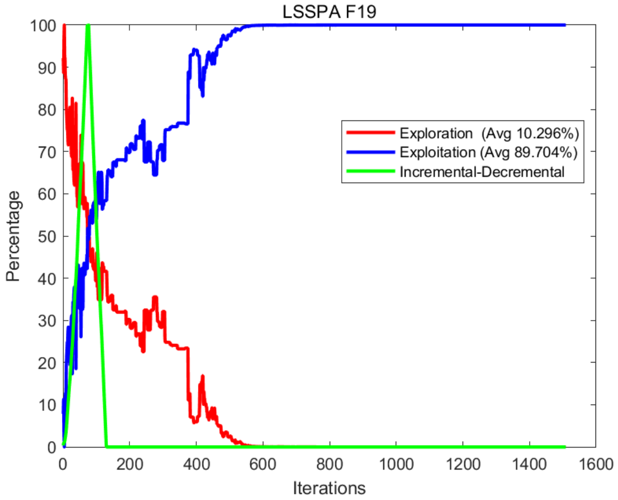


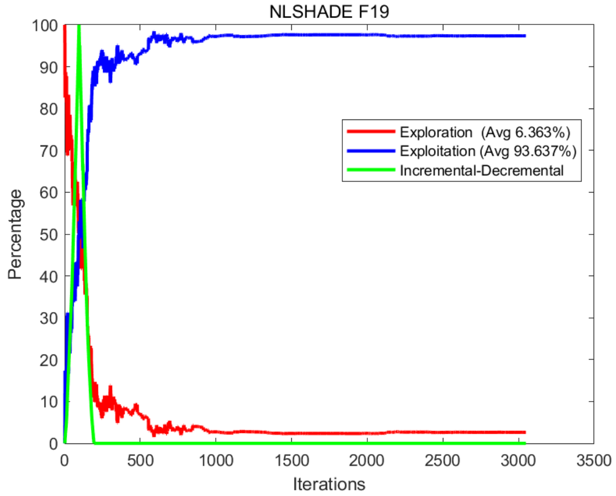
Function F19 with 50 variables


AO F19
Exploration (Avg 15.0901%)
Exploitation (Avg 84.9099%)
Incremental-Decremental
EO F19
Exploration (Avg 2.3787%)
Exploitation (Avg 97.6213%)
Incremental-Decremental
GSK F19
Exploration (Avg 6.5354%)
Exploitation (Avg 93.4646%)
Incremental-Decremental
HGSA F19
Exploration (Avg 0.26989%)
Exploitation (Avg 99.7301%)
Incremental-Decremental
IGOA F19
Exploration (Avg 23.5767%)
Exploitation (Avg 76.4233%)
Incremental-Decremental
IMFO F19
Exploration (Avg 7.7007%)
Exploitation (Avg 92.2993%)
Incremental-Decremental
Percentage
Iterations
×10^4

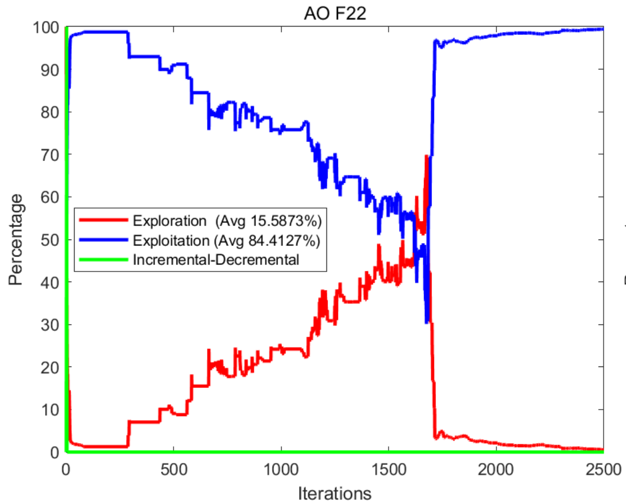

MFLA F19
Exploration (Avg 60.719%)
Exploitation (Avg 39.281%)
Incremental-Decremental
MPA F19
Exploration (Avg 6.0512%)
Exploitation (Avg 93.9488%)
Incremental-Decremental
MSCA F19
Exploration (Avg 47.0625%)
Exploitation (Avg 52.9375%)
Incremental-Decremental
SDCS F19
Exploration (Avg 2.0318%)
Exploitation (Avg 97.9682%)
Incremental-Decremental
EBCM F19
Exploration (Avg 6.7122%)
Exploitation (Avg 93.2878%)
Incremental-Decremental
EDEB F19
Exploration (Avg 5.242%)
Exploitation (Avg 94.758%)
Incremental-Decremental
Percentage
Iterations

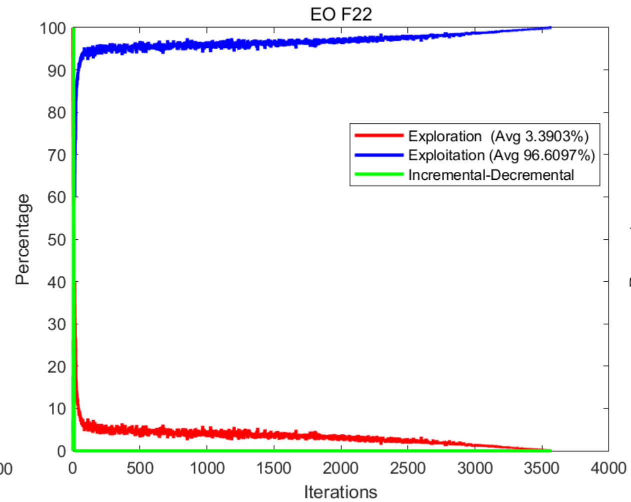


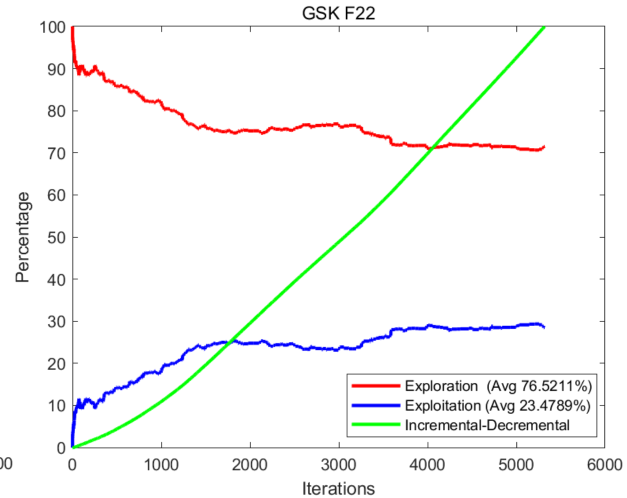


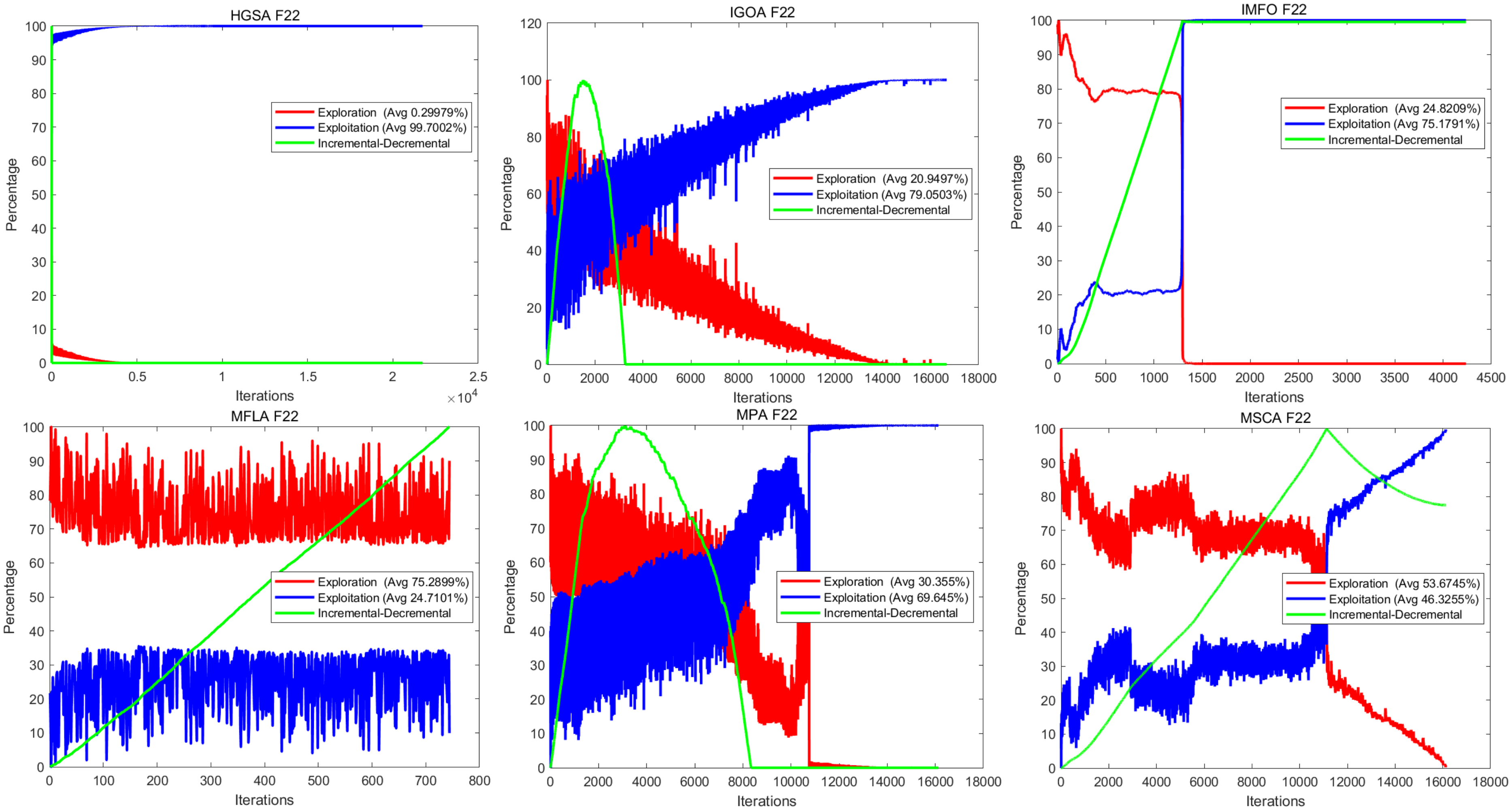


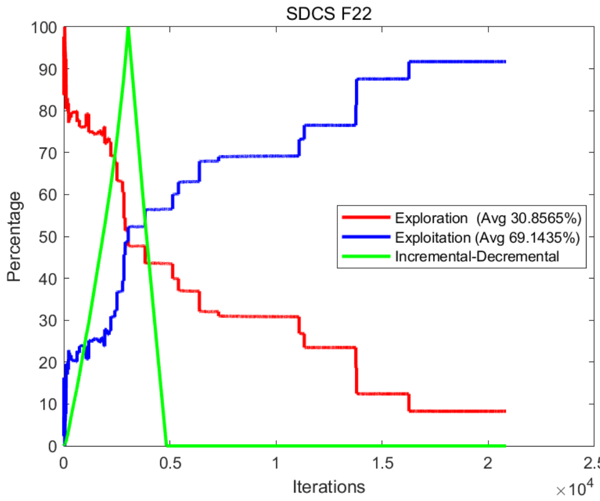
Function F22 with 50 variables

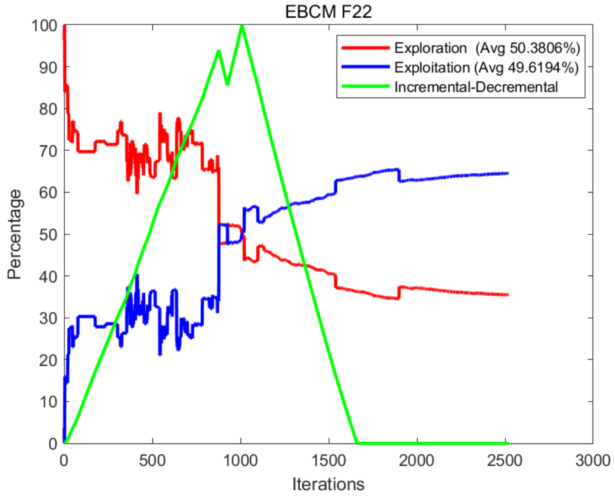


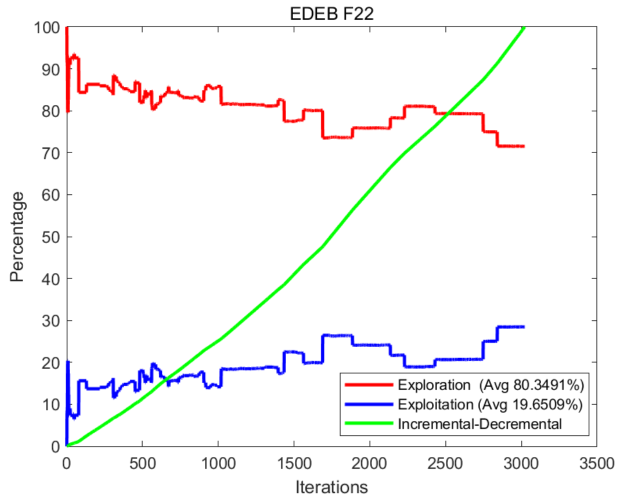


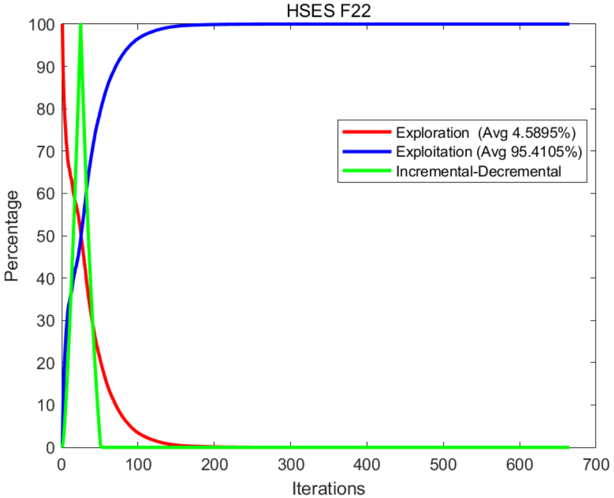


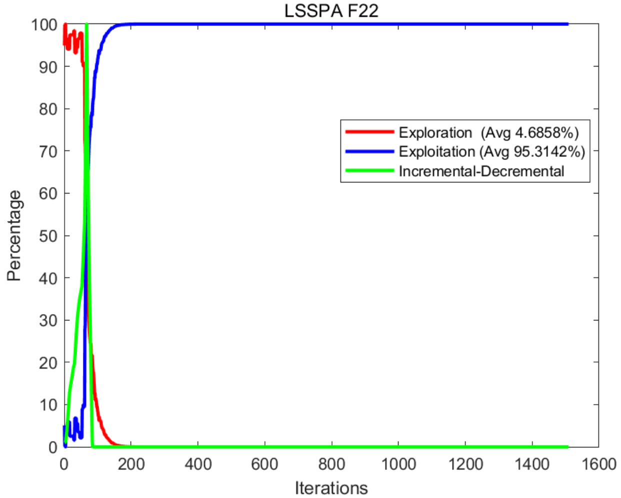

HGSA F22
Exploration (Avg 0.29979%)
Exploitation (Avg 99.7002%)
Incremental-Decremental
Percentage
Iterations
×10^4
IGOA F22
Exploration (Avg 20.9497%)
Exploitation (Avg 79.0503%)
Incremental-Decremental
Percentage
Iterations
IMFO F22
Exploration (Avg 24.8209%)
Exploitation (Avg 75.1791%)
Incremental-Decremental
Percentage
Iterations
MFLA F22
Exploration (Avg 75.2899%)
Exploitation (Avg 24.7101%)
Incremental-Decremental
Percentage
Iterations
MPA F22
Exploration (Avg 30.355%)
Exploitation (Avg 69.645%)
Incremental-Decremental
Percentage
Iterations
MSCA F22
Exploration (Avg 53.6745%)
Exploitation (Avg 46.3255%)
Incremental-Decremental
Percentage
Iterations

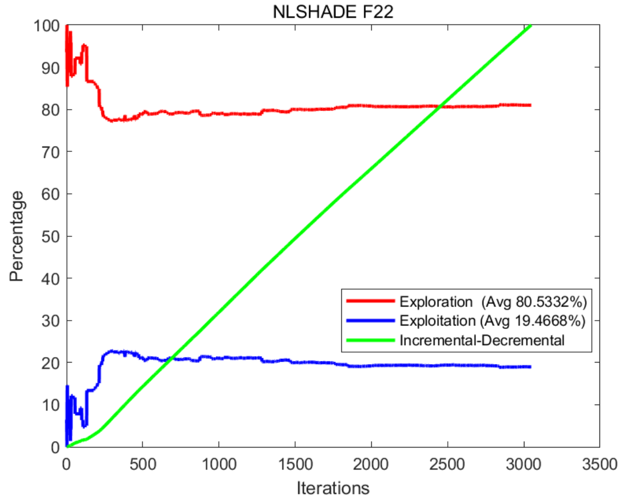




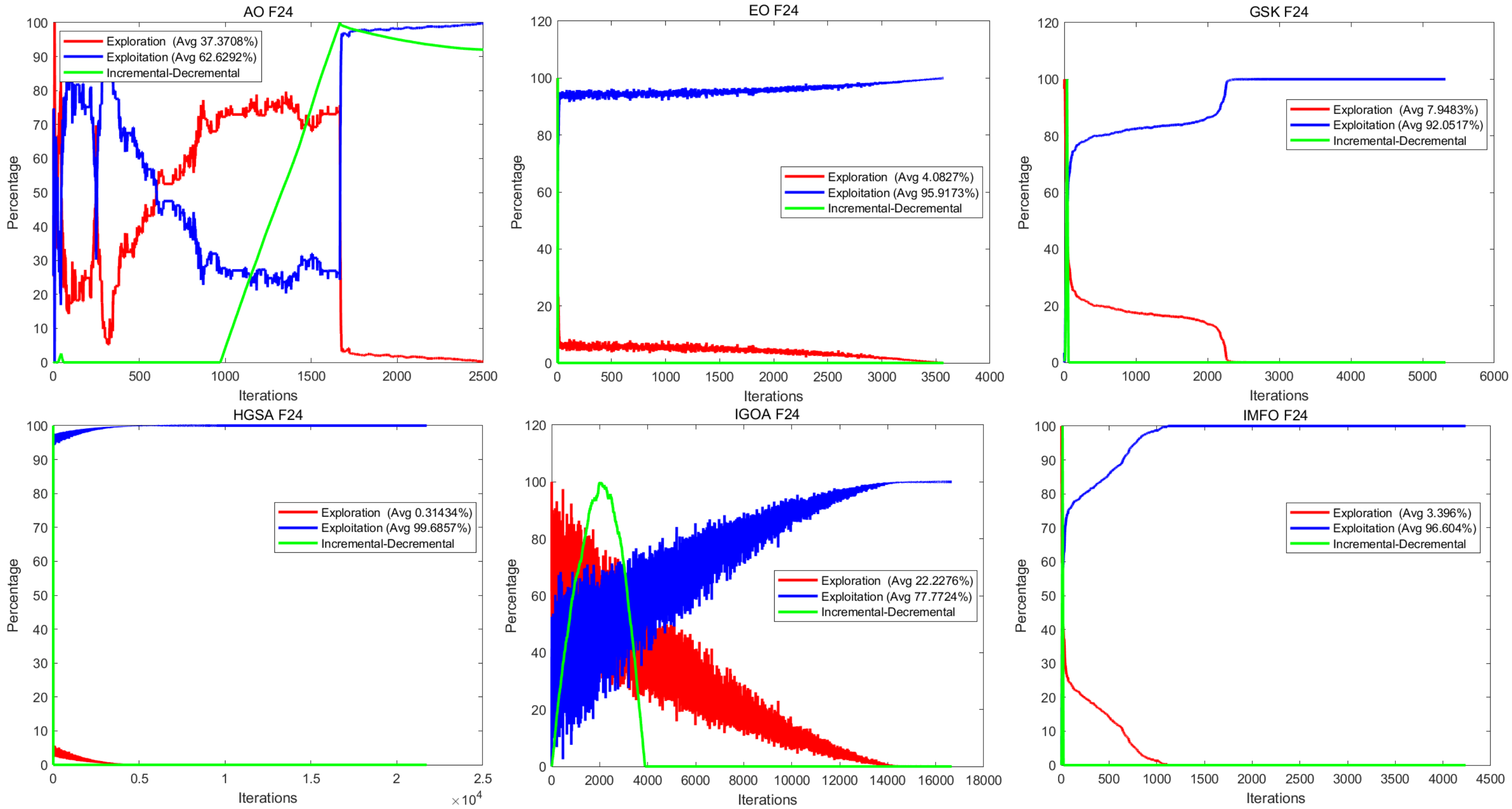


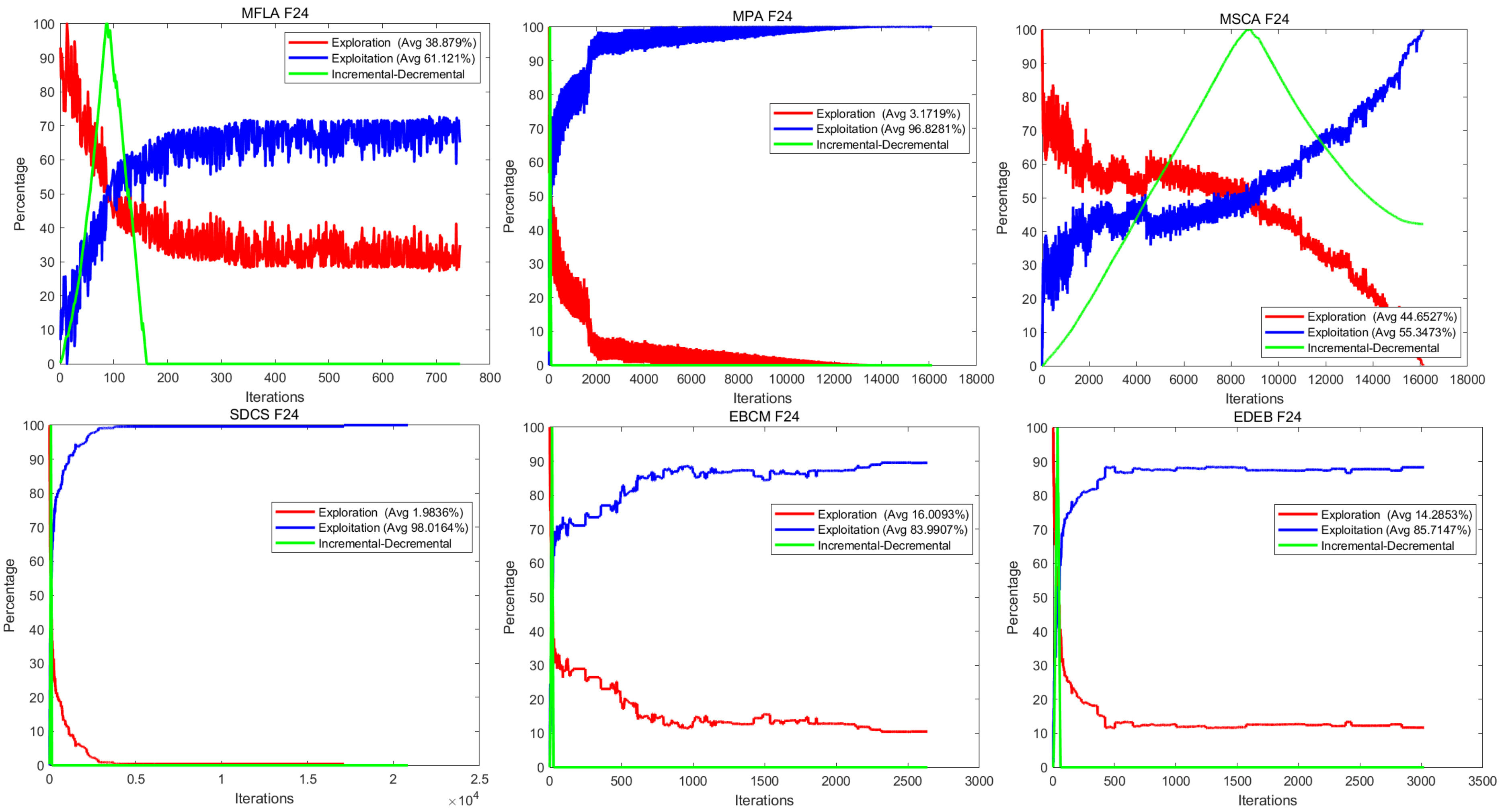






Function F24 with 50 variables


AO F24
Exploration (Avg 37.3708%)
Exploitation (Avg 62.6292%)
Incremental-Decremental
Percentage
Iterations
EO F24
Exploration (Avg 4.0827%)
Exploitation (Avg 95.9173%)
Incremental-Decremental
Percentage
Iterations
GSK F24
Exploration (Avg 7.9483%)
Exploitation (Avg 92.0517%)
Incremental-Decremental
Percentage
Iterations
HGSA F24
Exploration (Avg 0.31434%)
Exploitation (Avg 99.6857%)
Incremental-Decremental
Percentage
Iterations
×10^4
IGOA F24
Exploration (Avg 22.2276%)
Exploitation (Avg 77.7724%)
Incremental-Decremental
Percentage
Iterations
IMFO F24
Exploration (Avg 3.396%)
Exploitation (Avg 96.604%)
Incremental-Decremental
Percentage
Iterations



MFLA F24
Exploration (Avg 38.879%)
Exploitation (Avg 61.121%)
Incremental-Decremental
MPA F24
Exploration (Avg 3.1719%)
Exploitation (Avg 96.8281%)
Incremental-Decremental
MSCA F24
Exploration (Avg 44.6527%)
Exploitation (Avg 55.3473%)
Incremental-Decremental
SDCS F24
Exploration (Avg 1.9836%)
Exploitation (Avg 98.0164%)
Incremental-Decremental
EBCM F24
Exploration (Avg 16.0093%)
Exploitation (Avg 83.9907%)
Incremental-Decremental
EDEB F24
Exploration (Avg 14.2853%)
Exploitation (Avg 85.7147%)
Incremental-Decremental
Percentage
Iterations

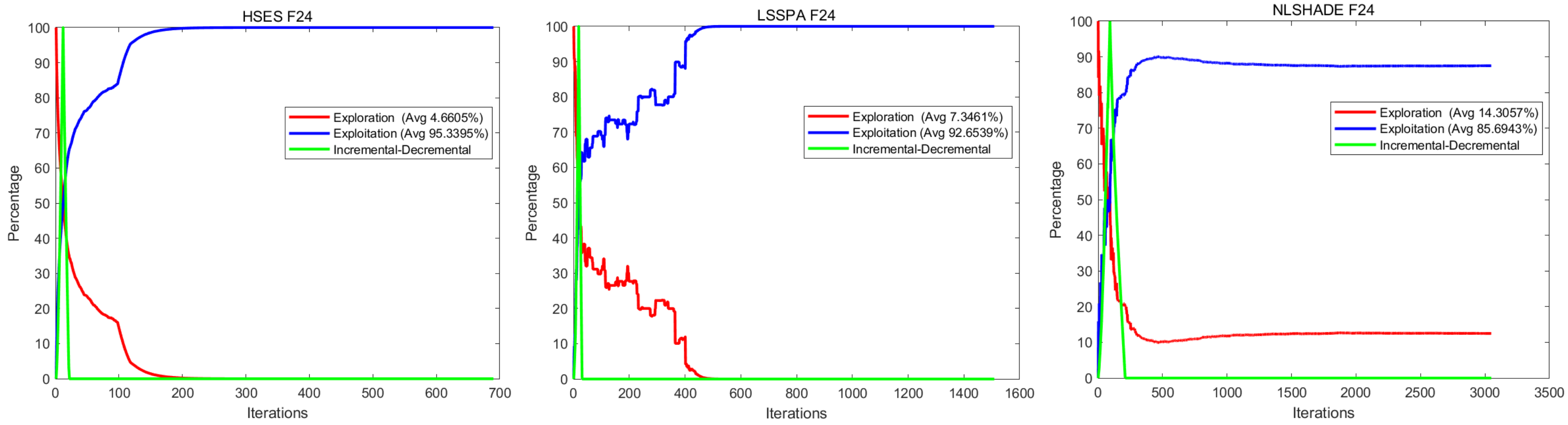
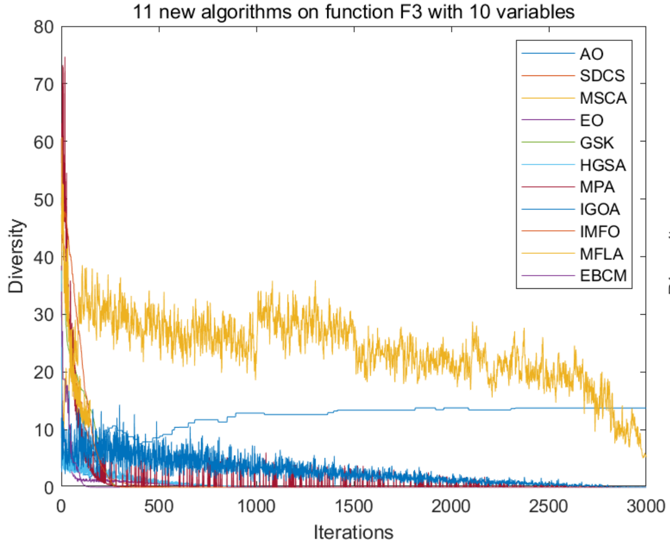
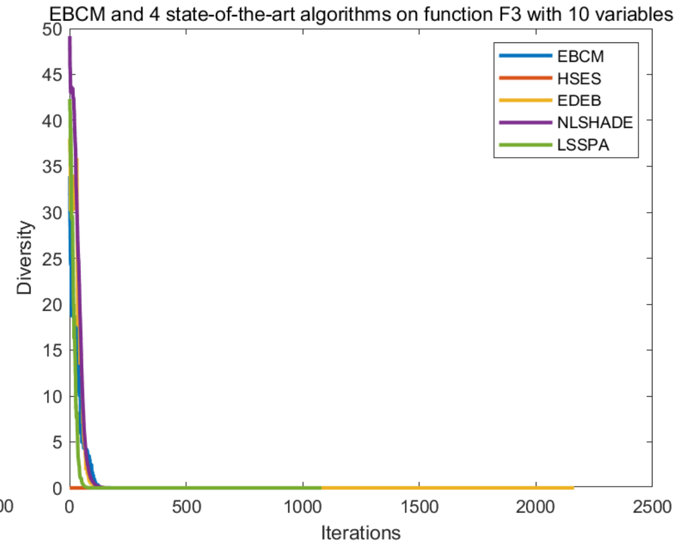
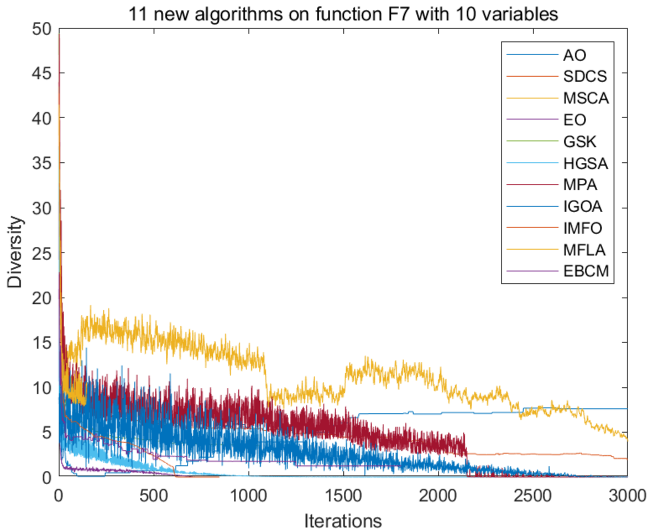
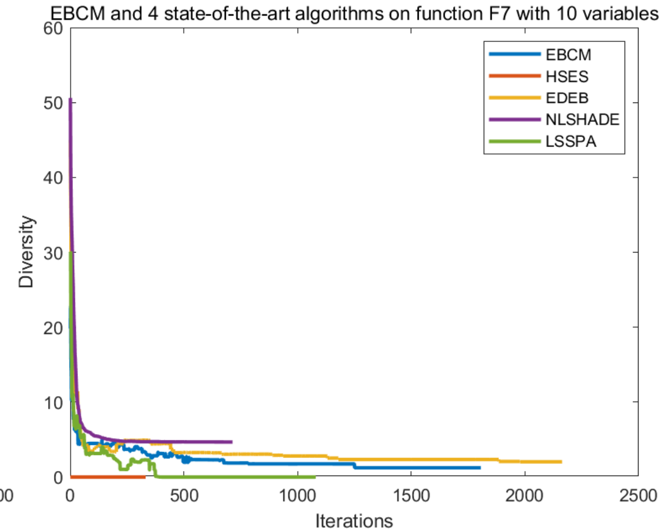

HSES F24
Exploration (Avg 4.6605%)
Exploitation (Avg 95.3395%)
Incremental-Decremental
Percentage
Iterations
LSSPA F24
Exploration (Avg 7.3461%)
Exploitation (Avg 92.6539%)
Incremental-Decremental
Percentage
Iterations
NLSHADE F24
Exploration (Avg 14.3057%)
Exploitation (Avg 85.6943%)
Incremental-Decremental
Percentage
Iterations

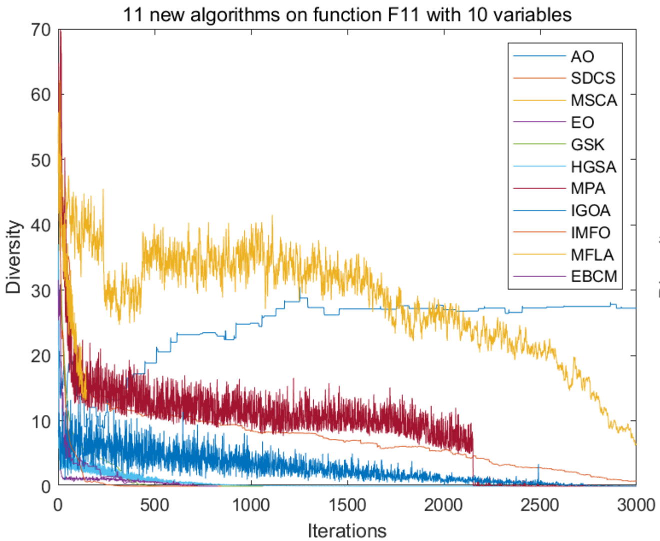
Fig.S10 Diversity analysis on functions F3, F7, F11, and F24 with 10 variables

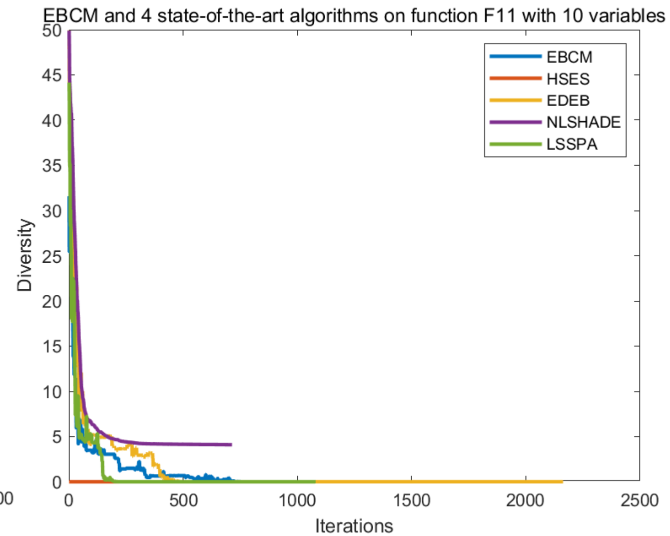


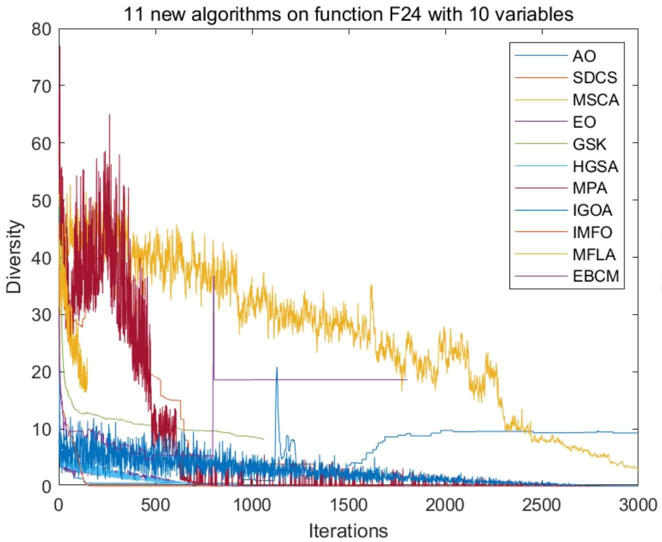



11 new algorithms on function F7 with 10 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM


EBCM and 4 state-of-the-art algorithms on function F7 with 10 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA


11 new algorithms on function F11 with 10 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM


EBCM and 4 state-of-the-art algorithms on function F11 with 10 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA


11 new algorithms on function F24 with 10 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM

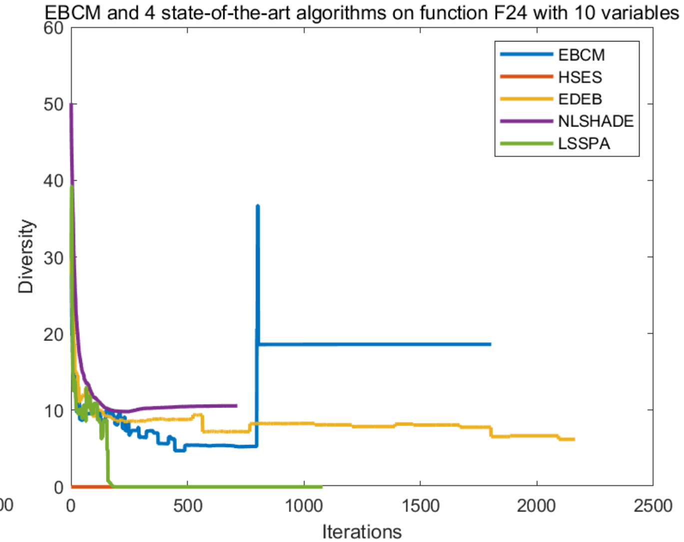
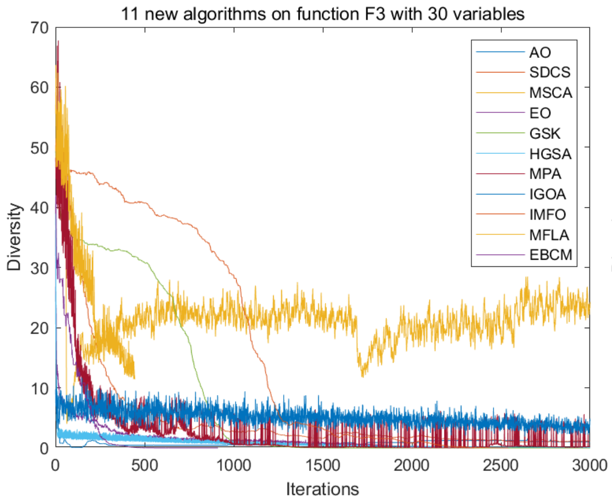
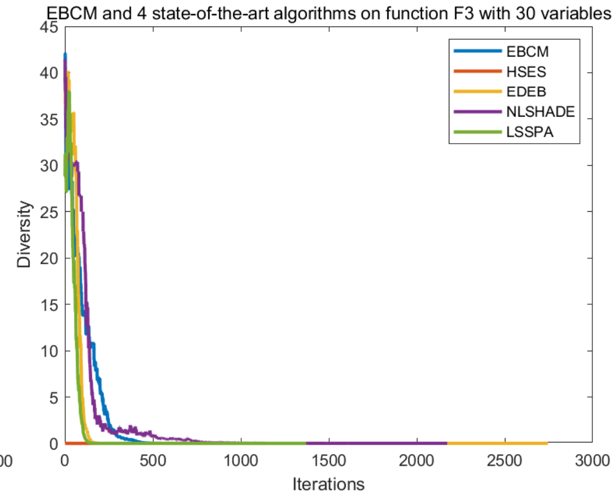
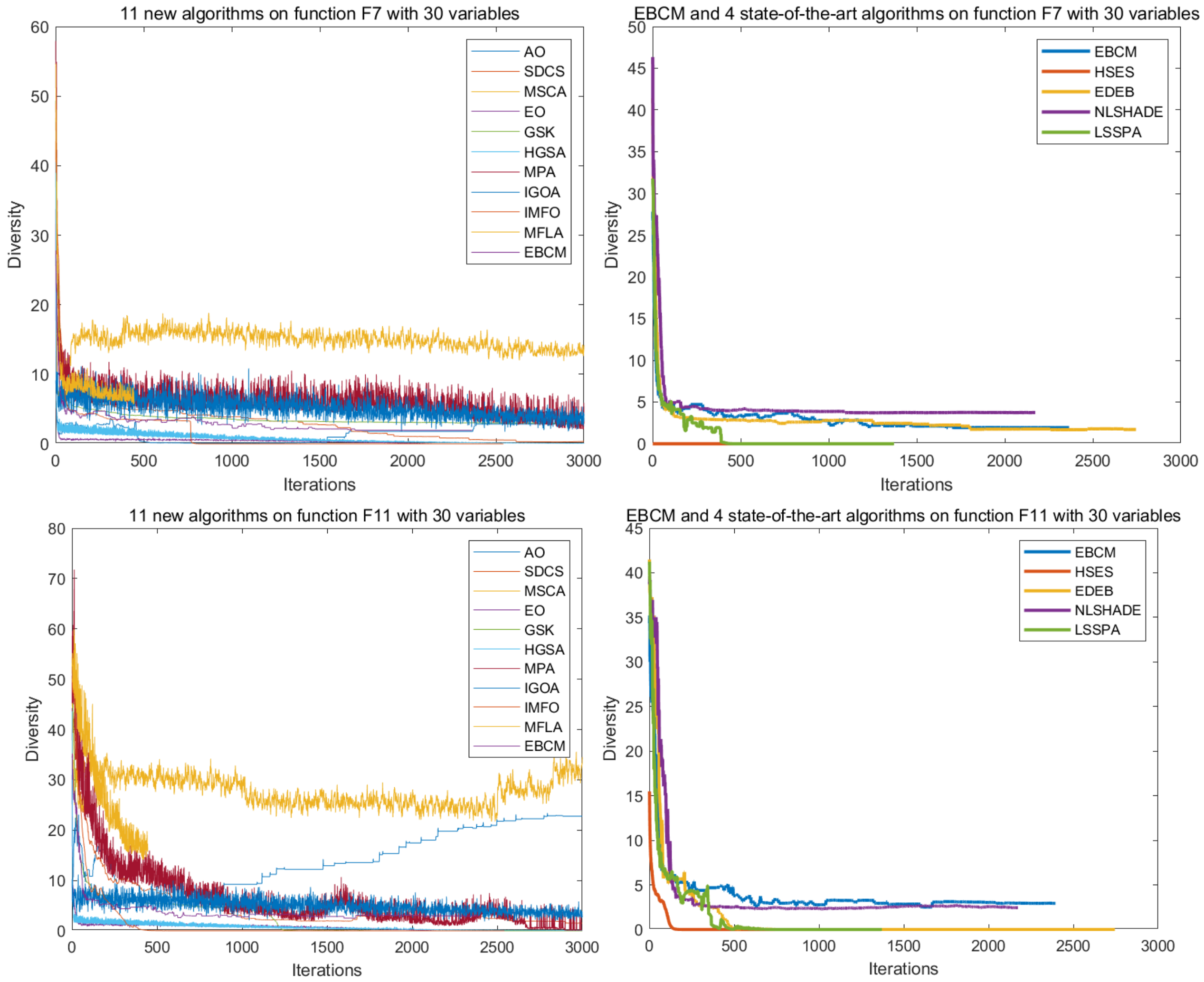

EBCM and 4 state-of-the-art algorithms on function F24 with 10 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA

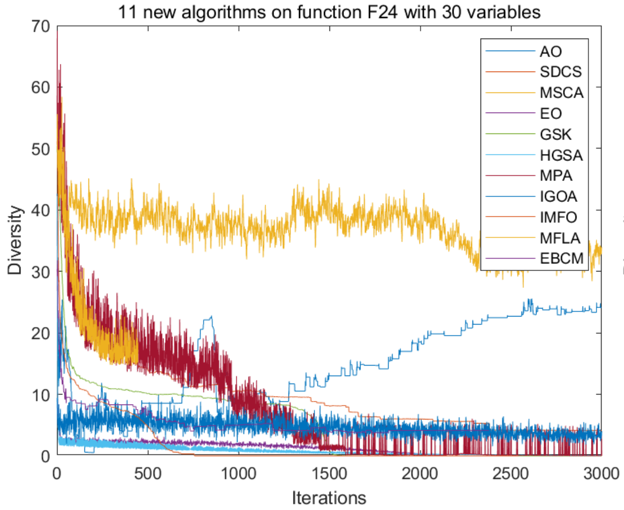
Fig.S11 Diversity analysis on functions F3, F7, F11, and F24 with 30 variables







11 new algorithms on function F7 with 30 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM
EBCM and 4 state-of-the-art algorithms on function F7 with 30 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA
11 new algorithms on function F11 with 30 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM
EBCM and 4 state-of-the-art algorithms on function F11 with 30 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA


11 new algorithms on function F24 with 30 variables
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM
Diversity
Iterations

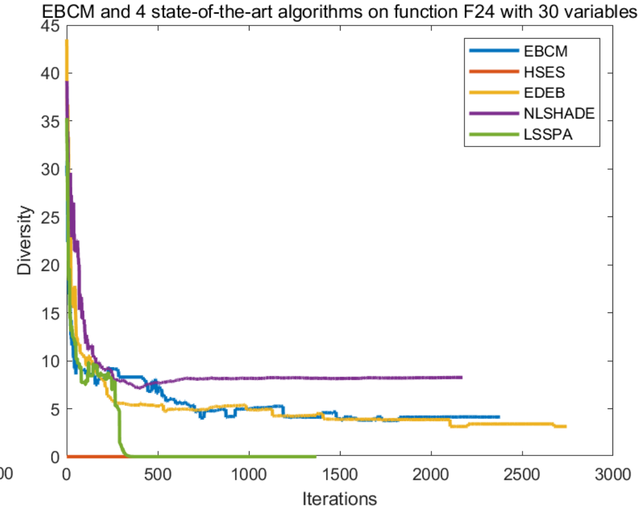
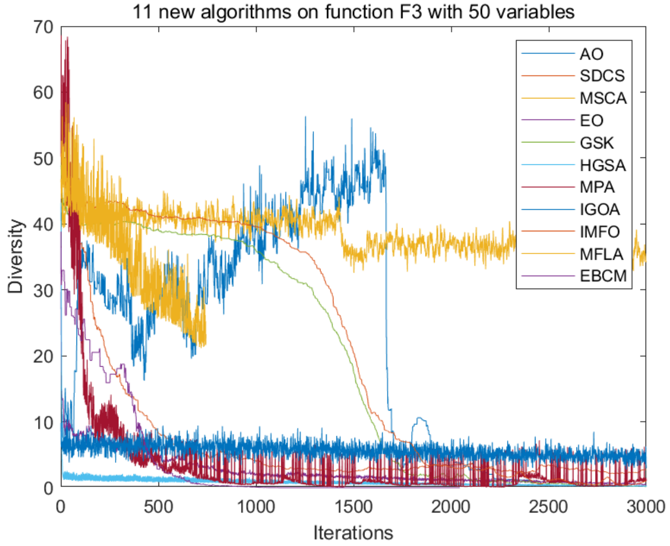
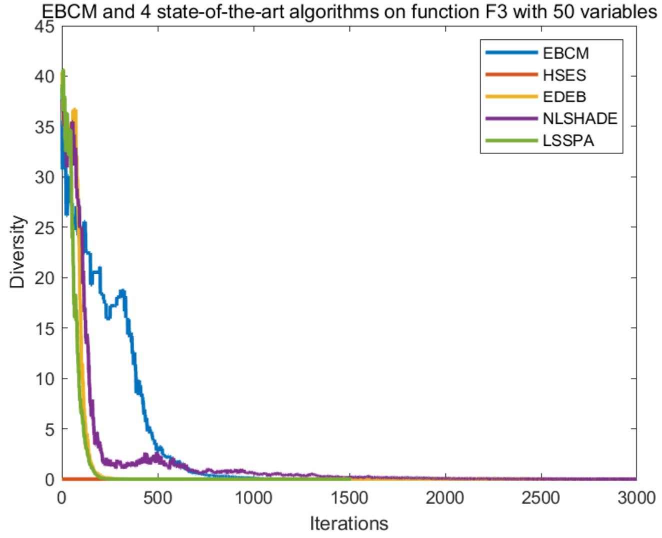
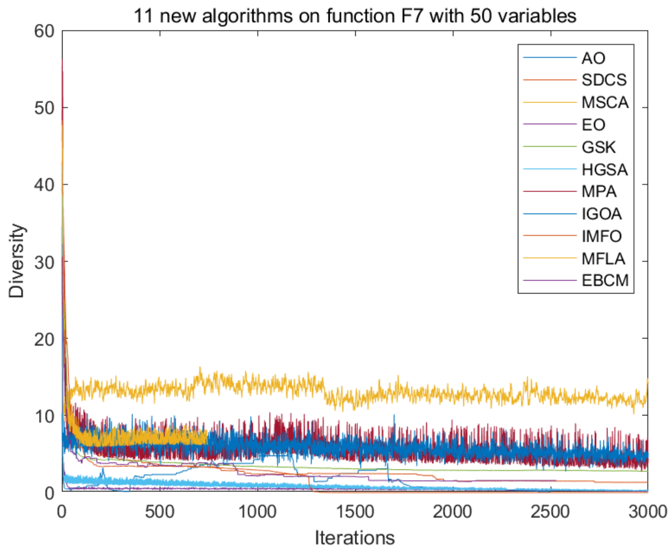
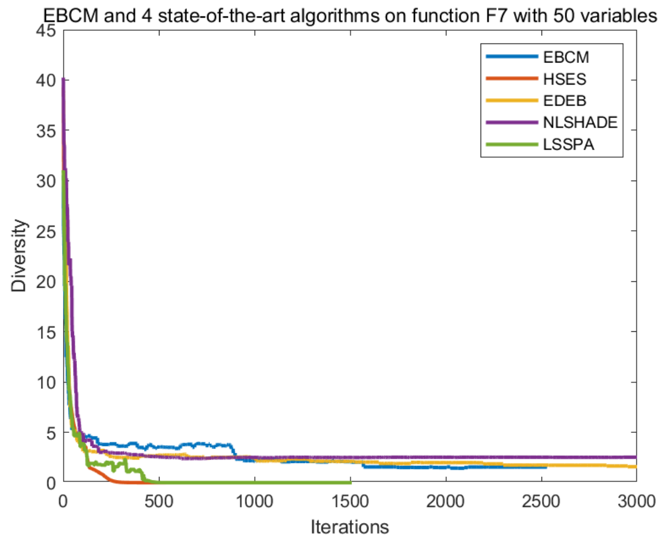

EBCM and 4 state-of-the-art algorithms on function F24 with 30 variables
EBCM
HSES
EDEB
NLSHADE
LSSPA
Diversity
Iterations

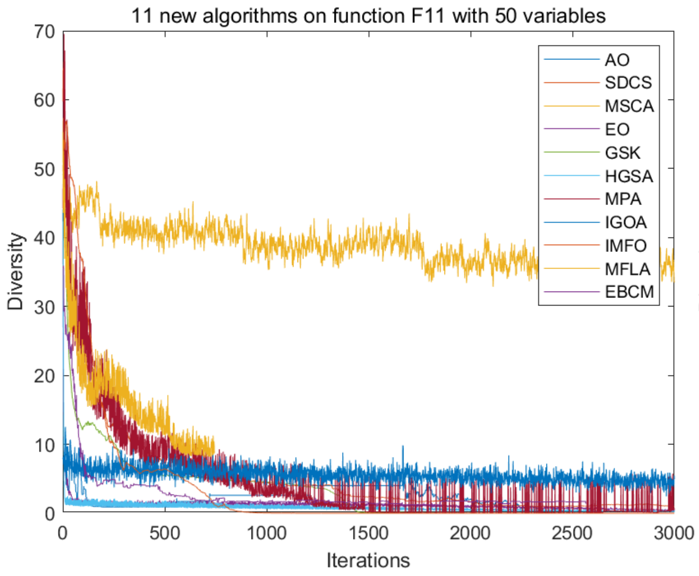
Fig.S12 Diversity analysis on functions F3, F7, F11, and F24 with 50 variables

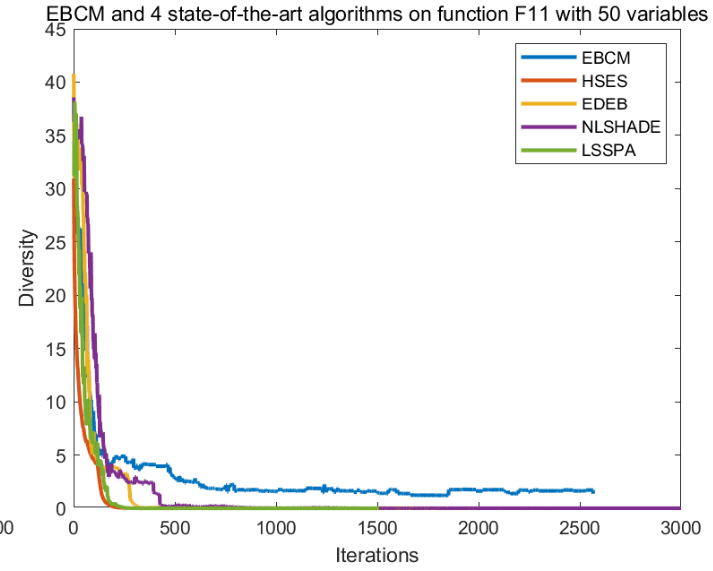


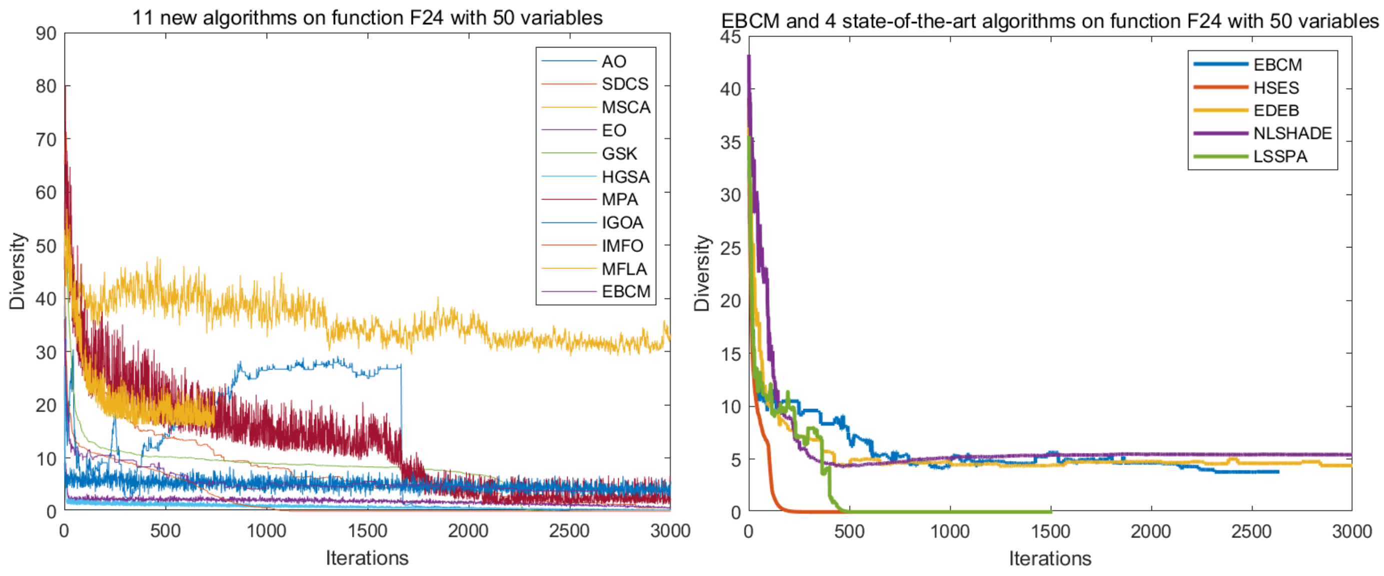



11 new algorithms on function F7 with 50 variables
Diversity
Iterations
0
500
1000
1500
2000
2500
3000
10
20
30
40
50
60
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM


EBCM and 4 state-of-the-art algorithms on function F7 with 50 variables
Diversity
Iterations
0
5
10
15
20
25
30
35
40
45
500
1000
1500
2000
2500
3000
EBCM
HSES
EDEB
NLSHADE
LSSPA


11 new algorithms on function F11 with 50 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM

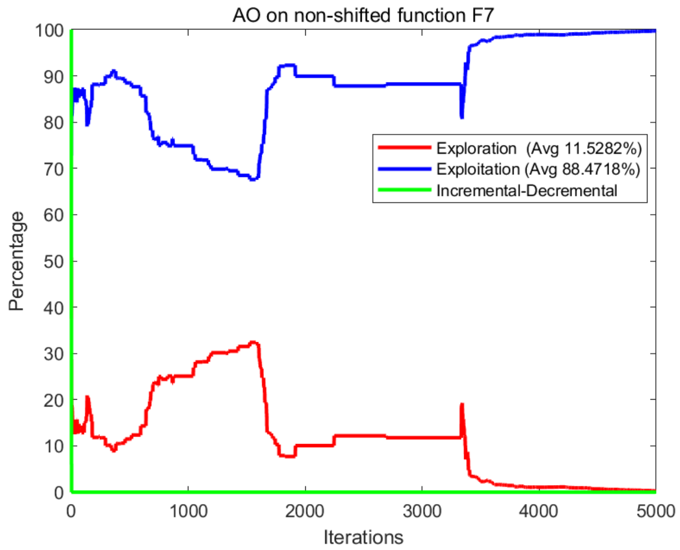

EBCM and 4 state-of-the-art algorithms on function F11 with 50 variables
Diversity
Iterations
EBCM
HSES
EDEB
NLSHADE
LSSPA

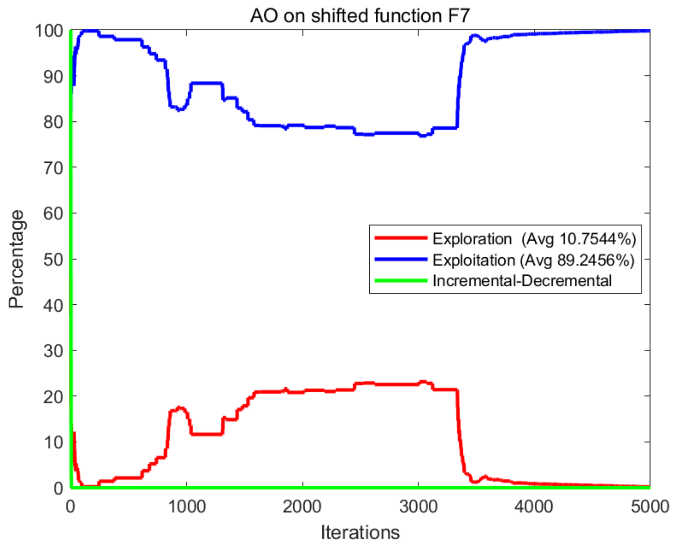


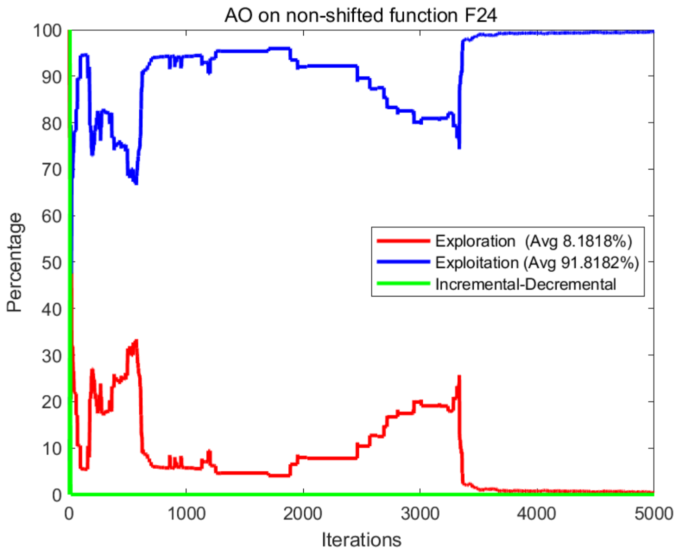
11 new algorithms on function F24 with 50 variables
Diversity
Iterations
AO
SDCS
MSCA
EO
GSK
HGSA
MPA
IGOA
IMFO
MFLA
EBCM
EBCM and 4 state-of-the-art algorithms on function F24 with 50 variables
EBCM
HSES
EDEB
NLSHADE
LSSPA

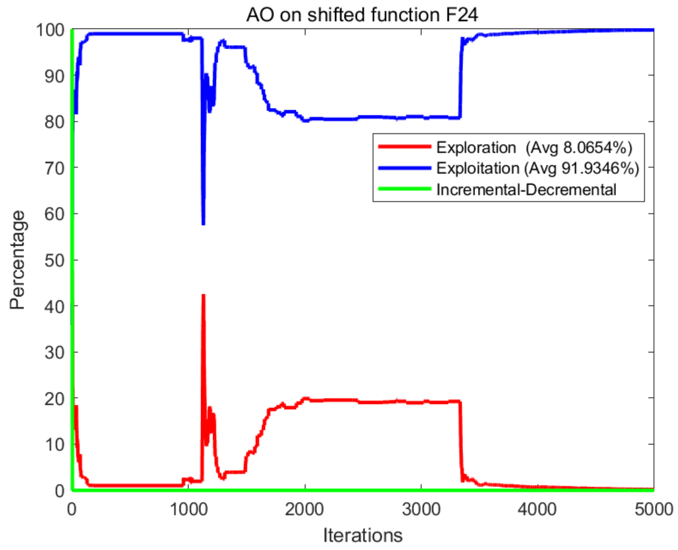
Fig.S13 Comparison results of trade-off responses of algorithms AO, MFLA, MSCA, and SDCS on shifted and non-shifted functions with 10 variables

(a) AO

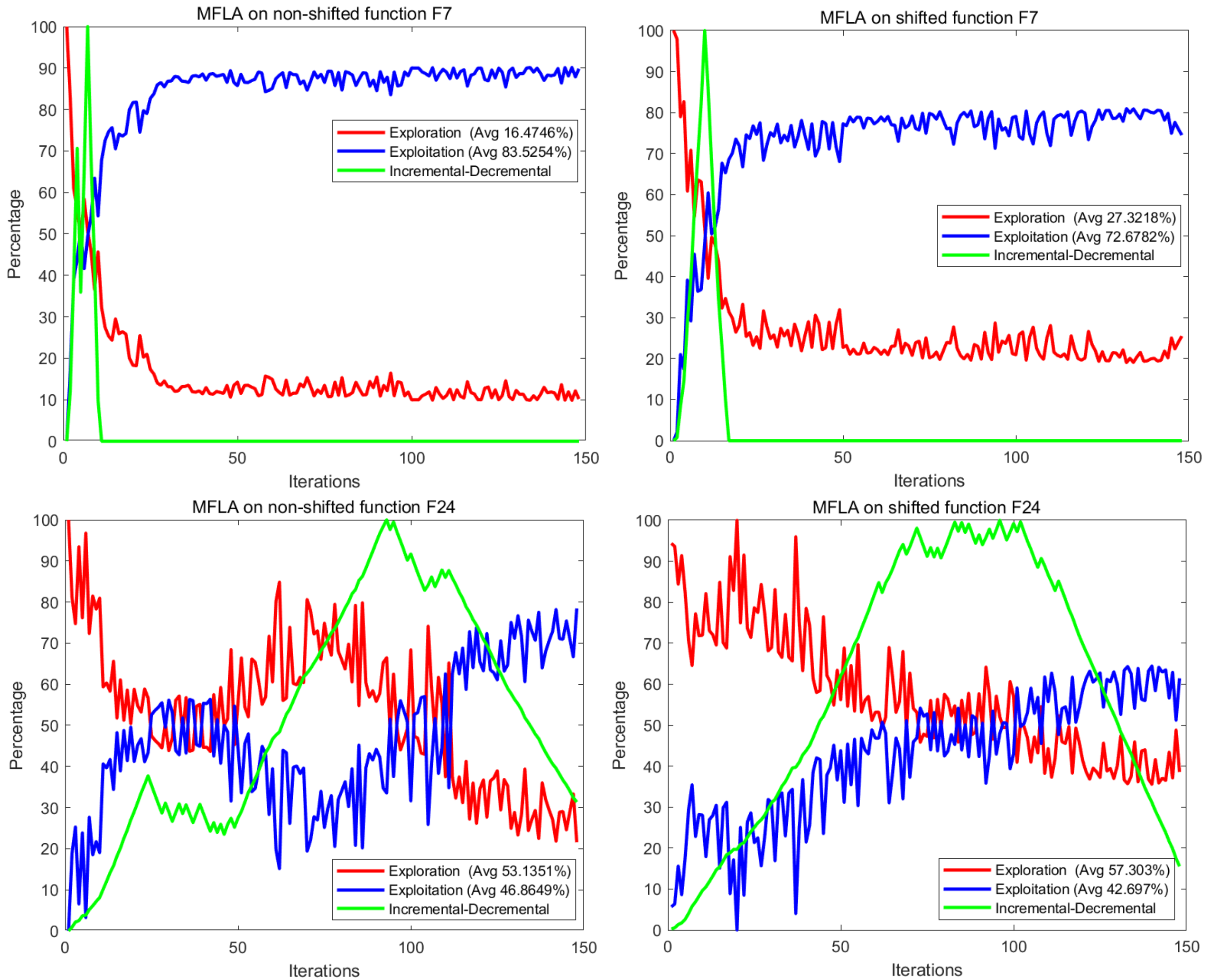




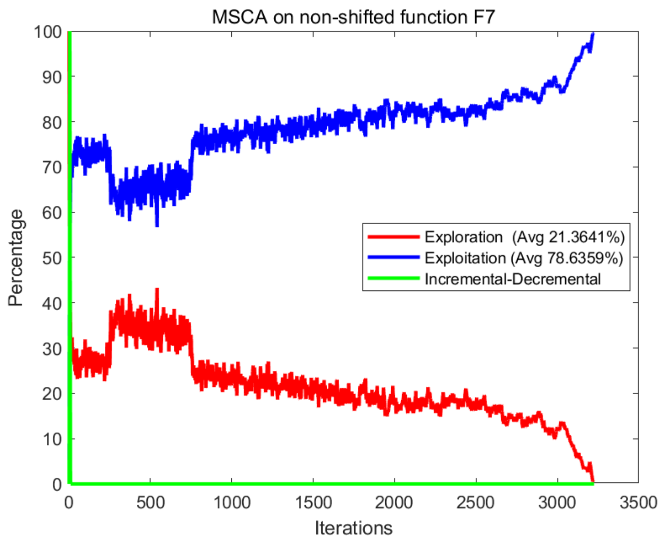

AO on non-shifted function F24
Percentage
Iterations
Exploration (Avg 8.1818%)
Exploitation (Avg 91.8182%)
Incremental-Decremental
0
10
20
30
40
50
60
70
80
90
100
0
1000
2000
3000
4000
5000


AO on shifted function F24
Percentage
Iterations
Exploration (Avg 8.0654%)
Exploitation (Avg 91.9346%)
Incremental-Decremental
0
10
20
30
40
50
60
70
80
90
100
0
1000
2000
3000
4000
5000

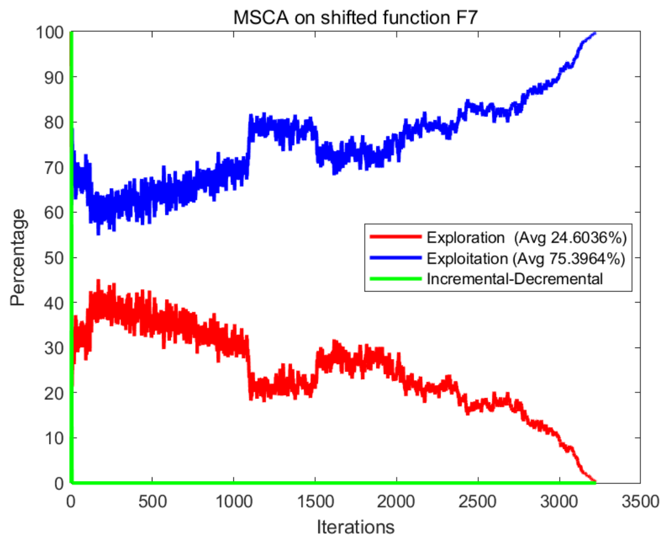
(b) MFLA


MFLA on non-shifted function F7
Exploration (Avg 16.4746%)
Exploitation (Avg 83.5254%)
Incremental-Decremental
MFLA on shifted function F7
Exploration (Avg 27.3218%)
Exploitation (Avg 72.6782%)
Incremental-Decremental
MFLA on non-shifted function F24
Exploration (Avg 53.1351%)
Exploitation (Avg 46.8649%)
Incremental-Decremental
MFLA on shifted function F24
Exploration (Avg 57.303%)
Exploitation (Avg 42.697%)
Incremental-Decremental
Percentage
Iterations

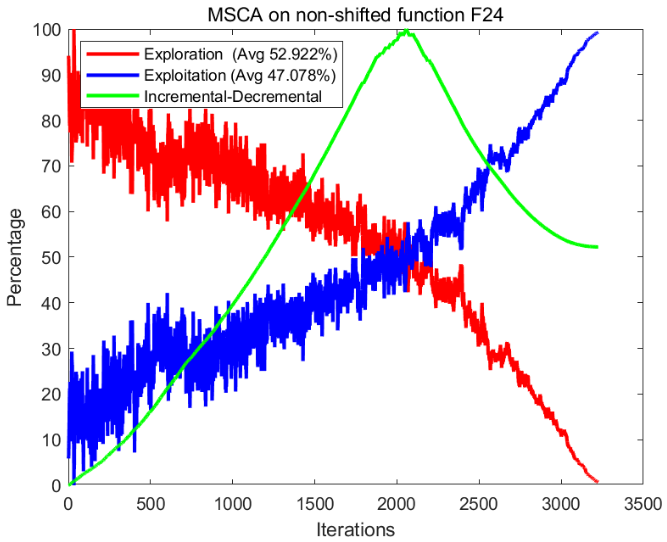
(c) MSCA

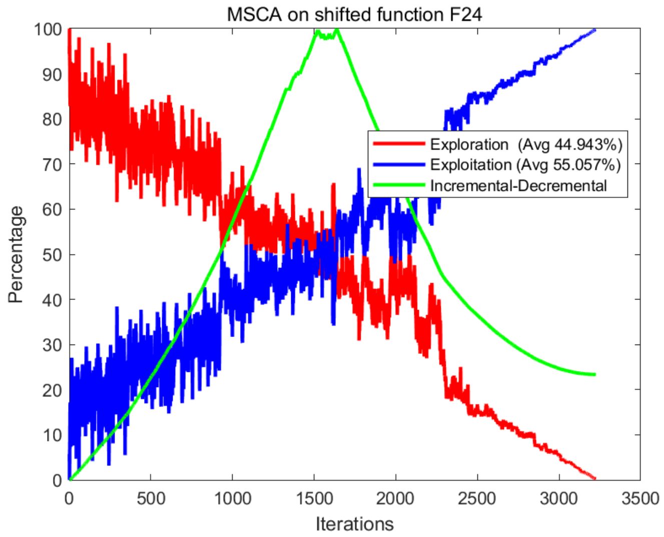


MSCA on non-shifted function F7
Percentage
Iterations
Exploration (Avg 21.3641%)
Exploitation (Avg 78.6359%)
Incremental-Decremental

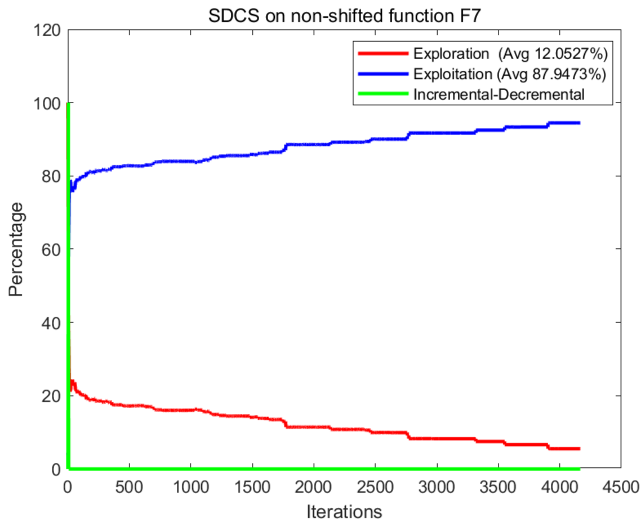


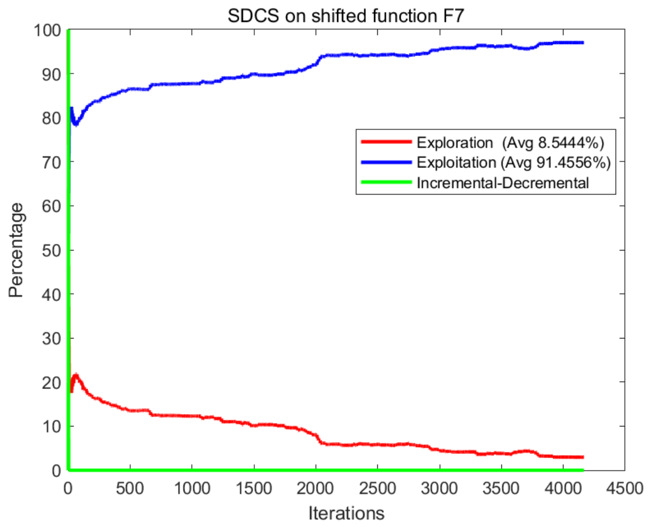
MSCA on shifted function F7
Percentage
Iterations
Exploration (Avg 24.6036%)
Exploitation (Avg 75.3964%)
Incremental-Decremental

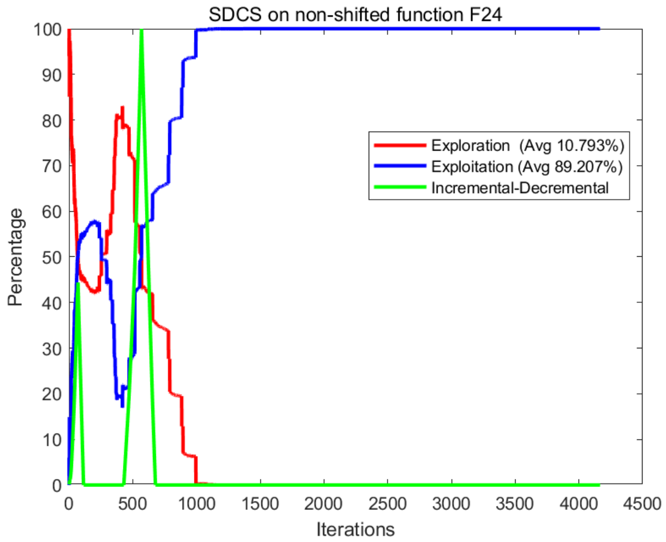

MSCA on non-shifted function F24
Exploration (Avg 52.922%)
Exploitation (Avg 47.078%)
Incremental-Decremental
Percentage
Iterations


MSCA on shifted function F24
Exploration (Avg 44.943%)
Exploitation (Avg 55.057%)
Incremental-Decremental
Percentage
Iterations

(d) SDCS


SDCS on non-shifted function F7
Exploration (Avg 12.0527%)
Exploitation (Avg 87.9473%)
Incremental-Decremental
Percentage
Iterations


SDCS on shifted function F7
Exploration (Avg 8.5444%)
Exploitation (Avg 91.4556%)
Incremental-Decremental
Percentage
Iterations


SDCS on non-shifted function F24
Exploration (Avg 10.793%)
Exploitation (Avg 89.207%)
Incremental-Decremental
Percentage
Iterations

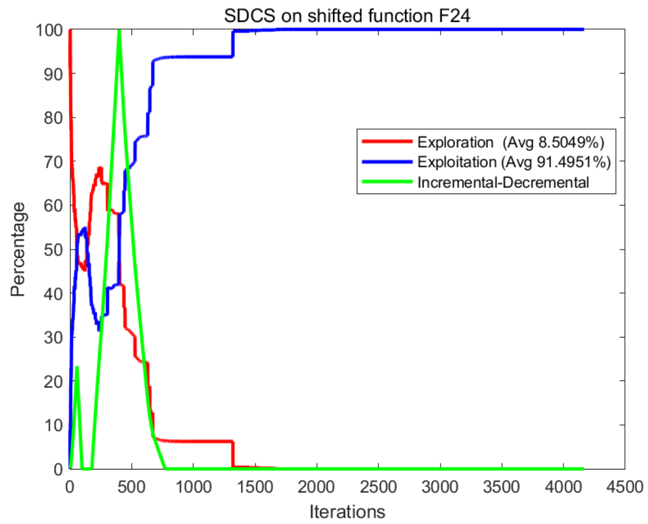
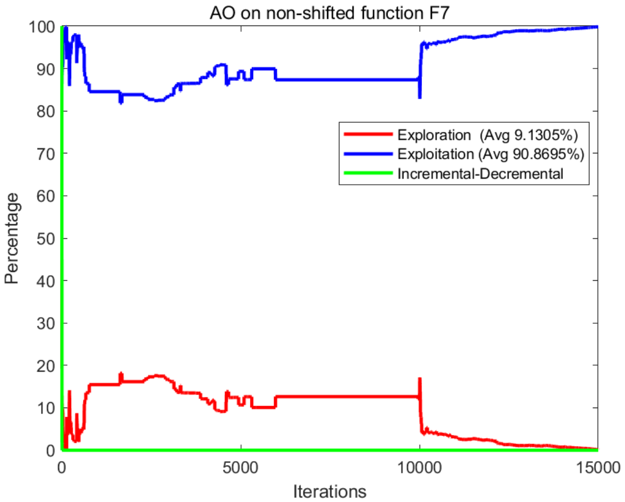
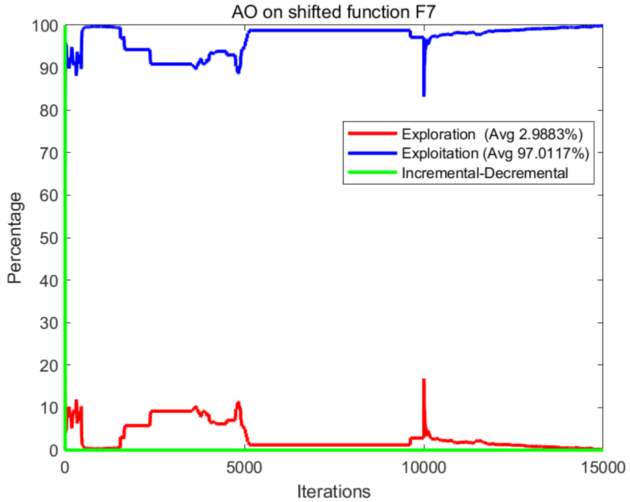
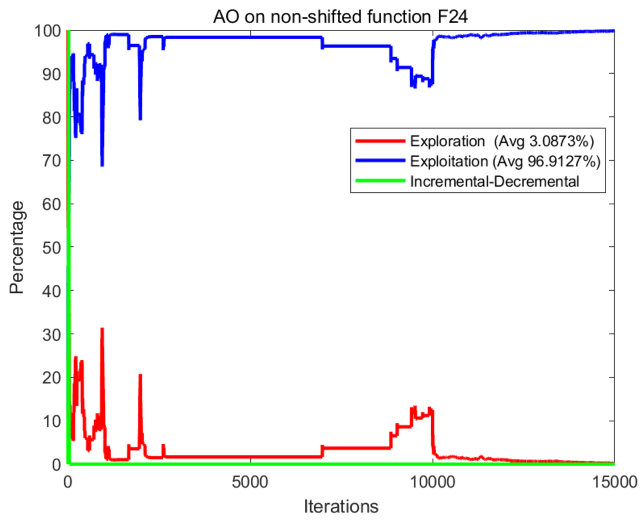

SDCS on shifted function F24
Exploration (Avg 8.5049%)
Exploitation (Avg 91.4951%)
Incremental-Decremental
Percentage
Iterations

Fig.S14 Comparison results of trade-off responses of algorithms AO, MFLA, MSCA, and SDCS on shifted and non-shifted functions with 30 variables

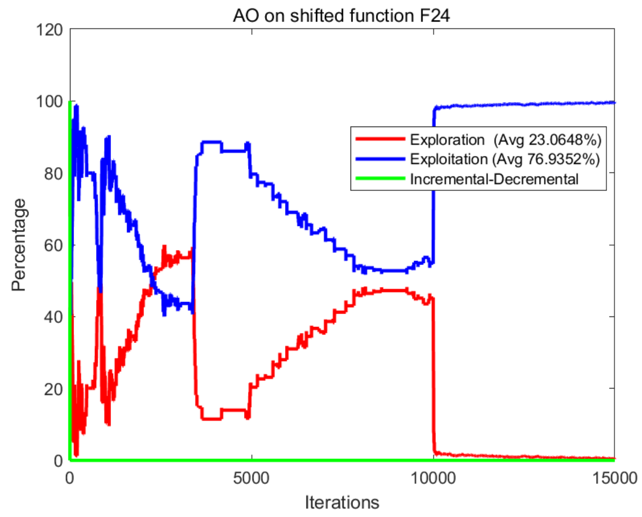
(a) AO





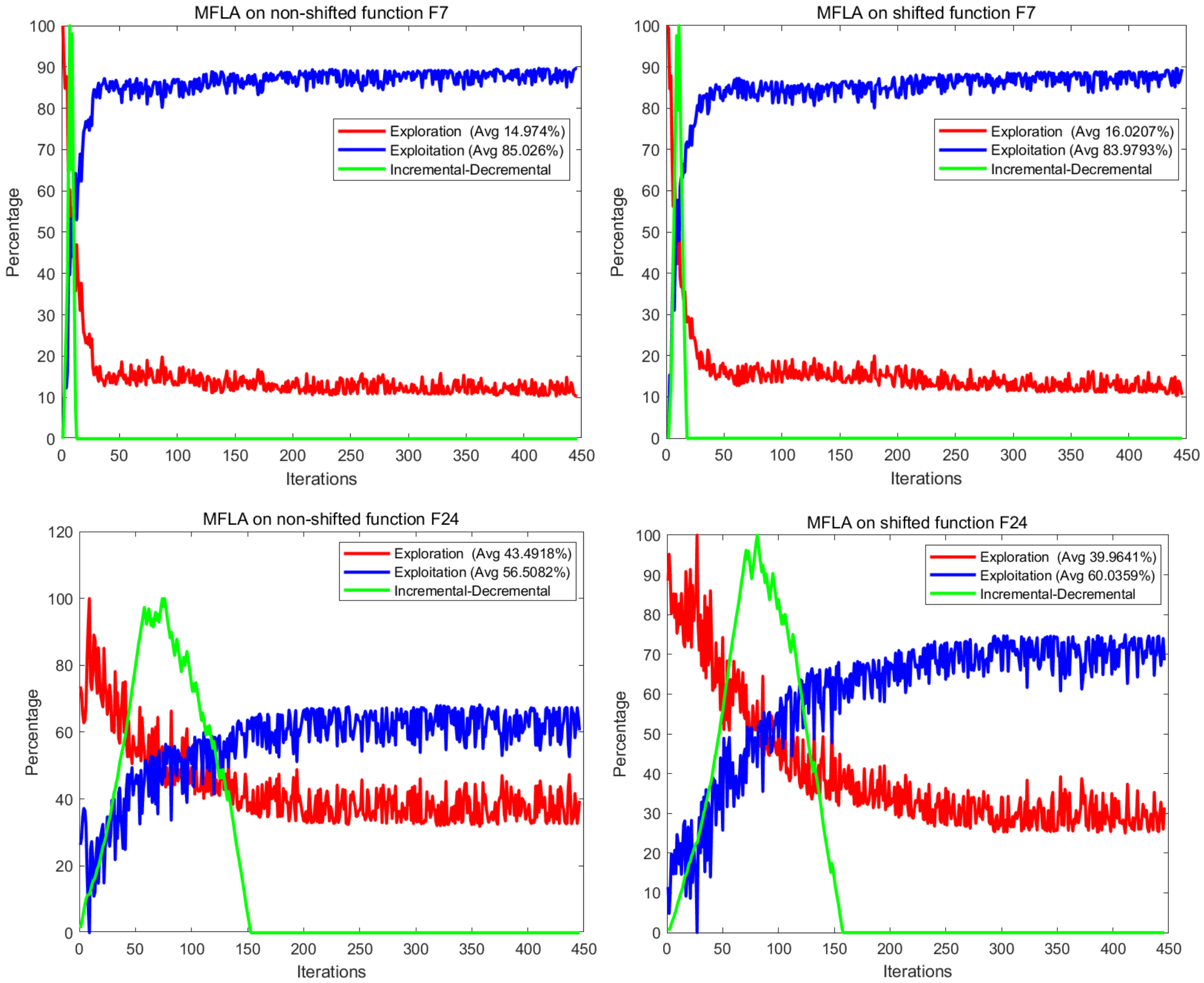


AO on non-shifted function F24
Percentage
Iterations
Exploration (Avg 3.0873%)
Exploitation (Avg 96.9127%)
Incremental-Decremental

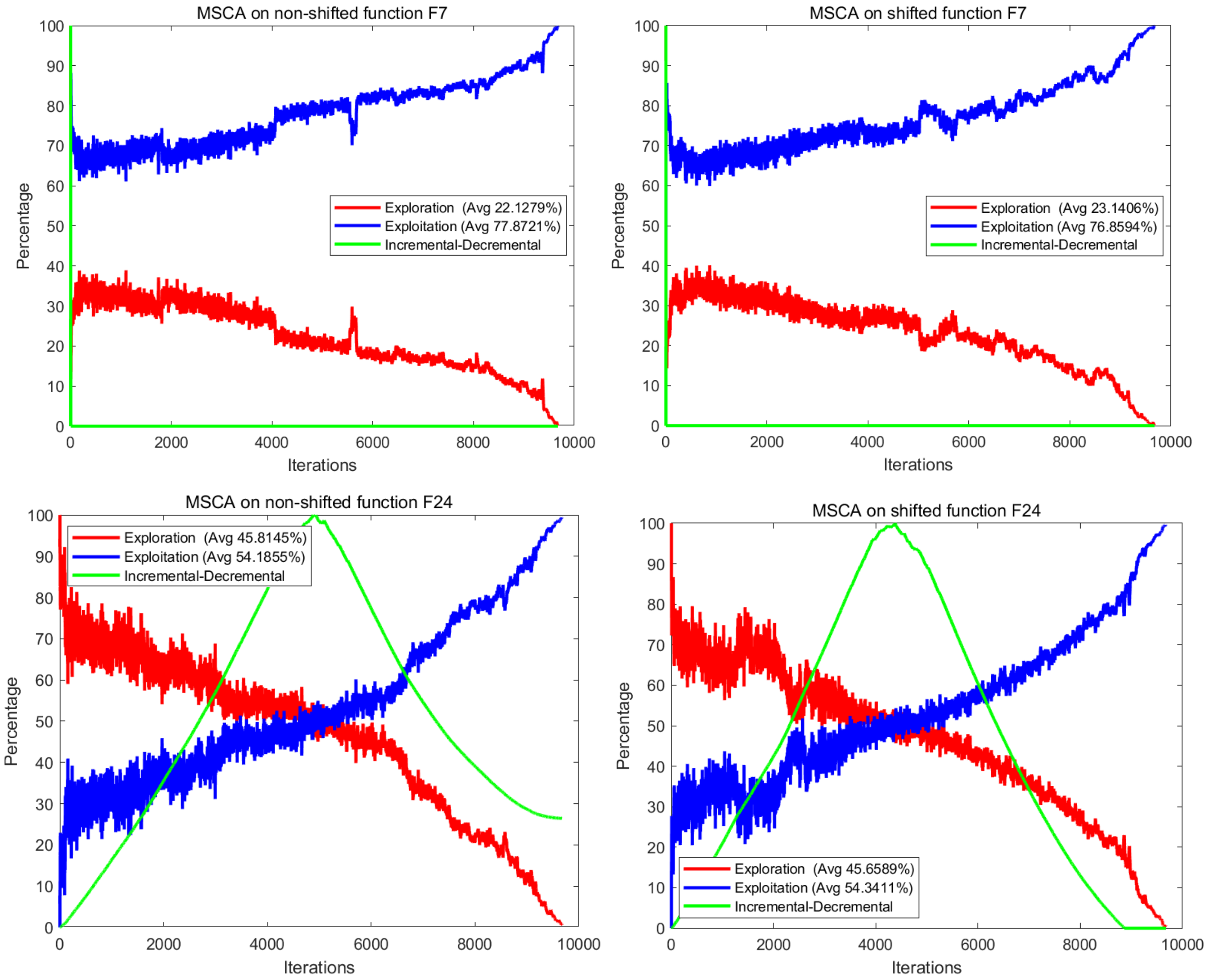


AO on shifted function F24
Percentage
Iterations
Exploration (Avg 23.0648%)
Exploitation (Avg 76.9352%)
Incremental-Decremental

(b) MFLA

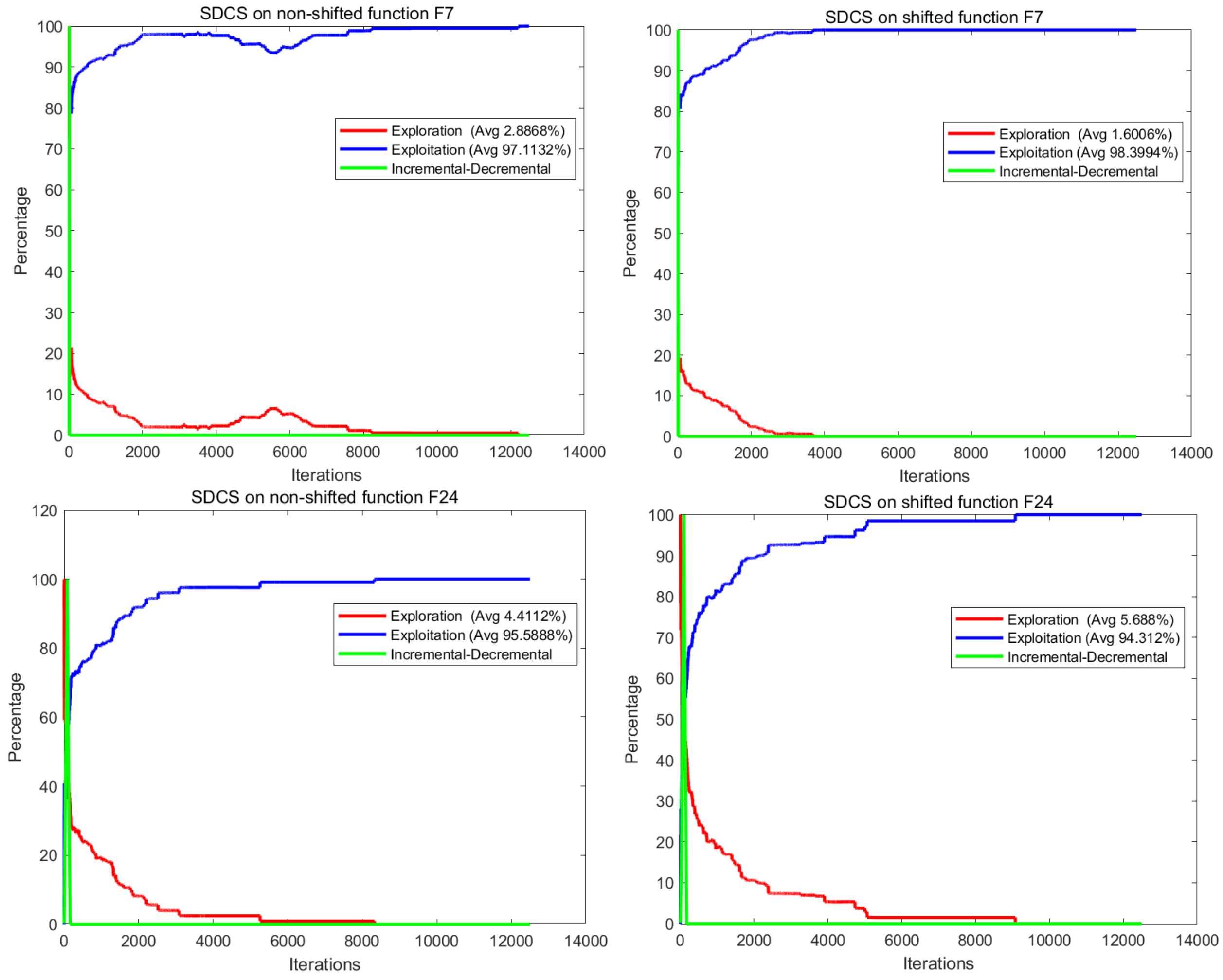

MFLA on non-shifted function F7
Exploration (Avg 14.974%)
Exploitation (Avg 85.026%)
Incremental-Decremental
Percentage
Iterations
MFLA on shifted function F7
Exploration (Avg 16.0207%)
Exploitation (Avg 83.9793%)
Incremental-Decremental
Percentage
Iterations
MFLA on non-shifted function F24
Exploration (Avg 43.4918%)
Exploitation (Avg 56.5082%)
Incremental-Decremental
Percentage
Iterations
MFLA on shifted function F24
Exploration (Avg 39.9641%)
Exploitation (Avg 60.0359%)
Incremental-Decremental
Percentage
Iterations

(c) MSCA



MSCA on non-shifted function F7
Exploration (Avg 22.1279%)
Exploitation (Avg 77.8721%)
Incremental-Decremental
Percentage
Iterations
MSCA on shifted function F7
Exploration (Avg 23.1406%)
Exploitation (Avg 76.8594%)
Incremental-Decremental
Percentage
Iterations
MSCA on non-shifted function F24
Exploration (Avg 45.8145%)
Exploitation (Avg 54.1855%)
Incremental-Decremental
Percentage
Iterations
MSCA on shifted function F24
Exploration (Avg 45.6589%)
Exploitation (Avg 54.3411%)
Incremental-Decremental
Percentage
Iterations

(d) SDCS



SDCS on non-shifted function F7
Exploration (Avg 2.8868%)
Exploitation (Avg 97.1132%)
Incremental-Decremental
Percentage
Iterations
SDCS on shifted function F7
Exploration (Avg 1.6006%)
Exploitation (Avg 98.3994%)
Incremental-Decremental
Percentage
Iterations
SDCS on non-shifted function F24
Exploration (Avg 4.4112%)
Exploitation (Avg 95.5888%)
Incremental-Decremental
Percentage
Iterations
SDCS on shifted function F24
Exploration (Avg 5.688%)
Exploitation (Avg 94.312%)
Incremental-Decremental
Percentage
Iterations

List of metaheuristics algorithms

No.	Algorithm	Acronym	Authors	Year
1	Evolutionary programming	EP	Fogel et al.[1]	1960
2	Evolution strategies	ES	Fogel et al.[2]	1964
3	Genetic algorithm	GA	Holland et al.[3]	1971
4	Scatter search algorithm	SSA	Glover[4]	1977
5	Genetic programming[1]	GP	Koza[7]	1981
6	Simulated annealing	SA	Kirkpatrick et al.[5]	1983
7	Tabu search algorithm	TS	Glover[6]	1986
8	Stochastic search network	SSN	Bishop[8]	1989
9	Memetic algorithm	MA	Moscato et al.[9]	1989
10	Ant colony optimization	ACO	Dorigo[10]	1992
11	Shuffled complex evolution	SCE	Duan et al.[11]	1993
12	Great deluge algorithm	GDA	Dueck[12]	1993
13	Cultural algorithms	CA	Reynolds[13]	1994
14	Differential evolution	DE	Storn et al.[14]	1995
15	Particle swarm optimization	PSO	Eberhart et al.[15]	1995
16	Old bachelor acceptance	OBA	Hu et al.[16]	1995
17	Bacterial evolutionary algorithm	BEA	Numaoka[17]	1996
18	Variable neighborhood descent algorithm	VND	Mladenović et al.[18]	1997
19	Bee system	BS1	Sato et al.[19]	1998
20	Photosynthetic learning algorithm	PLA	Murase et al.[20]	1998
21	Chaos optimization algorithm	COA	Jiang et al.[21]	1998
22	Sheep flocks heredity model	SFHD	Nara et al.[22]	1999
23	Extremal optimization	EO	Boettcher et al.[23]	1999
24	Gravitational clustering algorithm	GCA	Kundu S[24]	1999
25	Clonal selection algorithm	CSA	De Castro et al.[25]	2000
26	Harmony search algorithm	HSA	Geem et al.[26]	2001
27	Gene expression programming	GEP	Ferreira[27]	2001
28	Marriage in honey bees optimization	MBO	Abbass[28]	2001
29	Bacterial foraging algorithm	BFA	Passino[29]	2002
30	Bacteria chemotaxis algorithm	BCA	Muller et al.[30]	2002
31	Bee system	BS2	Lucic et al.[31]	2002
32	Popmusic algorithm	POPMUSIC	Taillard et al.[32]	2002
33	Social cognitive optimization	SCO	Xie et al.[33]	2002
34	Artificial fish swarm algorithm	AFSA	Li et al.[34]	2003
35	Covariance matrix adaptation–evolution strategy	CMA-ES	Hansen et al.[35]	2003
36	Society and civilization	SC	Ray et al.[36]	2003

[1] The first record of the proposal to evolve programs is probably that of Alan Turing in 1950[1]. There was a gap of 25 years before the publication of John Holland's 'Adaptation in Natural and Artificial Systems' laid out the theoretical and empirical foundations of the science. In 1981, Richard Forsyth demonstrated the successful evolution of small programs, represented as trees, to perform classification of crime scene evidence for the UK Home Office[2]. (https://en.wikipedia.org/wiki/Genetic_programming)

No.	Algorithm	Acronym	Authors	Year
37	Artificial immune system	AIS	Dasgupta et al.[37]	2003
38	Queen-bee evolution	QBE	Jung[38]	2003
39	Electromagnetism-like mechanism optimization	EMO	Birbil et al.[39]	2003
40	Beehive algorithm	BHA	Wedde et al.[40]	2004
41	Self-organizing migrating algorithm	SOMA	Zelinka[41]	2004
42	Artificial bee colony algorithm	ABCA	Karaboga et al.[42]	2005
43	Bee colony optimization	BCO	Teodorovic et al.[43]	2005
44	Bees swarm optimization algorithm	BSOA	Drias et al.[44]	2005
45	Dendritic cells algorithm	DCA	Greensmith et al.[45]	2005
46	The bees algorithm	BA	Pham et al.[46]	2005
47	Wasp swarm optimization	WSO	Pinto et al.[47]	2005
48	Shuffled frog-leaping algorithm	SFLA	Eusuff et al.[48]	2006
49	Big bang–big crunch	BBC	Erol et al.[49]	2006
50	Cat swarm optimization	CSO	Chu et al.[50]	2006
51	Flocking base algorithm	FA	Cui et al.[51]	2006
52	Honey-bees mating optimization algorithm	HBMO	Haddad et al.[52]	2006
53	Small-world optimization algorithm	SWOA	Du et al.[53]	2006
54	Saplings growing up algorithm	SGUA	Karci et al.[54]	2006
55	Seeker optimization algorithm	SOA	Dai et al.[55]	2006
56	Weed colonization optimization	WCO	Mehrabian et al.[56]	2006
57	Imperialist competitive algorithm	ICA	Atashpaz-Gargari et al.[57]	2007
58	Monkey search algorithm	MSA	Mucherino et al.[58]	2007
59	River formation dynamics	RFD	Rabanal et al.[59]	2007
60	Bacterial swarming algorithm	BSA	Tang et al.[60]	2007
61	Bacterial-GA foraging	BF	Chen et al.[61]	2007
62	Parliamentary optimization algorithm	POA	Borji[62]	2007
63	Simplex algorithm	SA	Pedroso[63]	2007
64	Good lattice swarm algorithm	GLSA	Su et al.[64]	2007
65	Central force optimization	CFO	Formato[65]	2007
66	Fast bacterial swarming algorithm	FBSA	Chu et al.[66]	2008
67	Biogeography-based optimization	BBO	Simon[67]	2008
68	Bar systems	BS	Del Acebo et al.[68]	2008
69	Catfish particle swarm optimization	CatfishPSO	Chuang et al[69]	2008
70	Goose team optimizer	GTO	Wang et al.[70]	2008
71	Harmony element algorithm	HEA	Cui et al.[71]	2008
72	Fish-school search	FSF	Bastos Filho et al.[72]	2008
73	Roach infestation optimization	RIO	Havens et al.[73]	2008
74	Viral search	VS	Cortés et al.[74]	2008
75	Plant growth optimization	PGO	Cai et al.[75]	2008
76	Artificial beehive algorithm	ABA	Munoz et al.[76]	2009
77	Artificial physics optimization	APO	Xie et al.[77]	2009

No.	Algorithm	Acronym	Authors	Year
78	Bee colony-inspired algorithm	BCiA	Häckel et al.[78]	2009
79	Gravitational emulation local search	GELS	Barzegar et al.[79]	2009
80	Group search optimizer	GBO	He et al.[80]	2009
81	Cuckoo search	CS	Yang et al.[81]	2009
82	Gravitational search algorithm	GSA	Rashedi et al.[82]	2009
83	Firefly algorithm	FA	Yang[83]	2009
84	Frog call inspired algorithm	FCA	Mutazono et al.[84]	2009
85	Glowworm swarm optimization	GSO	Krishnanand et al.[85]	2009
86	League championship algorithm	LCA	Kashan[86]	2009
87	Paddy field algorithm	PFA	Premaratne et al.[87]	2009
88	Dolphin partner optimization	DPO	Yang et al.[88]	2009
89	Dialectic search	DS	Kadioglu et al.[89]	2009
90	Human-inspired algorithms	HIA	Zhang et al.[90]	2009
91	Artificial searching swarm algorithm	ASSA	Chen[91]	2009
92	Bumble bees mating optimization	BBMO	Comellas et al.[92]	2009
93	Group counseling optimization	GCO	Eita et al.[93]	2009
94	Hunting search algorithm	HSA	Oftadeh et al.[94]	2009
95	Locust swarm	LS	Chen[95]	2009
96	Intelligent water drops algorithm	IWDA	Hamed Shah[96]	2009
97	Water flow algorithm	WFA	Hieu et al.[97]	2009
98	Asexual reproduction optimization	ARO	Farasat et al.[98]	2010
99	Bean optimization algorithm	BOA	Zhang et al.[99]	2010
100	Bat algorithm	BA	Yang[100]	2010
101	Bee swarm optimization	BSO	Akbari et al.[101]	2010
102	Charged system search	CSS	Kaveh et al.[102]	2010
103	Chemical reaction optimization algorithm	CRO	Xu et al.[103]	2010
104	Gravitational field algorithm	GFA	Zheng et al.[104]	2010
105	Fireworks algorithm	FA	Tan et al.[105]	2010
106	Eagle strategy	ES	Yang et al.[106]	2010
107	Grenade explosion algorithm	GEA	Ahrari et al.[107]	2010
108	Wind driven optimization	WDO	Bayraktar et al.[108]	2010
109	Termite colony optimization	TCO	Hedayatzadeh et al.[109]	2010
110	Consultant-guided search	CGS	Iordache et al.[110]	2010
111	Social emotional optimization algorithm	SEOA	Xu et al.[111]	2010
112	Hierarchical swarm model	HSM	Chen et al.[112]	2010
113	Reincarnation algorithm	RA	Sharma[113]	2010
114	Artificial plants optimization algorithm	APO	Zhao et al.[114]	2011
115	Brain storm optimization	BSO	Shi et al.[115]	2011
116	Bioluminescent swarm optimization algorithm	BSOA	Oliveira et al.[116]	2011
117	Cockroach swarm optimization	CSO	Chen[117]	2011
118	Group escape behavior	GEB	Min et al.[118]	2011
119	Group leaders optimization algorithm	GIOA	Daskin et al.[119]	2011

No.	Algorithm	Acronym	Authors	Year
120	Teaching-learning base optimization	TLBO	Rao et al.[120]	2011
121	Cuckoo optimization algorithm	COA	Rajabioun[121]	2011
122	Artificial chemical reaction optimization algorithm	ACROA	Alatas[122]	2011
123	Galaxy-based search algorithm	GBSA	Shah-Hosseini[123]	2011
124	Spiral dynamics inspired optimization	SDIO	Tamura et al.[124]	2011
125	Plant propagation algorithm	PPA	Salhi et al.[125]	2011
126	Eco-inspired evolutionary algorithm	EIEA	Parpinelli et al.[126]	2011
127	Gravitational interactions optimization	GIO	Flores et al.[127]	2011
128	Stem cells algorithm	SCA	Taherdangkoo et al.[128]	2011
129	Water-flow algorithm	WFA	Tran et al. [129]	2011
130	Anarchic society optimization	ASO	Ahmadi-Javid et al.[130]	2012
131	Artificial tribe algorithm	ATA	Chen et al.[131]	2012
132	Bat intelligence	BI	Malakooti et al.[132]	2012
133	Collective animal behavior	CAB	Cuevas et al.[133]	2012
134	Cloud model-based differential evolution algorithm	CMDE	Zhu et al.[134]	2012
135	Flower pollination algorithm	FPA	Yang[135]	2012
136	Flock by leader	FL	Bellaachia et al.[136]	2012
137	Krill herd algorithm	KHA	Gandomi et al.[137]	2012
138	Fruit fly optimization algorithm	FFOA	Pan[138]	2012
139	Water cycle algorithm	WCA	Eskandar et al.[139]	2012
140	Differential search algorithm	DSA	Civicioglu[140]	2012
141	Ray optimization	RO	Kaveh et al.[141]	2012
142	Migrating bird optimization	MBO	Duman et al.[142]	2012
143	Wolf search algorithm	WSA	Tang et al.[143]	2012
144	Mine blast algorithm	MBA	Sadollah et al.[144]	2012
145	Electro-magnetism optimization	EMO	Cuevas et al.[145]	2012
146	Bacterial colony optimization	BCO	Niu et al.[146]	2012
147	Great salmon run	GSR	Mozaffari et al.[147]	2012
148	Japanese tree frogs calling algorithm	JTFC	Hernández et al.[148]	2012
149	Community of scientist optimization	CSO	Milani et al.[149]	2012
150	Quantum-inspired bacterial swarming optimization	QBSO	Cao et al.[150]	2012
151	Hoopoe heuristic optimization	HH	El-Dosuky et al.[151]	2012
152	Intelligent gravitational search algorithm	IGSA	Askari et al.[152]	2012
153	Lion pride optimizer	LPO	Wang et al.[153]	2012
154	Zombie survival optimization	ZSO	Nguyen et al.[154]	2012
155	Artificial photosynthesis and phototropism mechanism	APPM	Cai[155]	2012
156	Superbug algorithm	SA	Anandaraman et al.[156]	2012
157	Artificial plant optimization algorithm	APOA	Cui et al.[157]	2013
158	Artificial reaction algorithm	ARA	Melin et al.[158]	2013
159	Adaptive social behavior optimization	ASBO	Singh M K[159]	2013
160	Bat-inspired algorithm	BI	Hasançebi et al.[160]	2013

No.	Algorithm	Acronym	Authors	Year
161	Co-operation of biology related algorithm	COBRA	Akhmedova et al.[161]	2013
162	Global neighborhood algorithm	GNA	Alazzam et al.[162]	2013
163	Mosquito host-seeking algorithm	MHSA	Feng et al.[163]	2013
164	Mobility aware-termite	MAT	Manjappa et al.[164]	2013
165	Backtracking search optimization	BSO	Civicioglu[165]	2013
166	Black holes algorithm	BHA	Hatamlou[166]	2013
167	Social spider optimization	SSO	Cuevas et al.[167]	2013
168	Dolphin echolocation	DE	Kaveh et al.[168]	2013
169	Artificial cooperative search	ACS	Civicioglu[169]	2013
170	Gases brownian motion optimization	GBMO	Abdechiri et al.[170]	2013
171	Swallow swarm optimization algorithm	SSOA	Neshat et al.[171]	2013
172	Penguins search optimization algorithm	PSOA	Gheraibia et al.[172]	2013
173	Egyptian vulture optimization	EVO	Sur et al.[173]	2013
174	Atmosphere clouds model optimization	ACMO	Yan et al.[174]	2013
175	Magnetotactic bacteria optimization algorithm	MBOA	Mo et al.[175]	2013
176	Blind, naked mole-rats algorithm	BNMR	Taherdangkoo et al.[176]	2013
177	Soccer game optimization	SGO	Purnomo et al.[177]	2013
178	Seven-spot ladybird optimization	SSLO	Wang et al.[178]	2013
179	Cuttlefish algorithm	CA	Eesa et al.[179]	2013
180	African wild dog algorithm	AWDA	Subramanian et al.[180]	2013
181	Mussels wandering optimization	MWO	An et al.[181]	2013
182	Swine influenza models based optimization	SIMB	Pattnaik et al.[182]	2013
183	Tree physiology optimization	TPO	Halim et al.[183]	2013
184	Animal behavior hunting	ABH	Naderi et al.[184]	2014
185	Artificial raindrop algorithm	ARA	Jiang et al.[185]	2014
186	Grey wolf optimizer	GWO	Mirjalili et al.[186]	2014
187	Symbiotic organisms search	SOS	Cheng et al.[187]	2014
188	Colliding bodies optimization	CBO	Kaveh et al.[188]	2014
189	Chicken swarm optimization	CSO	Meng et al.[189]	2014
190	Spider monkey optimization	SMO	Bansal et al.[190]	2014
191	Interior search algorithm	ISA	Gandomi[191]	2014
192	Animal migration optimization algorithm	AMOA	Li et al.[192]	2014
193	Coral reefs optimization algorithm	CROA	Salcedo-Sanz et al.[193]	2014
194	Bird mating optimizer	BMO	Askarzadeh[194]	2014
195	Shark smell optimization	SSO	Abedinia et al.[195]	2014
196	Exchange market algorithm	EMA	Ghorbani et al.[196]	2014
197	Forest optimization algorithm	FOA	Ghaemi et al.[197]	2014
198	Golden ball algorithm	GBA	Osaba et al.[198]	2014
199	Keshtel algorithm	KA	Hajiaghaei-Keshteli et al.[199]	2014
200	Kaizen programming	KP	De Melo[200]	2014
201	Kinetic gas molecule optimization	KGMO	Moein et al.[201]	2014

No.	Algorithm	Acronym	Authors	Year
202	Strawberry algorithm	SA	Merrikh-Bayat[202]	2014
203	Heart algorithm	HA	Hatamlou et al.[203]	2014
204	Artificial ecosystem algorithm	AEA	Adham et al.[204]	2014
205	The scientific algorithms	SA	Felipe et al.[205]	2014
206	Worm optimization	WO	Arnaout[206]	2014
207	Greedy politics optimization	GPO	Melvix[207]	2014
208	Human learning optimization	HLO	Wang et al.[208]	2014
209	Soccer league competition algorithm	SLCA	Moosavian et al.[209]	2014
210	Hyper-spherical search algorithm	HSSA	Karami et al.[210]	2014
211	Ecogeography-based optimization	EBO	Zheng et al.[211]	2014
212	Pigeon-inspired optimization	PIO	Duan et al.[212]	2014
213	Ant lion optimization	ALO	Mirjalili[213]	2015
214	Artificial algae algorithm	AAA	Uymaz et al.[214]	2015
215	Artificial showering algorithm	ASA	Ali et al.[215]	2015
216	Cricket algorithm	CA	Canayaz et al.[216]	2015
217	Gradient evolution algorithm	GEA	Kuo et al.[217]	2015
218	Moth-flame optimization algorithm	MFOA	Mirjalili[218]	2015
219	Monarch butterfly optimization	MBO	Wang et al.[219]	2015
220	Water wave optimization	WWO	Zheng et al.[220]	2015
221	Stochastic fractal search	SFS	Salimi et al.[221]	2015
222	Elephant herding optimization	EHO	Wang et al.[222]	2015
223	Vortex search algorithm	VSA	Doğan et al.[223]	2015
224	Earthworm optimization algorithm	EOA	Wang et al.[224]	2015
225	Lightning search algorithm	LSA	Shareef et al.[225]	2015
226	Heat transfer search algorithm	HTSA	Patel et al.[226]	2015
227	Ions motion algorithm	IMA	Javidy et al.[227]	2015
228	Optics inspired optimization	OIO	Kashan[228]	2015
229	Tree seed algorithm	TSA	Kiran[229]	2015
230	Runner-root algorithm	RRA	Merrikh-Bayat[230]	2015
231	Elephant search algorithm	ESA	Deb et al.[231]	2015
232	Election algorithm	EA	Emami et al.[232]	2015
233	Locust search	LS	Cuevas et al.[233]	2015
234	Invasive tumor growth optimization algorithm	ITWO	Tang et al.[234]	2015
235	Jaguar algorithm	JA	Chen et al.[235]	2015
236	General relativity search algorithm	GRSA	Beiranvand et al.[236]	2015
237	Root growth optimizer	RGO	He et al.[237]	2015
238	Bull optimization algorithm	BOA	FINDIK[238]	2015
239	Prey-predator algorithm	PPA	Tilahun et al.[239]	2015
240	African buffalo optimization	ABO	Odili et al.[240]	2015
241	Artificial infectious disease optimization	AID	Huang et al.[241]	2016
242	Across neighborhood search	ANS	Wu [242]	2016
243	Cricket behavior-based algorithm	CBBA	Canayaz et al.[243]	2016

No.	Algorithm	Acronym	Authors	Year
244	Competitive optimization algorithm	COOA	Sharafi et al.[244]	2016
245	Cognitive behavior optimization algorithm	COA	Li et al.[245]	2016
246	Electromagnetic field optimization	EFO	Abedinpourshotorban et al.[246]	2016
247	Football game algorithm	FGA	Fadakar et al.[247]	2016
248	Intrusive tumor growth inspired optimization algorithm	ITGO	Tang et al.[248]	2016
249	Galactic swarm optimization	GSO	Muthiah-Nakarajan et al.[249]	2016
250	Whale optimization algorithm	WOA	Mirjalili et al.[250]	2016
251	Sine cosine algorithm	SSA	Mirjalili et al.[251]	2016
252	Dragonfly algorithm	DA	Mirjalili et al.[252]	2016
253	Crow search algorithm	CSA	Askarzadeh et al.[253]	2016
254	Multi-verse optimizer	MVO	Mirjalili et al.[254]	2016
255	Bird swarm algorithm	BSA	Meng et al.[255]	2016
256	Virus colony search	VCS	Li et al.[256]	2016
257	Water evaporation optimization	WEO	Kaveh et al.[257]	2016
258	Root tree optimization algorithm	RTO	Labbi et al.[258]	2016
259	FIFA world cup algorithm	FIFAWC	Razmjooy et al.[259]	2016
260	Sperm whale algorithm	SWA	Ebrahimi et al.[260]	2016
261	Virus optimization algorithm	VOA	Liang et al.[261]	2016
262	Duelist algorithm	DA	Biyanto et al.[262]	2016
263	Raven roosting optimization algorithm	RROA	Brabazon et al.[263]	2016
264	Ring seal search	RSS	Saadi et al.[264]	2016
265	Flying elephant algorithm	FEA	Xavier et al.[265]	2016
266	Camel algorithm	CA	Ibrahim et al.[266]	2016
267	Crystal energy optimization algorithm	CEO	Feng et al.[267]	2016
268	Passing vehicle search	PVS	Savsani et al.[268]	2016
269	Tug of war optimization	TWO	Kaveh et al.[269]	2016
270	Dynamic virtual bats algorithm	DVBA	Topal et al.[270]	2016
271	Lion optimization algorithm	LOA	Yazdani et al.[271]	2016
272	Natural forest regeneration algorithm	NFR	Moez et al.[272]	2016
273	Simulated kalman filter	SKF	Ibrahim et al.[273]	2016
274	Shuffled multi-swarm micro-migrating birds optimization	SM^2-MBO	Gao et al.[274]	2016
275	Yin-Yang-pair optimization	YYPO	Punnathanam et al.[275]	2016
276	Virulence optimization algorithm	VOA	Jaderyan et al.[276]	2016
277	Artificial butterfly optimization	ABO	Qi et al.[277]	2017
278	Cyclical parthenogenesis algorithm	CPA	Kaveh et al.[278]	2017
279	Deterministic oscillatory search	DOS	Archana et al.[279]	2017
280	Fractal-based algorithm	FA	Kaedi M[280]	2017
281	Neuronal communication algorithm	NCA	Asil Gharebaghi et	2017

No.	Algorithm	Acronym	Authors	Year
			al.[281]	
282	Lightning attachment procedure optimization	LAPO	Nematollahi et al.[282]	2017
283	Bison behavior algorithm	BBA	Kazikova et al.[283]	2017
284	Drone squadron optimization	DSO	de Melo[284]	2017
285	Human behavior-based optimization	HBO	Ahmadi[285]	2017
286	Vibrating particles system	VPS	Kaveh et al.[286]	2017
287	Spotted hyena optimizer	SHO	Dhiman et al.[287]	2017
288	Salp swarm algorithm	SSA	Mirjalili et al.[288]	2017
289	Grasshopper optimisation algorithm	GOA	Saremi et al.[289]	2017
290	Rain fall optimization algorithm	RFO	Kaboli et al.[290]	2017
291	Hydrological cycle algorithm	HCA	Wedyan et al.[291]	2017
292	Killer whale algorithm	KWA	Biyanto et al.[292]	2017
293	Camel herd algorithm	CHA	Al-Obaidi et al.[293]	2017
294	Collective decision optimization algorithm	CDOA	Zhang et al.[294]	2017
295	Laying chicken algorithm	LCA	Hosseini[295]	2017
296	Kidney-inspired algorithm	KIA	Jaddi et al.[296]	2017
297	Golden sine algorithm	Gold-SA	Tanyildizi et al.[297]	2017
298	Sperm motility algorithm	SMA	Raouf et al.[298]	2017
299	Rain water algorithm	RWA	Biyanto[299]	2017
300	Thermal exchange optimization	TEO	Kaveh et al.[300]	2017
301	Porcellio scaber algorithm	PSA	Zhang et al.[301]	2017
302	Selfish herd optimizer	SHO	Fausto et al.[302]	2017
303	Polar bear optimization algorithm	PBO	Połap et al.[303]	2017
304	Social engineering optimization	SEO	Fard et al.[304]	2017
305	Sonar inspired optimization	SIO	Tzanetos et al.[305]	2017
306	Weighted superposition attraction	WSA	Baykasoğlu et al.[306]	2017
307	Satin bowerbird optimizer	SBO	Moosavi et al.[307]	2017
308	Artificial atom algorithm	A3	Yildirim et al.[308]	2018
309	Artificial swarm intelligence	ASI	Rosenberg et al.[309]	2018
310	Bees life algorithm	BLA	Bitam et al.[310]	2018
311	Beetle swarm optimization algorithm	BSOA	Wang et al.[311]	2018
312	Brunsvigia optimization algorithm	BVOA	Ghaemidizaji et al.[312]	2018
313	Car tracking optimization algorithm	CTOA	Chen et al.[313]	2018
314	Cheetah based algorithm	CBA	Klein et al.[314]	2018
315	Cheetah chase algorithm	CCA	Goudhaman et al.[315]	2018
316	Chaotic crow search algorithm	CCSA	Rizk-Allah et al.[316]	2018
317	Circular structures of puffer fish algorithm	CSPF	Catalbas et al.[317]	2018
318	Competitive learning algorithm	CLA	Afroughinia et al.[318]	2018
319	Cricket chirping algorithm	CCA	Deuri et al.[319]	2018
320	Fibonacci indicator algorithm	FIA	Etminaniesfahani et al.[320]	2018
321	Plant self-defense mechanism algorithm	PSDM	Caraveo et al.[321]	2018

No.	Algorithm	Acronym	Authors	Year
322	Emperor penguin optimizer	EPO	Dhiman et al.[322]	2018
323	Lion pride optimization algorithm	LPOA	Kaveh et al.[323]	2018
324	Multi-scale quantum harmonic oscillator algorithm	MQHO	Wang et al.[324]	2018
325	Mushroom reproduction optimization	MRO	Bidar et al.[325]	2018
326	Tree growth algorithm	TGA	Cheraghalipour et al.[326]	2018
327	Moth search algorithm	MSA	Wang et al.[327]	2018
328	Farmland fertility	FF	Shayanfar et al.[328]	2018
329	Pity beetle algorithm	PBA	Kallioras et al.[329]	2018
330	Mouth brooding fish algorithm	MBF	Jahani et al.[330]	2018
331	Artificial flora optimization algorithm	AFOA	Cheng et al.[331]	2018
332	Elephant swarm water search algorithm	ESWS	Mandal[332]	2018
333	Sperm swarm optimization algorithm	SSOA	Shehadeh et al.[333]	2018
334	Team game algorithm	TGA	Mahmoodabadi et al.[334]	2018
335	Coyote optimization algorithm	COA	Pierezan et al.[335]	2018
336	Queuing search algorithm	QSA	Zhang et al.[336]	2018
337	Supernova optimizer	SO	Hudaib et al.[337]	2018
338	Spiritual search	SS	Puangdownreong[338]	2018
339	School based optimization	SBO	Farshchin et al.[339]	2018
340	Weighted vertices optimizer	WVO	Dolatabadi et al.[340]	2018
341	Volleyball premier league algorithm	VPLA	Moghdani et al.[341]	2018
342	Yellow saddle goatfish algorithm	YSGA	Zaldívar et al.[342]	2018
343	Raccoon optimization algorithm	ROA	Koohi et al.[343]	2019
344	Andean condor algorithm	ACA	Almonacid et al.[344]	2019
345	Anglerfish algorithm	AA	Pook et al.[345]	2019
346	Artificial ecosystem-based optimization	AEO	Zhao et al.[346]	2019
347	Atom search optimization algorithm	ASOA	Zhao et al.[347]	2019
348	Artificial feeding birds	AFB	Lamy et al.[348]	2019
349	Artificial coronary circulation system	ACCS	Kaveh et al.[349]	2019
350	Artificial electric field algorithm	AEFA	Yadav[350]	2019
351	Bus transportation algorithm	BTA	Bodaghi et al.[351]	2019
352	Biology migration algorithm	BMA	Zhang et al.[352]	2019
353	Buzzard optimization algorithm	BUZOA	Arshaghi et al.[353]	2019
354	Blue monkey algorithm	BM	Mahmood et al.[354]	2019
355	Chaotic dragonfly algorithm	CDA	Sayed et al.[355]	2019
356	Cultural coyote optimization algorithm	CCOA	Pierezan et al.[356]	2019
357	Dice game optimizer	DGO	Dehghani et al.[357]	2019
358	Donkey theorem optimization	DTO	Dehghani et al.[358]	2019
359	Deer hunting optimization algorithm	DHOA	Brammya et al.[359]	2019
360	Falcon optimization algorithm	FOA	de Vasconcelos Segundo et al.[360]	2019
361	Find-fix-finish-exploit-analyze algorithm	F3EA	Kashan et al.[361]	2019
362	Flow regime algorithm	FRA	Tahani et al.[362]	2019

No.	Algorithm	Acronym	Authors	Year
363	Chaotic optimal foraging algorithm	COFA	Sayed et al.[363]	2019
364	Naked moled rat	NMR	Salgotra et al.[364]	2019
365	Xerus optimization algorithm	XOA	Yousefi et al.[365]	2019
366	Nuclear reaction optimization	NRO	Wei et al.[366]	2019
367	Hypercube natural aggregation algorithm	HNAA	Maciel et al.[367]	2019
368	Sailfish optimizer	SO	Shadravan et al.[368]	2019
369	The algorithm of the innovative gunner	AIG	Pijarski et al.[369]	2019
370	Supply-demand-based optimization	SDBO	Zhao et al.[370]	2019
371	Butterfly optimization algorithm	BOA	Arora et al.[371]	2019
372	Emperor penguins colony	EPC	Harifi et al.[372]	2019
373	Electron radar search algorithm	ERSA	Rahmanzadeh et al.[373]	2019
374	Henry gas solubility optimization	HGSO	Hashim et al.[374]	2019
375	Hitchcock bird-inspired algorithm	HBIA	Morais et al.[375]	2019
376	Hammerhead shark optimization algorithm	HOA	Ali et al.[376]	2019
377	Fitness dependent optimizer	FDO	Abdullah et al.[377]	2019
378	Life choice-based optimizer	LCBO	Khatri et al.[378]	2019
379	Parasitism–predation algorithm	PPA	Mohamed et al.[379]	2019
380	Pathfinder algorithm	PA	Yapici et al.[380]	2019
381	Poor and rich optimization algorithm	PROA	Moosavi et al.[381]	2019
382	Seagull optimization algorithm	SOA	Dhiman et al[382]	2019
383	Sooty tern optimization algorithm	STOA	Dhiman et al.[383]	2019
384	Harris hawks optimization	HHO	Heidari et al.[384]	2019
385	Bonobo optimizer	BO	Das et al.[385]	2019
386	Spherical search optimizer	SSO	Zhao et al.[386]	2019
387	Squirrel search algorithm	SSA	Jain et al.[387]	2019
388	Flying squirrel optimizer	FSO	Azizyan et al.[388]	2019
389	Bald eagle search optimisation algorithm	BESO	Alsattar et al.[389]	2019
390	Search and rescue optimization algorithm	SAR	Shabani et al.[390]	2019
391	Wild mice colony algorithm	WMC	Nejatian et al.[391]	2019
392	Thieves and police algorithm	TPA	Bagheri et al.[392]	2019
393	Artificial transgender longicorn algorithm	ATLA	Han et al.[393]	2020
394	Barnacles mating optimizer	BMO	Sulaiman et al.[394]	2020
395	Black hole mechanics optimization	BHMO	Kaveh et al.[395]	2020
396	Billiards-inspired optimization algorithm	BIOA	Kaveh et al.[396]	2020
397	Border collie optimization	BCO	Dutta et al.[397]	2020
398	Bear smell search algorithm	BSSA	Ghasemi-Marzbali[398]	2020
399	Buyer inspired meta-heuristic optimization Algorithm	BIMHO	Debnath et al.[399]	2020
400	Darts game optimizer	DGO	Dehghani et al.[400]	2020
401	Dynamic differential annealed optimization	DDAO	Ghafil et al.[401]	2020
402	Dynastic optimization algorithm	DOA	Wagan et al.[402]	2020
403	Forensic based investigation	FBI	Chou et al.[403]	2020

No.	Algorithm	Acronym	Authors	Year
404	Plasma generation optimization	PGO	Kaveh et al.[404]	2020
405	Newton metaheuristic algorithm	NMA	Gholizadeh et al.[405]	2020
406	Tunicate swarm algorithm	TSA	Kaur et al.[406]	2020
407	Marine predators algorithm	MPA	Faramarzi et al.[407]	2020
408	Equilibrium optimizer	EO	Faramarzi et al.[408]	2020
409	Electric fish optimization	EFO	Yilmaz et al.[409]	2020
410	Slime mould algorithm	SMA	Li et al.[410]	2020
411	Black widow optimization algorithm	BWOA	Hayyolalam et al.[411]	2020
412	Manta ray foraging optimization	MRFO	Zhao et al.[412]	2020
413	Mayfly algorithm	MA	Zervoudakis et al.[413]	2020
414	Orcas algorithm	OA	Drias et al.[414]	2020
415	Political optimizer	PO	Askari et al.[415]	2020
416	Group teaching optimization algorithm	GTOA	Zhang et al.[416]	2020
417	Turbulent flow of water-based optimization	TFWO	Ghasemi et al.[417]	2020
418	Human urbanization algorithm	HUA	Ghasemian et al.[418]	2020
419	Chimp optimization algorithm	COA	Khishe et al.[419]	2020
420	Coronavirus optimization algorithm	COA	Martínez-Álvarez et al.[420]	2020
421	COVID-19 optimizer algorithm	CVA	Hosseini et al.[421]	2020
422	Multivariable grey prediction evolution algorithm	MGPE	Xu et al.[422]	2020
423	Sandpiper optimization algorithm	SOA	Kaur et al.[423]	2020
424	Shuffled shepherd optimization method	SSOM	Kaveh et al.[424]	2020
425	Red deer algorithm	RDA	Fathollahi-Fard et al.[425]	2020
426	Golden ratio optimization method	GTOM	Nematollahi et al.[426]	2020
427	Gaining-sharing knowledge based algorithm	GSKA	Mohamed et al.[427]	2020
428	Adolescent identity search algorithm	AISA	Bogar et al.[428]	2020
429	Capuchin search algorithm	CSA	Braik et al[429]	2020
430	Giza pyramids construction	GPC	Harifi et al.[430]	2020
431	Grand tour algorithm	GTA	Meirelles et al.[431]	2020
432	Groundwater flow algorithm	GFA	Guha et al.[432]	2020
433	Gradient-based optimizer	GO	Ahmadianfar et al.[433]	2020
434	Interactive autodidactic school	IAS	Jahangiri et al.[434]	2020
435	Lévy flight distribution	LFD	Houssein et al.[435]	2020
436	Momentum search algorithm	MSA	Dehghani et al.[436]	2020
437	Nomadic people optimizer	NPO	Salih et al.[437]	2020
438	New caledonian crow learning algorithm	NCCL	Al-Sorori et al.[438]	2020
439	Horse optimization algorithm	HOA	Moldovan et al.[439]	2020
440	Rao algorithms	RA	Rao[440]	2020
441	Rat swarm optimizer	RSO	Dhiman et al.[441]	2020
442	Rain optimization algorithm	ROA	Moazzeni et al.[442]	2020
443	Student psychology based optimization algorithm	SPOA	Das et al.[443]	2020
444	Seasons optimization algorithm	SOA	Emami[444]	2020

No.	Algorithm	Acronym	Authors	Year
445	Shell game optimization	SGO	Dehghani et al.[445]	2020
446	Sparrow search algorithm	SSA	Xue et al.[446]	2020
447	Tiki-taka algorithm	TTA	Rashid et al.[447]	2020
448	Transient search optimization	TSO	Qais et al.[448]	2020
449	Vapor-liquid equilibrium algorithm	VLEA	Taramsco et al.[449]	2020
450	Virus spread optimization	VSO	Li et al.[450]	2020
451	Wingsuit flying search	WFS	Covic et al.[451]	2020
452	Water strider algorithm	WSA	Kaveh et al.[452]	2020
453	Woodpecker mating algorithm	WMA	Karimzadeh et al.[453]	2020
454	Solar system algorithm	SSA	Zitouni et al.[454]	2020
455	Arsh-fati-based cluster head selection algorithm	ARSH-FATI-CHS	Ali et al.[455]	2020
456	Teng-yue algorithm	TYA	Li et al.[456]	2020
457	Projectiles optimization	PO	Kahrizi et al.[457]	2020
458	Color harmony algorithm	CHA	Zaeimi et al.[458]	2020
459	Multi-objective beetle antennae search	MOBAS	Zhang et al.[459]	2020
460	Orca optimization algorithm	OOA	Golilarz et al.[460]	2020
461	Photon search algorithm	PSA	Liu et al.[461]	2020
462	Kernel search optimization	KSO	Dong et al.[462]	2020
463	Spherical search algorithm	SSA	Misra et al.[463]	2020
464	Triple distinct search dynamics	TDSD	Li et al.[464]	2020
465	Chaos game optimization	CGO	Talatahari et al.[465]	2021
466	Chameleon swarm algorithm	CSA	Braik et al.[466]	2021
467	Atomic orbital search	AOS	Azizi et al.[467]	2021
468	Artificial jellyfish search optimizer	JS	Chou et al.[468]	2021
469	Cooperation search algorithm	CSA	Feng et al.[469]	2021
470	Material generation algorithm	MGA	Talatahari et al.[470]	2021
471	Crystal structure algorithm	CryStAl	Talatahari et al.[471]	2021
472	Archimedes optimization algorithm	AOA	Hashim et al.[472]	2021
473	Archerfish hunting optimizer	AHO	Zitouni et al.[473]	2021
474	Battle royale optimization algorithm	BRO	Rahkar Farshi et al.[474]	2021
475	Artificial lizard search optimization	ALSO	Kumar et al.[475]	2021
476	Quantum firefly algorithm	QFA	Zitouni et al.[476]	2021
477	Flow direction algorithm	FDA	Karami et al.[477]	2021
478	Lichtenberg algorithm	LA	Pereira et al.[478]	2021
479	Pastoralist optimization algorithm	POA	Abdullahi et al.[479]	2021
480	Ebola optimization search algorithm	EOSA	Oyelade et al.[480]	2021
481	Elephant clan optimization	ECO	Jafari et al.[481]	2021
482	Red colobuses monkey	RCM	AL-kubaisy et al.[482]	2021
483	Golden eagle optimizer	GEO	Mohammadi-Balani et al.[483]	2021
484	Group mean-based optimizer	GMBO	Dehghani et al.[484]	2021

No.	Algorithm	Acronym	Authors	Year
485	Dingo optimizer	DO	Bairwa et al.[485]	2021
486	Coronavirus herd immunity optimizer	CHIO	Al-Betar et al.[486]	2021
487	Red fox optimization algorithm	RFO	Połap et al.[487]	2021
488	Arithmetic optimization algorithm	AOA	Abualigah et al.[488]	2021
489	African vultures optimization algorithm	AVOA	Abdollahzadeh et al.[489]	2021
490	Artificial gorilla troops optimizer	GTO	Abdollahzadeh et al.[490]	2021
491	Artificial hummingbird algorithm	AHA	Zhao et al.[491]	2021
492	Intelligent ice fishing algorithm	IIFA	Karpenko et al.[492]	2021
493	Komodo mlipir algorithm	KMA	Suyanto et al.[493]	2021
494	Linear prediction evolution algorithm	LPE	Gao et al.[494]	2021
495	Multi-objective trader algorithm	MOTR	Masoudi-Sobhanzadeh et al.[495]	2021
496	Optimal stochastic process optimizer	OSPO	Xu et al.[496]	2021
497	Remora optimization algorithm	ROA	Jia et al.[497]	2021
498	Ring toss game-based optimization algorithm	RTGBO	Doumari et al.[498]	2021
499	RUNge kutta optimizer	RUN	Ahmadianfar et al.[499]	2021
500	SaMW	--	Tychalas et al.[500]	2021
501	String theory algorithm	STA	Rodriguez et al.[501]	2021
502	Success history intelligent optimizer	SHIO	Fakhouri et al.[502]	2021
503	Tangent search algorithm	TSA	Layeb A[503]	2021
504	Tuna swarm optimization	TSO	Xie et al.[504]	2021
505	Volcano eruption algorithm	VCA	Hosseini et al.[505]	2021
506	Smart flower optimization algorithm	SFOA	Sattar et al.[506]	2021
507	Ali baba and the forty thieves optimization	AFT	Braik et al.[507]	2022
508	Honey badger algorithm	HBA	Hashim et al.[508]	2022
509	Orca predation algorithm	OPA	Jiang et al.[509]	2022
510	Reptile search algorithm	RSA	Abualigah et al.[510]	2022
511	Skip salp swam algorithm	SSSA	Arunekumar et al.[511]	2022

Appendix B

Note: An online updated list of summarized meta-heuristics is https://github.com/P-N-Suganthan/MHA-500Plus. Please send you feedbacks to epnsugan@ntu.edu.sg or p.n.suganthan@qu.edu.qa.

Reference

[1] L.J. Fogel, A.J. Owens, M.J. Walsh, Intelligent decision making through a simulation of evolution, Behav. Sci. 11 (1966) 253–272.

[2] I. Rechenberg, Cybernetic solution path of an experimental problem, R. Aircr. Establ. Libr. Transl. 1122. (1965).

[3] J.H. Holland, Adaptation in natural and artificial systems, univ. of mich. press, Ann Arbor. (1975).

[4] F. Glover, Heuristics for integer programming using surrogate constraints, Decis. Sci. 8 (1977) 156–166.

[5] S. Kirkpatrick, C.D. Gelatt, M.P. Vecchi, Optimization by simulated annealing, Science (80-.). 220 (1983) 671–680.

[6] F. Glover, Future paths for integer programming and links to artificial intelligence, Comput. Oper. Res. 13 (1986) 533–549.

[7] J.R. KOZA, Genetic programming: on the programming of computers machinc learning', (1989).

[8] J.M. Bishop, Stochastic searching networks, in: 1989 First IEE Int. Conf. Artif. Neural Networks,(Conf. Publ. No. 313), IET, 1989: pp. 329–331.

[9] P. Moscato, On evolution, search, optimization, genetic algorithms and martial arts: Towards memetic algorithms, Caltech Concurr. Comput. Program, C3P Rep. 826 (1989) 1989.

[10] M. Dorigo, Optimization, learning and natural algorithms, Ph. D. Thesis, Politec. Di Milano. (1992).

[11] Q.Y. Duan, V.K. Gupta, S. Sorooshian, Shuffled complex evolution approach for effective and efficient global minimization, J. Optim. Theory Appl. 76 (1993) 501–521.

[12] G. Dueck, New optimization heuristics: The great deluge algorithm and the record-to-record travel, J. Comput. Phys. 104 (1993) 86–92.

[13] R.G. Reynolds, An introduction to cultural algorithms, in: Proc. Third Annu. Conf. Evol. Program., World Scientific, 1994: pp. 131–139.

[14] R. Storn, K. Price, Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces, J. Glob. Optim. 11 (1997) 341–359.

[15] R. Eberhart, J. Kennedy, A new optimizer using particle swarm theory, in: MHS'95. Proc. Sixth Int. Symp. Micro Mach. Hum. Sci., Ieee, 1995: pp. 39–43.

[16] T.C. Hu, A.B. Kahng, C.-W.A. Tsao, Old bachelor acceptance: A new class of non-monotone threshold accepting methods, ORSA J. Comput. 7 (1995) 417–425.

[17] C. Numaoka, Bacterial evolution algorithm for rapid adaptation, in: Eur. Work. Model. Auton. Agents a Multi-Agent World, Springer, 1996: pp. 139–148.

[18] N. Mladenović, P. Hansen, Variable neighborhood search, Comput. Oper. Res. 24 (1997) 1097–1100.

[19] T. Sato, M. Hagiwara, Bee system: finding solution by a concentrated search, IEEJ Trans. Electron. Inf. Syst. 118 (1998) 721–726.

[20] H. Murase, A. Wadano, Photosynthetic algorithm for machine learning and TSP, IFAC Proc. Vol. 31 (1998) 19–24.

[21] B.L.I.W. JIANG, Optimizing complex functions by chaos search, Cybern. Syst. 29 (1998) 409–419.

[22] K. Nara, T. Takeyama, H. Kim, A new evolutionary algorithm based on sheep flocks heredity model and its application to scheduling problem, in: IEEE SMC'99 Conf. Proceedings. 1999 IEEE Int. Conf. Syst. Man, Cybern. (Cat. No. 99CH37028), IEEE, 1999: pp. 503–508.

[23] S. Boettcher, A.G. Percus, Extremal optimization: Methods derived from co-evolution, ArXiv Prepr. Math/9904056. (1999).

[24] S. Kundu, Gravitational clustering: a new approach based on the spatial distribution of the points, Pattern Recognit. 32 (1999) 1149–1160.

[25] L.N. De Castro, F.J. Von Zuben, The clonal selection algorithm with engineering applications, in: Proc. GECCO, 2000: pp. 36–39.

[26] Z.W. Geem, J.H. Kim, G.V. Loganathan, A new heuristic optimization algorithm: harmony search, Simulation. 76 (2001) 60–68.

[27] C. Ferreira, Gene expression programming: a new adaptive algorithm for solving problems, ArXiv Prepr. Cs/0102027. (2001).

[28] H.A. Abbass, MBO: Marriage in honey bees optimization-A haplometrosis polygynous swarming approach, in: Proc. 2001 Congr. Evol. Comput. (IEEE Cat. No. 01TH8546), IEEE, 2001: pp. 207–214.

[29] K.M. Passino, Biomimicry of bacterial foraging for distributed optimization and control, IEEE Control Syst. Mag. 22 (2002) 52–67.

[30] S.D. Muller, J. Marchetto, S. Airaghi, P. Kournoutsakos, Optimization based on bacterial chemotaxis, IEEE Trans. Evol. Comput. 6 (2002) 16–29.

[31] P. Lucic, D. Teodorovic, Transportation modeling: an artificial life approach, in: 14th IEEE Int. Conf. Tools with Artif. Intell. 2002.(ICTAI 2002). Proceedings., IEEE, 2002: pp. 216–223.

[32] É.D. Taillard, S. Voss, POPMUSIC—Partial optimization metaheuristic under special intensification conditions, in: Essays Surv. Metaheuristics, Springer, 2002: pp. 613–629.

[33] X.-F. Xie, W.-J. Zhang, Z.-L. Yang, Social cognitive optimization for nonlinear programming problems, in: Proceedings. Int. Conf. Mach. Learn. Cybern., IEEE, 2002: pp. 779–783.

[34] X.L. Li, J.X. Qian, Studies on artificial fish swarm optimization algorithm based on decomposition and coordination techniques, J. Circuits Syst. 1 (2003) 1–6.

[35] N. Hansen, S.D. Müller, P. Koumoutsakos, Reducing the time complexity of the derandomized evolution strategy with covariance matrix adaptation (CMA-ES), Evol. Comput. 11 (2003) 1–18.

[36] T. Ray, K.-M. Liew, Society and civilization: an optimization algorithm based on the simulation of social behavior, IEEE Trans. Evol. Comput. 7 (2003) 386–396.

[37] D. Dasgupta, Z. Ji, F. Gonzalez, Artificial immune system (AIS) research in the last five years, in: 2003 Congr. Evol. Comput. 2003. CEC'03., IEEE, 2003: pp. 123–130.

[38] S.H. Jung, Queen-bee evolution for genetic algorithms, Electron. Lett. 39 (2003) 575–576.

[39] Ş.İ. Birbil, S.-C. Fang, An electromagnetism-like mechanism for global optimization, J. Glob. Optim. 25 (2003) 263–282.

[40] H.F. Wedde, M. Farooq, Y. Zhang, Beehive: An efficient fault-tolerant routing algorithm inspired by honey bee behavior, in: Int. Work. Ant Colony Optim. Swarm Intell., Springer, 2004: pp. 83–94.

[41] I. Zelinka, SOMA—self-organizing migrating algorithm, in: New Optim. Tech. Eng., Springer, 2004: pp. 167–217.

[42] D. Karaboga, An idea based on honey bee swarm for numerical optimization, Technical report-tr06, Erciyes university, engineering faculty, computer …, 2005.

[43] D. Teodorovic, M. Dell'Orco, Bee colony optimization–a cooperative learning approach to complex transportation problems, Adv. OR AI Methods Transp. 51 (2005) 60.

[44] H. Drias, S. Sadeg, S. Yahi, Cooperative bees swarm for solving the maximum weighted satisfiability problem, in: Int. Work. Artif. Neural Networks, Springer, 2005: pp. 318–325.

[45] J. Greensmith, U. Aickelin, S. Cayzer, Introducing dendritic cells as a novel immune-inspired algorithm for anomaly detection, in: Int. Conf. Artif. Immune Syst., Springer, 2005: pp. 153–167.

[46] D.T. Pham, A. Ghanbarzadeh, E. Koç, S. Otri, S. Rahim, M. Zaidi, The bees algorithm—a novel tool for complex optimisation problems, in: Intell. Prod. Mach. Syst., Elsevier, 2006: pp. 454–459.

[47] P. Pinto, T.A. Runkler, J.M. Sousa, Wasp swarm optimization of logistic systems, in: Adapt. Nat. Comput. Algorithms, Springer, 2005: pp. 264–267.

[48] M. Eusuff, K. Lansey, F. Pasha, Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization, Eng. Optim. 38 (2006) 129–154.

[49] O.K. Erol, I. Eksin, A new optimization method: big bang–big crunch, Adv. Eng. Softw. 37 (2006) 106–111.

[50] S.-C. Chu, P.-W. Tsai, J.-S. Pan, Cat swarm optimization, in: Pacific Rim Int. Conf. Artif. Intell., Springer, 2006: pp. 854–858.

[51] X. Cui, J. Gao, T.E. Potok, A flocking based algorithm for document clustering analysis, J. Syst. Archit. 52 (2006) 505–515.

[52] O.B. Haddad, A. Afshar, M.A. Marino, Honey-bees mating optimization (HBMO) algorithm: a new heuristic approach for water resources optimization, Water Resour. Manag. 20 (2006) 661–680.

[53] H. Du, X. Wu, J. Zhuang, Small-world optimization algorithm for function optimization, in: Int. Conf. Nat. Comput., Springer, 2006: pp. 264–273.

[54] A. Karci, B. Alatas, Thinking capability of saplings growing up algorithm, in: Int. Conf. Intell. Data Eng. Autom. Learn., Springer, 2006: pp. 386–393.

[55] C. Dai, Y. Zhu, W. Chen, Seeker optimization algorithm, in: Int. Conf. Comput. Inf. Sci., Springer, 2006: pp. 167–176.

[56] A.R. Mehrabian, C. Lucas, A novel numerical optimization algorithm inspired from weed colonization, Ecol. Inform. 1 (2006) 355–366.

[57] E. Atashpaz-Gargari, C. Lucas, Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition, in: 2007 IEEE Congr. Evol. Comput., 2007: pp. 4661–4667. https://doi.org/10.1109/CEC.2007.4425083.

[58] A. Mucherino, O. Seref, Monkey search: a novel metaheuristic search for global optimization, in: AIP Conf. Proc., American Institute of Physics, 2007: pp. 162–173.

[59] P. Rabanal, I. Rodríguez, F. Rubio, Using river formation dynamics to design heuristic algorithms, in: Int. Conf. Unconv. Comput., Springer, 2007: pp. 163–177.

[60] W.J. Tang, Q.H. Wu, J.R. Saunders, A bacterial swarming algorithm for global optimization, in: 2007 IEEE Congr. Evol. Comput., IEEE, 2007: pp. 1207–1212.

[61] T.-C. Chen, P.-W. Tsai, S.-C. Chu, J.-S. Pan, A novel optimization approach: bacterial-GA foraging, in: Second Int. Conf. Innov. Comput. Informatio Control (ICICIC 2007), IEEE, 2007: p. 391.

[62] A. Borji, A new global optimization algorithm inspired by parliamentary political competitions, in: Mex. Int. Conf. Artif. Intell., Springer, 2007: pp. 61–71.

[63] J.P. Pedroso, Simple metaheuristics using the simplex algorithm for non-linear programming, in: Int. Work. Eng. Stoch. Local Search Algorithms, Springer, 2007: pp. 217–221.

[64] S. Su, J. Wang, W. Fan, X. Yin, Good lattice swarm algorithm for constrained engineering design optimization, in: 2007 Int. Conf. Wirel. Commun. Netw. Mob. Comput., IEEE, 2007: pp. 6421–6424.

[65] R.A. Formato, Central force optimization, Prog Electromagn Res. 77 (2007) 425–491.

[66] Y. Chu, H. Mi, H. Liao, Z. Ji, Q.H. Wu, A fast bacterial swarming algorithm for high-dimensional function optimization, in: 2008 IEEE Congr. Evol. Comput. (Ieee World Congr. Comput. Intell., IEEE, 2008: pp. 3135–3140.

[67] D. Simon, Biogeography-based optimization, IEEE Trans. Evol. Comput. 12 (2008) 702–713.

[68] E. Del Acebo, J.L. de-la Rosa, Introducing bar systems: a class of swarm intelligence optimization algorithms, in: AISB 2008 Conv. Commun. Interact. Soc. Intell., 2008: p. 18.

[69] L.-Y. Chuang, S.-W. Tsai, C.-H. Yang, Catfish particle swarm optimization, in: 2008 IEEE Swarm Intell. Symp., IEEE, 2008: pp. 1–5.

[70] J. Wang, D. Wang, Particle swarm optimization with a leader and followers, Prog. Nat. Sci. 18 (2008) 1437–1443.

[71] Y.H. Cui, R. Guo, R. V Rao, V.J. Savsani, Harmony element algorithm: A naive initial searching range, in: Int. Conf. Adv. Mech. Eng., 2008: pp. 1–6.

[72] C.J.A. Bastos Filho, F.B. de Lima Neto, A.J.C.C. Lins, A.I.S. Nascimento, M.P. Lima, A novel search algorithm based on fish school behavior, in: 2008 IEEE Int. Conf. Syst. Man Cybern., IEEE, 2008: pp. 2646–2651.

[73] T.C. Havens, C.J. Spain, N.G. Salmon, J.M. Keller, Roach infestation optimization, in: 2008 IEEE Swarm Intell. Symp., IEEE, 2008: pp. 1–7.

[74] P. Cortés, J.M. García, J. Muñuzuri, L. Onieva, Viral systems: A new bio-inspired optimisation approach, Comput. Oper. Res. 35 (2008) 2840–2860.

[75] W. Cai, W. Yang, X. Chen, A global optimization algorithm based on plant growth theory: plant growth optimization, in: 2008 Int. Conf. Intell. Comput. Technol. Autom., IEEE, 2008: pp. 1194–1199.

[76] M.A. Munoz, J.A. López, E. Caicedo, An artificial beehive algorithm for continuous optimization, Int. J. Intell. Syst. 24 (2009) 1080–1093.

[77] L. Xie, J. Zeng, Z. Cui, General framework of artificial physics optimization algorithm, in: 2009 World Congr. Nat. Biol. Inspired Comput., IEEE, 2009: pp. 1321–1326.

[78] S. Häckel, P. Dippold, The bee colony-inspired algorithm (BCiA) a two-stage approach for solving the vehicle routing problem with time windows, in: Proc. 11th Annu. Conf. Genet. Evol. Comput., 2009: pp. 25–32.

[79] B. Barzegar, A.M. Rahmani, K. Zamanifar, A. Divsalar, Gravitational emulation local search algorithm for advanced reservation and scheduling in grid computing systems, in: 2009 Fourth Int. Conf. Comput. Sci. Converg. Inf. Technol., IEEE, 2009: pp. 1240–1245.

[80] S. He, Q.H. Wu, J.R. Saunders, Group search optimizer: an optimization algorithm inspired by animal searching behavior, IEEE Trans. Evol. Comput. 13 (2009) 973–990.

[81] X.-S. Yang, S. Deb, Cuckoo search via Lévy flights, in: 2009 World Congr. Nat. Biol. Inspired Comput., Ieee, 2009: pp. 210–214.

[82] E. Rashedi, H. Nezamabadi-pour, S. Saryazdi, GSA: A Gravitational Search Algorithm, Inf. Sci. (Ny). 179 (2009) 2232–2248. https://doi.org/10.1016/j.ins.2009.03.004.

[83] X.-S. Yang, Firefly algorithms for multimodal optimization, in: Int. Symp. Stoch. Algorithms, Springer, 2009: pp. 169–178.

[84] A. Mutazono, M. Sugano, M. Murata, Frog call-inspired self-organizing anti-phase synchronization for wireless sensor networks, in: 2009 2nd Int. Work. Nonlinear Dyn. Synchronization, IEEE, 2009: pp. 81–88.

[85] K.N. Krishnanand, D. Ghose, Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions, Swarm Intell. 3 (2009) 87–124.

[86] A.H. Kashan, League championship algorithm: a new algorithm for numerical function optimization, in: 2009 Int. Conf. Soft Comput. Pattern Recognit., IEEE, 2009: pp. 43–48.

[87] U. Premaratne, J. Samarabandu, T. Sidhu, A new biologically inspired optimization algorithm, in: 2009 Int. Conf. Ind. Inf. Syst., IEEE, 2009: pp. 279–284.

[88] Y. Shiqin, J. Jianjun, Y. Guangxing, A dolphin partner optimization, in: 2009 WRI Glob. Congr. Intell. Syst., IEEE, 2009: pp. 124–128.

[89] S. Kadioglu, M. Sellmann, Dialectic search, in: Int. Conf. Princ. Pract. Constraint Program., Springer, 2009: pp. 486–500.

[90] L.M. Zhang, C. Dahlmann, Y. Zhang, Human-inspired algorithms for continuous function optimization, in: 2009 IEEE Int. Conf. Intell. Comput. Intell. Syst., IEEE, 2009: pp. 318–321.

[91] T. Chen, A simulative bionic intelligent optimization algorithm: artificial searching swarm algorithm and its performance analysis, in: 2009 Int. Jt. Conf. Comput. Sci. Optim., IEEE, 2009: pp. 864–866.

[92] F. Comellas, J. Martinez-Navarro, Bumblebees: a multiagent combinatorial optimization algorithm inspired by social

insect behaviour, in: Proc. First ACM/SIGEVO Summit Genet. Evol. Comput., 2009: pp. 811–814.

[93] M.A. Eita, M.M. Fahmy, Group counseling optimization: a novel approach, in: Res. Dev. Intell. Syst. XXVI, Springer, 2010: pp. 195–208.

[94] R. Oftadeh, M.J. Mahjoob, A new meta-heuristic optimization algorithm: Hunting Search, in: 2009 Fifth Int. Conf. Soft Comput. Comput. with Words Perceptions Syst. Anal. Decis. Control, IEEE, 2009: pp. 1–5.

[95] S. Chen, Locust Swarms-A new multi-optima search technique, in: 2009 IEEE Congr. Evol. Comput., IEEE, 2009: pp. 1745–1752.

[96] H. Shah-Hosseini, The intelligent water drops algorithm: a nature-inspired swarm-based optimization algorithm, Int. J. Bio-Inspired Comput. 1 (2009) 71–79.

[97] T.T. Hieu, N.K. Ming, A Water Flow Algorithm for Flexible Flow Shop Scheduling with Limited Intermediate Buffers, (2009).

[98] A. Farasat, M.B. Menhaj, T. Mansouri, M.R.S. Moghadam, ARO: A new model-free optimization algorithm inspired from asexual reproduction, Appl. Soft Comput. 10 (2010) 1284–1292.

[99] X. Zhang, B. Sun, T. Mei, R. Wang, Post-disaster restoration based on fuzzy preference relation and bean optimization algorithm, in: 2010 IEEE Youth Conf. Information, Comput. Telecommun., IEEE, 2010: pp. 271–274.

[100] X.-S. Yang, A new metaheuristic bat-inspired algorithm, in: Nat. Inspired Coop. Strateg. Optim. (NICSO 2010), Springer, 2010: pp. 65–74.

[101] R. Akbari, A. Mohammadi, K. Ziarati, A novel bee swarm optimization algorithm for numerical function optimization, Commun. Nonlinear Sci. Numer. Simul. 15 (2010) 3142–3155. https://doi.org/10.1016/j.cnsns.2009.11.003.

[102] A. Kaveh, S. Talatahari, A novel heuristic optimization method: charged system search, Acta Mech. 213 (2010) 267–289. https://doi.org/10.1007/s00707-009-0270-4.

[103] J. Xu, A.Y.S. Lam, V.O.K. Li, Chemical reaction optimization for the grid scheduling problem, in: 2010 IEEE Int. Conf. Commun., IEEE, 2010: pp. 1–5.

[104] M. Zheng, G. Liu, C. Zhou, Y. Liang, Y. Wang, Gravitation field algorithm and its application in gene cluster, Algorithms Mol. Biol. 5 (2010) 1–11.

[105] Y. Tan, Y. Zhu, Fireworks algorithm for optimization, in: Int. Conf. Swarm Intell., Springer, 2010: pp. 355–364.

[106] X.-S. Yang, S. Deb, Eagle strategy using Lévy walk and firefly algorithms for stochastic optimization, in: Nat. Inspired Coop. Strateg. Optim. (NICSO 2010), Springer, 2010: pp. 101–111.

[107] A. Ahrari, A.A. Atai, Grenade explosion method—a novel tool for optimization of multimodal functions, Appl. Soft Comput. 10 (2010) 1132–1140.

[108] Z. Bayraktar, M. Komurcu, D.H. Werner, Wind Driven Optimization (WDO): A novel nature-inspired optimization algorithm and its application to electromagnetics, in: 2010 IEEE Antennas Propag. Soc. Int. Symp., IEEE, 2010: pp. 1–4.

[109] R. Hedayatzadeh, F.A. Salmassi, M. Keshtgari, R. Akbari, K. Ziarati, Termite colony optimization: A novel approach for optimizing continuous problems, in: 2010 18th Iran. Conf. Electr. Eng., IEEE, 2010: pp. 553–558.

[110] S. Iordache, Consultant-guided search: a new metaheuristic for combinatorial optimization problems, in: Proc. 12th Annu. Conf. Genet. Evol. Comput., 2010: pp. 225–232.

[111] Y. Xu, Z. Cui, J. Zeng, Social emotional optimization algorithm for nonlinear constrained optimization problems, in: Int. Conf. Swarm, Evol. Memetic Comput., Springer, 2010: pp. 583–590.

[112] H. Chen, Y. Zhu, K. Hu, X. He, Hierarchical swarm model: a new approach to optimization, Discret. Dyn. Nat. Soc. 2010 (2010).

[113] A. Sharma, A new optimizing algorithm using reincarnation concept, in: 2010 11th Int. Symp. Comput. Intell. Informatics, IEEE, 2010: pp. 281–288.

[114] Z. Zhao, Z. Cui, J. Zeng, X. Yue, Artificial plant optimization algorithm for constrained optimization problems, in: 2011

Second Int. Conf. Innov. Bio-Inspired Comput. Appl., IEEE, 2011: pp. 120–123.

[115] Y. Shi, Brain storm optimization algorithm, in: Int. Conf. Swarm Intell., Springer, 2011: pp. 303–309.

[116] D.R. de Oliveira, R.S. Parpinelli, H.S. Lopes, Bioluminescent swarm optimization algorithm, in: Evol. Algorithms, IntechOpen, 2011.

[117] Z. Chen, A modified cockroach swarm optimization, Energy Procedia. (2011) 4–9.

[118] H. Min, Z. Wang, Design and analysis of group escape behavior for distributed autonomous mobile robots, in: 2011 IEEE Int. Conf. Robot. Autom., IEEE, 2011: pp. 6128–6135.

[119] A. Daskin, S. Kais, Group leaders optimization algorithm, Mol. Phys. 109 (2011) 761–772.

[120] R. V Rao, V.J. Savsani, D.P. Vakharia, Teaching–learning-based optimization: A novel method for constrained mechanical design optimization problems, Comput. Des. 43 (2011) 303–315. https://doi.org/https://doi.org/10.1016/j.cad.2010.12.015.

[121] R. Rajabioun, Cuckoo Optimization Algorithm, Appl. Soft Comput. 11 (2011) 5508–5518. https://doi.org/10.1016/j.asoc.2011.05.008.

[122] B. Alatas, ACROA: artificial chemical reaction optimization algorithm for global optimization, Expert Syst. Appl. 38 (2011) 13170–13180.

[123] H. Shah-Hosseini, Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimisation, Int. J. Comput. Sci. Eng. 6 (2011) 132–140.

[124] K. Tamura, K. Yasuda, Spiral dynamics inspired optimization, J. Adv. Comput. Intell. Intell. Informatics. 15 (2011) 1116–1122.

[125] A. Salhi, E.S. Fraga, Nature-inspired optimisation approaches and the new plant propagation algorithm, (2011).

[126] R.S. Parpinelli, H.S. Lopes, An eco-inspired evolutionary algorithm applied to numerical optimization, in: 2011 Third World Congr. Nat. Biol. Inspired Comput., IEEE, 2011: pp. 466–471.

[127] J.J. Flores, R. López, J. Barrera, Gravitational interactions optimization, in: Int. Conf. Learn. Intell. Optim., Springer, 2011: pp. 226–237.

[128] M. Taherdangkoo, M. Yazdi, M.H. Bagheri, Stem cells optimization algorithm, in: Int. Conf. Intell. Comput., Springer, 2011: pp. 394–403.

[129] T.H. Tran, K.M. Ng, A water-flow algorithm for flexible flow shop scheduling with intermediate buffers, J. Sched. 14 (2011) 483–500.

[130] A. Ahmadi-Javid, Anarchic Society Optimization: A human-inspired method, in: 2011 IEEE Congr. Evol. Comput., IEEE, 2011: pp. 2586–2592.

[131] T. Chen, Y. Wang, J. Li, Artificial Tribe Algorithm and Its Performance Analysis., J. Softw. 7 (2012) 651–656.

[132] B. Malakooti, H. Kim, S. Sheikh, Bat intelligence search with application to multi-objective multiprocessor scheduling optimization, Int. J. Adv. Manuf. Technol. 60 (2012) 1071–1086.

[133] E. Cuevas, M. Gonzalez, D. Zaldivar, M. Perez-Cisneros, G. García, An algorithm for global optimization inspired by collective animal behavior, Discret. Dyn. Nat. Soc. 2012 (2012).

[134] C. Zhu, J. Ni, Cloud model-based differential evolution algorithm for optimization problems, in: 2012 Sixth Int. Conf. Internet Comput. Sci. Eng., IEEE, 2012: pp. 55–59.

[135] X.-S. Yang, Flower pollination algorithm for global optimization, in: Int. Conf. Unconv. Comput. Nat. Comput., Springer, 2012: pp. 240–249.

[136] A. Bellaachia, A. Bari, Flock by leader: a novel machine learning biologically inspired clustering algorithm, in: Int. Conf. Swarm Intell., Springer, 2012: pp. 117–126.

[137] A.H. Gandomi, A.H. Alavi, Krill herd: a new bio-inspired optimization algorithm, Commun. Nonlinear Sci. Numer. Simul. 17 (2012) 4831–4845.

[138] W.-T. Pan, A new fruit fly optimization algorithm: taking the financial distress model as an example, Knowledge-Based

Syst. 26 (2012) 69–74.

[139] H. Eskandar, A. Sadollah, A. Bahreininejad, M. Hamdi, Water cycle algorithm–A novel metaheuristic optimization method for solving constrained engineering optimization problems, Comput. Struct. 110 (2012) 151–166.

[140] P. Civicioglu, Transforming geocentric cartesian coordinates to geodetic coordinates by using differential search algorithm, Comput. Geosci. 46 (2012) 229–247.

[141] A. Kaveh, M. Khayatazad, A new meta-heuristic method: Ray Optimization, Comput. Struct. 112–113 (2012) 283–294. https://doi.org/10.1016/j.compstruc.2012.09.003.

[142] E. Duman, M. Uysal, A.F. Alkaya, Migrating birds optimization: a new metaheuristic approach and its performance on quadratic assignment problem, Inf. Sci. (Ny). 217 (2012) 65–77.

[143] R. Tang, S. Fong, X.-S. Yang, S. Deb, Wolf search algorithm with ephemeral memory, in: Seventh Int. Conf. Digit. Inf. Manag. (ICDIM 2012), IEEE, 2012: pp. 165–172.

[144] A. Sadollah, A. Bahreininejad, H. Eskandar, M. Hamdi, Mine blast algorithm for optimization of truss structures with discrete variables, Comput. Struct. 102 (2012) 49–63.

[145] E. Cuevas, D. Oliva, D. Zaldivar, M. Pérez-Cisneros, H. Sossa, Circle detection using electro-magnetism optimization, Inf. Sci. (Ny). 182 (2012) 40–55. https://doi.org/10.1016/j.ins.2010.12.024.

[146] B. Niu, H. Wang, Bacterial colony optimization, Discret. Dyn. Nat. Soc. 2012 (2012).

[147] A. Mozaffari, A. Fathi, S. Behzadipour, The great salmon run: a novel bio-inspired algorithm for artificial system design and optimisation, Int. J. Bio-Inspired Comput. 4 (2012) 286–301.

[148] H. Hernández, C. Blum, Distributed graph coloring: an approach based on the calling behavior of Japanese tree frogs, Swarm Intell. 6 (2012) 117–150.

[149] A. Milani, V. Santucci, Community of scientist optimization: An autonomy oriented approach to distributed optimization, AI Commun. 25 (2012) 157–172.

[150] J. Cao, H. Gao, A quantum-inspired bacterial swarming optimization algorithm for discrete optimization problems, in: Int. Conf. Swarm Intell., Springer, 2012: pp. 29–36.

[151] M. El-Dosuky, A. El-Bassiouny, T. Hamza, M. Rashad, New hoopoe heuristic optimization, ArXiv Prepr. ArXiv1211.6410. (2012).

[152] H. Askari, S.-H. Zahiri, Intelligent gravitational search algorithm for optimum design of fuzzy classifier, in: 2012 2nd Int. EConference Comput. Knowl. Eng., IEEE, 2012: pp. 98–104.

[153] B. Wang, X. Jin, B. Cheng, Lion pride optimizer: An optimization algorithm inspired by lion pride behavior, Sci. China Inf. Sci. 55 (2012) 2369–2389.

[154] H.T. Nguyen, B. Bhanu, Zombie Survival Optimization: A swarm intelligence algorithm inspired by zombie foraging, in: Proc. 21st Int. Conf. Pattern Recognit., IEEE, 2012: pp. 987–990.

[155] X. Cai, Wireless sensor network coverage problem with artificial photosynthesis and phototropism mechanism, Sens. Lett. 10 (2012) 1653–1658.

[156] C. Anandaraman, A.V.M. Sankar, R. Natarajan, A new evolutionary algorithm based on bacterial evolution and its application for scheduling a flexible manufacturing system, J. Tek. Ind. 14 (2012) 1–12.

[157] Z. Cui, X. Cai, Artificial plant optimization algorithm, in: Swarm Intell. Bio-Inspired Comput., Elsevier, 2013: pp. 351–365.

[158] P. Melin, L. Astudillo, O. Castillo, F. Valdez, M. Garcia, Optimal design of type-2 and type-1 fuzzy tracking controllers for autonomous mobile robots under perturbed torques using a new chemical optimization paradigm, Expert Syst. Appl. 40 (2013) 3185–3195.

[159] M.K. Singh, A new optimization method based on adaptive social behavior: ASBO, in: Proc. Int. Conf. Adv. Comput., Springer, 2013: pp. 823–831.

[160] O. Hasançebi, T. Teke, O. Pekcan, A bat-inspired algorithm for structural optimization, Comput. Struct. 128 (2013) 77–

90.

[161] S. Akhmedova, E. Semenkin, Co-operation of biology related algorithms, in: 2013 IEEE Congr. Evol. Comput., IEEE, 2013: pp. 2207–2214.

[162] A. Alazzam, H.W. Lewis, A new optimization algorithm for combinatorial problems, IJARAI) Int. J. Adv. Res. Artif. Intell. 2 (2013).

[163] X. Feng, F.C.M. Lau, H. Yu, A novel bio-inspired approach based on the behavior of mosquitoes, Inf. Sci. (Ny). 233 (2013) 87–108.

[164] K. Manjappa, R.M.R. Guddeti, Mobility aware-termite: a novel bio inspired routing protocol for mobile ad-hoc networks, IET Networks. 2 (2013) 188–195.

[165] P. Civicioglu, Backtracking search optimization algorithm for numerical optimization problems, Appl. Math. Comput. 219 (2013) 8121–8144.

[166] A. Hatamlou, Black hole: A new heuristic optimization approach for data clustering, Inf. Sci. (Ny). 222 (2013) 175–184.

[167] E. Cuevas, M. Cienfuegos, D. Zaldívar, M. Pérez-Cisneros, A swarm optimization algorithm inspired in the behavior of the social-spider, Expert Syst. Appl. 40 (2013) 6374–6384. https://doi.org/10.1016/j.eswa.2013.05.041.

[168] A. Kaveh, N. Farhoudi, A new optimization method: Dolphin echolocation, Adv. Eng. Softw. 59 (2013) 53–70. https://doi.org/10.1016/j.advengsoft.2013.03.004.

[169] P. Civicioglu, Artificial cooperative search algorithm for numerical optimization problems, Inf. Sci. (Ny). 229 (2013) 58–76.

[170] M. Abdechiri, M.R. Meybodi, H. Bahrami, Gases Brownian motion optimization: an algorithm for optimization (GBMO), Appl. Soft Comput. 13 (2013) 2932–2946.

[171] M. Neshat, G. Sepidnam, M. Sargolzaei, Swallow swarm optimization algorithm: a new method to optimization, Neural Comput. Appl. 23 (2013) 429–454.

[172] Y. Gheraibia, A. Moussaoui, Penguins search optimization algorithm (PeSOA), in: Int. Conf. Ind. Eng. Other Appl. Appl. Intell. Syst., Springer, 2013: pp. 222–231.

[173] C. Sur, S. Sharma, A. Shukla, Egyptian vulture optimization algorithm–a new nature inspired meta-heuristics for knapsack problem, in: 9th Int. Conf. Comput. InformationTechnology, Springer, 2013: pp. 227–237.

[174] G.-W. Yan, Z.-J. Hao, A novel optimization algorithm based on atmosphere clouds model, Int. J. Comput. Intell. Appl. 12 (2013) 1350002.

[175] H. Mo, L. Xu, Magnetotactic bacteria optimization algorithm for multimodal optimization, in: 2013 IEEE Symp. Swarm Intell., IEEE, 2013: pp. 240–247.

[176] M. Taherdangkoo, M.H. Shirzadi, M. Yazdi, M.H. Bagheri, A robust clustering method based on blind, naked mole-rats (BNMR) algorithm, Swarm Evol. Comput. 10 (2013) 1–11.

[177] H.D. Purnomo, H.-M. Wee, Soccer game optimization: an innovative integration of evolutionary algorithm and swarm intelligence algorithm, in: Meta-Heuristics Optim. Algorithms Eng. Business, Econ. Financ., IGI Global, 2013: pp. 386–420.

[178] P. Wang, Z. Zhu, S. Huang, Seven-spot ladybird optimization: a novel and efficient metaheuristic algorithm for numerical optimization, Sci. World J. 2013 (2013).

[179] A.S. Eesa, A.M.A. Brifcani, Z. Orman, Cuttlefish algorithm-a novel bio-inspired optimization algorithm, Int. J. Sci. Eng. Res. 4 (2013) 1978–1986.

[180] C. Subramanian, A.S.S. Sekar, K. Subramanian, A new engineering optimization method: African wild dog algorithm, Int. J. Soft Comput. 8 (2013) 163–170.

[181] J. An, Q. Kang, L. Wang, Q. Wu, Mussels wandering optimization: an ecologically inspired algorithm for global optimization, Cognit. Comput. 5 (2013) 188–199.

[182] S.S. Pattnaik, K.M. Bakwad, B.S. Sohi, R.K. Ratho, S. Devi, Swine influenza models based optimization (SIMBO), Appl.

Soft Comput. 13 (2013) 628–653.

[183] A.H. Halim, I. Ismail, Nonlinear plant modeling using neuro-fuzzy system with Tree Physiology Optimization, in: 2013 IEEE Student Conf. Res. Dev., IEEE, 2013: pp. 295–300.

[184] B. Naderi, M. Khalili, A.A. Khamseh, Mathematical models and a hunting search algorithm for the no-wait flowshop scheduling with parallel machines, Int. J. Prod. Res. 52 (2014) 2667–2681.

[185] Q. Jiang, L. Wang, X. Hei, R. Fei, D. Yang, F. Zou, H. Li, Z. Cao, Y. Lin, Optimal approximation of stable linear systems with a novel and efficient optimization algorithm, in: 2014 IEEE Congr. Evol. Comput., IEEE, 2014: pp. 840–844.

[186] S. Mirjalili, S.M. Mirjalili, A. Lewis, Grey Wolf Optimizer, Adv. Eng. Softw. 69 (2014) 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007.

[187] M.-Y. Cheng, D. Prayogo, Symbiotic organisms search: a new metaheuristic optimization algorithm, Comput. Struct. 139 (2014) 98–112.

[188] A. Kaveh, V.R. Mahdavi, Colliding bodies optimization: A novel meta-heuristic method, Comput. Struct. 139 (2014) 18–27. https://doi.org/10.1016/j.compstruc.2014.04.005.

[189] X. Meng, Y. Liu, X. Gao, H. Zhang, A new bio-inspired algorithm: chicken swarm optimization, in: Int. Conf. Swarm Intell., Springer, 2014: pp. 86–94.

[190] J.C. Bansal, H. Sharma, S.S. Jadon, M. Clerc, Spider monkey optimization algorithm for numerical optimization, Memetic Comput. 6 (2014) 31–47.

[191] A.H. Gandomi, Interior search algorithm (ISA): a novel approach for global optimization, ISA Trans. 53 (2014) 1168–1183.

[192] X. Li, J. Zhang, M. Yin, Animal migration optimization: an optimization algorithm inspired by animal migration behavior, Neural Comput. Appl. 24 (2014) 1867–1877.

[193] S. Salcedo-Sanz, J. Del Ser, I. Landa-Torres, S. Gil-López, J.A. Portilla-Figueras, The coral reefs optimization algorithm: a novel metaheuristic for efficiently solving optimization problems, Sci. World J. 2014 (2014).

[194] A. Askarzadeh, Bird mating optimizer: An optimization algorithm inspired by bird mating strategies, Commun. Nonlinear Sci. Numer. Simul. 19 (2014) 1213–1228. https://doi.org/10.1016/j.cnsns.2013.08.027.

[195] O. Abedinia, N. Amjady, A. Ghasemi, A new metaheuristic algorithm based on shark smell optimization, Complexity. 21 (2016) 97–116.

[196] N. Ghorbani, E. Babaei, Exchange market algorithm, Appl. Soft Comput. 19 (2014) 177–187.

[197] M. Ghaemi, M.-R. Feizi-Derakhshi, Forest optimization algorithm, Expert Syst. Appl. 41 (2014) 6676–6687.

[198] E. Osaba, F. Diaz, E. Onieva, Golden ball: a novel meta-heuristic to solve combinatorial optimization problems based on soccer concepts, Appl. Intell. 41 (2014) 145–166.

[199] M. Hajiaghaei-Keshteli, M. Aminnayeri, Solving the integrated scheduling of production and rail transportation problem by Keshtel algorithm, Appl. Soft Comput. 25 (2014) 184–203.

[200] V.V. De Melo, Kaizen programming, in: Proc. 2014 Annu. Conf. Genet. Evol. Comput., 2014: pp. 895–902.

[201] S. Moein, R. Logeswaran, KGMO: A swarm optimization algorithm based on the kinetic energy of gas molecules, Inf. Sci. (Ny). 275 (2014) 127–144.

[202] F. Merrikh-Bayat, A numerical optimization algorithm inspired by the strawberry plant, ArXiv Prepr. ArXiv1407.7399. (2014).

[203] A. Hatamlou, Heart: a novel optimization algorithm for cluster analysis, Prog. Artif. Intell. 2 (2014) 167–173.

[204] M.T. Adham, P.J. Bentley, An artificial ecosystem algorithm applied to static and dynamic travelling salesman problems, in: 2014 IEEE Int. Conf. Evolvable Syst., IEEE, 2014: pp. 149–156.

[205] D. Felipe, E.F.G. Goldbarg, M.C. Goldbarg, Scientific algorithms for the car renter salesman problem, in: 2014 IEEE Congr. Evol. Comput., IEEE, 2014: pp. 873–879.

[206] J.-P. Arnaout, Worm optimization: a novel optimization algorithm inspired by C. Elegans, in: Proc. 2014 Int. Conf. Ind.

Eng. Oper. Manag. Indones., 2014: pp. 2499–2505.

[207] J.S.M.L. Melvix, Greedy politics optimization: Metaheuristic inspired by political strategies adopted during state assembly elections, in: 2014 IEEE Int. Adv. Comput. Conf., IEEE, 2014: pp. 1157–1162.

[208] L. Wang, H. Ni, R. Yang, M. Fei, W. Ye, A simple human learning optimization algorithm, in: Comput. Intell. Networked Syst. Their Appl., Springer, 2014: pp. 56–65.

[209] N. Moosavian, B. Kasaee Roodsari, Soccer league competition algorithm: A novel meta-heuristic algorithm for optimal design of water distribution networks, Swarm Evol. Comput. 17 (2014) 14–24. https://doi.org/10.1016/j.swevo.2014.02.002.

[210] H. Karami, M.J. Sanjari, G.B. Gharehpetian, Hyper-Spherical Search (HSS) algorithm: a novel meta-heuristic algorithm to optimize nonlinear functions, Neural Comput. Appl. 25 (2014) 1455–1465.

[211] Y.-J. Zheng, H.-F. Ling, J.-Y. Xue, Ecogeography-based optimization: enhancing biogeography-based optimization with ecogeographic barriers and differentiations, Comput. Oper. Res. 50 (2014) 115–127.

[212] H. Duan, P. Qiao, Pigeon-inspired optimization: a new swarm intelligence optimizer for air robot path planning, Int. J. Intell. Comput. Cybern. (2014).

[213] S. Mirjalili, The Ant Lion Optimizer, Adv. Eng. Softw. 83 (2015) 80–98. https://doi.org/10.1016/j.advengsoft.2015.01.010.

[214] S.A. Uymaz, G. Tezel, E. Yel, Artificial algae algorithm (AAA) for nonlinear global optimization, Appl. Soft Comput. 31 (2015) 153–171.

[215] J. Ali, M. Saeed, M. Luqman, M.F. Tabassum, Artificial showering algorithm: a new meta-heuristic for unconstrained optimization, (2015).

[216] M. Canayaz, A. Karcı, Investigation of cricket behaviours as evolutionary computation for system design optimization problems, Measurement. 68 (2015) 225–235.

[217] R.-J. Kuo, F.E. Zulvia, The gradient evolution algorithm: A new metaheuristic, Inf. Sci. (Ny). 316 (2015) 246–265.

[218] S. Mirjalili, Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm, Knowledge-Based Syst. 89 (2015) 228–249. https://doi.org/10.1016/j.knosys.2015.07.006.

[219] G.-G. Wang, S. Deb, Z. Cui, Monarch butterfly optimization, Neural Comput. Appl. 31 (2015) 1995–2014. https://doi.org/10.1007/s00521-015-1923-y.

[220] Y.-J. Zheng, Water wave optimization: a new nature-inspired metaheuristic, Comput. Oper. Res. 55 (2015) 1–11.

[221] H. Salimi, Stochastic fractal search: a powerful metaheuristic algorithm, Knowledge-Based Syst. 75 (2015) 1–18.

[222] G.-G. Wang, S. Deb, L. dos S. Coelho, Elephant Herding Optimization, 2015 3rd Int. Symp. Comput. Bus. Intell. (2015) 1–5. https://doi.org/10.1109/iscbi.2015.8.

[223] B. Doğan, T. Ölmez, A new metaheuristic for numerical function optimization: Vortex Search algorithm, Inf. Sci. (Ny). 293 (2015) 125–145. https://doi.org/10.1016/j.ins.2014.08.053.

[224] G.-G. Wang, S. Deb, L.D.S. Coelho, Earthworm optimisation algorithm: a bio-inspired metaheuristic algorithm for global optimisation problems, Int. J. Bio-Inspired Comput. 12 (2018) 1–22.

[225] H. Shareef, A.A. Ibrahim, A.H. Mutlag, Lightning search algorithm, Appl. Soft Comput. 36 (2015) 315–333.

[226] V.K. Patel, V.J. Savsani, Heat transfer search (HTS): a novel optimization algorithm, Inf. Sci. (Ny). 324 (2015) 217–246.

[227] B. Javidy, A. Hatamlou, S. Mirjalili, Ions motion algorithm for solving optimization problems, Appl. Soft Comput. 32 (2015) 72–79.

[228] A.H. Kashan, A new metaheuristic for optimization: optics inspired optimization (OIO), Comput. Oper. Res. 55 (2015) 99–125.

[229] M.S. Kiran, TSA: Tree-seed algorithm for continuous optimization, Expert Syst. Appl. 42 (2015) 6686–6698.

[230] F. Merrikh-Bayat, The runner-root algorithm: a metaheuristic for solving unimodal and multimodal optimization

problems inspired by runners and roots of plants in nature, Appl. Soft Comput. 33 (2015) 292–303.

[231] S. Deb, S. Fong, Z. Tian, Elephant search algorithm for optimization problems, in: 2015 Tenth Int. Conf. Digit. Inf. Manag., IEEE, 2015: pp. 249–255.

[232] H. Emami, F. Derakhshan, Election algorithm: A new socio-politically inspired strategy, AI Commun. 28 (2015) 591–603.

[233] E. Cuevas, A. González, D. Zaldívar, M. Pérez-Cisneros, An optimisation algorithm based on the behaviour of locust swarms, Int. J. Bio-Inspired Comput. 7 (2015) 402–407.

[234] D. Tang, S. Dong, Y. Jiang, H. Li, Y. Huang, ITGO: Invasive tumor growth optimization algorithm, Appl. Soft Comput. 36 (2015) 670–698.

[235] C.-C. Chen, Y.-C. Tsai, I.I. Liu, C.-C. Lai, Y.-T. Yeh, S.-Y. Kuo, Y.-H. Chou, A novel metaheuristic: Jaguar algorithm with learning behavior, in: 2015 IEEE Int. Conf. Syst. Man, Cybern., IEEE, 2015: pp. 1595–1600.

[236] H. Beiranvand, E. Rokrok, General relativity search algorithm: a global optimization approach, Int. J. Comput. Intell. Appl. 14 (2015) 1550017.

[237] X. He, S. Zhang, J. Wang, A novel algorithm inspired by plant root growth with self-similarity propagation, in: 2015 1st Int. Conf. Ind. Networks Intell. Syst., IEEE, 2015: pp. 157–162.

[238] O. FINDIK, Bull optimization algorithm based on genetic operators for continuous optimization problems., Turkish J. Electr. Eng. Comput. Sci. 23 (2015).

[239] S.L. Tilahun, H.C. Ong, Prey-predator algorithm: a new metaheuristic algorithm for optimization problems, Int. J. Inf. Technol. Decis. Mak. 14 (2015) 1331–1352.

[240] J.B. Odili, M.N.M. Kahar, African buffalo optimization (ABO): a new meta-heuristic algorithm, J. Adv. Appl. Sci. 3 (2015) 101–106.

[241] G. Huang, Artificial infectious disease optimization: A SEIQR epidemic dynamic model-based function optimization algorithm, Swarm Evol. Comput. 27 (2016) 31–67.

[242] G. Wu, Across neighborhood search for numerical optimization, Inf. Sci. (Ny). 329 (2016) 597–618.

[243] M. Canayaz, A. Karci, Cricket behaviour-based evolutionary computation technique in solving engineering optimization problems, Appl. Intell. 44 (2016) 362–376.

[244] Y. Sharafi, M.A. Khanesar, M. Teshnehlab, COOA: Competitive optimization algorithm, Swarm Evol. Comput. 30 (2016) 39–63.

[245] M. Li, H. Zhao, X. Weng, T. Han, Cognitive behavior optimization algorithm for solving optimization problems, Appl. Soft Comput. 39 (2016) 199–222.

[246] H. Abedinpourshotorban, S.M. Shamsuddin, Z. Beheshti, D.N.A. Jawawi, Electromagnetic field optimization: a physics-inspired metaheuristic optimization algorithm, Swarm Evol. Comput. 26 (2016) 8–22.

[247] E. Fadakar, M. Ebrahimi, A new metaheuristic football game inspired algorithm, in: 2016 1st Conf. Swarm Intell. Evol. Comput., IEEE, 2016: pp. 6–11.

[248] D. Tang, S. Dong, L. He, Y. Jiang, Intrusive tumor growth inspired optimization algorithm for data clustering, Neural Comput. Appl. 27 (2016) 349–374.

[249] V. Muthiah-Nakarajan, M.M. Noel, Galactic Swarm Optimization: A new global optimization metaheuristic inspired by galactic motion, Appl. Soft Comput. 38 (2016) 771–787.

[250] S. Mirjalili, A. Lewis, The Whale Optimization Algorithm, Adv. Eng. Softw. 95 (2016) 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008.

[251] S. Mirjalili, SCA: A Sine Cosine Algorithm for solving optimization problems, Knowledge-Based Syst. 96 (2016) 120–133. https://doi.org/10.1016/j.knosys.2015.12.022.

[252] S. Mirjalili, Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems, Neural Comput. Appl. 27 (2015) 1053–1073. https://doi.org/10.1007/s00521-015-1920-1.

[253] A. Askarzadeh, A novel metaheuristic method for solving constrained engineering optimization problems: Crow search algorithm, Comput. Struct. 169 (2016) 1–12. https://doi.org/10.1016/j.compstruc.2016.03.001.

[254] S. Mirjalili, S.M. Mirjalili, A. Hatamlou, Multi-Verse Optimizer: a nature-inspired algorithm for global optimization, Neural Comput. Appl. 27 (2015) 495–513. https://doi.org/10.1007/s00521-015-1870-7.

[255] X.-B. Meng, X.Z. Gao, L. Lu, Y. Liu, H. Zhang, A new bio-inspired optimisation algorithm: Bird Swarm Algorithm, J. Exp. Theor. Artif. Intell. 28 (2016) 673–687.

[256] M.D. Li, H. Zhao, X.W. Weng, T. Han, A novel nature-inspired algorithm for optimization: Virus colony search, Adv. Eng. Softw. 92 (2016) 65–88.

[257] A. Kaveh, T. Bakhshpoori, Water Evaporation Optimization: A novel physically inspired optimization algorithm, Comput. Struct. 167 (2016) 69–85. https://doi.org/10.1016/j.compstruc.2016.01.008.

[258] Y. Labbi, D. Ben Attous, H.A. Gabbar, B. Mahdad, A. Zidan, A new rooted tree optimization algorithm for economic dispatch with valve-point effect, Int. J. Electr. Power Energy Syst. 79 (2016) 298–311.

[259] N. Razmjooy, M. Khalilpour, M. Ramezani, A new meta-heuristic optimization algorithm inspired by FIFA world cup competitions: theory and its application in PID designing for AVR system, J. Control. Autom. Electr. Syst. 27 (2016) 419–440.

[260] A. Ebrahimi, E. Khamehchi, Sperm whale algorithm: an effective metaheuristic algorithm for production optimization problems, J. Nat. Gas Sci. Eng. 29 (2016) 211–222.

[261] Y.-C. Liang, J.R. Cuevas Juarez, A novel metaheuristic for continuous optimization problems: Virus optimization algorithm, Eng. Optim. 48 (2016) 73–93.

[262] T.R. Biyanto, H.Y. Fibrianto, G. Nugroho, A.M. Hatta, E. Listijorini, T. Budiati, H. Huda, Duelist algorithm: an algorithm inspired by how duelist improve their capabilities in a duel, in: Int. Conf. Swarm Intell., Springer, 2016: pp. 39–47.

[263] A. Brabazon, W. Cui, M. O'Neill, The raven roosting optimisation algorithm, Soft Comput. 20 (2016) 525–545.

[264] Y. Saadi, I.T.R. Yanto, T. Herawan, V. Balakrishnan, H. Chiroma, A. Risnumawan, Ringed seal search for global optimization via a sensitive search model, PLoS One. 11 (2016) e0144371.

[265] A.E. Xavier, V.L. Xavier, Flying elephants: a general method for solving non-differentiable problems, J. Heuristics. 22 (2016) 649–664.

[266] M.K. Ibrahim, R.S. Ali, Novel optimization algorithm inspired by camel traveling behavior, Iraq J. Electr. Electron. Eng. 12 (2016) 167–177.

[267] X. Feng, M. Ma, H. Yu, Crystal energy optimization algorithm, Comput. Intell. 32 (2016) 284–322.

[268] P. Savsani, V. Savsani, Passing vehicle search (PVS): A novel metaheuristic algorithm, Appl. Math. Model. 40 (2016) 3951–3978.

[269] A. Kaveh, A. Zolghadr, A novel meta-heuristic algorithm: tug of war optimization, Iran Univ. Sci. Technol. 6 (2016) 469–492.

[270] A.O. Topal, O. Altun, A novel meta-heuristic algorithm: dynamic virtual bats algorithm, Inf. Sci. (Ny). 354 (2016) 222–235.

[271] M. Yazdani, F. Jolai, Lion optimization algorithm (LOA): a nature-inspired metaheuristic algorithm, J. Comput. Des. Eng. 3 (2016) 24–36.

[272] H. Moez, A. Kaveh, N. Taghizadieh, Natural forest regeneration algorithm: a new meta-heuristic, Iran. J. Sci. Technol. Trans. Civ. Eng. 40 (2016) 311–326.

[273] Z. Ibrahim, N.H.A. Aziz, N.A.A. Aziz, S. Razali, M.S. Mohamad, Simulated Kalman filter: a novel estimation-based metaheuristic optimization algorithm, Adv. Sci. Lett. 22 (2016) 2941–2946.

[274] L. Gao, Q.-K. Pan, A shuffled multi-swarm micro-migrating birds optimizer for a multi-resource-constrained flexible job shop scheduling problem, Inf. Sci. (Ny). 372 (2016) 655–676.

[275] V. Punnathanam, P. Kotecha, Yin-Yang-pair Optimization: A novel lightweight optimization algorithm, Eng. Appl. Artif. Intell. 54 (2016) 62–79.

[276] M. Jaderyan, H. Khotanlou, Virulence optimization algorithm, Appl. Soft Comput. 43 (2016) 596–618.

[277] X. Qi, Y. Zhu, H. Zhang, A new meta-heuristic butterfly-inspired algorithm, J. Comput. Sci. 23 (2017) 226–239.

[278] A. Kaveh, A. Zolghadr, Cyclical parthenogenesis algorithm for guided modal strain energy based structural damage detection, Appl. Soft Comput. 57 (2017) 250–264.

[279] N. Archana, R. Vidhyapriya, A. Benedict, K. Chandran, Deterministic oscillatory search: a new meta-heuristic optimization algorithm, Sādhanā. 42 (2017) 817–826.

[280] M. Kaedi, Fractal-based algorithm: a new metaheuristic method for continuous optimization, Int J Artif Intell. 15 (2017) 76–92.

[281] S. Asil Gharebaghi, M. Ardalan Asl, New meta-heuristic optimization algorithm using neuronal communication, Iran Univ. Sci. Technol. 7 (2017) 413–431.

[282] A.F. Nematollahi, A. Rahiminejad, B. Vahidi, A novel physical based meta-heuristic optimization method known as Lightning Attachment Procedure Optimization, Appl. Soft Comput. 59 (2017) 596–621.

[283] A. Kazikova, M. Pluhacek, R. Senkerik, A. Viktorin, Proposal of a new swarm optimization method inspired in bison behavior, in: 23rd Int. Conf. Soft Comput., Springer, 2017: pp. 146–156.

[284] V.V. de Melo, A novel metaheuristic method for solving constrained engineering optimization problems: Drone Squadron Optimization, ArXiv Prepr. ArXiv1708.01368. (2017).

[285] S.-A. Ahmadi, Human behavior-based optimization: a novel metaheuristic approach to solve complex optimization problems, Neural Comput. Appl. 28 (2017) 233–244.

[286] A. Kaveh, M.I. Ghazaan, A new meta-heuristic algorithm: vibrating particles system, Sci. Iran. Trans. A, Civ. Eng. 24 (2017) 551.

[287] G. Dhiman, V. Kumar, Spotted hyena optimizer: a novel bio-inspired based metaheuristic technique for engineering applications, Adv. Eng. Softw. 114 (2017) 48–70.

[288] S. Mirjalili, A.H. Gandomi, S.Z. Mirjalili, S. Saremi, H. Faris, S.M. Mirjalili, Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems, Adv. Eng. Softw. 114 (2017) 163–191. https://doi.org/10.1016/j.advengsoft.2017.07.002.

[289] S. Saremi, S. Mirjalili, A. Lewis, Grasshopper Optimisation Algorithm: Theory and application, Adv. Eng. Softw. 105 (2017) 30–47. https://doi.org/10.1016/j.advengsoft.2017.01.004.

[290] S.H. Aghay Kaboli, J. Selvaraj, N.A. Rahim, Rain-fall optimization algorithm: A population based algorithm for solving constrained optimization problems, J. Comput. Sci. 19 (2017) 31–42. https://doi.org/10.1016/j.jocs.2016.12.010.

[291] A. Wedyan, J. Whalley, A. Narayanan, Hydrological cycle algorithm for continuous optimization problems, J. Optim. 2017 (2017).

[292] T.R. Biyanto, S. Irawan, H.Y. Febrianto, N. Afdanny, A.H. Rahman, K.S. Gunawan, J.A.D. Pratama, T.N. Bethiana, Killer whale algorithm: an algorithm inspired by the life of killer whale, Procedia Comput. Sci. 124 (2017) 151–157.

[293] A.T.S. Al-Obaidi, H.S. Abdullah, Camel herds algorithm: A new swarm intelligent algorithm to solve optimization problems, Int. J. Perceptive Cogn. Comput. 3 (2017).

[294] Q. Zhang, R. Wang, J. Yang, K. Ding, Y. Li, J. Hu, Collective decision optimization algorithm: a new heuristic optimization method, Neurocomputing. 221 (2017) 123–137.

[295] E. Hosseini, Laying chicken algorithm: A new meta-heuristic approach to solve continuous programming problems, J. Appl. Comput. Math. 6 (2017).

[296] N.S. Jaddi, J. Alvankarian, S. Abdullah, Kidney-inspired algorithm for optimization problems, Commun. Nonlinear Sci. Numer. Simul. 42 (2017) 358–369.

[297] E. Tanyildizi, G. Demir, Golden sine algorithm: A novel math-inspired algorithm, Adv. Electr. Comput. Eng. 17 (2017)

71–78.

[298] O.A. Raouf, I.M. Hezam, Sperm motility algorithm: a novel metaheuristic approach for global optimisation, Int. J. Oper. Res. 28 (2017) 143–163.

[299] T.R. Biyanto, Rain Water Optinization Algorithm: Newton's Law of Rain Water Movements, (2017).

[300] A. Kaveh, A. Dadras, A novel meta-heuristic optimization algorithm: Thermal exchange optimization, Adv. Eng. Softw. 110 (2017) 69–84. https://doi.org/10.1016/j.advengsoft.2017.03.014.

[301] Y. Zhang, P. Zhang, S. Li, PSA: A novel optimization algorithm based on survival rules of porcellio scaber, in: 2021 IEEE 5th Adv. Inf. Technol. Electron. Autom. Control Conf., IEEE, 2021: pp. 439–442.

[302] F. Fausto, E. Cuevas, A. Valdivia, A. González, A global optimization algorithm inspired in the behavior of selfish herds, Biosystems. 160 (2017) 39–55.

[303] D. Połap, Polar bear optimization algorithm: Meta-heuristic with fast population movement and dynamic birth and death mechanism, Symmetry (Basel). 9 (2017) 203.

[304] A.M.F. Fard, M. Hajiaghaei-Keshteli, Social Engineering Optimization (SEO); A New Single-Solution Meta-heuristic Inspired by Social Engineering, (n.d.).

[305] A. Tzanetos, G. Dounias, A new metaheuristic method for optimization: sonar inspired optimization, in: Int. Conf. Eng. Appl. Neural Networks, Springer, 2017: pp. 417–428.

[306] A. Baykasoğlu, Ş. Akpinar, Weighted Superposition Attraction (WSA): A swarm intelligence algorithm for optimization problems–Part 1: Unconstrained optimization, Appl. Soft Comput. 56 (2017) 520–540.

[307] S.H.S. Moosavi, V.K. Bardsiri, Satin bowerbird optimizer: A new optimization algorithm to optimize ANFIS for software development effort estimation, Eng. Appl. Artif. Intell. 60 (2017) 1–15.

[308] A.E. Yildirim, A. Karci, Applications of artificial atom algorithm to small-scale traveling salesman problems, Soft Comput. 22 (2018) 7619–7631.

[309] L. Rosenberg, M. Lungren, S. Halabi, G. Willcox, D. Baltaxe, M. Lyons, Artificial swarm intelligence employed to amplify diagnostic accuracy in radiology, in: 2018 IEEE 9th Annu. Inf. Technol. Electron. Mob. Commun. Conf., IEEE, 2018: pp. 1186–1191.

[310] S. Bitam, S. Zeadally, A. Mellouk, Fog computing job scheduling optimization based on bees swarm, Enterp. Inf. Syst. 12 (2018) 373–397.

[311] T. Wang, L. Yang, Beetle swarm optimization algorithm: Theory and application, ArXiv Prepr. ArXiv1808.00206. (2018).

[312] M. Ghaemidizaji, C. Dadkhah, H. Leung, A new optimization algorithm based on the behavior of BrunsVigia flower, in: 2018 IEEE Int. Conf. Syst. Man, Cybern., IEEE, 2018: pp. 263–267.

[313] J. Chen, H. Cai, W. Wang, A new metaheuristic algorithm: car tracking optimization algorithm, Soft Comput. 22 (2018) 3857–3878.

[314] C.E. Klein, V.C. Mariani, L. dos Santos Coelho, Cheetah Based Optimization Algorithm: A Novel Swarm Intelligence Paradigm., in: ESANN, Bruges, Belgium, 2018: pp. 685–690.

[315] M. Goudhaman, Cheetah chase algorithm (CCA): a nature-inspired metaheuristic algorithm, Int. J. Eng. Technol. 7 (2018) 1804–1811.

[316] R.M. Rizk-Allah, A.E. Hassanien, S. Bhattacharyya, Chaotic crow search algorithm for fractional optimization problems, Appl. Soft Comput. 71 (2018) 1161–1175.

[317] M.C. Catalbas, A. Gulten, Circular structures of puffer fish: a new metaheuristic optimization algorithm, in: 2018 Third Int. Conf. Electr. Biomed. Eng. Clean Energy Green Comput., IEEE, 2018: pp. 1–5.

[318] A. Afroughinia, R. Kardehi Moghaddam, Competitive learning: a new meta-heuristic optimization algorithm, Int. J. Artif. Intell. Tools. 27 (2018) 1850035.

[319] J. Deuri, S.S. Sathya, Cricket chirping algorithm: an efficient meta-heuristic for numerical function optimisation, Int. J.

Comput. Sci. Eng. 16 (2018) 162–172.

[320] A. Etminaniesfahani, A. Ghanbarzadeh, Z. Marashi, Fibonacci indicator algorithm: A novel tool for complex optimization problems, Eng. Appl. Artif. Intell. 74 (2018) 1–9.

[321] C. Caraveo, F. Valdez, O. Castillo, A new optimization meta-heuristic algorithm based on self-defense mechanism of the plants with three reproduction operators, Soft Comput. 22 (2018) 4907–4920.

[322] G. Dhiman, V. Kumar, Emperor penguin optimizer: A bio-inspired algorithm for engineering problems, Knowledge-Based Syst. 159 (2018) 20–50.

[323] A. Kaveh, S. Mahjoubi, Lion Pride Optimization Algorithm: A meta-heuristic method for global optimization problems, Sci. Iran. 0 (2018) 0. https://doi.org/10.24200/sci.2018.20833.

[324] P. Wang, X. Ye, B. Li, K. Cheng, Multi-scale quantum harmonic oscillator algorithm for global numerical optimization, Appl. Soft Comput. 69 (2018) 655–670.

[325] M. Bidar, H.R. Kanan, M. Mouhoub, S. Sadaoui, Mushroom Reproduction Optimization (MRO): a novel nature-inspired evolutionary algorithm, in: 2018 IEEE Congr. Evol. Comput., IEEE, 2018: pp. 1–10.

[326] A. Cheraghalipour, M. Hajiaghaei-Keshteli, M.M. Paydar, Tree Growth Algorithm (TGA): A novel approach for solving optimization problems, Eng. Appl. Artif. Intell. 72 (2018) 393–414.

[327] G.-G. Wang, Moth search algorithm: a bio-inspired metaheuristic algorithm for global optimization problems, Memetic Comput. 10 (2018) 151–164.

[328] H. Shayanfar, F.S. Gharehchopogh, Farmland fertility: A new metaheuristic algorithm for solving continuous optimization problems, Appl. Soft Comput. 71 (2018) 728–746.

[329] N.A. Kallioras, N.D. Lagaros, D.N. Avtzis, Pity beetle algorithm–A new metaheuristic inspired by the behavior of bark beetles, Adv. Eng. Softw. 121 (2018) 147–166.

[330] E. Jahani, M. Chizari, Tackling global optimization problems with a novel algorithm–Mouth Brooding Fish algorithm, Appl. Soft Comput. 62 (2018) 987–1002.

[331] L. Cheng, X. Wu, Y. Wang, Artificial flora (AF) optimization algorithm, Appl. Sci. 8 (2018) 329.

[332] S. Mandal, Elephant swarm water search algorithm for global optimization, Sādhanā. 43 (2018) 1–21.

[333] H.A. Shehadeh, I. Ahmedy, M.Y.I. Idris, Sperm swarm optimization algorithm for optimizing wireless sensor network challenges, in: Proc. 6th Int. Conf. Commun. Broadband Netw., 2018: pp. 53–59.

[334] M.J. Mahmoodabadi, M. Rasekh, T. Zohari, TGA: Team game algorithm, Futur. Comput. Informatics J. 3 (2018) 191–199.

[335] J. Pierezan, L.D.S. Coelho, Coyote optimization algorithm: a new metaheuristic for global optimization problems, in: 2018 IEEE Congr. Evol. Comput., IEEE, 2018: pp. 1–8.

[336] J. Zhang, M. Xiao, L. Gao, Q. Pan, Queuing search algorithm: A novel metaheuristic algorithm for solving engineering optimization problems, Appl. Math. Model. 63 (2018) 464–490. https://doi.org/10.1016/j.apm.2018.06.036.

[337] A.A. Hudaib, H.N. Fakhouri, Supernova optimizer: a novel natural inspired meta-heuristic, Mod. Appl. Sci. 12 (2018) 32–50.

[338] D. Puangdownreong, Spiritual search: a novel metaheuristic algorithm for control engineering optimization, Int. Rev. Autom. Control. 11 (2018) 86–97.

[339] M. Farshchin, M. Maniat, C. V Camp, S. Pezeshk, School based optimization algorithm for design of steel frames, Eng. Struct. 171 (2018) 326–335. https://doi.org/10.1016/j.engstruct.2018.05.085.

[340] S. Dolatabadi, Weighted vertices optimizer (WVO): A novel metaheuristic optimization algorithm, Numer. Algebr. Control Optim. 8 (2018) 461.

[341] R. Moghdani, K. Salimifard, Volleyball premier league algorithm, Appl. Soft Comput. 64 (2018) 161–185.

[342] D. Zaldívar, B. Morales, A. Rodríguez, A. Valdivia-G, E. Cuevas, M. Pérez-Cisneros, A novel bio-inspired optimization model based on Yellow Saddle Goatfish behavior, Biosystems. 174 (2018) 1–21.

[343] S.Z. Koohi, N.A.W.A. Hamid, M. Othman, G. Ibragimov, Raccoon optimization algorithm, IEEE Access. 7 (2018) 5383–5399.

[344] B. Almonacid, R. Soto, Andean Condor Algorithm for cell formation problems, Nat. Comput. 18 (2019) 351–381.

[345] M.F. Pook, E.I. Ramlan, The Anglerfish algorithm: a derivation of randomized incremental construction technique for solving the traveling salesman problem, Evol. Intell. 12 (2019) 11–20.

[346] W. Zhao, L. Wang, Z. Zhang, Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm, Neural Comput. Appl. 32 (2019) 9383–9425. https://doi.org/10.1007/s00521-019-04452-x.

[347] W. Zhao, L. Wang, Z. Zhang, A novel atom search optimization for dispersion coefficient estimation in groundwater, Futur. Gener. Comput. Syst. 91 (2019) 601–610. https://doi.org/10.1016/j.future.2018.05.037.

[348] J.-B. Lamy, Artificial Feeding Birds (AFB): a new metaheuristic inspired by the behavior of pigeons, in: Adv. Nature-Inspired Comput. Appl., Springer, 2019: pp. 43–60.

[349] A. Kaveh, M. Kooshkebaghi, Artificial coronary circulation system: A new bio-inspired metaheuristic algorithm, Sci. Iran. 26 (2019) 2731–2747.

[350] A. Yadav, AEFA: Artificial electric field algorithm for global optimization, Swarm Evol. Comput. 48 (2019) 93–108.

[351] M. Bodaghi, K. Samieefar, Meta-heuristic bus transportation algorithm, Iran J. Comput. Sci. 2 (2019) 23–32.

[352] Q. Zhang, R. Wang, J. Yang, A. Lewis, F. Chiclana, S. Yang, Biology migration algorithm: a new nature-inspired heuristic methodology for global optimization, Soft Comput. 23 (2019) 7333–7358.

[353] A. Arshaghi, M. Ashourian, L. Ghabeli, Buzzard optimization algorithm: A nature-inspired metaheuristic algorithm, Majlesi J. Electr. Eng. 13 (2019) 83–98.

[354] M. Mahmood, B. Al-Khateeb, The blue monkey: A new nature inspired metaheuristic optimization algorithm, Period. Eng. Nat. Sci. 7 (2019) 1054–1066.

[355] G.I. Sayed, A. Tharwat, A.E. Hassanien, Chaotic dragonfly algorithm: an improved metaheuristic algorithm for feature selection, Appl. Intell. 49 (2019) 188–205.

[356] J. Pierezan, G. Maidl, E.M. Yamao, L. dos Santos Coelho, V.C. Mariani, Cultural coyote optimization algorithm applied to a heavy duty gas turbine operation, Energy Convers. Manag. 199 (2019) 111932.

[357] M. DEHGHANI, Z. MONTAZERI, O.P. MALIK, DGO: Dice game optimizer, Gazi Univ. J. Sci. 32 (2019) 871–882.

[358] M. Dehghani, M. Mardaneh, O.P. Malik, S.M. NouraeiPour, DTO: Donkey theorem optimization, in: 2019 27th Iran. Conf. Electr. Eng., IEEE, 2019: pp. 1855–1859.

[359] G. Brammya, S. Praveena, N.S. Ninu Preetha, R. Ramya, B.R. Rajakumar, D. Binu, Deer hunting optimization algorithm: a new nature-inspired meta-heuristic paradigm, Comput. J. (2019).

[360] E.H. de Vasconcelos Segundo, V.C. Mariani, L. dos Santos Coelho, Design of heat exchangers using Falcon Optimization Algorithm, Appl. Therm. Eng. 156 (2019) 119–144.

[361] A.H. Kashan, R. Tavakkoli-Moghaddam, M. Gen, Find-Fix-Finish-Exploit-Analyze (F3EA) meta-heuristic algorithm: An effective algorithm with new evolutionary operators for global optimization, Comput. Ind. Eng. 128 (2019) 192–218.

[362] M. Tahani, N. Babayan, Flow Regime Algorithm (FRA): a physics-based meta-heuristics algorithm, Knowl. Inf. Syst. 60 (2019) 1001–1038.

[363] G.I. Sayed, M. Solyman, A.E. Hassanien, A novel chaotic optimal foraging algorithm for unconstrained and constrained problems and its application in white blood cell segmentation, Neural Comput. Appl. 31 (2019) 7633–7664.

[364] R. Salgotra, U. Singh, The naked mole-rat algorithm, Neural Comput. Appl. 31 (2019) 8837–8857.

[365] F. Samie Yousefi, N. Karimian, A. Ghodousian, Xerus Optimization Algorithm (XOA): a novel nature-inspired metaheuristic algorithm for solving global optimization problems, J. Algorithms Comput. 51 (2019) 111–126.

[366] Z. Wei, C. Huang, X. Wang, T. Han, Y. Li, Nuclear reaction optimization: A novel and powerful physics-based algorithm for global optimization, IEEE Access. 7 (2019) 66084–66109.

[367] O. Maciel, A. Valdivia, D. Oliva, E. Cuevas, D. Zaldívar, M. Pérez-Cisneros, A novel hybrid metaheuristic optimization

method: hypercube natural aggregation algorithm, Soft Comput. (2019) 1–34.

[368] S. Shadravan, H.R. Naji, V.K. Bardsiri, The Sailfish Optimizer: A novel nature-inspired metaheuristic algorithm for solving constrained engineering optimization problems, Eng. Appl. Artif. Intell. 80 (2019) 20–34.

[369] P. Pijarski, P. Kacejko, A new metaheuristic optimization method: the algorithm of the innovative gunner (AIG), Eng. Optim. (2019).

[370] W. Zhao, L. Wang, Z. Zhang, Supply-Demand-Based Optimization: A Novel Economics-Inspired Algorithm for Global Optimization, IEEE Access. 7 (2019) 73182–73206. https://doi.org/10.1109/access.2019.2918753.

[371] S. Arora, S. Singh, Butterfly optimization algorithm: a novel approach for global optimization, Soft Comput. 23 (2019) 715–734.

[372] S. Harifi, M. Khalilian, J. Mohammadzadeh, S. Ebrahimnejad, Emperor Penguins Colony: a new metaheuristic algorithm for optimization, Evol. Intell. 12 (2019) 211–226.

[373] S. Rahmanzadeh, M.S. Pishvaee, Electron radar search algorithm: a novel developed meta-heuristic algorithm, Soft Comput. (2019) 1–23.

[374] F.A. Hashim, E.H. Houssein, M.S. Mabrouk, W. Al-Atabany, S. Mirjalili, Henry gas solubility optimization: A novel physics-based algorithm, Futur. Gener. Comput. Syst. 101 (2019) 646–667. https://doi.org/10.1016/j.future.2019.07.015.

[375] R.G. Morais, N. Nedjah, L.M. Mourelle, A novel metaheuristic inspired by Hitchcock birds' behavior for efficient optimization of large search spaces of high dimensionality, Soft Comput. (2019) 1–23.

[376] A. Ali, K. Zafar, T. Bakhshi, On Nature-Inspired Dynamic Route Planning: Hammerhead Shark Optimization Algorithm, in: 2019 15th Int. Conf. Emerg. Technol., IEEE, 2019: pp. 1–6.

[377] J.M. Abdullah, T. Ahmed, Fitness dependent optimizer: inspired by the bee swarming reproductive process, IEEE Access. 7 (2019) 43473–43486.

[378] A. Khatri, A. Gaba, K.P.S. Rana, V. Kumar, A novel life choice-based optimizer, Soft Comput. 24 (2019) 9121–9141. https://doi.org/10.1007/s00500-019-04443-z.

[379] A.-A.A. Mohamed, S.A. Hassan, A.M. Hemeida, S. Alkhalaf, M.M.M. Mahmoud, A.M.B. Eldin, Parasitism–Predation algorithm (PPA): A novel approach for feature selection, Ain Shams Eng. J. 11 (2020) 293–308.

[380] H. Yapici, N. Cetinkaya, A new meta-heuristic optimizer: pathfinder algorithm, Appl. Soft Comput. 78 (2019) 545–568.

[381] S.H. Samareh Moosavi, V.K. Bardsiri, Poor and rich optimization algorithm: A new human-based and multi populations algorithm, Eng. Appl. Artif. Intell. 86 (2019) 165–181. https://doi.org/10.1016/j.engappai.2019.08.025.

[382] G. Dhiman, V. Kumar, Seagull optimization algorithm: Theory and its applications for large-scale industrial engineering problems, Knowledge-Based Syst. 165 (2019) 169–196. https://doi.org/10.1016/j.knosys.2018.11.024.

[383] G. Dhiman, A. Kaur, STOA: A bio-inspired based optimization algorithm for industrial engineering problems, Eng. Appl. Artif. Intell. 82 (2019) 148–174. https://doi.org/10.1016/j.engappai.2019.03.021.

[384] A.A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, H. Chen, Harris hawks optimization: Algorithm and applications, Futur. Gener. Comput. Syst. 97 (2019) 849–872.

[385] A.K. Das, D.K. Pratihar, A new bonobo optimizer (BO) for real-parameter optimization, in: 2019 IEEE Reg. 10 Symp., IEEE, 2019: pp. 108–113.

[386] J. Zhao, D. Tang, Z. Liu, Y. Cai, S. Dong, Spherical search optimizer: a simple yet efficient meta-heuristic approach, Neural Comput. Appl. (2019) 1–32.

[387] M. Jain, V. Singh, A. Rani, A novel nature-inspired algorithm for optimization: Squirrel search algorithm, Swarm Evol. Comput. 44 (2019) 148–175.

[388] G. Azizyan, F. Miarnaeimi, M. Rashki, N. Shabakhty, Flying Squirrel Optimizer (FSO): A novel SI-based optimization algorithm for engineering problems, Iran. J. Optim. 11 (2019) 177–205.

[389] H.A. Alsattar, A.A. Zaidan, B.B. Zaidan, Novel meta-heuristic bald eagle search optimisation algorithm, Artif. Intell. Rev. 53 (2020) 2237–2264.

[390] A. Shabani, B. Asgarian, S.A. Gharebaghi, M.A. Salido, A. Giret, A new optimization algorithm based on search and rescue operations, Math. Probl. Eng. 2019 (2019).

[391] S. Nejatian, R. Omidvar, H. Parvin, V. Rezaei, M. Yasrebi, A New Algorithm: Wild Mice Colony Algorithm (WMC), TABRIZ J. Electr. Eng. 49 (2019) 425–437.

[392] H. Bagheri, A. Lashkar Ara, R. Hosseini, Thieves and Police, a New Optimization Algorithm: Theory and Application in Probabilistic Power Flow, IETE J. Res. (2019) 1–18.

[393] X. Han, X. Du, P. Yu, ATLA: A novel metaheuristic optimization algorithm inspired by the mating search behavior of longicorn beetles in the nature, in: IOP Conf. Ser. Mater. Sci. Eng., IOP Publishing, 2020: p. 52028.

[394] M.H. Sulaiman, Z. Mustaffa, M.M. Saari, H. Daniyal, Barnacles Mating Optimizer: A new bio-inspired algorithm for solving engineering optimization problems, Eng. Appl. Artif. Intell. 87 (2020). https://doi.org/10.1016/j.engappai.2019.103330.

[395] A. Kaveh, M.R. Seddighian, E. Ghanadpour, Black Hole Mechanics Optimization: a novel meta-heuristic algorithm, Asian J. Civ. Eng. 21 (2020) 1129–1149. https://doi.org/10.1007/s42107-020-00282-8.

[396] A. Kaveh, M. Khanzadi, M. Rastegar Moghaddam, Billiards-inspired optimization algorithm; a new meta-heuristic method, Structures. 27 (2020) 1722–1739. https://doi.org/10.1016/j.istruc.2020.07.058.

[397] T. Dutta, S. Bhattacharyya, S. Dey, J. Platos, Border collie optimization, IEEE Access. 8 (2020) 109177–109197.

[398] A. Ghasemi-Marzbali, A novel nature-inspired meta-heuristic algorithm for optimization: bear smell search algorithm, Soft Comput. 24 (2020) 13003–13035.

[399] S. Debnath, W. Arif, S. Baishya, Buyer Inspired Meta-Heuristic Optimization Algorithm, Open Comput. Sci. 10 (2020) 194–219. https://doi.org/10.1515/comp-2020-0101.

[400] M. Dehghani, Z. Montazeri, H. Givi, J. Guerrero, G. Dhiman, Darts Game Optimizer: A New Optimization Technique Based on Darts Game, Int. J. Intell. Eng. Syst. 13 (2020) 286–294. https://doi.org/10.22266/ijies2020.1031.26.

[401] H.N. Ghafil, K. Jármai, Dynamic differential annealed optimization: New metaheuristic optimization algorithm for engineering applications, Appl. Soft Comput. 93 (2020). https://doi.org/10.1016/j.asoc.2020.106392.

[402] A.I. Wagan, M.M. Shaikh, Numerical data for wind turbine micrositing inspired by human dynasties by use of the Dynastic Optimization Algorithm (DOA), 3C Tecnol. Glosas Innovación Apl. a La Pyme. (2020) 71–85.

[403] J.-S. Chou, N.-M. Nguyen, FBI inspired meta-optimization, Appl. Soft Comput. 93 (2020) 106339.

[404] A. Kaveh, H. Akbari, S.M. Hosseini, Plasma generation optimization: a new physically-based metaheuristic algorithm for solving constrained optimization problems, Eng. Comput. (2020).

[405] S. Gholizadeh, M. Danesh, C. Gheyratmand, A new Newton metaheuristic algorithm for discrete performance-based design optimization of steel moment frames, Comput. Struct. 234 (2020) 106250.

[406] S. Kaur, L.K. Awasthi, A.L. Sangal, G. Dhiman, Tunicate Swarm Algorithm: A new bio-inspired based metaheuristic paradigm for global optimization, Eng. Appl. Artif. Intell. 90 (2020) 103541.

[407] A. Faramarzi, M. Heidarinejad, S. Mirjalili, A.H. Gandomi, Marine Predators Algorithm: A nature-inspired metaheuristic, Expert Syst. Appl. 152 (2020) 113377. https://doi.org/https://doi.org/10.1016/j.eswa.2020.113377.

[408] A. Faramarzi, M. Heidarinejad, B. Stephens, S. Mirjalili, Equilibrium optimizer: A novel optimization algorithm, Knowledge-Based Syst. 191 (2020) 105190. https://doi.org/https://doi.org/10.1016/j.knosys.2019.105190.

[409] S. Yilmaz, S. Sen, Electric fish optimization: a new heuristic algorithm inspired by electrolocation, Neural Comput. Appl. 32 (2020) 11543–11578.

[410] S. Li, H. Chen, M. Wang, A.A. Heidari, S. Mirjalili, Slime mould algorithm: A new method for stochastic optimization, Futur. Gener. Comput. Syst. 111 (2020) 300–323.

[411] V. Hayyolalam, A.A.P. Kazem, Black widow optimization algorithm: a novel meta-heuristic approach for solving engineering optimization problems, Eng. Appl. Artif. Intell. 87 (2020) 103249.

[412] W. Zhao, Z. Zhang, L. Wang, Manta ray foraging optimization: An effective bio-inspired optimizer for engineering

applications, Eng. Appl. Artif. Intell. 87 (2020). https://doi.org/10.1016/j.engappai.2019.103300.

[413] K. Zervoudakis, S. Tsafarakis, A mayfly optimization algorithm, Comput. Ind. Eng. 145 (2020) 106559.

[414] H. Drias, Y. Drias, I. Khennak, A new swarm algorithm based on orcas intelligence for solving maze problems, in: World Conf. Inf. Syst. Technol., Springer, 2020: pp. 788–797.

[415] Q. Askari, I. Younas, M. Saeed, Political Optimizer: A novel socio-inspired meta-heuristic for global optimization, Knowledge-Based Syst. 195 (2020). https://doi.org/10.1016/j.knosys.2020.105709.

[416] Y. Zhang, Z. Jin, Group teaching optimization algorithm: A novel metaheuristic method for solving global optimization problems, Expert Syst. Appl. 148 (2020). https://doi.org/10.1016/j.eswa.2020.113246.

[417] M. Ghasemi, I.F. Davoudkhani, E. Akbari, A. Rahimnejad, S. Ghavidel, L. Li, A novel and effective optimization algorithm for global optimization and its engineering applications: Turbulent Flow of Water-based Optimization (TFWO), Eng. Appl. Artif. Intell. 92 (2020) 103666.

[418] H. Ghasemian, F. Ghasemian, H. Vahdat-Nejad, Human urbanization algorithm: A novel metaheuristic approach, Math. Comput. Simul. 178 (2020) 1–15. https://doi.org/10.1016/j.matcom.2020.05.023.

[419] M. Khishe, M.R. Mosavi, Chimp optimization algorithm, Expert Syst. Appl. 149 (2020) 113338.

[420] F. Martínez-Álvarez, G. Asencio-Cortés, J.F. Torres, D. Gutiérrez-Avilés, L. Melgar-García, R. Pérez-Chacón, C. Rubio-Escudero, J.C. Riquelme, A. Troncoso, Coronavirus optimization algorithm: a bioinspired metaheuristic based on the COVID-19 propagation model, Big Data. 8 (2020) 308–322.

[421] E. Hosseini, K.Z. Ghafoor, A.S. Sadiq, M. Guizani, A. Emrouznejad, Covid-19 optimizer algorithm, modeling and controlling of coronavirus distribution process, IEEE J. Biomed. Heal. Informatics. 24 (2020) 2765–2775.

[422] X. Xu, Z. Hu, Q. Su, Y. Li, J. Dai, Multivariable grey prediction evolution algorithm: a new metaheuristic, Appl. Soft Comput. 89 (2020) 106086.

[423] A. Kaur, S. Jain, S. Goel, Sandpiper optimization algorithm: a novel approach for solving real-life engineering problems, Appl. Intell. 50 (2020) 582–619.

[424] A. Kaveh, A. Zaerreza, Shuffled shepherd optimization method: a new Meta-heuristic algorithm, Eng. Comput. 37 (2020) 2357–2389. https://doi.org/10.1108/ec-10-2019-0481.

[425] A.M. Fathollahi-Fard, M. Hajiaghaei-Keshteli, R. Tavakkoli-Moghaddam, Red deer algorithm (RDA): a new nature-inspired meta-heuristic, Soft Comput. 24 (2020) 14637–14665.

[426] A.F. Nematollahi, A. Rahiminejad, B. Vahidi, A novel meta-heuristic optimization method based on golden ratio in nature, Soft Comput. 24 (2020) 1117–1151.

[427] A.W. Mohamed, A.A. Hadi, A.K. Mohamed, Gaining-sharing knowledge based algorithm for solving optimization problems: a novel nature-inspired algorithm, Int. J. Mach. Learn. Cybern. 11 (2020) 1501–1529. https://doi.org/10.1007/s13042-019-01053-x.

[428] E. Bogar, S. Beyhan, Adolescent Identity Search Algorithm (AISA): A novel metaheuristic approach for solving optimization problems, Appl. Soft Comput. 95 (2020). https://doi.org/10.1016/j.asoc.2020.106503.

[429] M. Braik, A. Sheta, H. Al-Hiary, A novel meta-heuristic search algorithm for solving optimization problems: capuchin search algorithm, Neural Comput. Appl. 33 (2021) 2515–2547.

[430] S. Harifi, J. Mohammadzadeh, M. Khalilian, S. Ebrahimnejad, Giza Pyramids Construction: an ancient-inspired metaheuristic algorithm for optimization, Evol. Intell. (2020) 1–19.

[431] G. Meirelles, B. Brentan, J. Izquierdo, E. Luvizotto, Grand Tour Algorithm: Novel Swarm-Based Optimization for High-Dimensional Problems, Processes. 8 (2020) 980.

[432] R. Guha, S. Ghosh, K.K. Ghosh, R. Sarkar, Groundwater Flow Algorithm: A Novel Hydro-geology based Optimization Algorithm, (2020).

[433] I. Ahmadianfar, O. Bozorg-Haddad, X. Chu, Gradient-based optimizer: A new metaheuristic optimization algorithm, Inf. Sci. (Ny). 540 (2020) 131–159.

[434] M. Jahangiri, M.A. Hadianfard, M.A. Najafgholipour, M. Jahangiri, M.R. Gerami, Interactive autodidactic school: A new metaheuristic optimization algorithm for solving mathematical and structural design optimization problems, Comput. Struct. 235 (2020) 106268.

[435] E.H. Houssein, M.R. Saad, F.A. Hashim, H. Shaban, M. Hassaballah, Lévy flight distribution: A new metaheuristic algorithm for solving engineering optimization problems, Eng. Appl. Artif. Intell. 94 (2020) 103731.

[436] M. Dehghani, H. Samet, Momentum search algorithm: A new meta-heuristic optimization algorithm inspired by momentum conservation law, SN Appl. Sci. 2 (2020) 1–15.

[437] S.Q. Salih, A.A. Alsewari, A new algorithm for normal and large-scale optimization problems: Nomadic People Optimizer, Neural Comput. Appl. 32 (2020) 10359–10386.

[438] W. Al-Sorori, A.M. Mohsen, New Caledonian crow learning algorithm: A new metaheuristic algorithm for solving continuous optimization problems, Appl. Soft Comput. 92 (2020). https://doi.org/10.1016/j.asoc.2020.106325.

[439] D. Moldovan, Horse Optimization Algorithm: A Novel Bio-Inspired Algorithm for Solving Global Optimization Problems, in: Comput. Sci. On-Line Conf., Springer, 2020: pp. 195–209.

[440] R. Rao, Rao algorithms: Three metaphor-less simple algorithms for solving optimization problems, Int. J. Ind. Eng. Comput. 11 (2020) 107–130.

[441] G. Dhiman, M. Garg, A. Nagar, V. Kumar, M. Dehghani, A novel algorithm for global optimization: Rat Swarm Optimizer, J. Ambient Intell. Humaniz. Comput. (2020). https://doi.org/10.1007/s12652-020-02580-0.

[442] A.R. Moazzeni, E. Khamehchi, Rain optimization algorithm (ROA): A new metaheuristic method for drilling optimization solutions, J. Pet. Sci. Eng. 195 (2020) 107512.

[443] B. Das, V. Mukherjee, D. Das, Student psychology based optimization algorithm: a new population based optimization algorithm for solving optimization problems, Adv. Eng. Softw. 146 (2020) 102804.

[444] H. Emami, Seasons optimization algorithm, Eng. Comput. (2020) 1–21.

[445] M. Dehghani, Z. Montazeri, O. Malik, H. Givi, J. Guerrero, Shell Game Optimization: A Novel Game-Based Algorithm, Int. J. Intell. Eng. Syst. 13 (2020) 246–255. https://doi.org/10.22266/ijies2020.0630.23.

[446] J. Xue, B. Shen, A novel swarm intelligence optimization approach: sparrow search algorithm, Syst. Sci. Control Eng. 8 (2020) 22–34.

[447] M.F.F.A. Rashid, Tiki-taka algorithm: a novel metaheuristic inspired by football playing style, Eng. Comput. (2020).

[448] M.H. Qais, H.M. Hasanien, S. Alghuwainem, Transient search optimization: a new meta-heuristic optimization algorithm, Appl. Intell. 50 (2020) 3926–3941. https://doi.org/10.1007/s10489-020-01727-y.

[449] C. Taramasco, B. Crawford, R. Soto, E.M. Cortés-Toro, R. Olivares, A new metaheuristic based on vapor-liquid equilibrium for solving a new patient bed assignment problem, Expert Syst. Appl. 158 (2020) 113506.

[450] Z. Li, V. Tam, A novel meta-heuristic optimization algorithm inspired by the spread of viruses, ArXiv Prepr. ArXiv2006.06282. (2020).

[451] N. Covic, B. Lacevic, Wingsuit flying search—A novel global optimization algorithm, IEEE Access. 8 (2020) 53883–53900.

[452] A. Kaveh, A. Dadras Eslamlou, Water strider algorithm: A new metaheuristic and applications, Structures. 25 (2020) 520–541. https://doi.org/https://doi.org/10.1016/j.istruc.2020.03.033.

[453] M. Karimzadeh Parizi, F. Keynia, A. Khatibi Bardsiri, Woodpecker Mating Algorithm (WMA): a nature-inspired algorithm for solving optimization problems, Int. J. Nonlinear Anal. Appl. 11 (2020) 137–157.

[454] F. Zitouni, S. Harous, R. Maamri, The Solar System Algorithm: a novel metaheuristic method for global optimization, IEEE Access. 9 (2020) 4542–4565.

[455] H. Ali, U.U. Tariq, M. Hussain, L. Lu, J. Panneerselvam, X. Zhai, ARSH-FATI: A Novel Metaheuristic for Cluster Head Selection in Wireless Sensor Networks, IEEE Syst. J. 15 (2020) 2386–2397.

[456] T. Li, S. Fong, A.J. Tallón-Ballesteros, Teng-Yue algorithm: A novel metaheuristic search method for fast cancer

classification, in: Proc. 2020 Genet. Evol. Comput. Conf. Companion, 2020: pp. 47–48.

[457] M.R. Kahrizi, S.J. Kabudian, Projectiles Optimization: A Novel Metaheuristic Algorithm for Global Optimization, Int. J. Eng. 33 (2020) 1924–1938.

[458] M. Zaeimi, A. Ghoddosian, Color harmony algorithm: an art-inspired metaheuristic for mathematical function optimization, Soft Comput. 24 (2020) 12027–12066.

[459] J. Zhang, Y. Huang, G. Ma, B. Nener, Multi-objective beetle antennae search algorithm, ArXiv Prepr. ArXiv2002.10090. (2020).

[460] N.A. Golilarz, H. Gao, A. Addeh, S. Pirasteh, ORCA optimization algorithm: a new meta-heuristic tool for complex optimization problems, in: 2020 17th Int. Comput. Conf. Wavelet Act. Media Technol. Inf. Process., IEEE, 2020: pp. 198–204.

[461] Y. Liu, R. Li, PSA: a photon search algorithm, J. Inf. Process. Syst. 16 (2020) 478–493.

[462] R. Dong, S. Wang, New optimization algorithm inspired by kernel tricks for the economic emission dispatch problem with valve point, IEEE Access. 8 (2020) 16584–16594.

[463] R.K. Misra, D. Singh, A. Kumar, Spherical search algorithm: A metaheuristic for bound-constrained optimization, in: Indo-French Semin. Optim. Var. Anal. Appl., Springer, 2020: pp. 421–441.

[464] X. Li, Z. Cai, Y. Wang, Y. Todo, J. Cheng, S. Gao, TDSD: A new evolutionary algorithm based on triple distinct search dynamics, IEEE Access. 8 (2020) 76752–76764.

[465] S. Talatahari, M. Azizi, Chaos Game Optimization: a novel metaheuristic algorithm, Artif. Intell. Rev. 54 (2021) 917–1004.

[466] M.S. Braik, Chameleon Swarm Algorithm: A bio-inspired optimizer for solving engineering design problems, Expert Syst. Appl. 174 (2021) 114685.

[467] M. Azizi, Atomic orbital search: A novel metaheuristic algorithm, Appl. Math. Model. 93 (2021) 657–683.

[468] J.-S. Chou, D.-N. Truong, A novel metaheuristic optimizer inspired by behavior of jellyfish in ocean, Appl. Math. Comput. 389 (2021). https://doi.org/10.1016/j.amc.2020.125535.

[469] Z. Feng, W. Niu, Hybrid artificial neural network and cooperation search algorithm for nonlinear river flow time series forecasting in humid and semi-humid regions, Knowledge-Based Syst. 211 (2021) 106580.

[470] S. Talatahari, M. Azizi, A.H. Gandomi, Material Generation Algorithm: A Novel Metaheuristic Algorithm for Optimization of Engineering Problems, Processes. 9 (2021) 859.

[471] S. Talatahari, M. Azizi, M. Tolouei, B. Talatahari, P. Sareh, Crystal Structure Algorithm (CryStAl): A Metaheuristic Optimization Method, IEEE Access. 9 (2021) 71244–71261.

[472] F.A. Hashim, K. Hussain, E.H. Houssein, M.S. Mabrouk, W. Al-Atabany, Archimedes optimization algorithm: a new metaheuristic algorithm for solving optimization problems, Appl. Intell. (2020). https://doi.org/10.1007/s10489-020-01893-z.

[473] F. Zitouni, S. Harous, A. Belkeram, L.E.B. Hammou, The Archerfish Hunting Optimizer: a novel metaheuristic algorithm for global optimization, ArXiv Prepr. ArXiv2102.02134. (2021).

[474] T. Rahkar Farshi, Battle royale optimization algorithm, Neural Comput. Appl. 33 (2021) 1139–1157.

[475] N. Kumar, N. Singh, D.P. Vidyarthi, Artificial lizard search optimization (ALSO): a novel nature-inspired meta-heuristic algorithm, Soft Comput. 25 (2021) 6179–6201.

[476] F. Zitouni, S. Harous, R. Maamri, A Novel Quantum Firefly Algorithm for Global Optimization, Arab. J. Sci. Eng. (2021) 1–19.

[477] H. Karami, M.V. Anaraki, S. Farzin, S. Mirjalili, Flow Direction Algorithm (FDA): A Novel Optimization Approach for Solving Optimization Problems, Comput. Ind. Eng. 156 (2021) 107224.

[478] J.L.J. Pereira, M.B. Francisco, C.A. Diniz, G.A. Oliver, S.S. Cunha Jr, G.F. Gomes, Lichtenberg algorithm: A novel hybrid physics-based meta-heuristic for global optimization, Expert Syst. Appl. 170 (2021) 114522.

[479] I.M. Abdullahi, M.B. Mu'azu, O.M. Olaniyi, J. Agajo, Pastoralist Optimization Algorithm (POA): A Culture-Inspired Metaheuristic for Uncapacitated Facility Location Problem (UFLP), (2021).

[480] O.N. Oyelade, A.E. Ezugwu, Ebola Optimization Search Algorithm (EOSA): A new metaheuristic algorithm based on the propagation model of Ebola virus disease, ArXiv Prepr. ArXiv2106.01416. (2021).

[481] M. Jafari, E. Salajegheh, J. Salajegheh, Elephant clan optimization: a nature-inspired metaheuristic algorithm for the optimal design of structures, Appl. Soft Comput. 113 (2021) 107892.

[482] W.J. AL-kubaisy, M. Yousif, B. Al-Khateeb, M. Mahmood, D.-N. Le, The Red Colobuses Monkey: A New Nature–Inspired Metaheuristic Optimization Algorithm, Int. J. Comput. Intell. Syst. 14 (2021) 1108–1118.

[483] A. Mohammadi-Balani, M.D. Nayeri, A. Azar, M. Taghizadeh-Yazdi, Golden eagle optimizer: A nature-inspired metaheuristic algorithm, Comput. Ind. Eng. 152 (2021) 107050.

[484] M. Dehghani, Z. Montazeri, Š. Hubálovský, GMBO: Group Mean-Based Optimizer for Solving Various Optimization Problems, Mathematics. 9 (2021) 1190.

[485] A.K. Bairwa, S. Joshi, D. Singh, Dingo Optimizer: A Nature-Inspired Metaheuristic Approach for Engineering Problems, Math. Probl. Eng. 2021 (2021).

[486] M.A. Al-Betar, Z.A.A. Alyasseri, M.A. Awadallah, I.A. Doush, Coronavirus herd immunity optimizer (CHIO), Neural Comput. Appl. 33 (2021) 5011–5042.

[487] D. Połap, M. Woźniak, Red fox optimization algorithm, Expert Syst. Appl. 166 (2021) 114107.

[488] L. Abualigah, A. Diabat, S. Mirjalili, M. Abd Elaziz, A.H. Gandomi, The arithmetic optimization algorithm, Comput. Methods Appl. Mech. Eng. 376 (2021) 113609.

[489] B. Abdollahzadeh, F.S. Gharehchopogh, S. Mirjalili, African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems, Comput. Ind. Eng. 158 (2021) 107408.

[490] B. Abdollahzadeh, F. Soleimanian Gharehchopogh, S. Mirjalili, Artificial gorilla troops optimizer: A new nature-inspired metaheuristic algorithm for global optimization problems, Int. J. Intell. Syst. 36 (2021) 5887–5958.

[491] W. Zhao, L. Wang, S. Mirjalili, Artificial hummingbird algorithm: A new bio-inspired optimizer with its engineering applications, Comput. Methods Appl. Mech. Eng. 388 (2022) 114194.

[492] A. Karpenko, I. Kuzmina, Meta-Heuristic Algorithm for the Global Optimization: Intelligent Ice Fishing Algorithm, in: Inven. Syst. Control, Springer, 2021: pp. 147–160.

[493] S. Suyanto, A.A. Ariyanto, A.F. Ariyanto, Komodo Mlipir Algorithm, Appl. Soft Comput. (2021) 108043.

[494] C. Gao, Z. Hu, W. Tong, Linear prediction evolution algorithm: a simplest evolutionary optimizer, Memetic Comput. 13 (2021) 319–339.

[495] Y. Masoudi-Sobhanzadeh, B. Jafari, S. Parvizpour, M.M. Pourseif, Y. Omidi, A novel multi-objective metaheuristic algorithm for protein-peptide docking and benchmarking on the LEADS-PEP dataset, Comput. Biol. Med. 138 (2021) 104896.

[496] J. Xu, L. Xu, Optimal Stochastic Process Optimizer: A New Metaheuristic Algorithm With Adaptive Exploration-Exploitation Property, IEEE Access. 9 (2021) 108640–108664.

[497] H. Jia, X. Peng, C. Lang, Remora optimization algorithm, Expert Syst. Appl. 185 (2021) 115665.

[498] S.A. Doumari, H. Givi, M. Dehghani, O.P. Malik, Ring Toss Game-Based Optimization Algorithm for Solving Various Optimization Problems, Int. J. Intell. Eng. Syst. 14 (2021) 545–554.

[499] I. Ahmadianfar, A.A. Heidari, A.H. Gandomi, X. Chu, H. Chen, RUN beyond the metaphor: an efficient optimization algorithm based on Runge Kutta method, Expert Syst. Appl. 181 (2021) 115079.

[500] D. Tychalas, H. Karatza, SaMW: a probabilistic meta-heuristic algorithm for job scheduling in heterogeneous distributed systems powered by microservices, Cluster Comput. 24 (2021) 1735–1759.

[501] L. Rodriguez, O. Castillo, M. Garcia, J. Soria, A new meta-heuristic optimization algorithm based on a paradigm from physics: string theory, J. Intell. Fuzzy Syst. 41 (2021) 1657–1675.

[502] H.N. Fakhouri, F. Hamad, A. Alawamrah, Success history intelligent optimizer, J. Supercomput. (2021) 1–42.

[503] A. Layeb, The Tangent Search Algorithm for Solving Optimization Problems, ArXiv Prepr. ArXiv2104.02559. (2021).

[504] L. Xie, T. Han, H. Zhou, Z.-R. Zhang, B. Han, A. Tang, Tuna swarm optimization: a novel swarm-based metaheuristic algorithm for global optimization, Comput. Intell. Neurosci. 2021 (2021).

[505] E. Hosseini, A.S. Sadiq, K.Z. Ghafoor, D.B. Rawat, M. Saif, X. Yang, Volcano eruption algorithm for solving optimization problems, Neural Comput. Appl. 33 (2021) 2321–2337.

[506] D. Sattar, R. Salim, A smart metaheuristic algorithm for solving engineering problems, Eng. Comput. 37 (2021) 2389–2417.

[507] M. Braik, M.H. Ryalat, H. Al-Zoubi, A novel meta-heuristic algorithm for solving numerical optimization problems: Ali Baba and the forty thieves, Neural Comput. Appl. 34 (2022) 409–455.

[508] F.A. Hashim, E.H. Houssein, K. Hussain, M.S. Mabrouk, W. Al-Atabany, Honey Badger Algorithm: New metaheuristic algorithm for solving optimization problems, Math. Comput. Simul. 192 (2022) 84–110.

[509] Y. Jiang, Q. Wu, S. Zhu, L. Zhang, Orca predation algorithm: A novel bio-inspired algorithm for global optimization problems, Expert Syst. Appl. 188 (2022) 116026.

[510] L. Abualigah, M. Abd Elaziz, P. Sumari, Z.W. Geem, A.H. Gandomi, Reptile Search Algorithm (RSA): A nature-inspired meta-heuristic optimizer, Expert Syst. Appl. 191 (2022) 116158.

[511] N.B. Arunekumar, K.S. Joseph, Skip Salp Swam Algorithm for Feature Selection, in: Inf. Commun. Technol. Compet. Strateg. (ICTCS 2020), Springer, 2022: pp. 231–240.