Complex & Intelligent Systems manuscript No.
(will be inserted by the editor)

Supplementary Materials for "Evolutionary Multiobjective Optimization via Efficient Sampling Based Offspring Generation"

Received: date / Accepted: date

1 Parameter Settings for TREE Problems

Six TREE problems exacted from real-world application problems are tested as well. These TREE problems are data-driven LSMOPs with complicated variable interactions. The PSs of TREE problems are irregular compared with the nine LSMOP problems, which reflect the smooth variation of ratio errors over time. The number of decision variables d is set to $\{3000, 6000, 15000\}$ for TREE1$\sim$TREE2 and $\{6000, 12000, 30000\}$ for TREE3$\sim$TREE6. Due to a large number of decision variables, the maximum number of FEs is set to$10\times d$ to obtain acceptable solution sets within bearable computational cost. The maximum number of FEs is relatively small compared to the settings in [1,2,3,4]. Nevertheless, many real-world applications require the solution of an LSMOP with limited computational resources and acceptable time cost. The consumption of FEs for solving LSMOPs close to the consumption for solving conventional MOPs is practical even though the obtained solutions are not converged to the PFs [5].

1.1 Performance on TREE Problems

To further investigate the performance of SLSEA in solving real-world applications, Table 1 shows the statistics of HV results achieved by the five compared large-scale MOEAs on six TREE problems with up to 30000 decision variables. Different from the results on LSMOP problems, LSMOF has achieved the most best results, followed by SLSEA. In contrast, MOEA/DVA and LMOCSO have failed to obtain any feasible solution that Pareto dominates the nadir point.

Meanwhile, the final non-dominated solutions obtained by the five compared algorithms on TREE1 to TREE2 with 15000 decision variables and TREE3 to TREE6 with 30000 decision variables in the run associated with the best HV values are given in Fig. 1. According to the results in Table 1 and this figure, it can be observed that SLSEA has shown competitive performance in comparison with LSMOF, where LSMOF is capable of obtaining solutions around the top left corner in the objective space.

Based on the "No free lunch" theory, the number of iterations affects the performance of optimization algorithms. Thus, no algorithm performs the best in all cases regarding the number of iterations. The compared algorithms are tested on five representative LSMOP test problems with 1000 decision variables to show the impact of computational cost on the performance ranking. The convergence profiles of the compared algorithms in terms of IGD values are given in Fig. 2. Once a large number of FEs is given to the algorithm, the ranks of the compared algorithms may differ from those with a relatively small number of FEs. As can be observed, SLSEA converges fast before 1×10^6 and stagnates around 4×10^6, while LMOCSO converges late and is capable of maintaining good diversity for avoiding stagnation even around 5×10^6. Thus, if a limited number of FEs is given, SLSEA can be used, and LMOCSO is suggested to be used if a large number of FEs is available.

To show the performance difference between the proposed SLSEA and some state-of-the-art large-scale MOEAs, two SOTA algorithms, i.e., FLEA [6] and LMOEA-DS [7], are compared with SLSEA. Statistics of the IGD results achieved by FLEA, LMOEA-DS, and SLSEA on nine LSMOP problems with 1000, 2000, and 5000 decision variables are given in Fig. 3. As can be observed, almost no statistical difference can be observed in most cases, and the proposed SLSEA has shown competitive performance in comparison with the two SOTA algorithms.

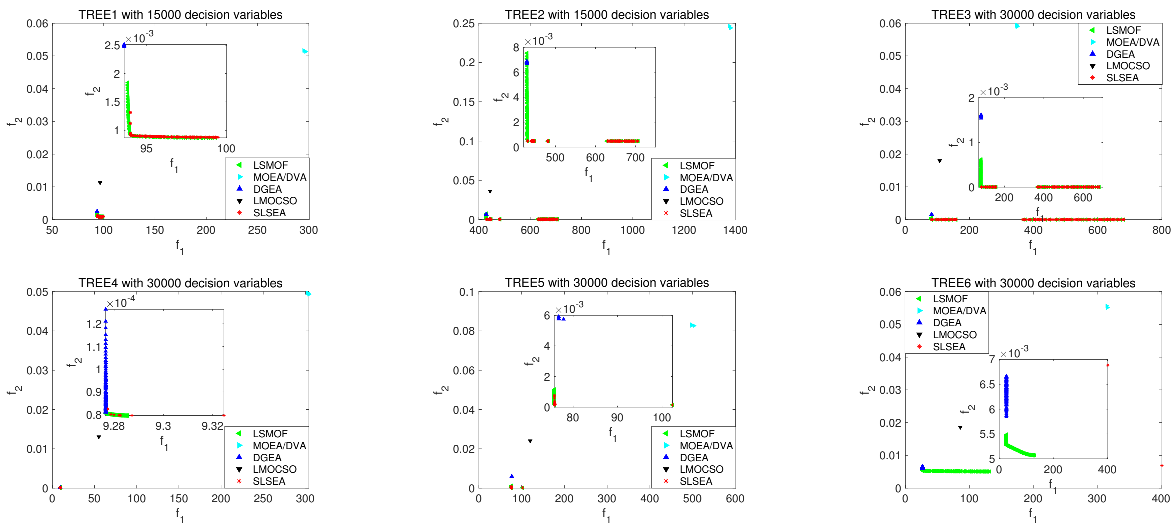

Fig. 1 The non-dominated solutions achieved by the five compared algorithms on TREE1 to LSMOP6 with up to 30000 decision variables in the run associated with the best IGD values.

Table 1 The Statistics of HV Results Achieved by LSMOF, MOEA/DVA, DGEA, LMOCSO and SLSEA on 18 Test Instances. The Best Result in Each Row is Highlighted.

Problem	d	LSMOF	MOEA/DVA	DGEA	LMOCSO	SLSEA
TREE1	1000	**4.53e-3(6.39e-4)**≈	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	4.38e-3(4.62e-5)
	2000	1.26e-3(9.38e-5)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	**1.36e-3(8.98e-5)**
	5000	**3.35e-2(5.02e-4)**+	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	3.25e-2(1.28e-4)
TREE2	1000	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
	2000	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
	5000	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
TREE3	1000	1.11e-2(2.63e-5)≈	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	**1.11e-2(1.22e-5)**
	2000	9.96e-3(4.50e-5)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	**9.98e-3(9.06e-6)**
	5000	5.52e-2(9.86e-3)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	**6.00e-2(3.00e-6)**
TREE4	1000	**3.91e-1(1.58e-4)**+	0.00e+0(0.00e+0)−	5.74e-2(1.14e-1)−	0.00e+0(0.00e+0)−	3.90e-1(2.30e-4)
	2000	**4.27e-1(5.38e-5)**+	0.00e+0(0.00e+0)−	2.03e-2(9.07e-2)−	0.00e+0(0.00e+0)−	4.27e-1(7.31e-5)
	5000	**5.54e-1(6.67e-5)**+	0.00e+0(0.00e+0)−	7.79e-2(1.91e-1)−	0.00e+0(0.00e+0)−	5.54e-1(2.28e-4)
TREE5	1000	**2.87e-1(1.73e-4)**+	0.00e+0(0.00e+0)−	3.30e-2(8.67e-2)−	0.00e+0(0.00e+0)−	2.86e-1(3.35e-4)
	2000	**2.66e-1(5.10e-6)**+	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	2.66e-1(1.46e-4)
	5000	**2.48e-1(4.46e-5)**+	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	0.00e+0(0.00e+0)−	2.48e-1(1.29e-4)
TREE6	1000	**1.10e-1(5.12e-3)**+	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
	2000	**1.10e-1(5.46e-3)**+	0.00e+0(0.00e+0)≈	2.63e-3(1.18e-2)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
	5000	**1.09e-1(6.58e-3)**+	0.00e+0(0.00e+0)≈	1.35e-3(6.02e-3)≈	0.00e+0(0.00e+0)≈	0.00e+0(0.00e+0)
+/−/≈		10/3/5	0/12/6	0/12/6	0/12/6	

'+', '−' and '≈' indicate that the result is significantly better, significantly worse and statistically similar to that obtained by SLSEA, respectively.

References

1. Tian Y, Zheng X, Zhang X, Jin Y (2020) Efficient large-scale multiobjective optimization based on a competitive swarm optimizer. IEEE Transactions on Cybernetics 50(8):3696–3708
2. Zhang X, Tian Y, Jin Y, Cheng R (2016) A decision variable clustering-based evolutionary algorithm for large-scale many-objective optimization. IEEE Transactions on Evolutionary Computation 22:97–112
3. Chen H, Cheng R, Wen J, Li H, Weng J (2020) Solving large-scale many-objective optimization problems by covariance matrix adaptation evolution strategy with scalable small subpopulations. Information Sciences 509:457–469
4. Hong W, Tang K, Zhou A, Ishibuchi H, Yao X (2018) A scalable indicator-based evolutionary algorithm for large-scale multiobjective optimization. IEEE Transactions on Evolutionary Computation 23(3):525–537
5. He C, Cheng R, Zhang C, Tian Y, Chen Q, Yao X (2020) Evolutionary large-scale multiobjective optimization for ratio error estimation of voltage transformers. IEEE Transactions on Evolutionary Computation 24(5):868–881
6. Li L, He C, Cheng R, Li H, Pan L, Jin Y (2022) A fast sampling based evolutionary algorithm for million-dimensional multiobjective optimization. Swarm and Evolutionary Computation 75:101181
7. Qin S, Sun C, Jin Y, Tan Y, Fieldsend J (2021) Large-scale evolutionary multiobjective optimization assisted by directed sampling. IEEE Transactions on Evolutionary Computation 25(4):724–738

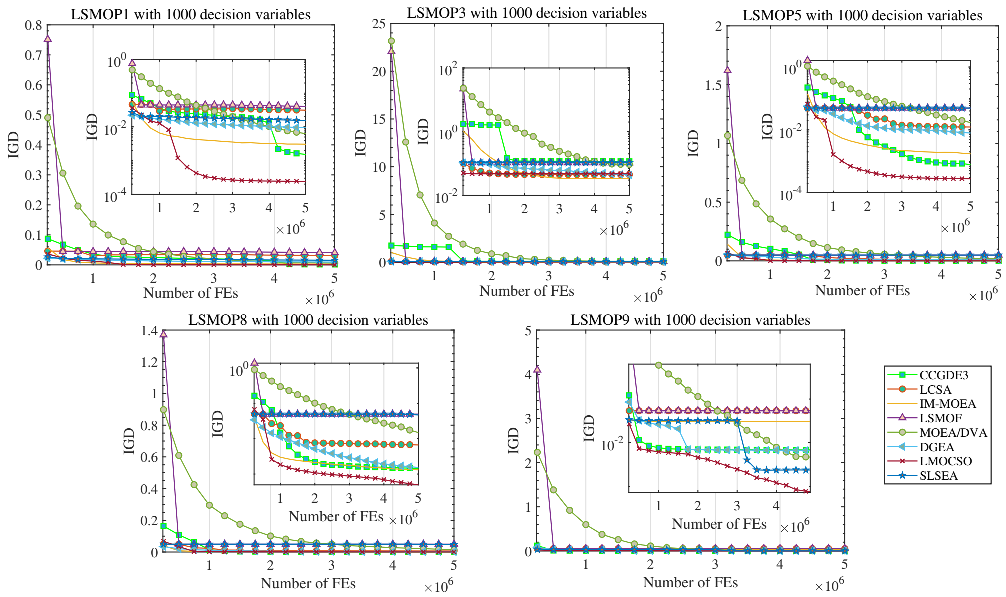

Fig. 2 Convergence profiles of eight compared large-scale MOEAs on five representative LSMOP problems with 1000 decision variables in terms of IGD values. The maximum number of FEs is set to 5×10^6. The subplots show the IGD values in the logarithmic scale.

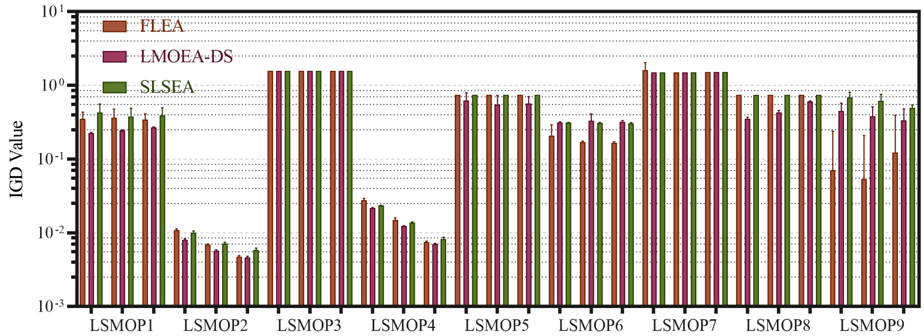

Fig. 3 Statistics of the IGD results achieved by FLEA, LMOEA-DS, and SLSEA on nine LSMOP problems with 1000, 2000, and 5000 decision variables.