Supplementary material

A Multi-Stage Expensive Constrained Multi-Objective Optimization Algorithm Based on Ensemble Infill Criterion

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I. Related Work and Preliminaries

Fig. S1 shows the general framework of the first category of SAEA [1], [2]. In each iteration, the surrogate model is updated. Then, the evolutionary algorithm is used to optimize the infill criterion or acquisition function constructed by the model to find the next solutions to be sampled. Finally, these solutions are evaluated using the expensive objective and constraint functions, and the new data is obtained. The algorithm stops when the predefined maximum number of objective evaluations is reached.

II. Proposed Algorithm

A. Comparison of Optimizers

In $Stage1$ and $Stage2$, we mathematically express the optimization problems as (12) and (13), solving them using NSGA-III. In $Stage3$, we address the optimization problem formulated in (15) with NSGA-III-CDP. Although NSGA-II and NSGA-II-CDP could similarly tackle multi-objective optimization problems, NSGA-III and NSGA-III-CDP exhibit greater advantages when dealing with many-objective optimization problems. To verify this viewpoint in EIC-MSSAEA, we have replaced the optimizers corresponding to $Stage1$, $Stage2$, and $Stage3$ with NSGA-II and NSGA-II-CDP, forming a modified EIC-MSSAEA(NSGA-II). We have applied EIC-MSSAEA (NSGA-II) and EIC-MSSAEA to 2, 3, and 5-objective optimization problems to analyze the impact of the optimizer. Refer to Section IV-A in this paper for the parameter settings of the experiment.

TABLE SI
IGD Values Obtained by EIC-MSSAEA(NSGA-II) and EIC-MSSAEA on LIRCMOP Test Suite.

Problem	M/D	EIC-MSSAEA(NSGA-II)	EIC-MSSAEA
LIRCMOP1	2/10	1.8445e-1 (1.12e-1) =	2.2246e-1 (1.66e-1)
LIRCMOP2	2 /10	2.2628e-1 (1.52e-1) =	1.9448e-1 (1.10e-1)
LIRCMOP3	2 /10	2.2106e-1 (1.13e-1) =	2.4271e-1 (1.49e-1)
LIRCMOP4	2 /10	2.4304e-1 (1.92e-1) =	2.2224e-1 (1.60e-1)
LIRCMOP5	2 /10	5.8781e-2 (2.29e-2) =	5.5751e-2 (1.33e-2)
LIRCMOP6	2/10	5.5096e-2 (1.84e-2) =	5.0099e-2 (1.18e-2)
LIRCMOP7	2/10	1.0961e-1 (3.08e-2) =	1.0509e-1 (3.45e-2)
LIRCMOP8	2 /10	9.2183e-2 (4.42e-2) =	9.2308e-2 (5.13e-2)
LIRCMOP9	2 /10	2.0319e-1 (1.08e-1) =	2.0538e-1 (9.25e-2)
LIRCMOP10	2 /10	7.1623e-2 (4.17e-2) =	5.1161e-2 (4.64e-2)
LIRCMOP11	2 /10	2.0805e-1 (1.48e-1) =	2.0073e-1 (1.28e-1)
LIRCMOP12	2 /10	2.0254e-1 (9.20e-2) =	2.0907e-1 (5.01e-2)
LIRCMOP13	3 /10	1.2206e-1 (3.51e-2) -	9.0673e-2 (7.55e-3)
LIRCMOP14	3 /10	1.3519e-1 (1.15e-2) -	1.1661e-1 (1.00e-2)
+/-/≈		0/2/12	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively. The gray background represents the best result for each test instance.

Table SI showcases the IGD results of EIC-MSSAEA(NSGA-II) and EIC-MSSAEA on the LIRCMOP. Although NSGA-II is primarily tailored for 2 or 3 objective optimization problems, NSGA-III still outperforms NSGA-II, particularly noticeable in cases like LIRCMOP13 and LIRCMOP14. As shown in Table SII, the IGD results of EIC-MSSAEA compared to EIC-MSSAEA(NSGA-II) are displayed for the C-DTLZ test suite with 3 and 5 objectives. EIC-MSSAEA prevails over EIC-MSSAEA(NSGA-II) in 3 out of 14 test scenarios, while no test cases exhibit inferior results for EIC-MSSAEA(NSGA-II). To further scrutinize the optimization prowess of NSGA-III with many objectives, we assessed the performance of $Stage1$ (EIC-S1) of EIC-MSSAEA on unconstrained expensive many-objective

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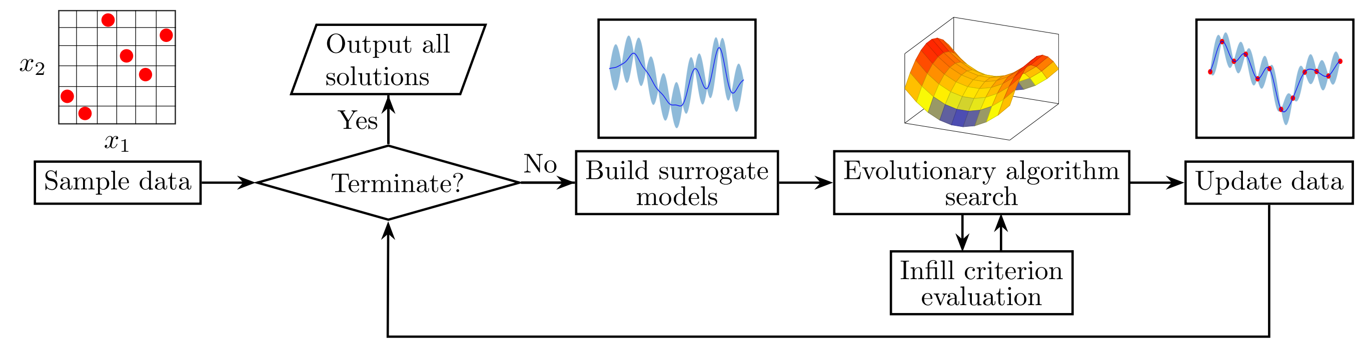


Fig. S1. The framework of the first type of SAEAs.

TABLE SII
IGD VALUES OBTAINED BY EIC-MSSAEA(NSGA-II) AND EIC-MSSAEA ON C-DTLZ TEST SUITE.

Problem	M/D	EIC-MSSAEA(NSGA-II)	EIC-MSSAEA
C1-DTLZ3	3/10	1.3465e+1 (3.47e+0) =	1.2240e+1 (2.58e+0)
	5/10	1.4676e+1 (1.81e+0) =	1.3943e+1 (1.65e+0)
C2-DTLZ2	3/10	4.8965e-2 (1.84e-2) =	5.2308e-2 (3.08e-2)
	5 /10	2.1515e-1 (2.91e-2) -	1.9057e-1 (3.02e-2)
C3-DTLZ4	3 /10	3.3871e-1 (7.77e-2) =	3.2178e-1 (8.86e-2)
	5 /10	4.8851e-1 (4.92e-2) =	4.8255e-1 (3.66e-2)
DC1-DTLZ1	3 /10	4.7730e+1 (9.53e+0) -	3.6999e+1 (1.07e+1)
	5 /10	4.4494e+1 (1.38e+1) =	4.1177e+1 (1.70e+1)
DC1-DTLZ3	3 /10	1.3697e+1 (3.69e+0) =	1.2771e+1 (2.33e+0)
	5 /10	1.3477e+1 (3.78e+0) -	1.1727e+1 (4.29e+0)
DC3-DTLZ1	3 / 10	5.6687e+1 (2.30e+1) =	5.1704e+1 (2.01e+1)
	5 /10	3.8179e+1 (1.85e+1) =	3.6196e+1 (2.18e+1)
DC3-DTLZ3	3 /10	1.5493e+1 (5.79e+0) =	1.3349e+1 (3.93e+0)
	5 /10	1.3092e+1 (6.19e+0) =	1.0637e+1 (3.80e+0)
+/-/≈		0/3/11	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively. The gray background represents the best result for each test instance.

TABLE SIII
IGD VALUES OBTAINED BY EIC-S1(NSGA-II) AND EIC-S1 ON DTLZ AND WFG TEST SUITES.

Problem	M/D	EIC-S1(NSGA-II)	EIC-S1
DTLZ1	5 / 10	6.2533e+1 (1.30e+1) -	5.0442e+1 (1.02e+1)
DTLZ2	5 / 10	3.8863e-1 (2.79e-2) -	2.4296e-1 (1.91e-2)
DTLZ3	5 / 10	1.9201e+2 (3.45e+1) -	1.3070e+2 (3.29e+1)
DTLZ4	5 / 10	5.6981e-1 (7.91e-2) -	4.8614e-1 (7.83e-2)
DTLZ5	5 / 10	4.8783e-2 (1.46e-2) -	3.7969e-2 (2.18e-2)
DTLZ6	5 / 10	3.7673e+0 (3.97e-1) -	2.6867e+0 (2.98e-1)
DTLZ7	5 / 10	3.7844e-1 (2.31e-2) -	3.1773e-1 (1.46e-2)
WFG1	5 / 10	2.2167e+0 (8.11e-2) =	2.2108e+0 (6.58e-2)
WFG2	5 / 10	6.8945e-1 (3.56e-2) -	5.2169e-1 (4.16e-2)
WFG3	5 / 10	8.0044e-1 (1.09e-1) -	6.9770e-1 (1.40e-1)
WFG4	5 / 10	1.2078e+0 (3.88e-2) =	1.2117e+0 (3.59e-2)
WFG5	5 / 10	1.2485e+0 (4.30e-2) =	1.2307e+0 (5.70e-2)
WFG6	5 / 10	1.4372e+0 (5.08e-2) -	1.3530e+0 (5.93e-2)
WFG8	5 / 10	1.5575e+0 (2.57e-2) -	1.4610e+0 (4.99e-2)
WFG7	5 / 10	1.3137e+0 (4.28e-2) -	1.2351e+0 (4.79e-2)
WFG9	5 / 10	1.5282e+0 (8.70e-2) =	1.5511e+0 (1.32e-1)
+/-/≈		0/12/4	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-S1, respectively. The gray background represents the best result for each test instance.

optimization problems. In this evaluation, NSGA-III is replaced by NSGA-II, named EIC-S1(NSGA-II). As outlined in Table SIII, the findings reveal that EIC-S1 outperforms EIC-S1(NSGA-II) in 12 out of 16 test cases. The rationale for employing NSGA-III and NSGA-III-CDP as optimizers is well-founded, evident from the empirical results.

B. Empirical Analysis of Ensemble Infill Criterion Serial and Parallel Methods

EIC can select three potential solutions to be evaluated in each round. These selections can be made either in a serial or parallel manner. The serial method has been elucidated in the main text. In contrast, the parallel approach, referred to as EIC(parallel)-MSSAEA, involves using each infill criterion member in EIC to select a potential solution simultaneously. The experimental results of IGD values are shown in Table SIV. The experimental results indicate that EIC-MSSAEA performs at least as well as EIC(parallel)-MSSAEA on the LIRCMOP test suite, with no instances of test examples performing worse. Moreover, on LIRCMOP13 and LIRCMOP14, EIC-MSSAEA outperforms EIC (parallel)-MSSAEA. Notably, EIC-MSSAEA exhibits significant improvements over EIC(parallel)-MSSAEA, especially on MW1, where convergence is achieved even under conditions of limited function evaluations. This improvement can be attributed to the ability of the serial method to filter out similar solutions, enhancing solution diversity and overall performance.

TABLE SIV
IGD VALUES OBTAINED BY EIC-MSSAEA(PARALLEL) AND EIC-MSSAEA.

Problem	M/D	EIC-MSSAEA(parallel)	EIC-MSSAEA
LIRCMOP1	2 /10	2.3042e-1 (1.73e-1) =	2.2246e-1 (1.66e-1)
LIRCMOP2	2 /10	2.1050e-1 (1.66e-1) =	1.9448e-1 (1.10e-1)
LIRCMOP3	2 / 10	2.5019e-1 (1.62e-1) =	2.4271e-1 (1.49e-1)
LIRCMOP4	2 / 10	2.6643e-1 (1.72e-1) =	2.2224e-1 (1.60e-1)
LIRCMOP5	2 / 10	5.8840e-2 (2.11e-2) =	5.5751e-2 (1.33e-2)
LIRCMOP6	2 / 10	4.4629e-2 (5.92e-3) =	5.0099e-2 (1.18e-2)
LIRCMOP7	2 / 10	1.0233e-1 (3.75e-2) =	1.0509e-1 (3.45e-2)
LIRCMOP8	2 / 10	9.4040e-2 (7.02e-2) =	9.2308e-2 (5.13e-2)
LIRCMOP9	2 / 10	1.8816e-1 (8.53e-2) =	2.0538e-1 (9.25e-2)
LIRCMOP10	2 / 10	5.8199e-2 (3.21e-2) =	5.1161e-2 (4.64e-2)
LIRCMOP11	2 / 10	1.4995e-1 (7.18e-2) =	2.0073e-1 (1.28e-1)
LIRCMOP12	2 / 10	2.2885e-1 (7.09e-2) =	2.0907e-1 (5.01e-2)
LIRCMOP13	3 / 10	1.0231e-1 (2.94e-2) -	9.0673e-2 (7.55e-3)
LIRCMOP14	3 / 10	1.2445e-1 (9.20e-3) -	1.1661e-1 (1.00e-2)
MW1	2 / 10	2.8030e-1 (2.62e-1) -	1.7636e-1 (2.11e-1)
+/-/≈		0/3/12	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively. The gray background represents the best result for each test instance.

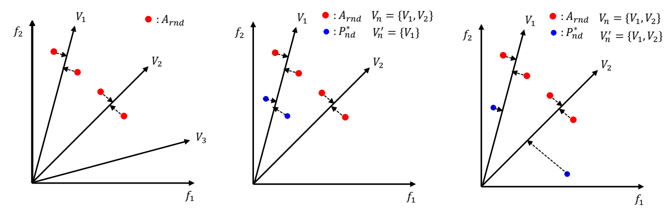
C. Ensemble Infill Criterion

For $V'_n \in V_n$, we make the following explanation, let us consider a multi-objective optimization problem. First, we associate the solutions in A_{rnd} with the reference vector $V = \{V_1, V_2, V_3\}$ based on their vertical distance from the reference vector. As shown in Fig. S2(a), the non-empty reference vectors $V_n = \{V_1, V_2\}$ indicate that there are solutions associated with these reference vectors. A reference vector is called empty reference if no solution is assigned to this vector, e.g., V_3. Next, we associate the solutions in P^*_{nd} with V_n and the resulting non-empty reference vectors, denoted by V'_n. In Fig. S2(b), depending on the vertical distance of the solution to the reference vector, multiple solutions may be associated to the same reference vector, resulting in the count of V'_n being less than V_n. Another scenario is shown in Fig. S2(c), where each solution in P^*_{nd} is separately associated with a different reference vector, making the number of V'_n equal to V_n.

III. EXPERIMENTAL STUDIES

A. Experimental Setting

Moreover, MultiObjectiveEGO employs the proposed selection function to scalarize multiple objectives. A genetic algorithm (GA) is utilized to optimize the EI criterion, with the maximum FEs set to 100 * 10D. In MultiObjectiveEGO, GP is constructed using 0.7 times the current data. In EIM-PoF, the EI criterion is optimized using a GA, with a maximum evaluation frequency of 10,000. In USeMOC, multi-objective acquisition functions



(a) (b) (c)

Fig. S2. An illustration of why the reference vector associated with the candidate solutions in P^*_{nd} may be different from the reference vector associated with the solutions in A_{rnd}.

are optimized using the NSGA-II-CDP, with 2,500 FEs. In HSMEA, local search is conducted using the interior point method, with a maximum FE of 1,000. If no feasible solution is obtained from two consecutive local searches, the solution with the minimum constraint violation value is selected for expensive FE. In NSGA-III-EHVI, NSGA-III optimizes the objective function approximated by the surrogate model to obtain a potential population. 300 FEs are consumed to obtain a potential population, and the best solution is selected using the EHVI. The importance sampling method calculates EHVI with a sample size of 10,000. In ASA-MOEA/D, to reduce the misprediction of the feasibility of candidate solutions caused by the constraint surrogate model error, the error bound in the feasible region driven local search strategy is set to 1e-3, which is used to appropriately narrow the predicted feasible region. Two search modes are included in KTS, which are adaptively switched according to the correlation coefficient ρ between the objective and the constraint violation values of the already evaluated solutions, where $\rho \in [-0.2, 0.6]$.

B. Sensitivity Analysis of τ_1, τ_2, T_r

To analyze the sensitivity of these newly introduced parameters in EIC-MSSAEA, we conducted experiments on LIRCMOP1 and LIRCMOP12. LIRCMOP1 has a tiny feasible region, while LIRCMOP12 has significant infeasible obstacles and a discontinuous CPF. These two testing problems pose challenges in finding a complete CPF. Hence, we select them as test examples.

Setting τ_1 too small can make the effect of $Stage1$ less noticeable while setting it too large can lead to wasted FEs and a degradation in algorithm performance. To find a suitable value for τ_1, we conducted experiments on LIRCMOP12 using the test set $\tau_1 \in \{0.40, 0.45, 0.50, 0.55, 0.60, 0.65, 0.70\}$, with $\tau_2 = 0.8$ and $T_r = 10$. Fig. S3 presents the results of 20 experiments. It can be seen that EIC-MSSAEA achieved the best results when τ_1 = 0.55 and the second-best result when τ_1 = 0.5. Considering the ECMOP with smaller infeasible obstacles requiring a reduction in $Stage1$ optimization, we set τ_1 = 0.5 as a universal setting for all test suites.

$Stage2$ aims to explore more feasible regions and improve the diversity performance of solutions. If τ_2 is set too small, $Stage2$ will not be practical; otherwise, it will affect the feasibility ratio. Therefore, after determining

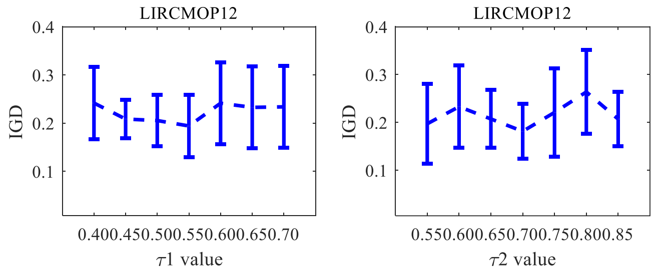


Fig. S3. Sensitivity analysis of τ_1, τ_2.

τ_1, we varied the parameter τ_2 to assess its impact. We tested different $\tau_2 \in \{0.55, 0.60, 0.65, 0.70, 0.75, 0.80\}$ when $\tau_1 = 0.5$ and $T_r = 10$. As shown in Fig. S3, the experimental results indicate that EIC-MSSAEA has achieved its best performance when $\tau_2 = 0.7$.

Finally, to save FEs on $Stage1$ and $Stage2$ when solving problems far from CPF and UPF, we allocate as few resources as possible to determine if FEs should be given to $Stage1$ and $Stage2$. Hence, we set $T_r \in \{6, 8, 10, 12, 14, 16\}$ with $t_1 = 0.5$ and $t_2 = 0.7$, the experimental results are shown in Fig. S4, where EIC-MSSAEA achieved good performance when $T_r = 8$. Therefore, it is reasonable to set $T_r = 8$.

C. Effect of Ensemble Infill Criterion

Table SV, Table SVI, Table SVII, Table SVIII and Table SIX show the median and standard deviation of the GD, PD, FR, IGD and CPU time results obtained by EICp11, EICp21, EICp31, EICp12, EICp22 and EICp32 on the LIR-CMOP benchmark suite, respectively.

D. Comparisons with Peers on Expensive Constrained Multi-Objective Optimization Problems

Table SX summarizes the comparison results of EIC-MSSAEA and USeMOC, HSMEA, EIM-PoF, MultiObjectiveEGO for HV on LIRCMOP and MW. Fig. S5 depicts the distribution of the solutions obtained by all algorithms on MW13, based on the minimum IGD.

Table SXI presents the IGD statistical results for EIC-MSSAEA and other state-of-the-art algorithms applied to the C-DTLZ test suite. Fig. S6 depicts the distribution of the solutions obtained by all algorithms on C2-DTLZ2, based on the minimum IGD.

E. A Real-World Case Study

When ASPEN HYSYS simulation software simulates complex chemical processes, such as an oil refinery distillation column, it must consider a series of ordinary differential equations, including the conservation of matter and energy at each distillation column. These equations often describe reaction kinetics, thermodynamic equilibria, and fluid flow. They are highly coupled, resulting in the need to perform many iterative calculations to find parameters that satisfy all of the established process conditions and performance criteria. The evaluation time of a solution will vary according to the complexity of the chemical process, and it takes about ten minutes in our experiment.

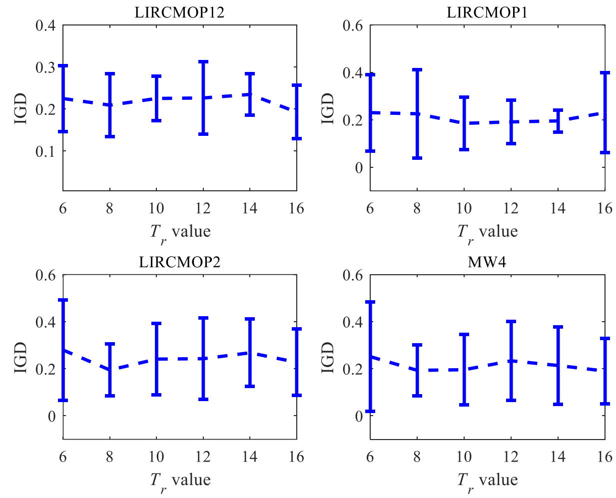


Fig. S4. Sensitivity analysis of T_r.

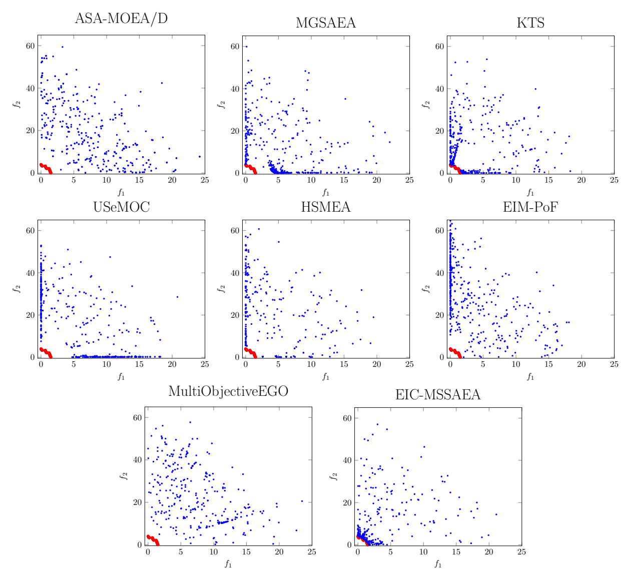


Fig. S5. In 20 experiments, the distribution of solutions corresponding to the minimum value of IGD obtained by ASA-MOEA/D, MGSAEA, KTS, USeMOC, HSMEA, EIM-PoF, MultiObjectiveEGO, and EIC-MSSAEA on MW13.

The detailed mathematical description is as follows:

$$\begin{aligned} &\min_{\boldsymbol{x}\in\Omega} \ (f_1(\boldsymbol{x}), ..., f_2(\boldsymbol{x})) \\ &s.t. \ \ T_{95i} - T^u_{95i} \leq 0, i \in \{1,2,3,4\}, \\ &\qquad -T_{95i} + T^l_{95i} \leq 0, i \in \{1,2,3,4\}, \end{aligned} \tag{1}$$

where

$$f_1(\boldsymbol{x}) = -\sum_{i=1}^{4} P_i F_i - P_s \sum_{j=1}^{3} F_{s_j} - P_c F_c, \tag{2}$$

$$f_2(\boldsymbol{x}) = P_f \cdot gcc(F, Q, F_p, T) + P_{cw} \cdot gcc(F, Q, F_p, T). \tag{3}$$

The meaning of variables is shown in Table SXII. Table SXIII shows the HV results obtained by the seven compared algorithms, including the mean and standard

TABLE SV
THE GD VALUES OBTAINED BY EICP11, EICP21, EICP31, EICP12, EICP22, AND EICP32 ON LIRCMOP TEST SUITE.

Problem	EICp11	EICp21	EICp31	EICp12	EICp22	EICp32
LIRCMOP1	1.9354e-3 (2.69e-3)	1.7614e-3 (2.58e-3)	1.9509e-3 (6.55e-4)	2.0576e-3 (1.53e-3)	5.9896e-4 (1.44e-3)	1.9921e-3 (1.13e-3)
LIRCMOP2	2.7083e-3 (2.95e-3)	2.0433e-3 (1.14e-3)	2.6413e-3 (1.60e-3)	2.9129e-3 (2.65e-3) =	1.0475e-3 (1.10e-3)	2.0167e-3 (1.23e-3)
LIRCMOP3	7.7303e-4 (6.25e-4)	1.2569e-3 (9.98e-4)	2.8980e-3 (1.71e-3)	2.1982e-3 (2.79e-3)	8.8181e-4 (2.16e-3)	2.7600e-3 (1.28e-3)
LIRCMOP4	1.7078e-3 (1.49e-3)	2.5585e-4 (1.17e-4)	2.8213e-3 (2.53e-3)	1.6073e-3 (1.32e-3) +	4.2371e-4 (6.40e-4)	2.7149e-3 (1.48e-3)
LIRCMOP5	2.4640e-2 (4.99e-2)	1.0353e-4 (1.74e-4)	3.9153e-2 (2.86e-2)	1.6472e-1 (1.28e-1) -	1.6999e-3 (4.46e-3)	2.3149e-2 (2.64e-2)
LIRCMOP6	7.9680e-2 (1.69e-1)	1.6184e-4 (1.89e-4)	3.8908e-2 (9.91e-2)	2.7960e-1 (3.70e-1) -	1.8969e-2 (3.44e-2)	5.6639e-2 (1.07e-1)
LIRCMOP7	3.2456e-1 (7.40e-1)	1.4087e-1 (2.64e-1)	6.7173e-2 (8.56e-2)	4.9113e-1 (3.59e-1)	2.7955e-3 (4.81e-3)	4.1163e-2 (6.97e-2)
LIRCMOP8	1.0445e-1 (1.60e-1)	6.0523e-2 (1.14e-1)	5.8061e-2 (7.58e-2)	5.3342e-1 (3.43e-1)	3.8950e-2 (7.62e-2)	3.9461e-2 (6.05e-2)
LIRCMOP9	2.2605e+0 (1.67e+0)	1.6424e-1 (2.13e-1)	4.2493e-1 (5.73e-1)	1.2618e-1 (1.00e-1)	5.7169e-3 (7.60e-3)	2.2186e-1 (4.25e-1)
LIRCMOP10	2.0944e+0 (2.68e+0)	2.3766e-3 (1.14e-3)	1.3477e-1 (1.45e-1)	2.2925e-2 (3.81e-2)	2.3815e-3 (2.03e-3)	1.3381e-1 (1.89e-1)
LIRCMOP11	2.2523e+0 (1.92e+0)	4.3197e-1 (5.36e-1)	1.2023e+0 (8.49e-1)	1.4079e-1 (1.53e-1)	3.7943e-2 (4.27e-2)	5.4534e-1 (6.26e-1)
LIRCMOP12	3.5973e+0 (2.00e+0)	1.6037e+0 (1.49e+0)	1.1431e+0 (1.71e+0)	2.6967e-1 (2.52e-1)	6.1585e-2 (8.12e-2)	6.0616e-1 (1.14e+0)
LIRCMOP13	6.0682e-1 (2.06e-1)	9.9622e-3 (9.56e-3)	1.8693e-2 (4.63e-2)	3.3121e-1 (1.14e-1)	1.9180e-1 (1.82e-1)	1.1708e-2 (1.01e-2)
LIRCMOP14	5.0977e-1 (2.23e-1)	2.0570e-2 (2.22e-2)	2.1537e-2 (2.81e-2)	3.2977e-1 (1.25e-1)	1.6594e-1 (1.30e-1)	2.3666e-2 (2.50e-2)
Average Rank	2.6429	1.2857	2.0714	2.5714	1.1429	2.2857

The gray background represents the best result for each test instance. The second to fourth columns show the comparative results between EICp11, EICp21 and EICp31. The fifth to last columns show the comparisons between EICp12, EICp22, and EICp32.

TABLE SVI
THE PD VALUES OBTAINED BY EICP11, EICP21, EICP31, EICP12, EICP22, AND EICP32 ON LIRCMOP TEST SUITE.

Problem	EICp11	EICp21	EICp31	EICp12	EICp22	EICp32
LIRCMOP1	7.3995e+3 (3.12e+2)	7.6177e+3 (3.60e+2)	8.3301e+3 (4.57e+2)	8.3509e+3 (9.46e+2)	7.9113e+3 (9.43e+2)	8.8364e+3 (1.07e+3)
LIRCMOP2	6.5630e+3 (5.38e+2)	6.4892e+3 (3.26e+2)	7.4907e+3 (4.68e+2)	7.4529e+3 (5.80e+2)	7.0220e+3 (5.69e+2)	7.5436e+3 (7.49e+2)
LIRCMOP3	6.4598e+3 (3.43e+2)	6.4761e+3 (3.78e+2)	7.2894e+3 (7.16e+2)	7.3342e+3 (9.24e+2)	7.1109e+3 (1.03e+3)	8.1218e+3 (1.20e+3)
LIRCMOP4	6.6305e+3 (4.49e+2)	6.4655e+3 (4.52e+2)	7.3775e+3 (6.57e+2)	7.2594e+3 (6.06e+2)	7.1130e+3 (7.37e+2)	8.0374e+3 (1.13e+3)
LIRCMOP5	5.9068e+4 (3.46e+3)	5.9937e+4 (4.01e+3)	5.8113e+4 (4.06e+3)	5.8294e+4 (3.06e+3)	5.6932e+4 (2.98e+3)	5.7865e+4 (3.28e+3)
LIRCMOP6	5.8716e+4 (4.12e+3)	5.8625e+4 (5.26e+3)	5.9291e+4 (3.94e+3)	5.8010e+4 (4.59e+3)	5.8215e+4 (3.72e+3)	5.9924e+4 (3.24e+3)
LIRCMOP7	5.9555e+4 (3.47e+3)	5.8122e+4 (3.95e+3)	5.8350e+4 (4.04e+3)	5.7955e+4 (4.03e+3)	5.7507e+4 (3.59e+3)	5.8955e+4 (3.76e+3)
LIRCMOP8	5.9725e+4 (4.10e+3)	5.8179e+4 (4.19e+3)	6.0089e+4 (4.16e+3)	6.0453e+4 (3.79e+3)	5.8544e+4 (3.37e+3)	5.8737e+4 (3.19e+3)
LIRCMOP9	5.5680e+4 (3.34e+3)	6.4610e+4 (3.29e+3)	6.2851e+4 (3.09e+3)	5.2164e+4 (2.98e+3)	5.8955e+4 (3.53e+3)	6.1814e+4 (3.57e+3)
LIRCMOP10	4.1010e+4 (2.26e+3)	4.4166e+4 (2.56e+3)	4.3998e+4 (2.38e+3)	4.0553e+4 (3.58e+3)	4.3918e+4 (1.91e+3) =	4.4543e+4 (2.14e+3)
LIRCMOP11	3.9633e+4 (2.26e+3)	4.5151e+4 (2.31e+3)	4.5060e+4 (1.67e+3)	3.8907e+4 (3.25e+3)	4.2164e+4 (2.12e+3)	4.4158e+4 (1.64e+3)
LIRCMOP12	5.5392e+4 (3.39e+3)	6.3081e+4 (3.46e+3)	6.3646e+4 (2.63e+3)	5.2132e+4 (3.04e+3)	5.8956e+4 (3.34e+3)	6.1552e+4 (2.29e+3)
LIRCMOP13	2.3256e+6 (1.60e+5)	2.5211e+6 (1.41e+5)	2.7035e+6 (8.39e+4)	2.3382e+6 (1.37e+5)	2.4864e+6 (1.32e+5)	2.6635e+6 (9.81e+4)
LIRCMOP14	2.2714e+6 (1.56e+5)	2.4735e+6 (1.14e+5)	2.6322e+6 (9.36e+4)	2.3760e+6 (1.71e+5)	2.4416e+6 (2.18e+5)	2.6522e+6 (1.21e+5)
Average Rank	2.5000	2.0714	1.4286	2.3571	2.5000	1.1429

The gray background represents the best result for each test instance. The second to fourth columns show the comparative results between EICp11, EICp21 and EICp31. The fifth to last columns show the comparisons between EICp12, EICp22, and EICp32.

deviation, on the problem of optimizing the operating parameters of a crude oil distillation unit. As shown in Table SXIII, our algorithm achieves relatively good performance. In Fig. S7, we draw box plots of their HV values for the algorithms that can find a feasible solution. In addition, as shown in Fig. S8, we plot the distribution of feasible non-dominated solutions corresponding to the best HV value obtained by each algorithm. In Fig. S8, KTS, USeMOC, EIM-PoF, MultiObjectiveEGO, and EIC-MSSAEA obtain 5, 25, 10, and 37 feasible nondominated solutions, respectively, and the convergence of feasible nondominated solutions obtained by our algorithm is better than other algorithms.

F. Discussion

In terms of the mechanics of the algorithm, in GP-assisted multi-stage search, GPs guide evolutionary algorithms, such as NSGA-III and NSGA-III-CDP, to explore the feasible region where the global optimum is located. Notably, constraints are disregarded in $Stage1$, allowing for rapid convergence towards promising regions. Subsequently, in $Stage2$ and $Stage3$, we focus on identifying potential populations based on feasibility and non-dominance of solutions. In $Stage2$ and $Stage3$, the populations are evaluated using an ensemble infill cri-

TABLE SVII
THE FR VALUES OBTAINED BY EICP11, EICP21, EICP31, EICP12, EICP22, AND EICP32 ON LIRCMOP TEST SUITE.

Problem	EICp11	EICp12	EICp13	EICp12	EICp22	EICp22
LIRCMOP1	5.7804e-2 (6.83e-2)	6.0295e-2 (6.92e-2)	4.9944e-2 (4.07e-2)	3.1578e-2 (3.40e-2)	7.9601e-2 (6.82e-2)	6.4499e-2 (4.82e-2)
LIRCMOP2	2.0956e-2 (3.31e-2)	1.9812e-2 (3.52e-2)	2.4354e-2 (2.06e-2)	1.7608e-2 (2.64e-2)	5.4558e-2 (6.55e-2)	5.4801e-2 (3.98e-2)
LIRCMOP3	4.4310e-2 (4.91e-2)	1.3951e-2 (3.17e-2)	3.4213e-2 (4.71e-2)	4.5145e-2 (6.40e-2)	7.3421e-2 (7.88e-2)	4.8224e-2 (5.90e-2)
LIRCMOP4	1.7986e-2 (3.90e-2)	3.2085e-2 (5.35e-2)	3.4699e-2 (5.44e-2)	4.3571e-2 (4.28e-2)	5.9231e-2 (6.51e-2)	5.3444e-2 (7.72e-2)
LIRCMOP5	9.5934e-1 (3.92e-2)	9.7068e-1 (1.44e-2)	7.4995e-1 (3.02e-2)	8.6037e-1 (6.10e-2)	9.0205e-1 (7.63e-2)	7.6327e-1 (3.64e-2)
LIRCMOP6	9.6965e-1 (1.79e-2)	9.6412e-1 (1.02e-2)	7.4104e-1 (6.73e-2)	8.5781e-1 (7.18e-2)	8.7473e-1 (9.80e-2)	7.3611e-1 (7.00e-2)
LIRCMOP7	3.3468e-1 (6.74e-2)	4.6889e-1 (1.44e-1)	4.8837e-1 (6.29e-2)	6.0507e-1 (1.00e-1)	4.4802e-1 (4.02e-2)	4.6188e-1 (4.32e-2)
LIRCMOP8	4.0755e-1 (8.70e-2)	4.9004e-1 (1.36e-1)	4.8342e-1 (5.51e-2)	6.3714e-1 (7.79e-2)	4.4730e-1 (6.16e-2)	4.9990e-1 (5.81e-2)
LIRCMOP9	7.1199e-1 (3.81e-2)	6.3117e-1 (4.79e-2)	5.3283e-1 (2.58e-2)	8.2194e-1 (3.46e-2)	6.2625e-1 (8.21e-2)	5.2637e-1 (3.06e-2)
LIRCMOP10	8.2339e-1 (1.09e-1)	6.6393e-1 (2.92e-2)	6.3210e-1 (4.13e-2)	9.0430e-1 (2.26e-2)	7.9770e-1 (5.79e-2)	6.5111e-1 (2.54e-2)
LIRCMOP11	6.6935e-1 (3.18e-2)	4.5480e-1 (3.98e-2)	3.8827e-1 (4.13e-2)	7.7397e-1 (4.38e-2)	6.0501e-1 (4.12e-2)	4.1385e-1 (3.76e-2)
LIRCMOP12	6.6616e-1 (6.71e-2)	3.3683e-1 (2.23e-2)	3.7901e-1 (2.44e-2)	8.0029e-1 (3.99e-2)	5.1483e-1 (4.14e-2)	3.9042e-1 (1.10e-2)
LIRCMOP13	8.3006e-1 (4.67e-2)	7.9191e-1 (3.17e-2)	7.9424e-1 (6.81e-2)	8.3391e-1 (7.42e-2)	6.9659e-1 (8.06e-2)	7.8416e-1 (3.16e-2)
LIRCMOP14	8.1411e-1 (6.07e-2)	6.1128e-1 (4.77e-2)	6.0821e-1 (2.93e-2)	8.2354e-1 (8.56e-2)	6.9409e-1 (9.95e-2)	6.1588e-1 (2.77e-2)
Average Rank	1.6429	2.0714	2.2857	1.7143	1.8571	2.4286

The gray background represents the best result for each test instance. The second to fourth columns show the comparative results between EICp11, EICp21 and EICp31. The fifth to last columns show the comparisons between EICp12, EICp22, and EICp32.

TABLE SVIII
THE IGD VALUES OBTAINED BY EICP11, EICP21, EICP31, EICP12, EICP22, AND EICP32 ON LIRCMOP TEST SUITE.

Problem	EICp11	EICp21	EICp31	EICp12	EICp22	EICp32
LIRCMOP1	3.8679e-1 (1.47e-1) -	4.3578e-1 (8.99e-2) -	1.6587e-1 (5.75e-2)	3.4494e-1 (1.77e-1) -	4.4538e-1 (1.30e-1) -	2.2443e-1 (1.53e-1)
LIRCMOP2	3.4766e-1 (8.24e-2) -	3.8360e-1 (7.57e-2) -	2.1368e-1 (1.10e-1)	3.7921e-1 (1.72e-1) -	4.4420e-1 (1.58e-1) -	1.5740e-1 (6.58e-2)
LIRCMOP3	3.9824e-1 (1.17e-1) -	3.7372e-1 (8.95e-2) -	2.5305e-1 (1.74e-1)	4.4602e-1 (1.49e-1) -	4.4770e-1 (1.08e-1) -	1.9282e-1 (8.61e-2)
LIRCMOP4	3.4166e-1 (4.89e-2) =	3.5361e-1 (2.72e-2) =	2.5396e-1 (1.23e-1)	4.3710e-1 (2.01e-1) -	4.4718e-1 (1.39e-1) -	1.8999e-1 (9.27e-2)
LIRCMOP5	3.9944e-1 (1.18e-1) -	2.9962e-1 (5.49e-2) -	6.9935e-2 (2.04e-2)	2.4315e-1 (1.10e-1) -	2.0657e-1 (8.34e-2) -	6.5587e-2 (2.46e-2)
LIRCMOP6	4.3364e-1 (8.93e-2) -	2.8157e-1 (1.03e-1) -	1.3851e-1 (3.06e-1)	2.7224e-1 (1.85e-1) -	2.3681e-1 (1.02e-1) -	1.4230e-1 (3.46e-1)
LIRCMOP7	4.2910e-1 (1.57e-1) -	5.5963e-1 (3.12e-1) -	1.2046e-1 (4.62e-2)	2.9666e-1 (2.62e-1) -	3.3494e-1 (1.65e-1) -	1.2683e-1 (4.29e-2)
LIRCMOP8	7.2194e-1 (2.07e-1) -	4.9691e-1 (2.84e-1) -	9.8585e-2 (3.34e-2)	3.6732e-1 (3.04e-1) -	2.6730e-1 (1.31e-1) -	1.2212e-1 (7.14e-2)
LIRCMOP9	1.1212e+0 (2.53e-1) -	5.7254e-1 (3.31e-1) -	2.4120e-1 (8.70e-2)	7.2021e-1 (1.92e-1) -	4.8073e-1 (1.42e-1) -	2.2011e-1 (1.03e-1)
LIRCMOP10	8.5904e-1 (1.98e-1) -	1.9771e-1 (7.46e-2) -	6.9810e-2 (7.06e-2)	5.8230e-1 (1.18e-1) -	3.5271e-1 (9.60e-2) -	8.8079e-2 (8.35e-2)
LIRCMOP11	9.5617e-1 (3.10e-1) -	3.7405e-1 (1.66e-1) =	3.2856e-1 (1.68e-1)	5.0051e-1 (1.35e-1) -	3.3524e-1 (1.05e-1) =	2.7940e-1 (1.11e-1)
LIRCMOP12	1.4719e+0 (2.94e-1) -	7.5373e-1 (3.04e-1) -	2.4062e-1 (7.41e-2)	8.2423e-1 (2.26e-1) -	4.8213e-1 (1.84e-1) -	2.1015e-1 (4.76e-2)
LIRCMOP13	1.3123e+0 (4.17e-1) -	2.9195e-1 (1.39e-1) -	1.2871e-1 (9.22e-2)	9.0522e-1 (4.77e-1) -	8.0934e-1 (4.05e-1) -	1.1087e-1 (1.00e-2)
LIRCMOP14	1.2275e+0 (2.59e-1) -	4.4427e-1 (1.94e-1) -	1.4776e-1 (4.34e-2)	1.0524e+0 (4.40e-1) -	7.6480e-1 (3.47e-1) -	1.5035e-1 (1.39e-2)
Average Rank	2.7143	2.2857	1	2.6429	2.3571	1

The gray background represents the best result for each test instance. The second to fourth columns show the comparative results between EICp11, EICp21 and EICp31. The fifth to last columns show the comparisons between EICp12, EICp22, and EICp32.

terion, prioritizing solutions with higher feasibility and probability of feasibility (PoF). Critically, our method for evaluating feasibility and PoF is not constrained by the number of constraints. Thus, our proposed algorithm is can handle any number of constraints.

In terms of formulas, the feasibility of a solution is evaluated by the overall constraint violation degree, which is calculated as follows:

$$C(\boldsymbol{x}) = \sum_{j=1}^{q} \max(0, \hat{g}_j(\boldsymbol{x})), \tag{4}$$

where $\hat{g}_j(x)$ denotes the jth constraint function approximated by GP, q denotes the number of constraint functions, and q can be any integer. The feasible probability (PoF) of a solution is calculated as follows:

$$PoF(\boldsymbol{z}^*) = \prod_{j=1}^{q} \left[\Phi\left(\frac{0 - \hat{g}_j(\boldsymbol{z}^*)}{\hat{\delta}_{g_j}(\boldsymbol{z}^*)} \right) \right], \tag{5}$$

where $\hat{\delta}_{g_j}(x)$ denotes the standard deviation of the jth constraint function approximated by GP, q is the number of constraint functions, and q can be any integer. These formulations demonstrate the flexibility of the algorithm in accommodating varying numbers of constraints.

However, it's essential to acknowledge that an excessive number of constraints can introduce challenges. First, the efficiency of our algorithm will decrease. This is

TABLE SIX
THE CPU TIME(S) OBTAINED BY EICP11, EICP21, EICP31, EICP12, EICP22, AND EICP32 ON LIRCMOP TEST SUITE.

Problem	EICp11	EICp21	EICp31	EICp12	EICp22	EICp32
LIRCMOP1	3.0003e+2 (8.51e+1)	2.7441e+2 (4.07e+1)	7.8290e+2 (9.43e+1)	5.2464e+2 (1.17e+2)	5.5673e+2 (1.22e+2)	1.6798e+3 (5.92e+2)
LIRCMOP2	3.2705e+2 (4.51e+1)	4.2661e+2 (3.51e+1)	1.9116e+3 (1.10e+2)	3.8272e+2 (8.02e+1)	3.5889e+2 (1.15e+2)	6.5224e+2 (1.52e+2)
LIRCMOP3	5.7189e+2 (1.06e+2)	5.2074e+2 (5.10e+1)	2.0360e+3 (1.87e+2)	4.4592e+2 (1.09e+2)	4.7120e+2 (1.15e+2)	6.1752e+2 (2.08e+2)
LIRCMOP4	4.3978e+2 (1.52e+2)	3.2060e+2 (4.61e+1)	7.8877e+2 (1.20e+2)	4.0978e+2 (1.02e+2)	4.5492e+2 (1.31e+2)	6.7408e+2 (2.81e+2)
LIRCMOP5	4.2879e+2 (1.08e+2)	2.7632e+2 (3.82e+1)	8.7723e+2 (9.71e+1)	3.6396e+2 (4.68e+1)	2.8563e+2 (4.17e+1)	2.4033e+3 (1.47e+2)
LIRCMOP6	4.0868e+2 (1.05e+2)	2.8197e+2 (4.18e+1)	9.3177e+2 (1.52e+2)	5.4371e+2 (5.85e+1)	4.6555e+2 (4.88e+1) +	2.4863e+3 (2.54e+2)
LIRCMOP7	4.1931e+2 (1.18e+2)	4.6332e+2 (1.02e+2)	8.1663e+2 (7.98e+1)	6.5760e+2 (6.57e+1)	6.7491e+2 (9.26e+1)	2.0798e+3 (7.98e+1)
LIRCMOP8	6.0243e+2 (3.77e+2)	5.1224e+2 (1.34e+2)	8.2512e+2 (8.59e+1)	6.0840e+2 (6.80e+1)	6.1091e+2 (6.94e+1)	2.1782e+3 (5.61e+1)
LIRCMOP9	2.6771e+2 (3.71e+1)	2.8853e+2 (4.09e+1)	7.9195e+2 (9.28e+1)	4.8031e+2 (9.60e+1)	5.4249e+2 (1.60e+2)	2.2713e+3 (1.58e+2)
LIRCMOP10	2.7781e+2 (3.69e+1)	3.0295e+2 (4.41e+1)	8.2091e+2 (9.95e+1)	6.2654e+2 (2.27e+2)	5.8988e+2 (1.75e+2)	2.3176e+3 (1.08e+2)
LIRCMOP11	2.7793e+2 (4.24e+1)	3.1123e+2 (3.93e+1)	7.6824e+2 (8.53e+1)	5.9658e+2 (2.00e+2)	6.8060e+2 (2.14e+2)	2.0484e+3 (1.04e+2)
LIRCMOP12	2.6218e+2 (3.50e+1)	2.9037e+2 (3.85e+1)	7.7394e+2 (8.05e+1)	4.8054e+2 (8.44e+1)	5.3786e+2 (1.35e+2)	2.0420e+3 (8.11e+1)
LIRCMOP13	3.6472e+2 (9.20e+1)	3.5028e+2 (5.24e+1)	7.2779e+2 (7.43e+1)	6.0745e+2 (1.14e+2)	5.9085e+2 (6.06e+1)	1.8280e+3 (4.19e+1)
LIRCMOP14	4.4631e+2 (1.24e+2)	4.2526e+2 (6.19e+1)	7.8842e+2 (8.63e+1)	7.0667e+2 (8.20e+1)	7.0511e+2 (7.01e+1)	1.9509e+3 (4.72e+1)
Average Rank	1.5714	1.4286	3	1.4286	1.5714	3

The gray background represents the best result for each test instance. The second to fourth columns show the comparative results between EICp11, EICp21 and EICp31. The fifth to last columns show the comparisons between EICp12, EICp22, and EICp32.

TABLE SX
SUMMARIZE THE COMPARISON RESULTS OF EIC-MSSAEA AND OTHER ALGORITHMS FOR HV ON LIRCMOP AND MW.

Comparison			Summary HV		
			+	-	=
USeMOC	vs	EIC-MSSAEA	0	25	3
HSMEA	vs	EIC-MSSAEA	1	23	4
EIM-PoF	vs	EIC-MSSAEA	0	25	3
MultiObjectiveEGO	vs	EIC-MSSAEA	0	27	1

'+', '−' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively.

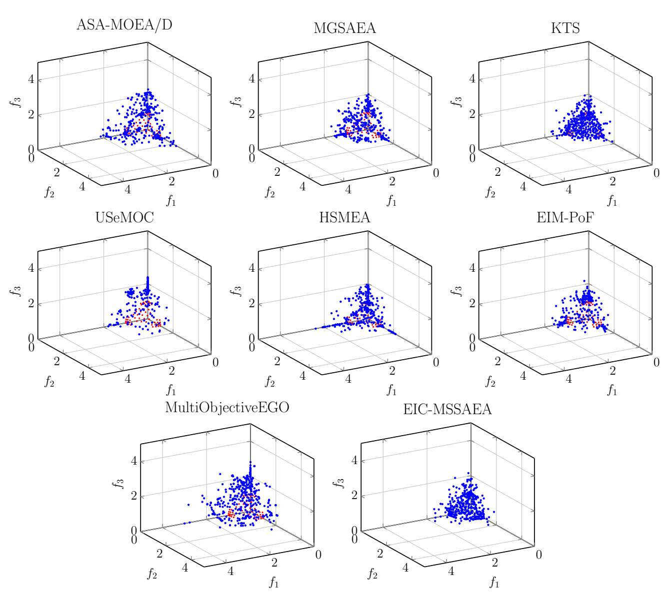


Fig. S6. In 20 experiments, the solutions distribution corresponding to the minimum value of IGD obtained by ASA-MOEA/D, MGSAEA, KTS, USeMOC, HSMEA, EIM-PoF, MultiObjectiveEGO, and EIC-MSSAEA on C2-DTLZ2.

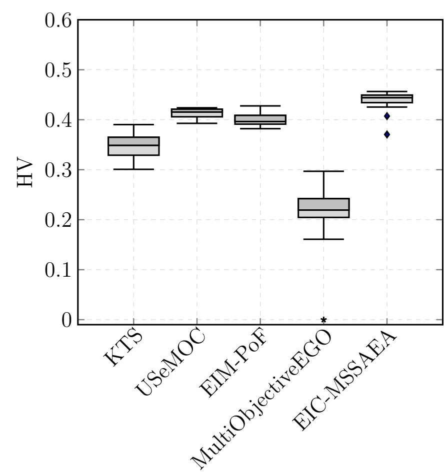


Fig. S7. The HV values obtained by USeMOC, EIMEGO-PoF, MultiObjectiveEGO, and EIC-MSSAEA on optimization of operating parameters of crude distillation units.

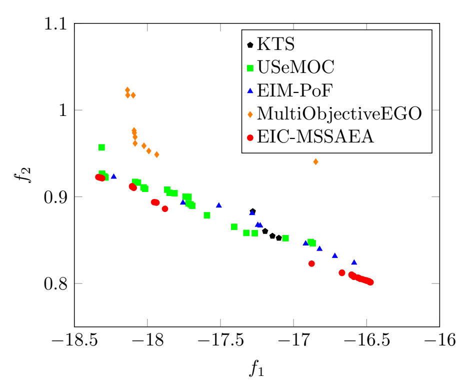


Fig. S8. In 20 experiments, the solutions distribution corresponding to the minimum value of IGD obtained by KTS, USeMOC, HSMEA, EIM-PoF, MultiObjectiveEGO, and EIC-MSSAEA on optimization of operating parameters of crude distillation units.

TABLE SXI
THE IGD VALUES OBTAINED BY ASA-MOEA/D, MGSAEA, KTS, USEMOC, HSMEA, EIMEGO-POF, MULTIOBJECTIVEEGO AND EIC-MSSAEA ON C-DTLZ TEST SUITE WITH 3 AND 5 OBJECTIVES.

Problem	ASA-MOEA/D	MGSAEA	KTS	USeMOC	HSMEA	EIM-PoF	MultiObjectiveEGO	EIC-MSSAEA
C1-DTLZ3	2.5639e+1 (5.16e+0) -	2.2657e+1 (5.05e+0) -	1.4867e+1 (3.86e+0) -	1.9482e+1 (2.19e+0) -	1.7540e+1 (1.80e+0) -	2.0151e+1 (3.82e+0) -	1.9167e+1 (4.31e+0) -	1.4406e+1 (2.57e+0)
	1.8908e+1 (3.96e+0) -	1.6619e+1 (3.17e+0) -	1.4256e+1 (2.35e+0) =	1.5199e+1 (1.76e+0) -	1.3228e+1 (7.61e-1) =	1.3422e+1 (8.76e-1) =	1.3834e+1 (1.78e+0) =	1.3992e+1 (2.44e+0)
C2-DTLZ2	1.5063e-1 (2.04e-2) -	1.6118e-1 (2.67e-2) -	5.0050e-2 (1.40e-2) -	5.6687e-1 (1.10e-1) -	7.1213e-2 (9.44e-3) -	1.2386e-1 (2.09e-2) -	5.2131e-1 (2.19e-1) -	4.2477e-2 (1.21e-3)
	3.9321e-1 (6.15e-2) -	3.7159e-1 (3.21e-2) -	2.1551e-1 (9.10e-3) -	6.6622e-1 (1.51e-1) -	3.3854e-1 (6.34e-2) -	3.0397e-1 (1.72e-2) -	5.9731e-1 (6.66e-2) -	1.8714e-1 (2.38e-2)
C3-DTLZ4	3.9153e-1 (6.86e-2) =	4.4982e-1 (1.77e-1) =	3.5878e-1 (1.00e-1) =	5.9087e-1 (1.10e-1) -	4.5490e-1 (6.61e-2) -	6.4781e-1 (9.90e-2) -	6.7382e-1 (8.76e-2) -	3.7263e-1 (8.78e-2)
	6.9501e-1 (6.77e-1) -	6.5313e-1 (7.45e-2) -	5.3287e-1 (6.90e-2) =	6.9302e-1 (7.01e-2) -	7.5241e-1 (7.50e-2) -	8.5379e-1 (6.01e-2) -	9.2440e-1 (6.21e-2) -	4.9673e-1 (5.24e-2)
DC1-DTLZ1	7.8357e+1 (1.28e+1) -	8.4657e+1 (2.35e+1) -	6.8713e+1 (2.33e+1) -	9.1623e+1 (1.44e+1) -	3.6805e+1 (4.17e+0) =	6.7267e+1 (9.21e+0) -	7.8786e+1 (1.66e+1) -	3.7151e+1 (7.84e+0)
	5.0728e+1 (1.17e+1) -	6.1266e+1 (1.81e+1) -	5.1295e+1 (1.84e+1) -	6.5428e+1 (1.09e+1) -	3.4167e+1 (5.64e+0) =	5.0684e+1 (9.79e+0) -	3.6805e+1 (4.17e+0) =	3.7853e+1 (1.31e+1)
DC1-DTLZ3	1.9460e+1 (1.25e+0) -	2.5655e+1 (3.86e+0) -	1.9266e+1 (4.45e+0) -	2.2081e+1 (7.21e+0) -	1.6456e+1 (2.70e+0) =	1.9866e+1 (3.26e+0) -	1.9504e+1 (1.68e+0) -	1.2307e+1 (2.96e+0)
	1.4064e+1 (1.84e+0) -	1.9320e+1 (3.16e+0) -	1.2830e+1 (4.42e+0) =	1.6800e+1 (5.95e+0) -	1.1034e+1 (2.35e+0) =	1.4604e+1 (1.77e+0) =	1.2586e+1 (1.56e+0) =	1.2459e+1 (3.38e+0)
DC3-DTLZ1	1.2563e+2 (4.04e+1) -	1.2112e+2 (6.80e+1) -	7.9440e+1 (3.17e+1) -	1.2474e+2 (3.26e+1) -	4.9619e+1 (2.42e+1) =	1.2850e+2 (3.39e+1) -	7.4788e+1 (1.63e+1) -	4.8038e+1 (2.42e+1)
	1.0293e+2 (3.19e+1) -	1.2127e+2 (1.02e+2) -	6.0347e+1 (2.91e+1) -	8.2382e+1 (2.94e+1) -	3.1464e+1 (1.31e+1) =	1.9729e+2 (1.02e+2) -	1.6594e+2 (7.72e+1) -	3.3806e+1 (2.35e+1)
DC3-DTLZ3	3.3250e+1 (1.17e+1) -	3.3706e+1 (9.81e+0) -	1.9113e+1 (6.93e+0) -	3.0402e+1 (7.22e+0) -	1.4205e+1 (6.95e+0) =	2.0481e+1 (2.95e+0) -	4.4256e+1 (1.07e+1) -	1.4985e+1 (4.66e+0)
	3.0359e+1 (9.17e+0) -	2.5561e+1 (1.29e+1) -	1.8542e+1 (1.09e+1) =	2.4926e+1 (9.34e+0) -	1.1955e+1 (8.11e+0) =	4.8662e+1 (1.68e+1) -	1.4624e+1 (3.03e+0) -	1.1730e+1 (5.64e+0)
$+/-/=$	0/13/1	0/13/1	0/9/5	0/14/0	0/5/9	0/12/2	0/11/3	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively. The gray background represents the best result for each test instance.

TABLE SXII
OPERATIONAL CONDITIONS IN CRUDE OIL DISTILLATION UNITS.

Variable	Meaning (Unit)	Variable	Meaning (Unit)
F_1	Naphtha flow rate (bbl/h)	$F_{p,1}$	1st pump-around flowrate (bbl/h)
F_2	Kerosene flow rate (bbl/h)	$F_{p,2}$	2nd pump-around flowrate (bbl/h)
F_3	Light diesel flow rate (bbl/h)	$F_{p,3}$	3rd pump-around flowrate (bbl/h)
F_4	Heavy diesel flow rate (bbl/h)	Q_1	1st pump-around duty (MW)
F_{s_1}	Main column steam flow rate (kmol/h)	Q_2	2nd pump-around duty (MW)
F_{s_2}	1st stripper steam flow rate (kmol/h)	Q_3	3rd pump-around duty (MW)
F_{s_3}	2nd stripper steam flow rate (kmol/h)	T	Furnace outlet temperature (°C)

TABLE SXIII
THE HV VALUES OBTAINED BY ASA-MOEA/D, MGSAEA, KTS, USEMOC, EIM-POF, MULTIOBJECTIVEEGO AND EIC-MSSAEA ON OPTIMIZATION OF OPERATIONAL PARAMETERS OF CRUDE OIL DISTILLATION UNITS.

Problem	ASA-MOEA/D	MGSAEA	KTS	USeMOC	EIM-PoF	MultiObjectiveEGO	EIC-MSSAEA
Optimization of operational parameters for crude oil distillation units	NaN(NaN)	NaN(NaN)	3.4880e-1(2.72e-2) -	4.1550e-1(8.80e-3) =	3.9640e-1 (1.20e-2) -	2.1930e-1 (5.96e-2) -	4.4410e-1 (1.98e-2)

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-MSSAEA, respectively. The gray background represents the best result.

because our algorithm builds a surrogate model for each constraint function, and as the number of constraints increases, the corresponding number of surrogate constraint models also increases. Second, the performance of the algorithm will degrade. This is because an increased number of constraints leads to a larger cumulative error in the surrogate models, which affects the feasibility evaluation of solutions.

In our experiments, we have validated the performance of the proposed algorithm across diverse problem including LIRCMOP, MW, C-DTLZ, and operational parameter optimization for crude oil distillation units. Our algorithm shows excellent overall performance and achieves optimal results in most cases. The crude oil distillation units operational parameter optimization problem contains eight constraints, which is the maximum number of constraints among these problems.

G. Comparisons with Peers on Expensive Multi-Objective Optimization Problems

The comparison results of EIC-S1 with ABSAEA, EIMEGO, and NSGA-III-EHVI are provided in Table SXV and Table SXVI.

TABLE SXIV
THE IGD VALUES OBTAINED BY MCCMO, C3M, MSCMO AND EIC-MSSAEA ON LIRCMOP, MW AND C-DTLZ TEST SUITES.

Problem	M/D	MCCMO	C3M	MSCMO	EIC-MSSAEA
LIRCMOP1	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.2246e-1 (1.66e-1)
LIRCMOP2	2/10	NaN (NaN)	NaN (NaN)	3.1583e-1 (3.51e-2) -	1.9448e-1 (1.10e-1)
LIRCMOP3	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.4271e-1 (1.49e-1)
LIRCMOP4	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.2224e-1 (1.60e-1)
LIRCMOP5	2/10	3.0558e+0 (3.52e-1) -	8.5130e+0 (1.61e+0) -	6.7673e+0 (1.21e+0) -	5.5751e-2 (1.33e-2)
LIRCMOP6	2/10	2.7889e+0 (6.45e-1) -	2.9490e+0 (5.03e-1) -	2.4110e+0 (6.92e-1) -	5.0099e-2 (1.18e-2)
LIRCMOP7	2/10	2.9096e+0 (8.20e-1)	2.9267e+0 (7.53e-1) -	1.9380e+0 (4.81e-1) -	1.0509e-1 (3.45e-2)
LIRCMOP8	2/10	3.0629e+0 (7.75e-1) -	3.3198e+0 (6.55e-1) -	1.9793e+0 (4.22e-1) -	9.2308e-2 (5.13e-2)
LIRCMOP9	2/10	1.8327e+0 (4.63e-1) -	1.9787e+0 (2.97e-1) -	1.9336e+0 (3.55e-1) -	2.0538e-1 (9.25e-2)
LIRCMOP10	2/10	1.4986e+0 (1.92e-1) -	1.3946e+0 (2.42e-1) -	1.3712e+0 (1.67e-1) -	5.1161e-2 (4.64e-2)
LIRCMOP11	2/10	1.4993e+0 (2.26e-1) -	1.5000e+0 (2.40e-1) -	1.3635e+0 (1.86e-1) -	2.0073e-1 (1.28e-1)
LIRCMOP12	2/10	1.9560e+0 (5.41e-1) -	1.8506e+0 (3.71e-1) -	1.7469e+0 (1.91e-1) -	2.0907e-1 (5.01e-2)
LIRCMOP13	3/10	2.0036e+0 (1.94e-1) -	1.9837e+0 (1.94e-1) -	1.7931e+0 (1.58e-1) -	9.0673e-2 (7.55e-3)
LIRCMOP14	3/10	2.1501e+0 (1.97e-1) -	2.1119e+0 (2.47e-1) -	1.7856e+0 (1.66e-1) -	1.1661e-1 (1.00e-2)
MW1	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	1.7636e-1 (2.11e-1)
MW2	2/10	6.0228e-1 (2.11e-1) -	4.8958e-1 (0.00e+0) =	5.2334e-1 (7.52e-2) -	1.8489e-1 (9.99e-2)
MW3	2/10	5.9465e-1 (3.46e-1) -	8.0589e-1 (3.08e-1) -	7.6819e-1 (2.54e-1) -	2.0739e-2 (3.66e-3)
MW4	3/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	1.9307e-1 (1.09e-1)
MW5	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	3.0920e-1 (2.37e-1)
MW6	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	7.2755e-1 (2.71e-1)
MW7	2/10	7.6170e-1 (1.16e-1) -	7.4093e-1 (0.00e+0) -	6.1408e-1 (1.58e-1) -	3.8656e-2 (1.65e-2)
MW8	3/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.1587e-1 (9.43e-2)
MW9	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.3107e-1 (2.20e-1)
MW10	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	3.2735e-1 (2.35e-1)
MW11	2/10	8.9088e-1 (0.00e+0)	7.0566e-1 (0.00e+0) -	8.1964e-1 (1.50e-1) -	1.5771e-1 (7.21e-2)
MW12	2/10	NaN (NaN)	NaN (NaN)	NaN (NaN)	2.2863e-1 (2.55e-1)
MW13	2/10	4.8064e+0 (2.24e+0) -	4.8628e+0 (1.57e+0) -	3.0034e+0 (1.54e+0) -	7.1978e-1 (5.35e-1)
MW14	3/10	2.6483e+0 (3.66e-1) -	3.0335e+0 (3.45e-1) -	2.5527e+0 (3.07e-1) -	7.4283e-1 (3.82e-1)
C1-DTLZ3	3/10	2.1876e+1 (3.68e+0) -	2.2623e+1 (4.04e+0) -	2.4567e+1 (6.79e+0) -	1.4406e+1 (2.57e+0)
	5/10	1.6436e+1 (3.23e+0) -	1.3994e+1 (2.03e+0) =	1.5084e+1 - (2.34e+0) -	1.3992e+1 (2.44e+0)
C2-DTLZ2	3/10	2.8000e-1 (6.04e-2) -	3.9849e-1 (6.22e-2) -	3.3359e-1 (6.03e-2) -	4.2477e-2 (1.21e-3)
	5/10	4.5884e-1 (6.34e-2) -	6.1749e-1 (9.58e-2) -	5.0472e-1 (6.16e-2) -	1.8714e-1 (2.38e-2)
C3-DTLZ4	3/10	6.9911e-1 (1.27e-1) -	7.8294e-1 (1.22e-1) -	1.0623e+0 (4.19e-1) -	3.7263e-1 (8.78e-2)
	5/10	8.9435e-1 (5.70e-2) -	1.1337e+0 (1.45e-1) -	1.2260e+0 (1.93e-1) -	4.9673e-1 (5.24e-2)
DC1-DTLZ1	3/10	9.0699e+1 (2.23e+1) -	9.8201e+1 (1.64e+1) -	1.0547e+2 (3.64e+1) -	3.7151e+1 (7.84e+0)
	5/10	4.8652e+1 (1.29e+1) -	5.0840e+1 (1.16e+1) -	6.2902e+1 (1.81e+1) -	3.7853e+1 (1.31e+1)
DC1-DTLZ3	3/10	3.0650e+1 (5.59e+0) -	2.5252e+1 (5.76e+0) -	2.7730e+1 (7.30e+0) -	1.2307e+1 (2.96e+0)
	5/10	1.7435e+1 (3.27e+0) -	1.4191e+1 (3.75e+0) -	1.7449e+1 (5.03e+0) -	1.2459e+1 (3.38e+0)
DC3-DTLZ1	3/10	1.8593e+2 (5.38e+1) -	1.4652e+2 (6.14e+1) -	1.6013e+2 (5.64e+1) -	4.8038e+1 (2.42e+1)
	5/10	1.6901e+2 (7.23e+1) -	1.1530e+2 (2.55e+1) -	1.5933e+2 (6.23e+1) -	3.3806e+1 (2.35e+1)
DC3-DTLZ3	3/10	5.4690e+1 (8.72e+0) -	4.0065e+1 (1.01e+1) -	4.9625e+1 (1.83e+1) -	1.4985e+1 (4.66e+0)
	5/10	5.2281e+1 (1.66e+1) -	4.0557e+1 (1.53e+1) -	4.7892e+1 (1.25e+1) -	1.1730e+1 (5.64e+0)
$+/-/=$		0/42/0	0/40/2	0/42/0	

’NaN’ represents no feasible solutions. The gray background represents the best result for each test instance.

TABLE SXV
THE IGD VALUES OBTAINED BY ABSAEA, EIMEGO, NSGA-III-EHVI AND EIC-S1 ON DTLZ AND WFG TEST SUITES.

Problem	M/D	ABSAEA	EIMEGO	NSGA-III-EHVI	EIC-S1
DTLZ1	3/10	9.5281e+1 (2.01e+1) -	7.7974e+1 (1.71e+1) -	1.0112e+2 (2.28e+1) -	4.9040e+1 (1.21e+1)
DTLZ2	3/10	1.1476e-1 (1.73e-2) -	1.5495e-1 (9.13e-3) -	7.5268e-2 (6.13e-3) -	5.7162e-2 (6.54e-3)
DTLZ3	3/10	2.3791e+2 (4.20e+1) -	2.2374e+2 (6.02e+1) -	2.4381e+2 (5.61e+1) -	1.4631e+2 (5.06e+1)
DTLZ4	3/10	2.9958e-1 (7.67e-2) =	6.2696e-1 (1.03e-1) -	3.2141e-1 (8.56e-2) =	3.0961e-1 (1.20e-1)
DTLZ5	3/10	9.7160e-2 (2.65e-2) -	8.8037e-2 (1.28e-2) -	2.6809e-2 (4.96e-3) -	1.0064e-2 (1.60e-3)
DTLZ6	3/10	3.3353e+0 (2.38e-1) -	1.4997e+0 (2.79e-1) +	3.3358e+0 (5.21e-1) -	1.9178e+0 (4.51e-1)
DTLZ7	3/10	2.2879e-1 (2.23e-1) -	8.0229e-1 (2.81e-1) -	4.2043e-1 (3.90e-1) -	6.3229e-2 (1.86e-3)
WFG1	3/10	1.7534e+0 (1.13e-1) =	1.7396e+0 (1.09e-1) =	1.8808e+0 (1.12e-1) -	1.7926e+0 (1.19e-1)
WFG2	3/10	3.9889e-1 (5.64e-2) -	4.5685e-1 (6.52e-2) -	3.0220e-1 (2.35e-2) -	2.4019e-1 (2.47e-2)
WFG3	3/10	3.3517e-1 (6.24e-2) -	3.9490e-1 (4.42e-2) -	2.7758e-1 (2.61e-2) -	2.3192e-1 (5.72e-2)
WFG4	3/10	4.2581e-1 (1.87e-2) =	5.2619e-1 (1.80e-2) -	4.3359e-1 (1.86e-2) =	4.2987e-1 (2.33e-2)
WFG5	3/10	4.1723e-1 (7.18e-2) -	2.6556e-1 (3.58e-2) +	4.4942e-1 (1.44e-1) -	3.5295e-1 (6.73e-2)
WFG6	3/10	6.9096e-1 (4.35e-2) -	6.1388e-1 (4.56e-2) =	4.8323e-1 (8.50e-2) +	6.0004e-1 (1.06e-1)
WFG7	3/10	5.6099e-1 (4.14e-2) =	6.5173e-1 (2.31e-2) -	5.6000e-1 (2.45e-2) =	5.4539e-1 (3.33e-2)
WFG8	3/10	6.4486e-1 (4.38e-2) -	5.8333e-1 (3.14e-2) -	5.0096e-1 (1.82e-2) =	5.0776e-1 (2.73e-2)
WFG9	3/10	6.1922e-1 (8.42e-2) =	7.1620e-1 (8.08e-2) -	6.1491e-1 (6.12e-2) =	6.3190e-1 (8.63e-2)
$+/-/=$		0/11/5	2/12/2	1/10/5	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-S1, respectively. The gray background represents the best result for each test instance.

TABLE SXVI
THE IGD VALUES OBTAINED BY ABSAEA, EIMEGO, NSGA-III-EHVI, AND EIC-S1 ON DTLZ AND WFG TEST SUITES.

Problem	M/D	ABSAEA	EIMEGO	NSGA-III-EHVI	EIC-S1
DTLZ1	5 / 10	3.7581e+1 (1.32e+1) +	4.0572e+1 (6.06e+0) +	5.3854e+1 (1.32e+1) =	5.0442e+1 (1.02e+1)
DTLZ2	5 / 10	2.7568e-1 (2.33e-2) -	2.6133e-1 (1.17e-2) -	2.8463e-1 (1.74e-2) -	2.4296e-1 (1.91e-2)
DTLZ3	5 / 10	1.2498e+2 (3.99e+1) =	1.2771e+2 (1.66e+1) =	1.3460e+2 (3.62e+1) =	1.3070e+2 (3.29e+1)
DTLZ4	5 / 10	5.0049e-1 (7.02e-2) =	7.0251e-1 (5.38e-2) -	4.4315e-1 (3.75e-2) =	4.8614e-1 (7.83e-2)
DTLZ5	5 / 10	5.1044e-2 (1.49e-2) -	8.3940e-2 (1.00e-2) -	9.5809e-2 (9.24e-3) -	3.7969e-2 (2.18e-2)
DTLZ6	5 / 10	2.3628e+0 (4.11e-1) +	1.0160e+0 (1.37e-1) +	2.8562e+0 (4.57e-1) =	2.6867e+0 (2.98e-1)
DTLZ7	5 / 10	1.0833e+0 (3.13e-1) -	9.6651e-1 (2.65e-1) -	5.0804e-1 (1.14e-1) -	3.1773e-1 (1.46e-2)
WFG1	5 / 10	2.2739e+0 (7.61e-2) -	2.1515e+0 (6.72e-2) +	2.3199e+0 (9.80e-2) -	2.2108e+0 (6.58e-2)
WFG2	5 / 10	5.9174e-1 (7.13e-2) -	7.2356e-1 (1.27e-1) -	7.3229e-1 (3.96e-2) -	5.2169e-1 (4.16e-2)
WFG3	5 / 10	4.5142e-1 (1.00e-1) +	6.2817e-1 (5.84e-2) +	7.3422e-1 (7.00e-2) =	6.9770e-1 (1.40e-1)
WFG4	5 / 10	1.2502e+0 (6.09e-2) -	1.3308e+0 (3.19e-2) -	1.1181e+0 (2.68e-2) +	1.2117e+0 (3.59e-2)
WFG5	5 / 10	1.2306e+0 (6.89e-2) =	1.0881e+0 (8.14e-2) +	1.1666e+0 (5.92e-2) +	1.2307e+0 (5.70e-2)
WFG6	5 / 10	1.6743e+0 (5.75e-2) -	1.3895e+0 (5.59e-2) =	1.3805e+0 (3.89e-2) =	1.3530e+0 (5.93e-2)
WFG7	5 / 10	1.4089e+0 (9.47e-2) -	1.4432e+0 (2.89e-2) -	1.2221e+0 (2.67e-2) =	1.2351e+0 (4.79e-2)
WFG8	5 / 10	1.9339e+0 (8.43e-2) -	1.5758e+0 (4.66e-2) -	1.5189e+0 (2.10e-2) -	1.4610e+0 (4.99e-2)
WFG9	5 / 10	1.5193e+0 (9.82e-2) =	1.7006e+0 (1.35e-1) -	1.5600e+0 (1.35e-1) =	1.5511e+0 (1.32e-1)
$+/-/=$		3/9/4	5/9/2	2/6/8	

'+', '-' and '=' indicate that the result is significantly better, significantly worse and statistically similar to that of EIC-S1, respectively. The gray background represents the best result for each test instance.

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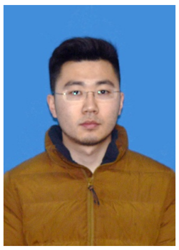

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