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# A many-objective evolutionary algorithm based on decomposition with dynamic resource allocation for irregular optimization

**Key words:** Many-objective optimization problems; Irregular Pareto front; External archive; Dynamic resource allocation; Shift-based density estimation; Tchebycheff approach

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# Motivation

The multi-objective optimization problem (MOP) has been encountered in numerous fields such as high-speed train head shape design, overlapping community detection, and power dispatch. Specifically, if an MOP has more than three objectives, it is called a many-objective optimization problem (MaOP).

Because these objectives often conflict with each other, no single solution satisfies all the objectives to achieve optimum values at the same time. With the increase of the number of objectives, the difficulty in solving MaOPs increases.

Current approaches are considered mainly for problems of regular Pareto front (PF). For problems with irregular PF, it is difficult for these algorithms to achieve satisfying results.

# Main idea

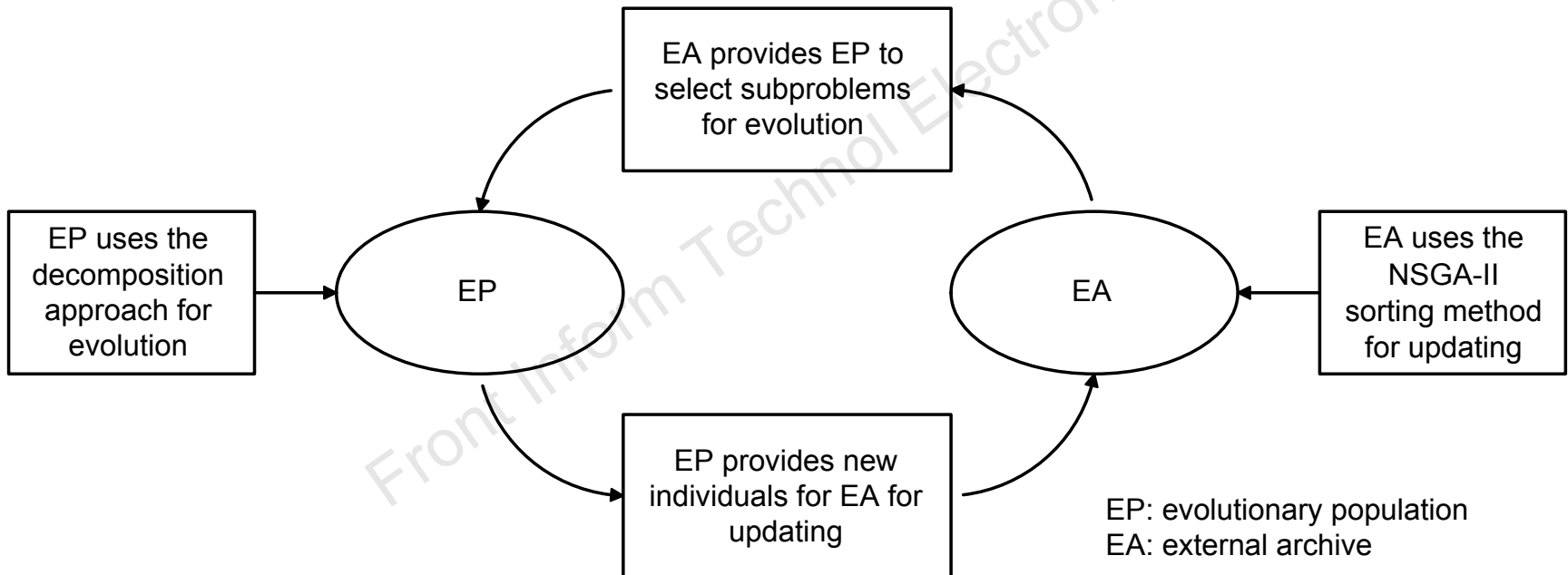
We propose a many-objective evolutionary algorithm based on decomposition with dynamic resource allocation (MaOEA/D-DRA) for irregular optimization.

The proposed algorithm can dynamically allocate computing resources to different search areas according to different shapes of the problem's Pareto front.

An evolutionary population and an external archive are used in the search process, and information extracted from the external archive is used to guide the evolutionary population to different search regions.

# Method (DRA)

Illustration of the framework of dynamic resource allocation (DRA)



# Method (Tchebycheff approach)

The original MOP is decomposed into  $N$  subproblems, which are optimized in a cooperative manner. Specifically, the objective function of the  $j^{\text{th}}$  subproblem is

$$\begin{aligned} \min \quad & g(\mathbf{x} \mid \boldsymbol{\lambda}^j, \mathbf{z}^*) = \max_{1 \leq i \leq m} \left( \lambda_i^j \left| f_i(\mathbf{x}) - z_i^* \right| \right) \\ \text{s.t.} \quad & \mathbf{x} \in \Omega, \quad j = 1, 2, \dots, N, \end{aligned}$$

# Method (SDE)

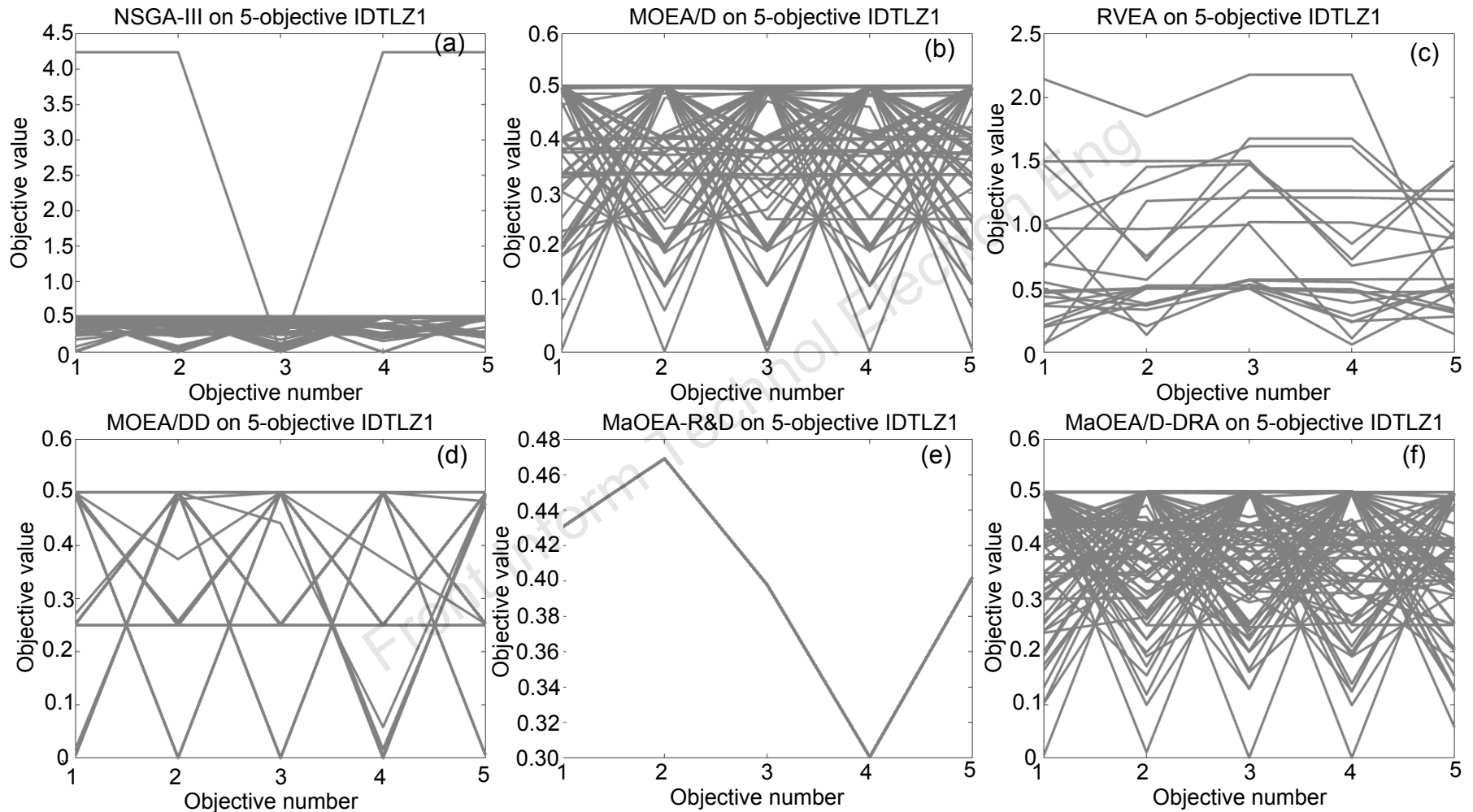
The approach of shift-based density estimation (SDE) computes the convergence of the solution by adjusting the relative positions of other solutions in the population. The new density  $D'(\mathbf{p}, P)$  of solution  $\mathbf{p}$  in population  $P$  can be defined as follows:

$$D'(\mathbf{p}, P) = D(\text{dist}(\mathbf{p}, \mathbf{q}'_1), \text{dist}(\mathbf{p}, \mathbf{q}'_2), \dots, \text{dist}(\mathbf{p}, \mathbf{q}'_{N-1})).$$

where  $\text{dist}(\mathbf{p}, \mathbf{q}'_i)$  denotes the similarity degree between solutions  $\mathbf{p}$  and  $\mathbf{q}'_i$ ,  $N$  is the size of  $P$ , and  $\mathbf{q}'_i$  is the shifted version of solution  $\mathbf{q}_i$  ( $\mathbf{q}_i \in P$  and  $\mathbf{q}_i \neq \mathbf{p}$ ), which is formulated as follows:

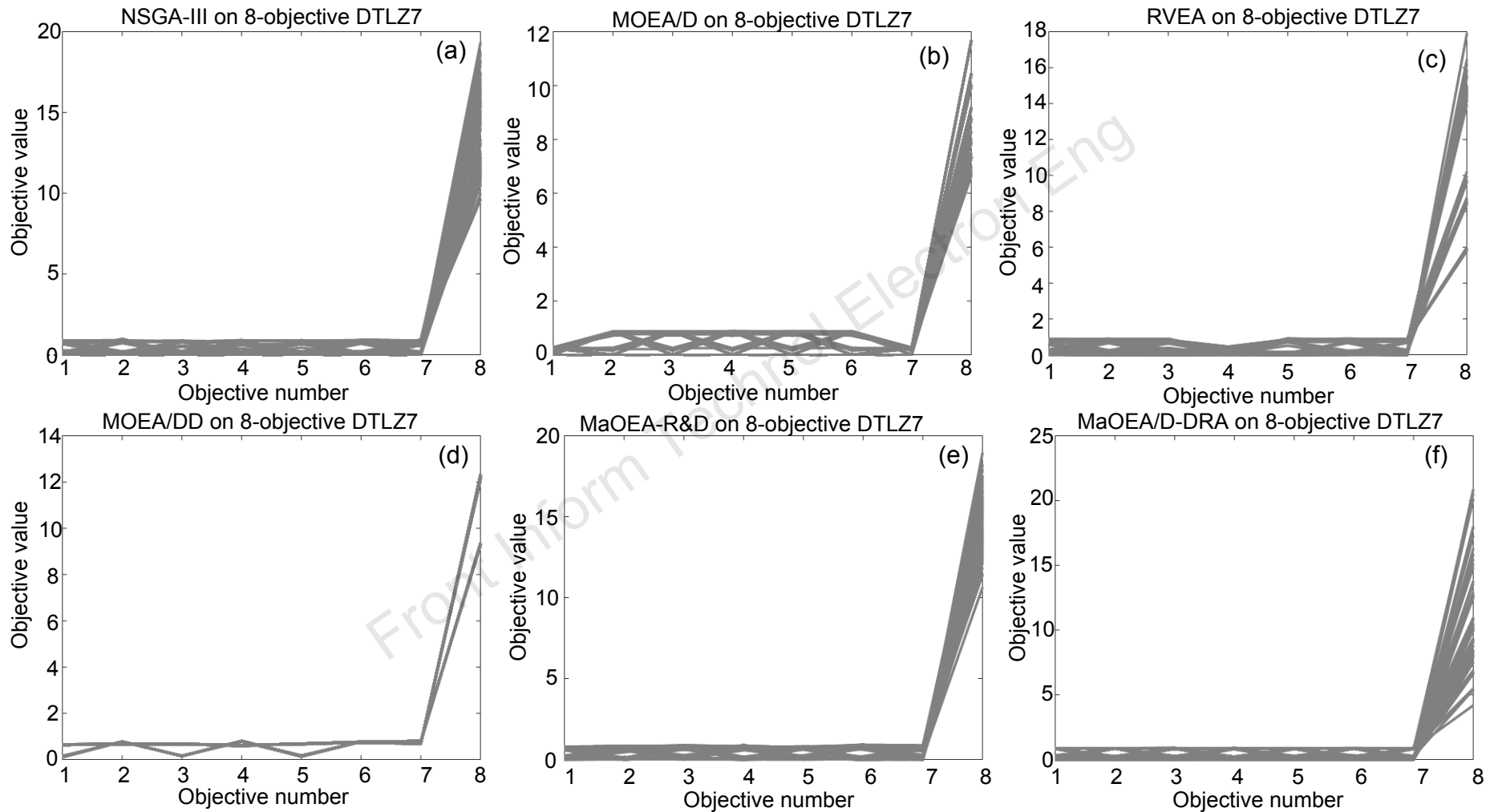
$$\mathbf{q}'_{i(j)} = \begin{cases} \mathbf{p}_{(j)}, & \text{if } \mathbf{q}_{i(j)} < \mathbf{p}_{i(j)}, \\ \mathbf{q}_{i(j)}, & \text{otherwise,} \end{cases} \quad j = 1, 2, \dots, m.$$

# Major results (1)



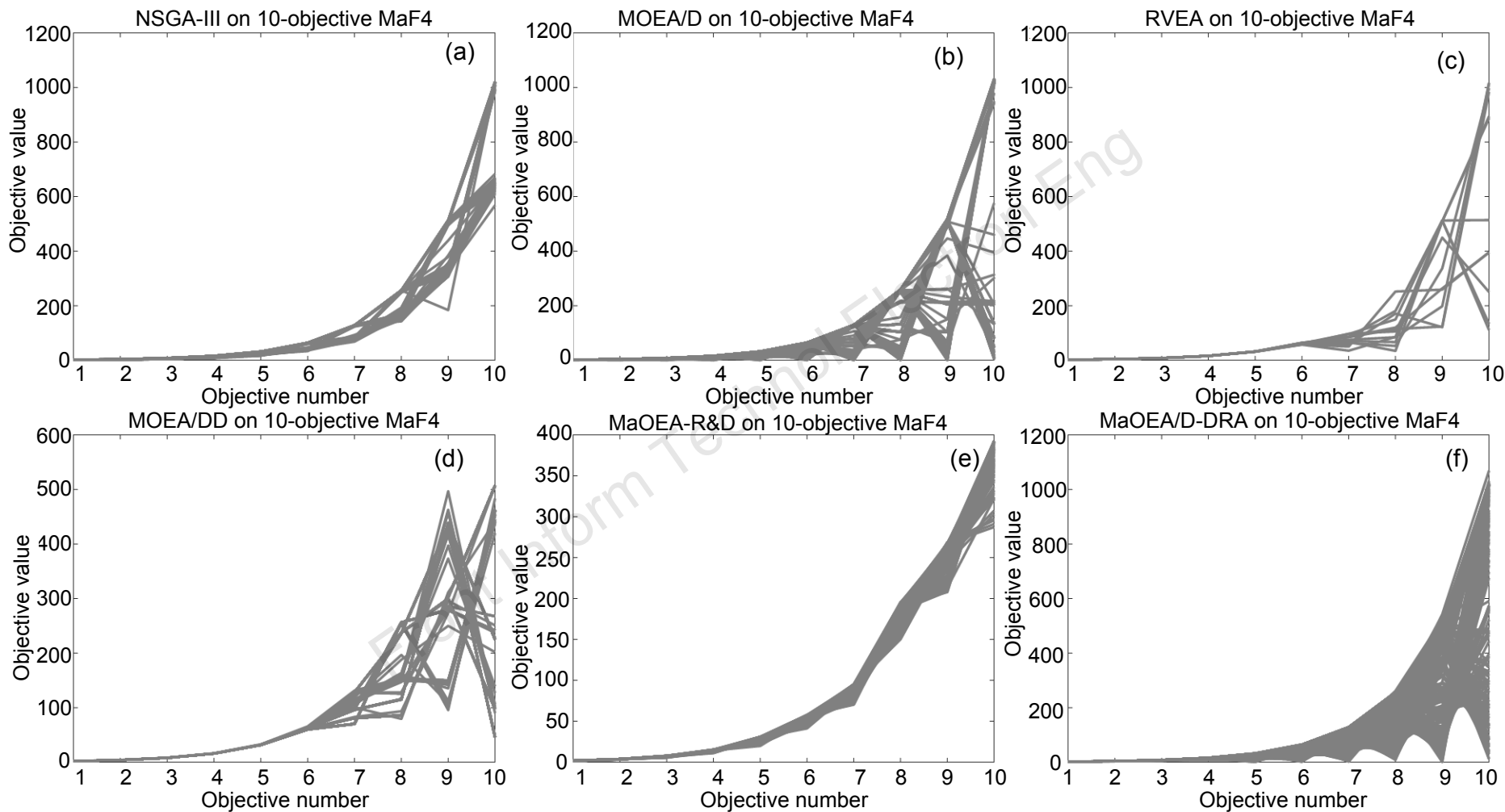
**Fig. 3** Illustration of parallel coordinates of the non-dominated fronts on 5-objective IDTLZ1, obtained by NSGA-III (a), MOEA/D (b), RVEA (c), MOEA/DD (d), MaOEA-R&D (e), and MaOEA/D-DRA (f) with the median IGD value in 30 runs

# Major results (2)



**Fig. 4** Illustration of parallel coordinates of the non-dominated fronts on 8-objective DTLZ7, obtained by NSGA-III (a), MOEA/D (b), RVEA (c), MOEA/DD (d), MaOEA-R&D (e), and MaOEA/D-DRA (f) with the median IGD value in 30 runs

# Major results (3)



**Fig. 5** Illustration of parallel coordinates of the non-dominated fronts on 10-objective MaF4, obtained by NSGA-III (a), MOEA/D (b), RVEA (c), MOEA/DD (d), MaOEA-R&D (e), and MaOEA/D-DRA (f) with the median IGD value in 30 runs

# Major results (4)

**Table 7 IGD results of sensitivity to the number of previous learning generations  $L$  in MaOEA/D-DRA**

Problem	$M$	IGD		
		MaOEA/D-DRA-4	MaOEA/D-DRA-12	MaOEA/D-DRA-8
DTLZ5	5	6.8958e-2 (8.75e-3) $\approx$	7.0693e-2 (1.02e-2) $\approx$	<b>6.8462e-2 (8.55e-3)</b>
	8	1.3346e-1 (2.13e-2) $\approx$	1.4333e-1 (3.16e-2) $\approx$	<b>1.2975e-1 (2.78e-2)</b>
	10	1.2062e-1 (1.81e-2) $\approx$	<b>1.1905e-1 (1.22e-2) <math>\approx</math></b>	1.2222e-1 (1.96e-2)
+/-/ $\approx$		0/0/3	0/0/3	

$M$ : number of objectives. The best result in each row is highlighted in bold

**Table 8 HV results of sensitivity to the number of previous learning generations  $L$  in MaOEA/D-DRA**

Problem	$M$	HV		
		MaOEA/D-DRA-4	MaOEA/D-DRA-12	MaOEA/D-DRA-8
DTLZ5	5	8.0344e-3 (1.62e-4) $\approx$	7.9592e-3 (1.71e-4) $\approx$	<b>8.0387e-3 (1.49e-4)</b>
	8	1.7096e-5 (1.66e-7) $\approx$	1.7041e-5 (1.99e-7) $\approx$	<b>1.7126e-5 (2.18e-7)</b>
	10	5.6536e-8 (3.52e-10) $\approx$	<b>5.6593e-8 (2.53e-10) <math>\approx</math></b>	5.6561e-8 (2.69e-10)
+/-/ $\approx$		0/0/3	0/0/3	

$M$ : number of objectives. The best result in each row is highlighted in bold

# Conclusions

We have proposed an MaOEA based on decomposition with DRA, termed MaOEA/D-DRA. A new DRA method is designed to solve MaOPs with irregular PF (MaDRA), where MaOP is decomposed into a number of single optimization subproblems with the Tchebycheff approach, and each subproblem is associated with a solution in an evolutionary population. Computational resources are allocated to different subproblems dynamically based on the contribution of each subproblem to EA in the search process.

Experimental results show that the proposed algorithm outperforms these five algorithms with respect to convergence speed and diversity of population members.

MaOEA/D-DRA has shown competitive performance in the studied MaOPs with irregular PF. However, MaOEA/D-DRA does not perform well on the constrained problem C1\_DTLZ1. Investigations into application of MaOEA/D-DRA for the constrained MaOPs is one future line of work.