Review of the CEC14 Computationally Expensive Optimization Competition

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Outline

- Introduction
- Test functions
- Ranking method and final scores
- Analysis and comparison

Introduction

- Part of Real-Parameter Numerical Optimization Competition
- Single Objective
- Computationally expensive
- Test functions
  - 8 test functions
  - 24 problems
  - 3 dimensions: 10, 20, 30
- Participations
  - Validate results: 6

Introduction

- Participants

Algorithm	Author	Paper
WA	Md Asafuddoula Tapabrata Ray	An Approach to Solve Computationally Expensive Optimization Problems of CEC-2014 Without Approximation
SA-DE-DPS	Saber M. Elsayed T. Ray Ruhul A. Sarker	A Surrogate-assisted Differential Evolution algorithm with Dynamic Parameters Selection for Solving Expensive Optimization Problems
HSBA	Hemant Kumar Singh Amitay Isaacs Tapabrata Ray	A Hybrid Surrogate based Algorithm (HSBA) to Solve Computationally Expensive Optimization Problems
GCO	Subhodip Biswas Mohammad A. Eita Swagatam Das Athanasios V. Vasilakos	Evaluating the performance of Group Counselling Optimizer on CEC 2014 problems for Computational Expensive Optimization
MVMO	István Erlich José L. Rueda Sebastian Wildenhues	Solving the IEEE-CEC 2014 Expensive Optimization Test Problems by Using Single-Particle MVMO
SOMODS	Tipaluck Krityakierne Juliane Müller Christine A. Shoemaker	SO-MODS: Optimization for High Dimensional Computationally Expensive Multi-Modal Functions with Surrogate Search

Test functions

Function	Properties	
Shifted Sphere	unimodal	Unimodal
Shifted Ellipsoid	unimodal	
Shifted Rotated Ellipsoid	unimodal	
Shifted Step	unimodal, discontinuous	
Shifted Ackley	multimodal	Typical multimodal
Shifted Griewank	multimodal, landscape smoother with higher dimensionality	
Shifted Rotated Rosenbrock	multimodal, non-separable, narrow search valley	Very complex multimodal
Shifted Rotated Rastrigin	multimodal, rugged landscapes	

Final Scores

- Ranking method:

$$\text{Total score} = \sum_{i=1}^{24} score_i \text{ (using mean value)} + \sum_{i=1}^{24} score_i \text{ (using median value)}$$

Rank#	Algorithm	Total Score
1	MVMO	318
2	SOMODS	249
3	Without-Approx	222
4	SA-DE-DPS	207
5	HSBA	144
6	GCO	81

Analysis and comparison

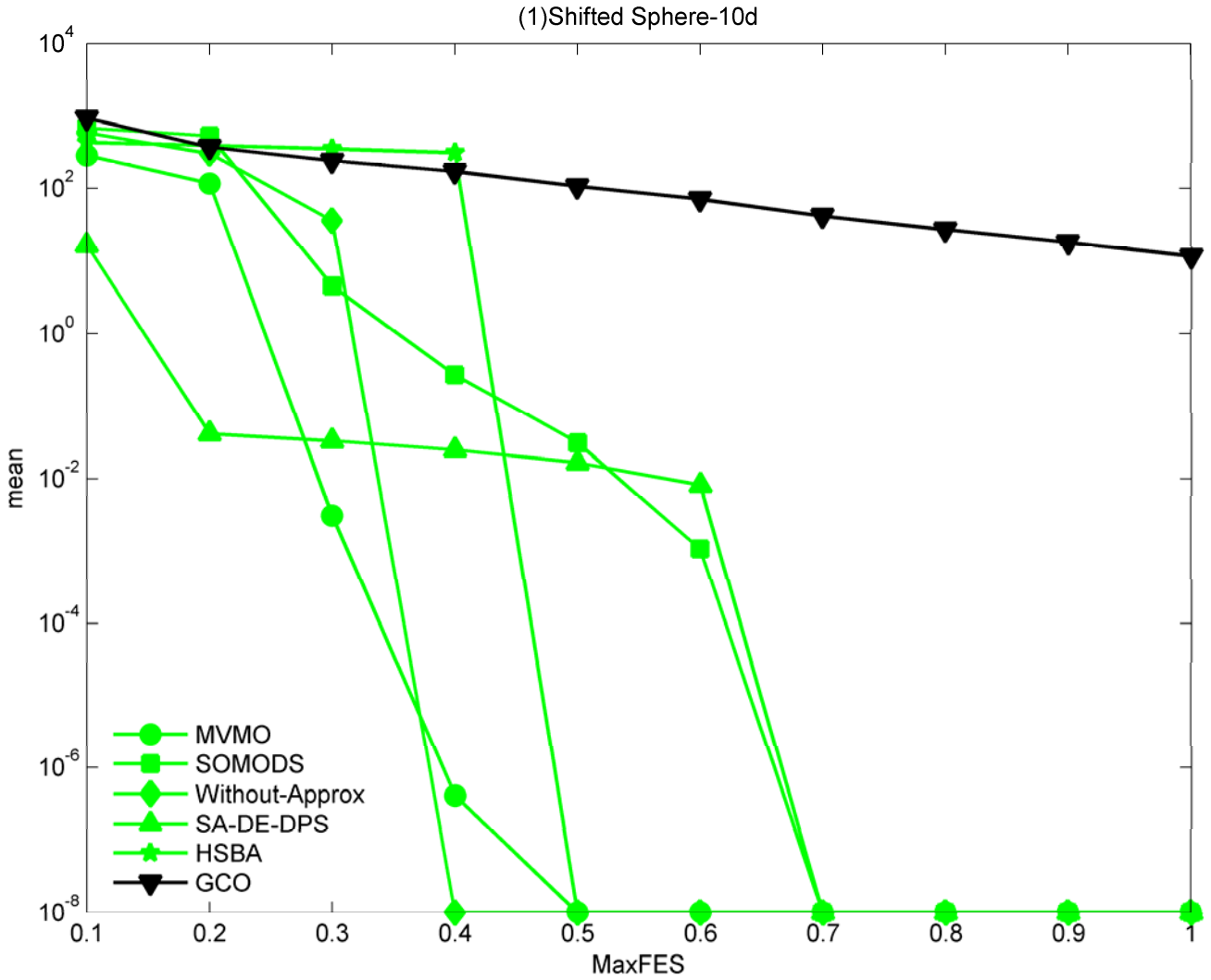
#	Function	D	MVMO	SOMODS	WA	SA-DE-DPS	HSBA	GCO
1	Shifted Sphere	10	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	1.139E+01
2		20	0.000E+00	0.000E+00	0.000E+00	0.000E+00	0.000E+00	1.138E+01
3		30	0.000E+00	9.342E-05	0.000E+00	0.000E+00	0.000E+00	7.774E+00
4	Shifted Ellipsoid	10	0.000E+00	5.235E-07	0.000E+00	0.000E+00	9.210E-08	3.233E+01
5		20	0.000E+00	1.024E-02	0.000E+00	3.007E-01	1.114E-01	8.918E+01
6		30	2.647E-02	3.278E-01	3.900E-06	1.249E+01	6.867E+00	1.644E+02
7	Shifted Rotated Ellipsoid	10	0.000E+00	2.145E-03	0.000E+00	0.000E+00	1.020E-07	8.246E+01
8		20	0.000E+00	2.296E-03	0.000E+00	5.700E-02	2.658E-01	1.386E+02
9		30	8.849E-01	2.024E+01	2.115E-03	1.923E+01	1.451E+01	7.184E+02
10	Shifted Step	10	2.650E+00	0.000E+00	2.450E+00	9.000E-01	1.705E+01	9.250E+00
11		20	6.550E+00	0.000E+00	5.305E+01	1.030E+01	1.207E+02	8.200E+00
12		30	1.270E+01	0.000E+00	1.642E+02	8.643E+02	3.071E+02	7.350E+00
13	Shifted Ackley	10	4.919E+00	1.156E-01	1.034E+01	1.278E+01	7.816E+00	6.176E+00
14		20	7.935E+00	9.389E-05	1.250E+01	1.276E+01	9.465E+00	4.360E+00
15		30	7.918E+00	2.418E-04	1.497E+01	1.177E+01	1.067E+01	4.041E+00
16	Shifted Griewank	10	4.397E-01	1.538E-02	1.406E-01	3.450E-02	5.808E-02	1.993E+00
17		20	0.000E+00	3.761E-03	4.668E-03	0.000E+00	7.000E-07	1.841E+00
18		30	0.000E+00	1.095E-02	2.864E-02	0.000E+00	3.140E-07	1.824E+00
19	Shifted Rotated Rosenbrock	10	1.074E+00	1.043E+01	3.590E+00	3.146E+00	3.788E+00	8.842E+01
20		20	1.073E+01	1.790E+01	1.388E+01	2.028E+01	2.403E+01	1.097E+02
21		30	3.440E+01	3.660E+01	2.980E+01	2.869E+01	3.329E+01	2.374E+02
22	Shifted Rotated Rastrigin	10	2.617E+01	2.701E+01	6.953E+01	1.975E+01	3.647E+01	4.649E+01
23		20	4.253E+01	5.975E+01	1.400E+02	4.831E+01	3.440E+01	7.676E+01
24		30	8.493E+01	1.095E+02	3.065E+02	1.026E+02	1.021E+02	1.781E+02

Mean Value (green: <1e-2; red: >1e-2,best of all methods)

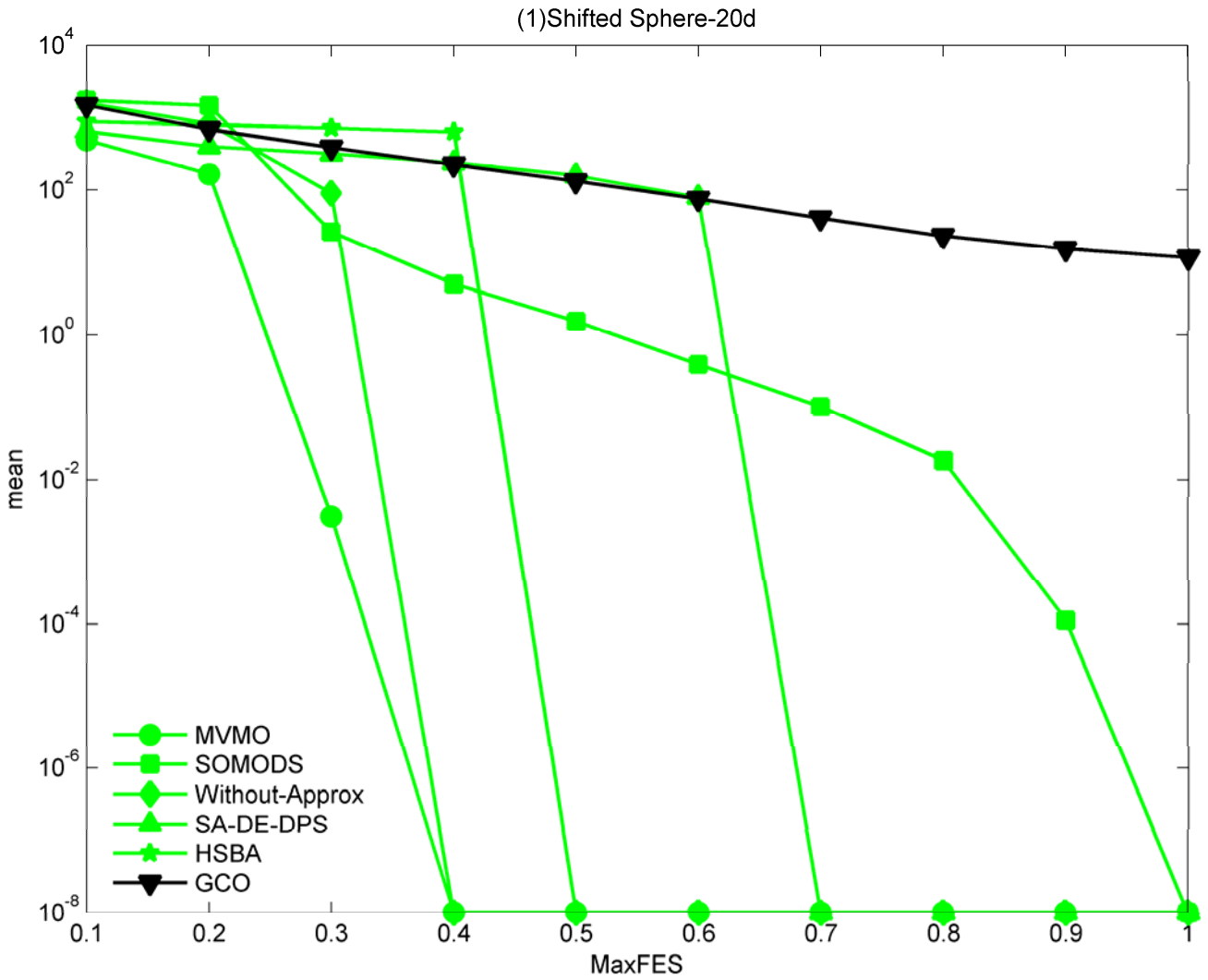
Analysis and comparison

- Top 3 methods: MVMO, SOMODS, and WA [we may change according to new results]
  - MVMO and WA do not use surrogate model(s)
  - SOMODS uses surrogate model
- Some interesting finds
  - SOMODS obtains excellent results on Step function
  - MVMO and SA-DE-DPS obtains the global optimum and outperform other methods with higher dimensional Griewank problems

Unimodal problems



Unimodal problems



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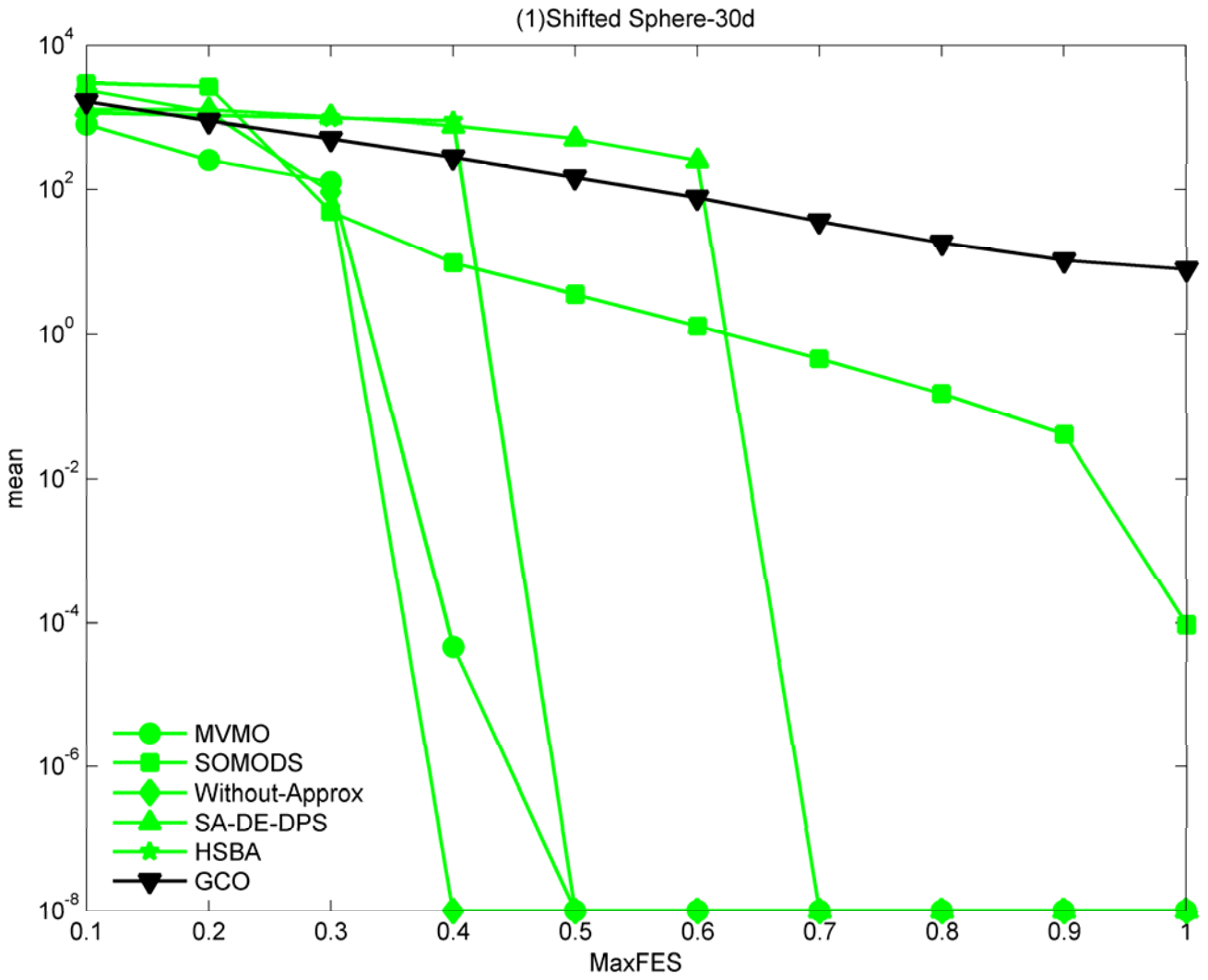
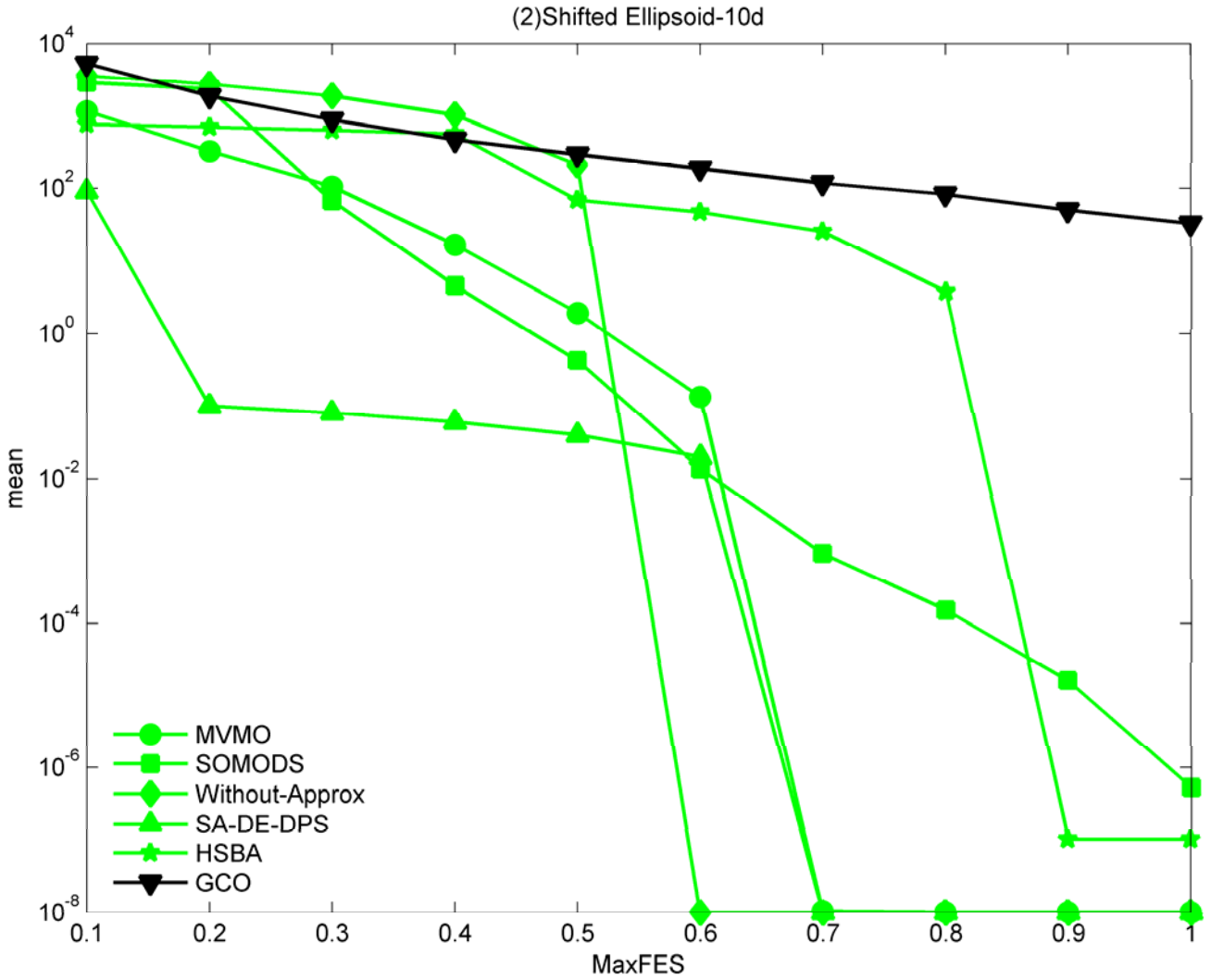


Unimodal problems



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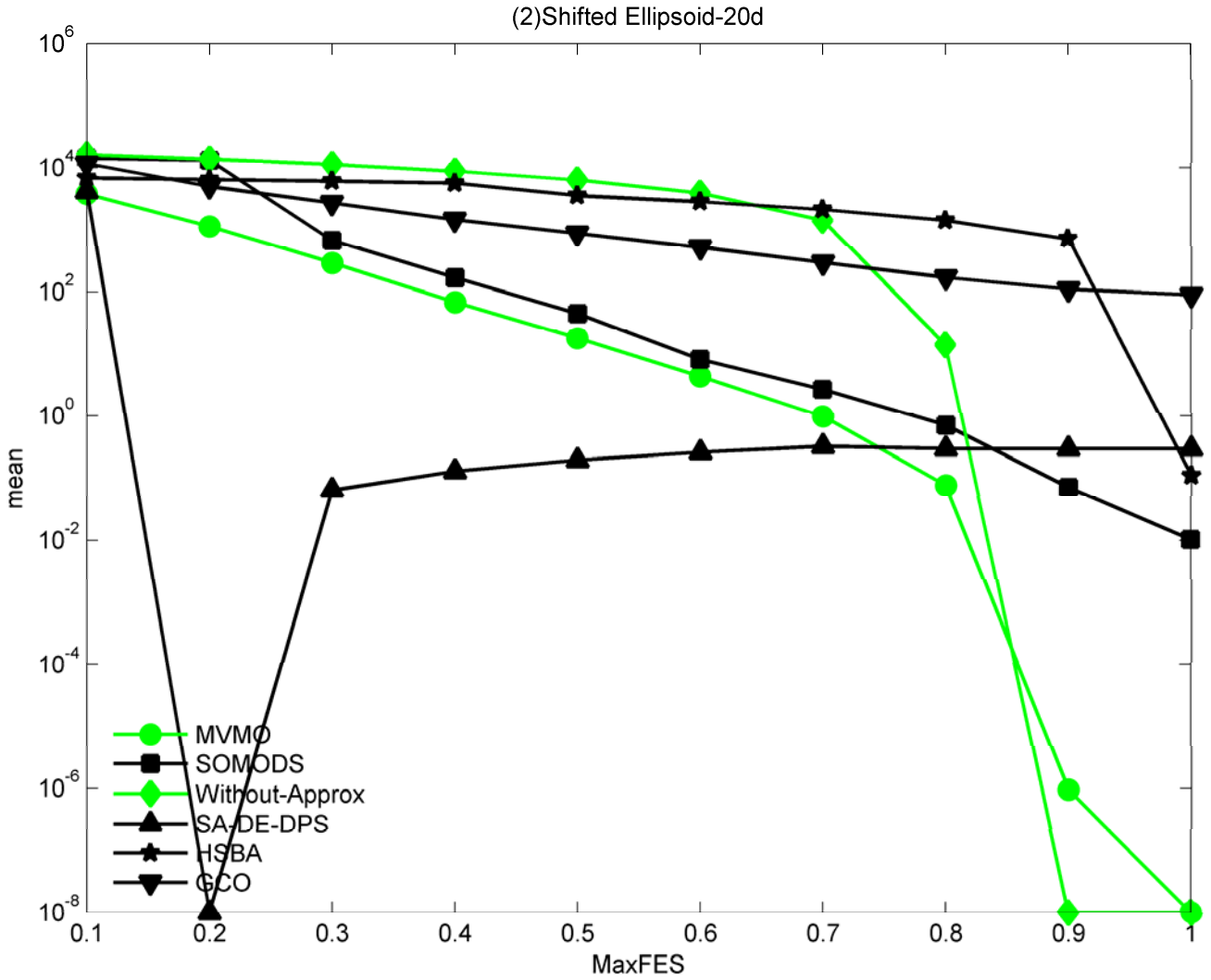

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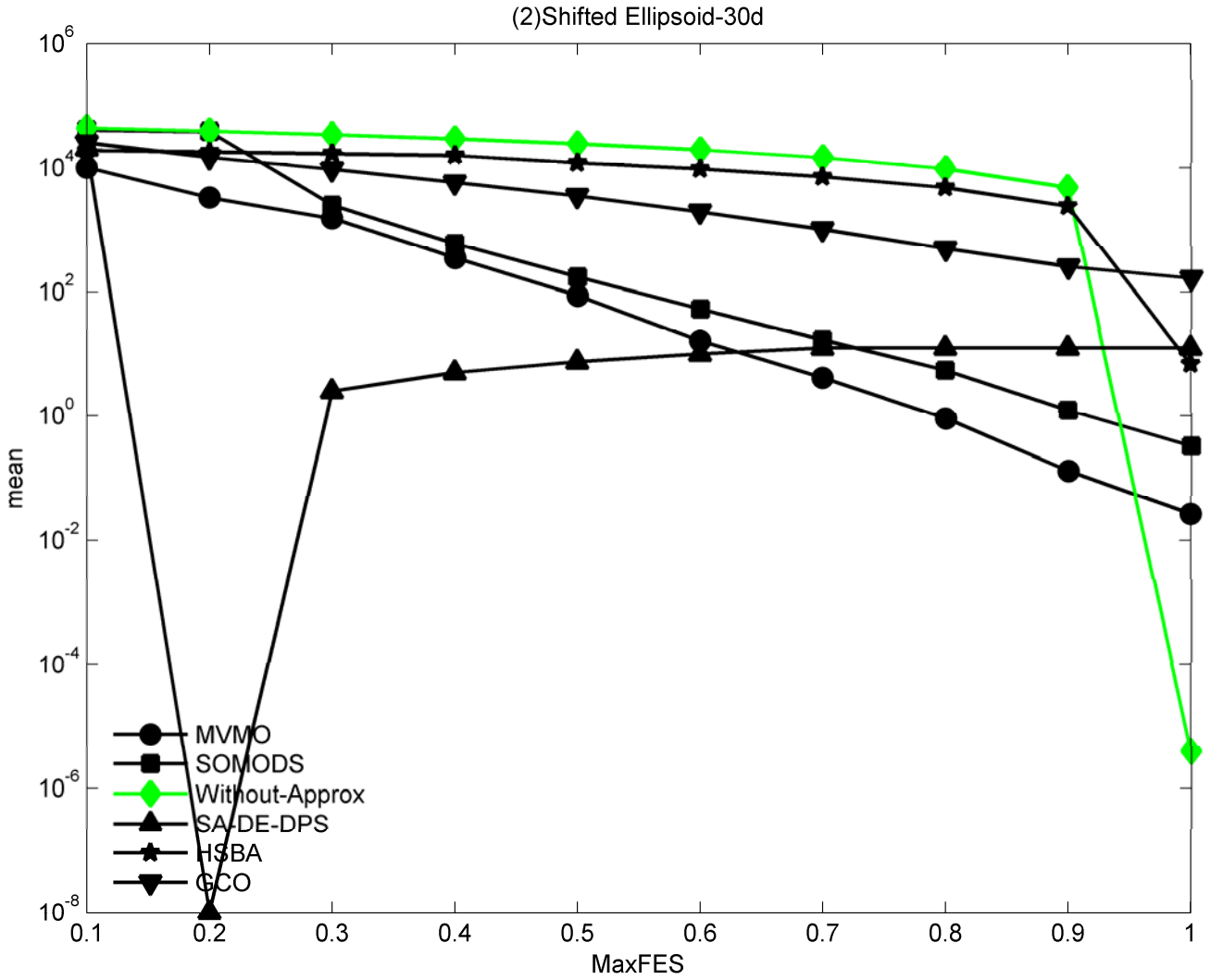

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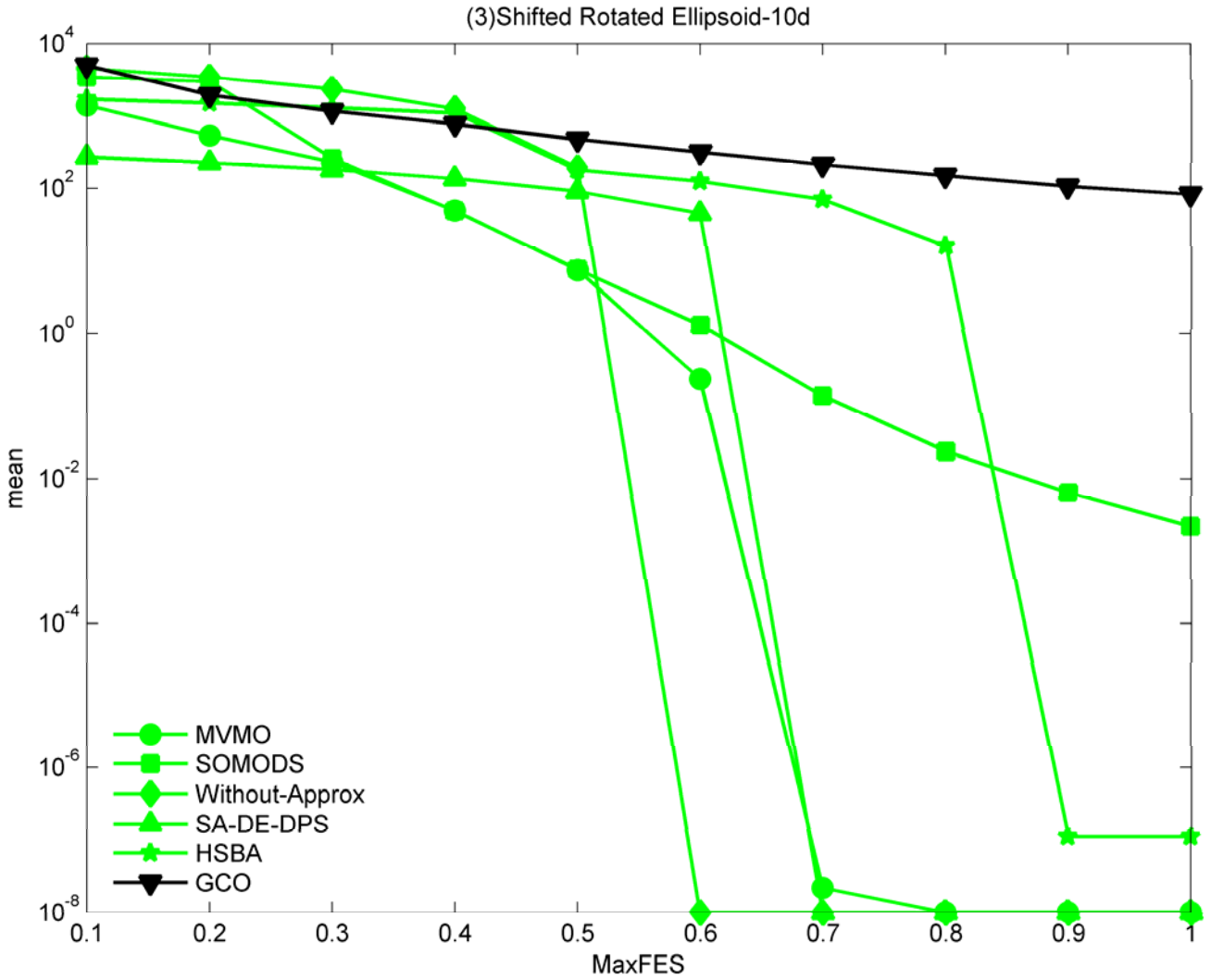

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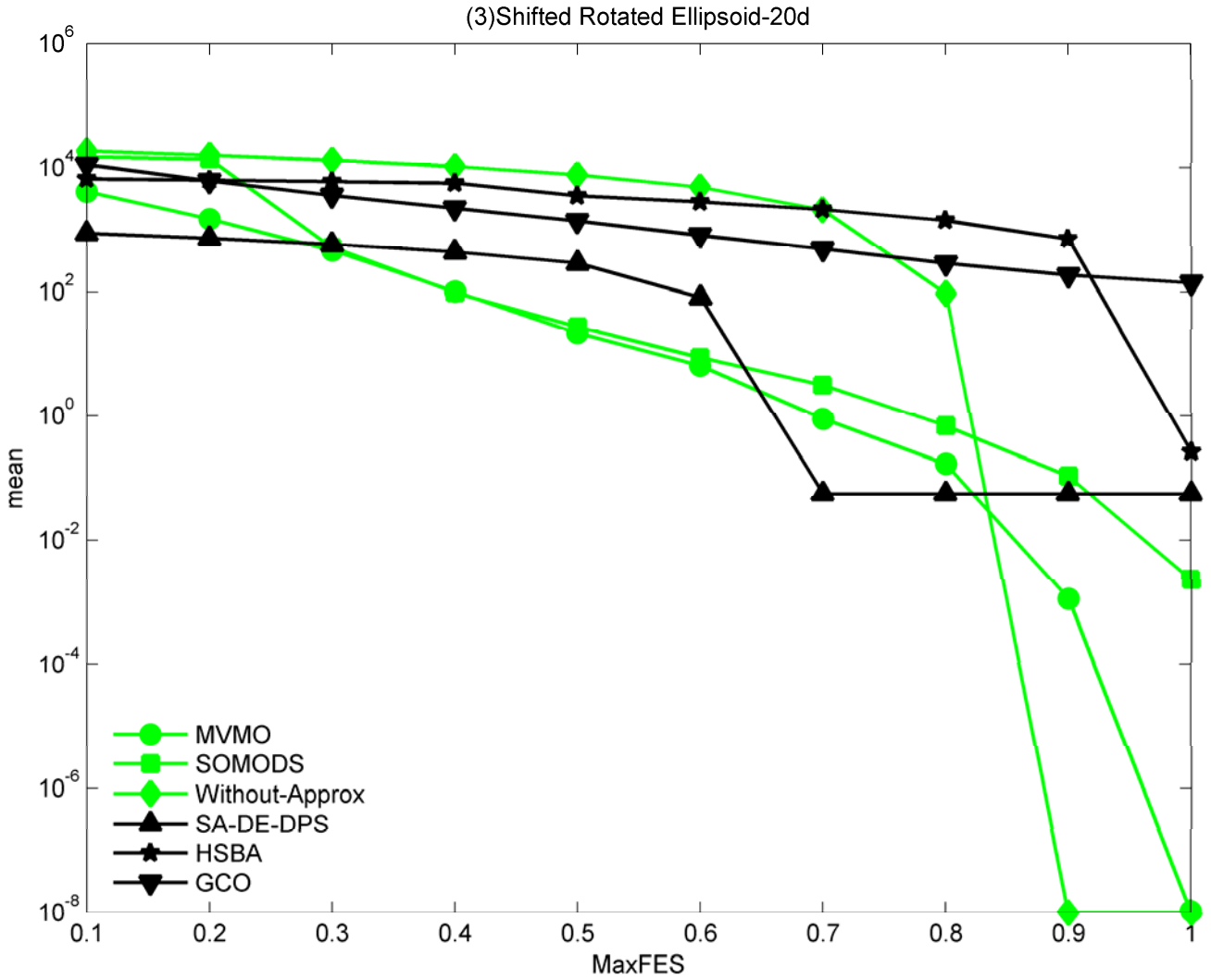

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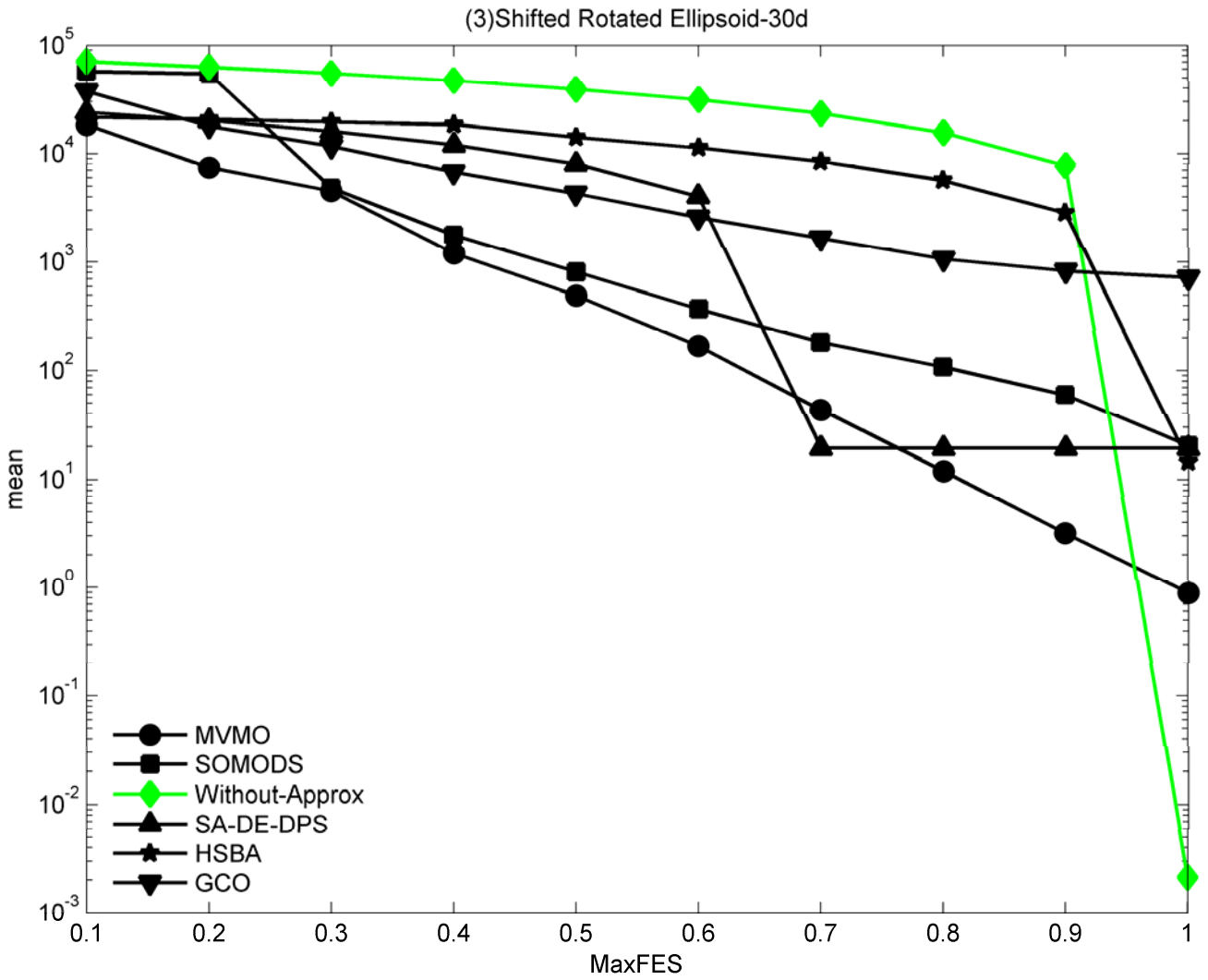

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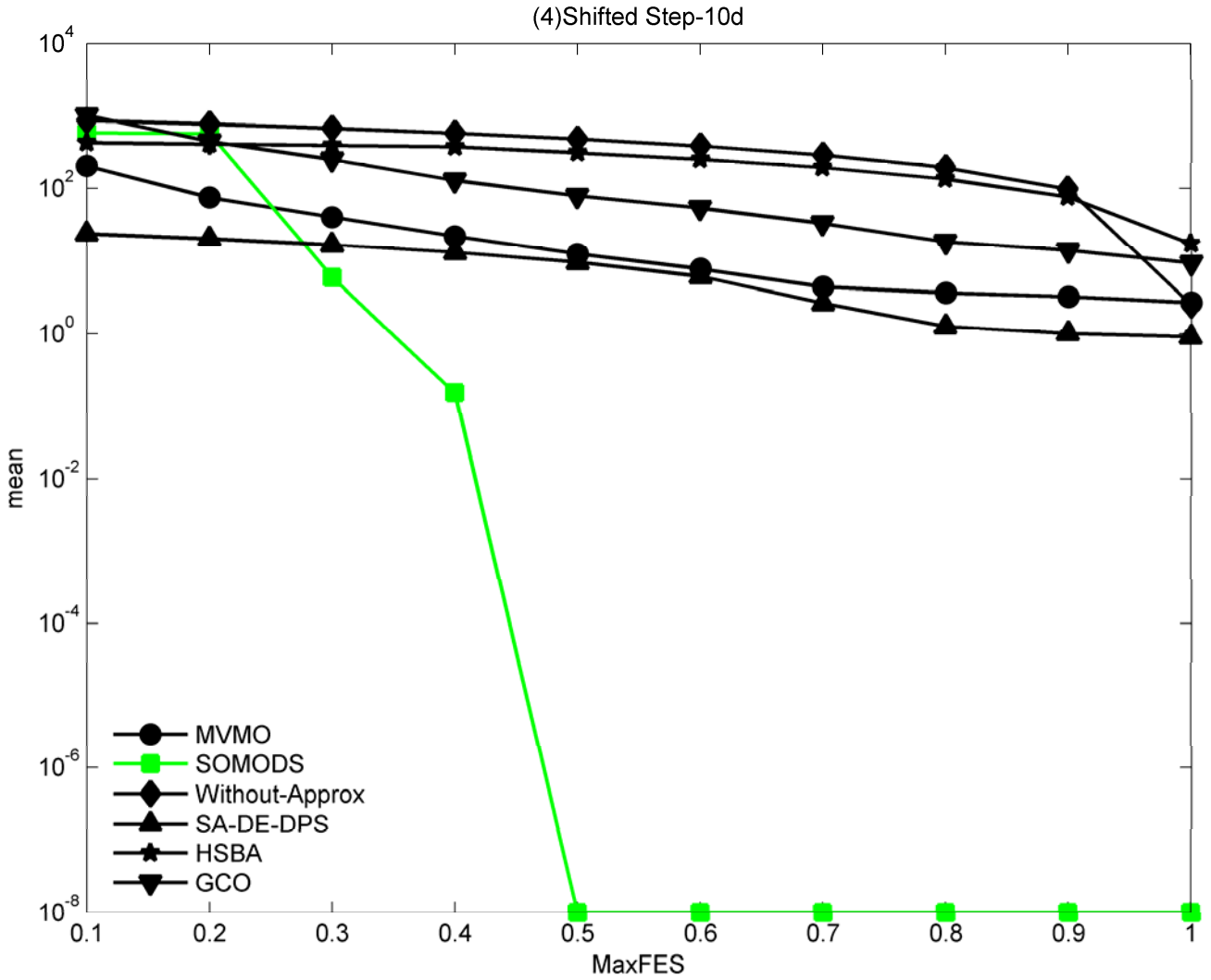

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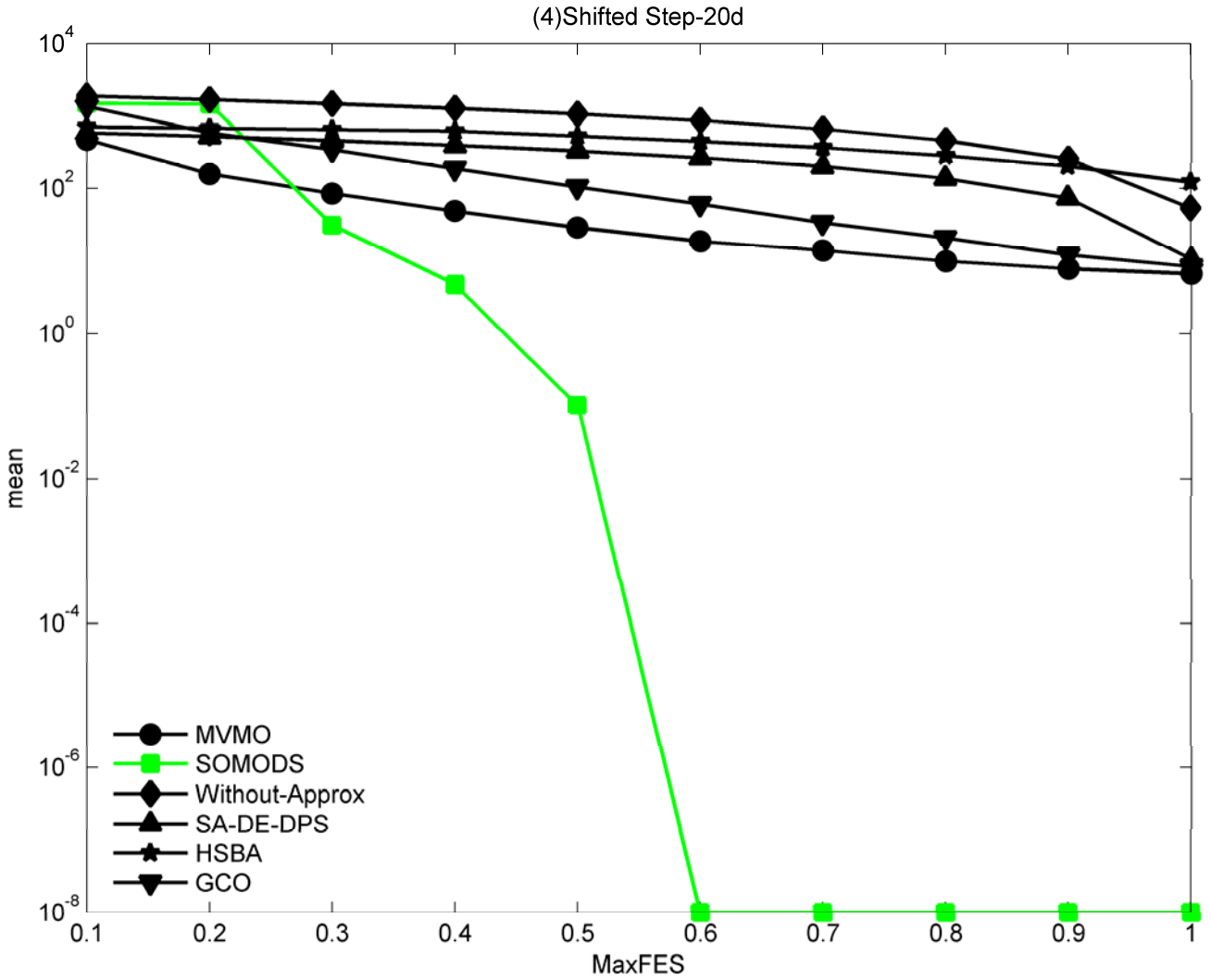

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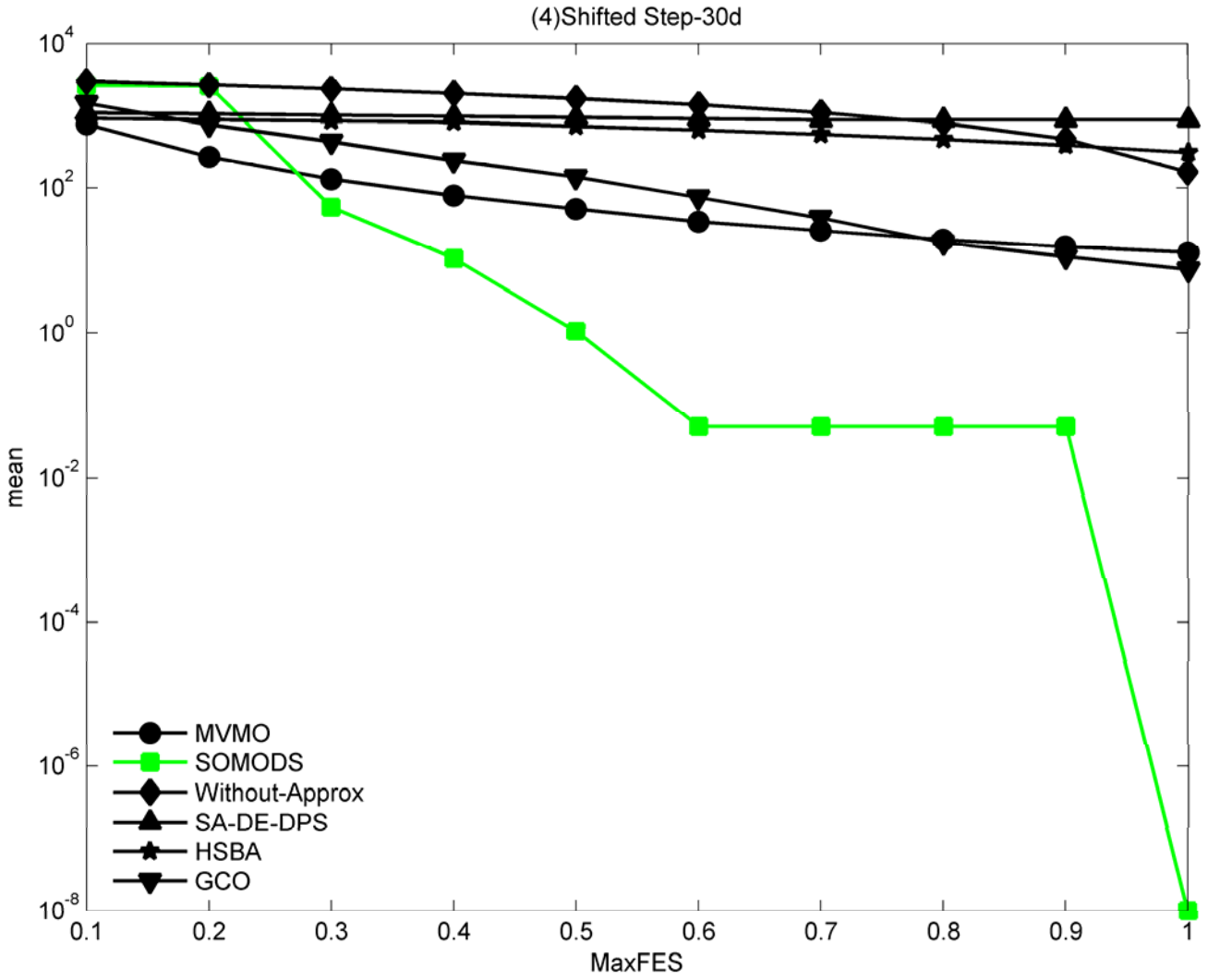


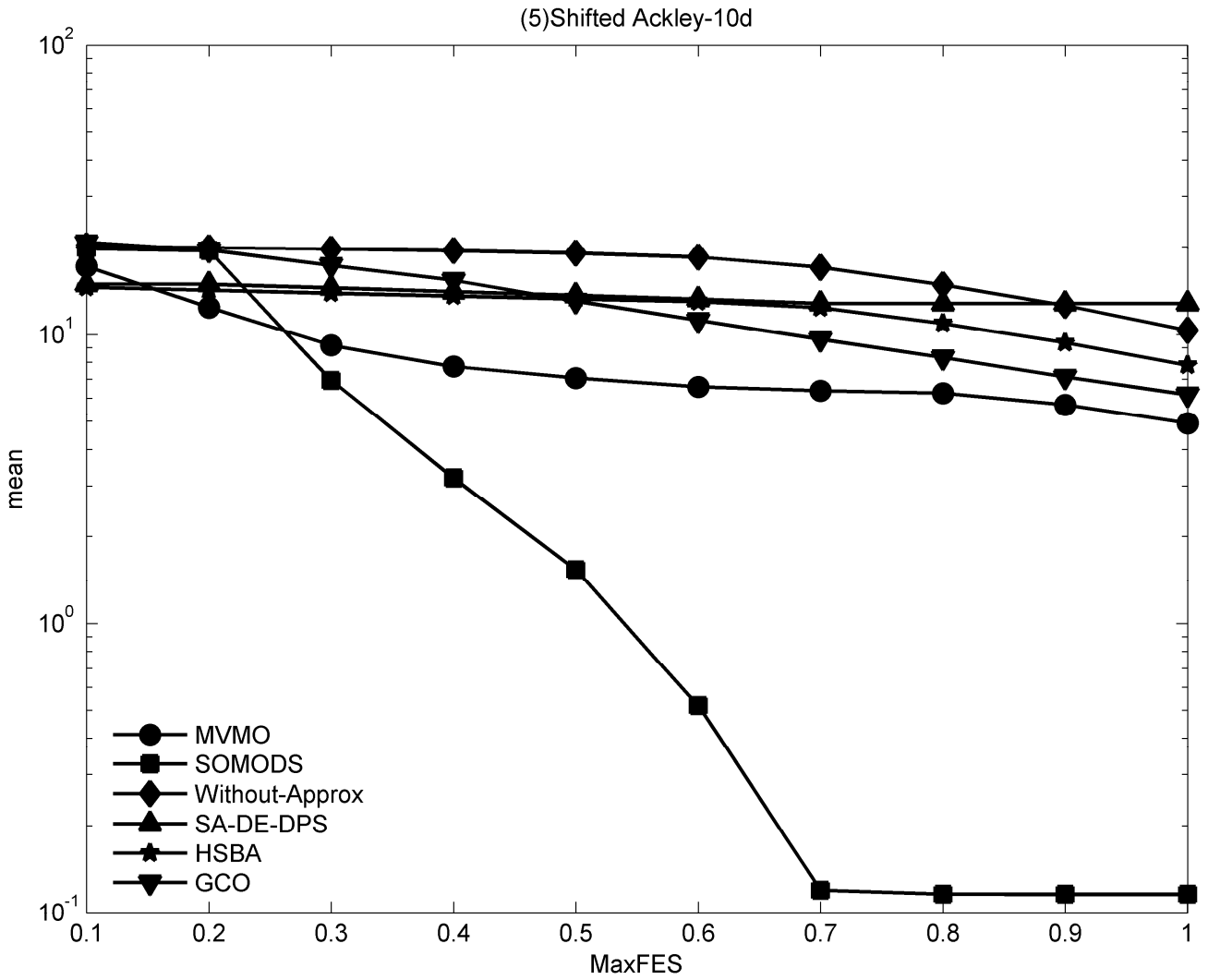
Unimodal problems

Summary for unimodal problems

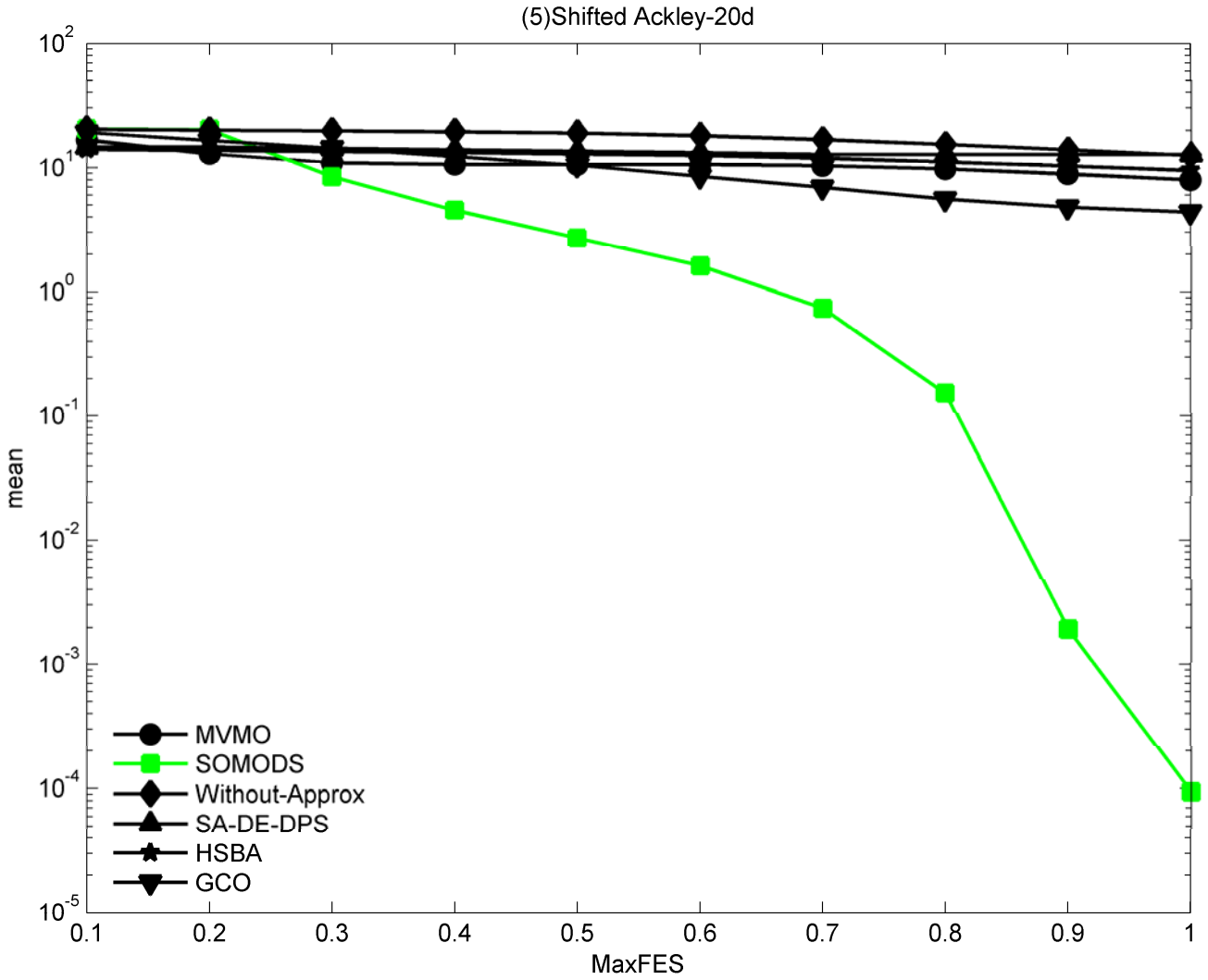
- Methods obtaining best results for ALL unimodal continuous problems: MVMO, WA

- Methods obtaining good result for unimodal discrete problem (step problem): SOMODS

Typical multimodal problems



Typical multimodal problems



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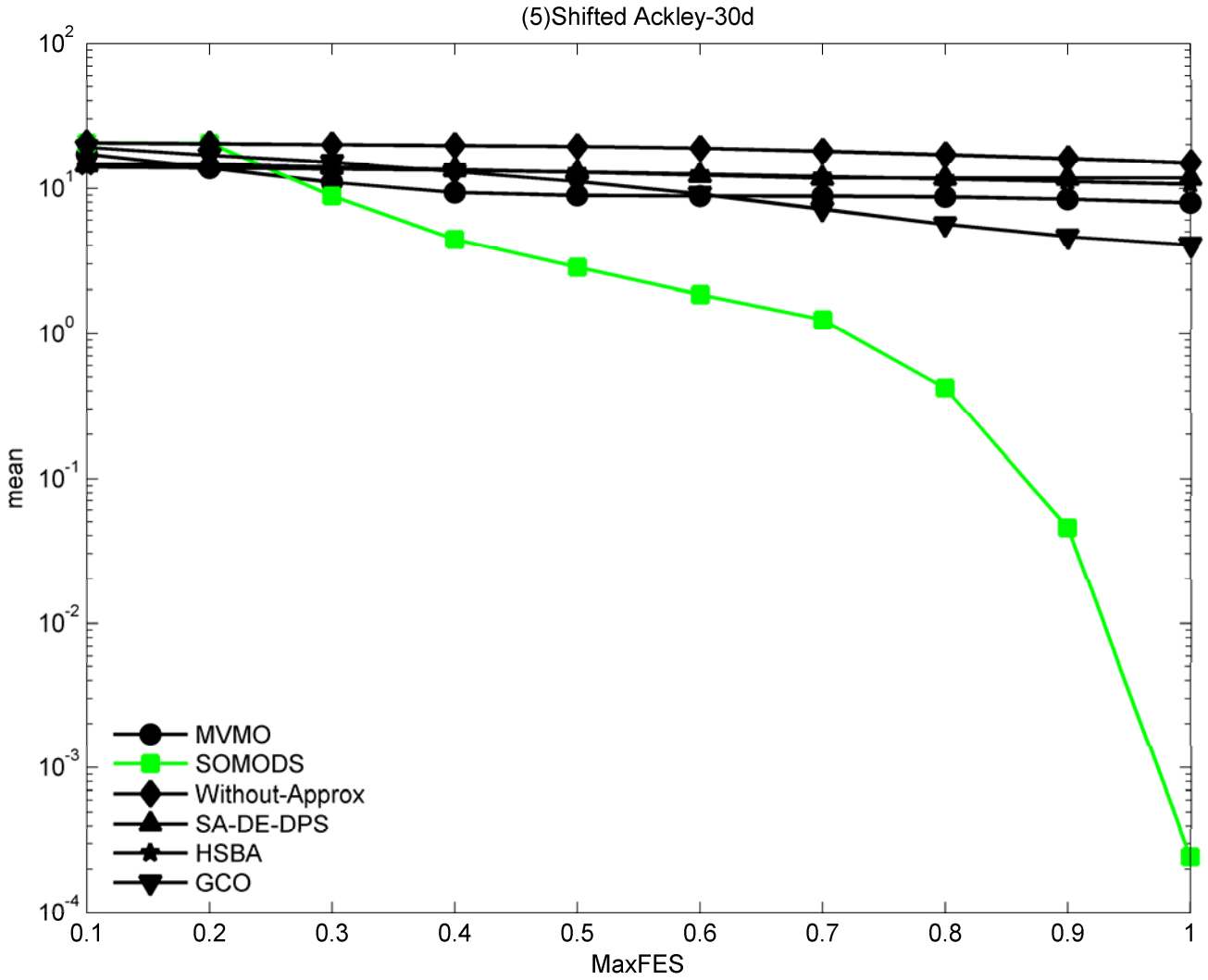
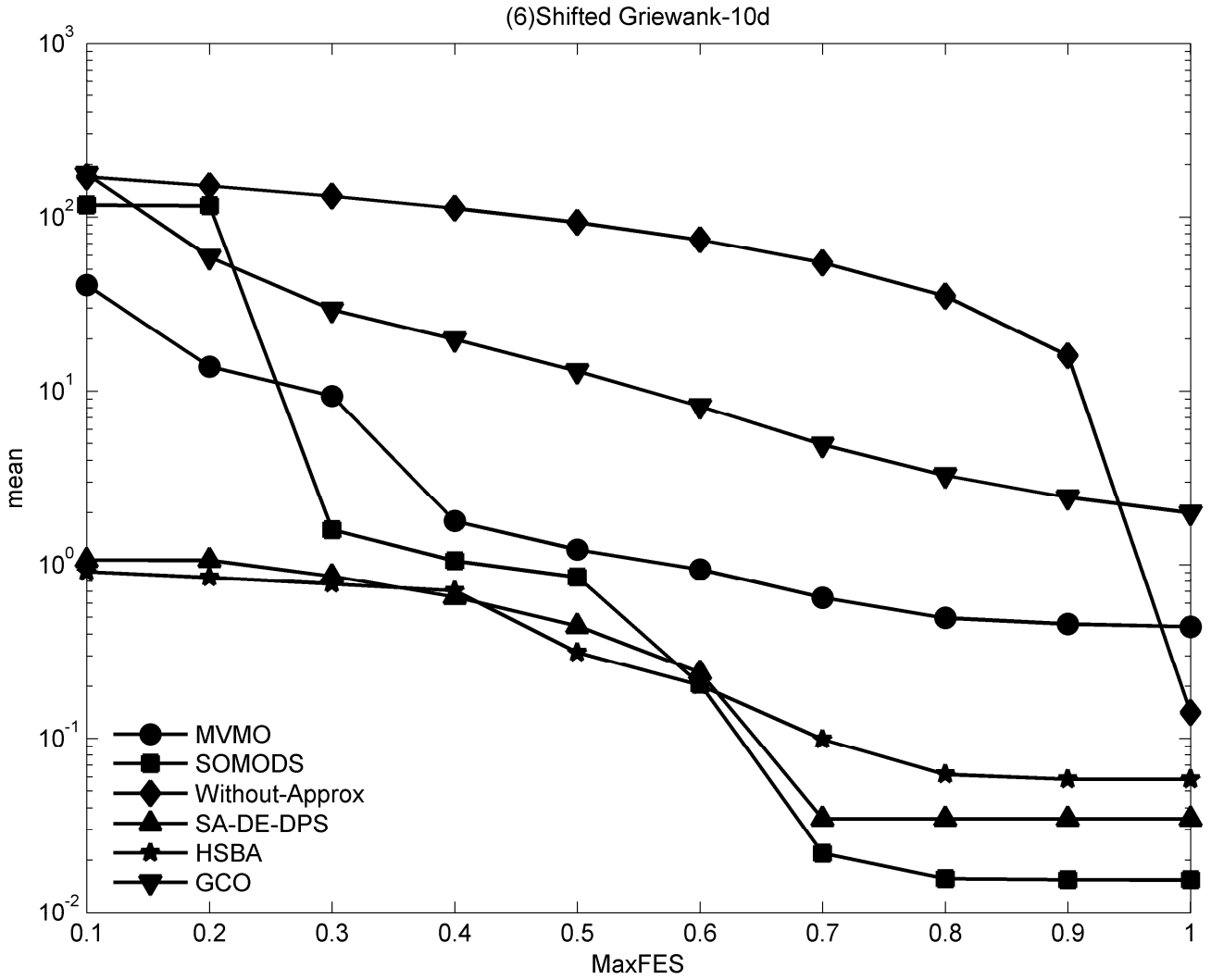


Typical multimodal problems



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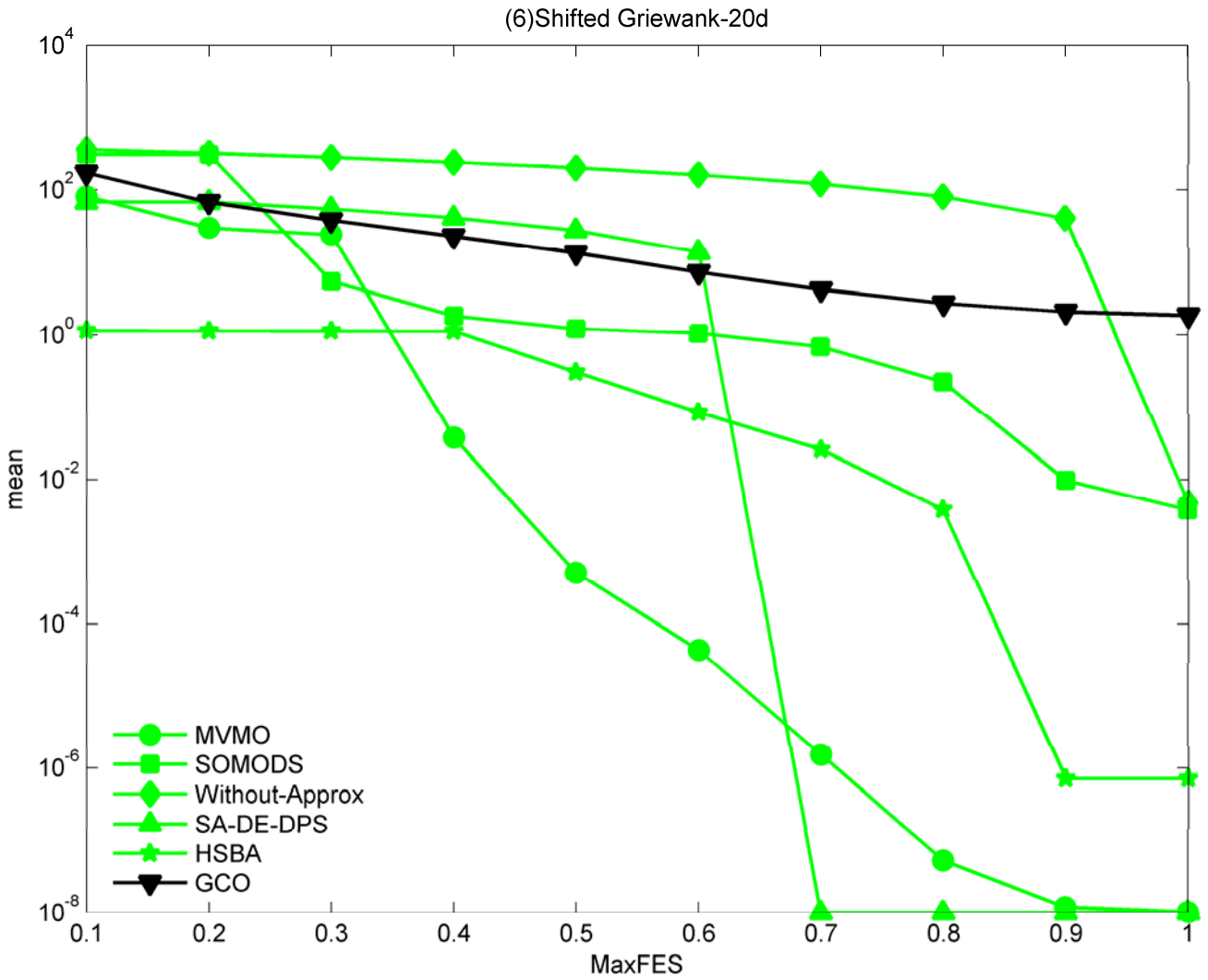

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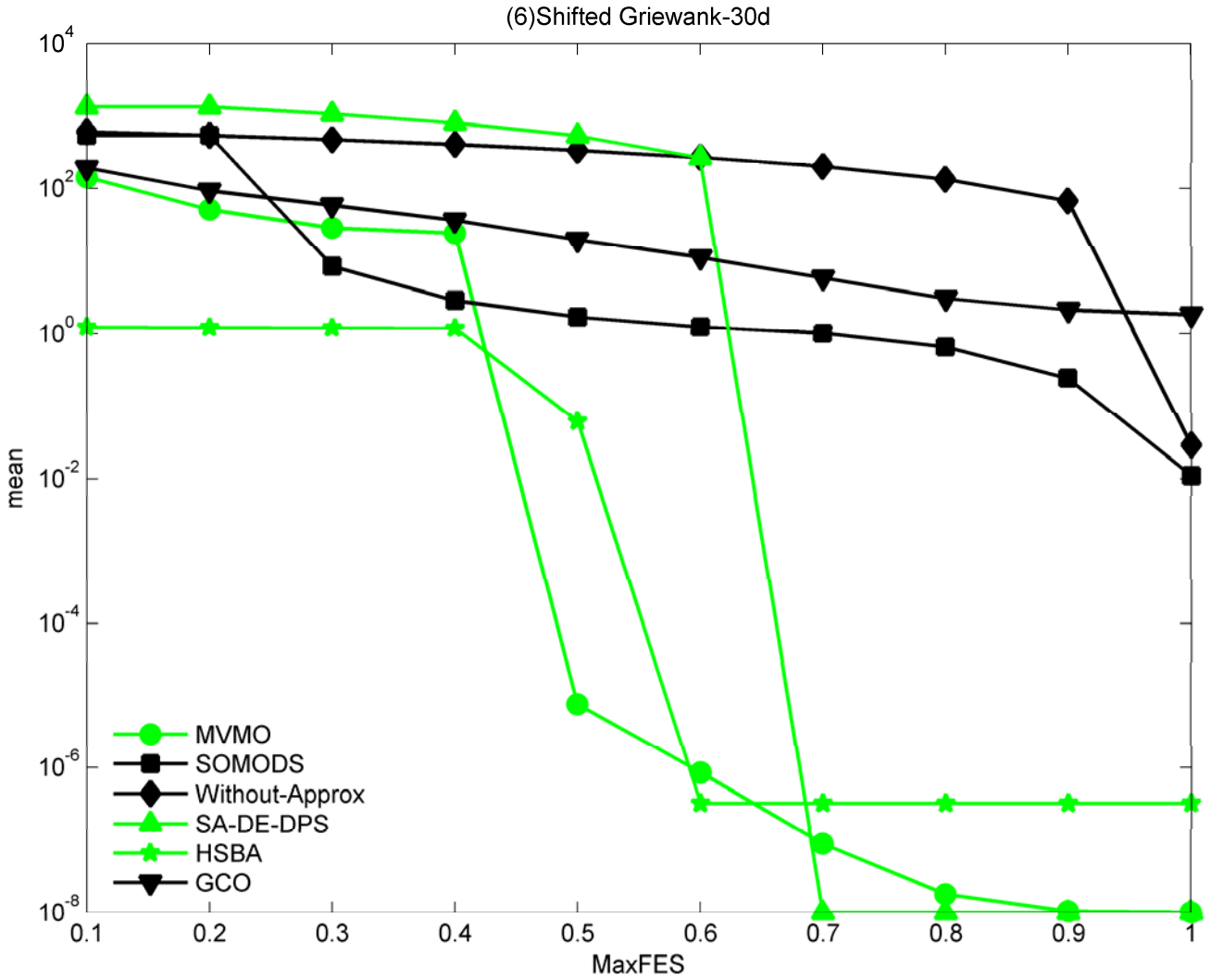
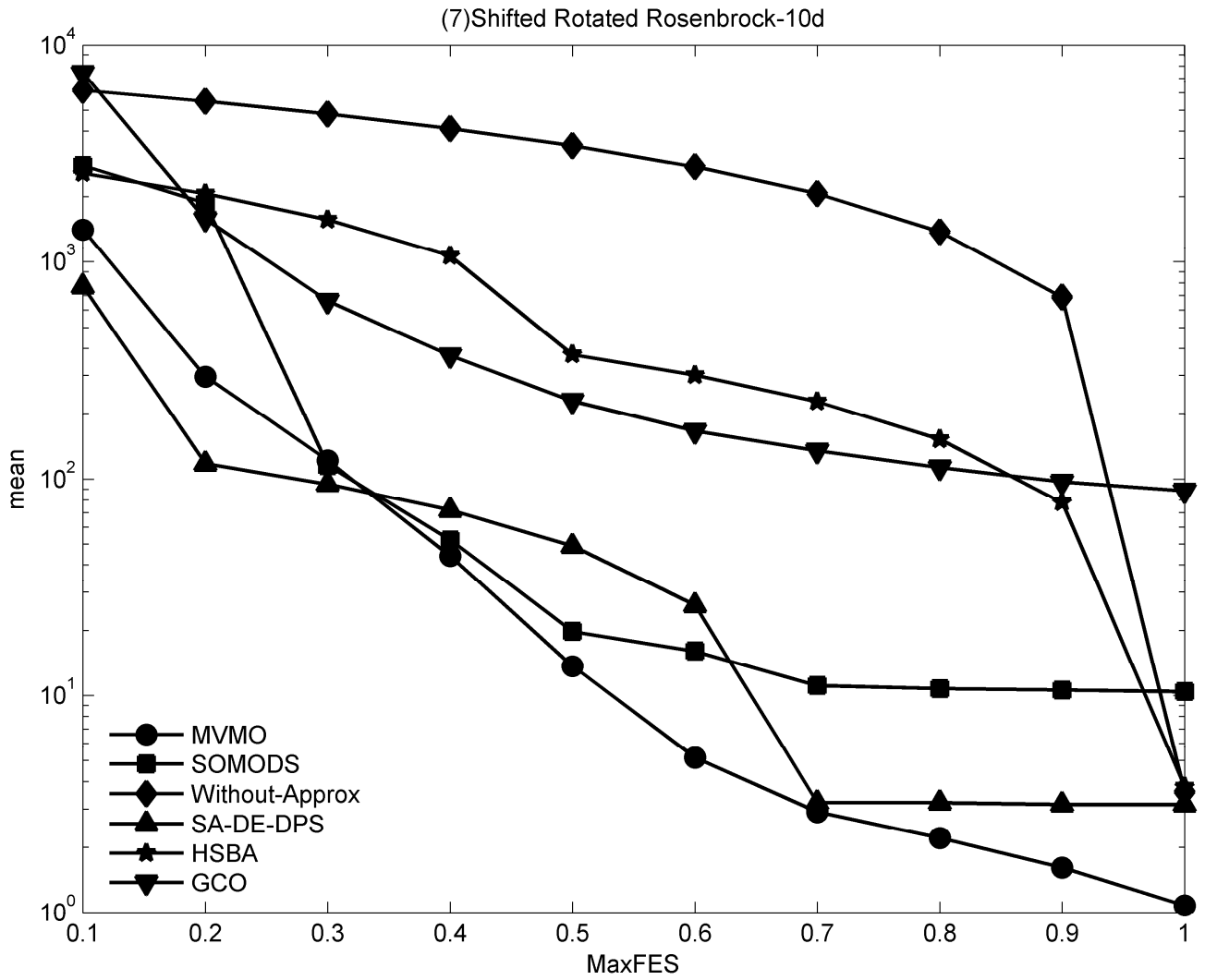


Typical multimodal problems

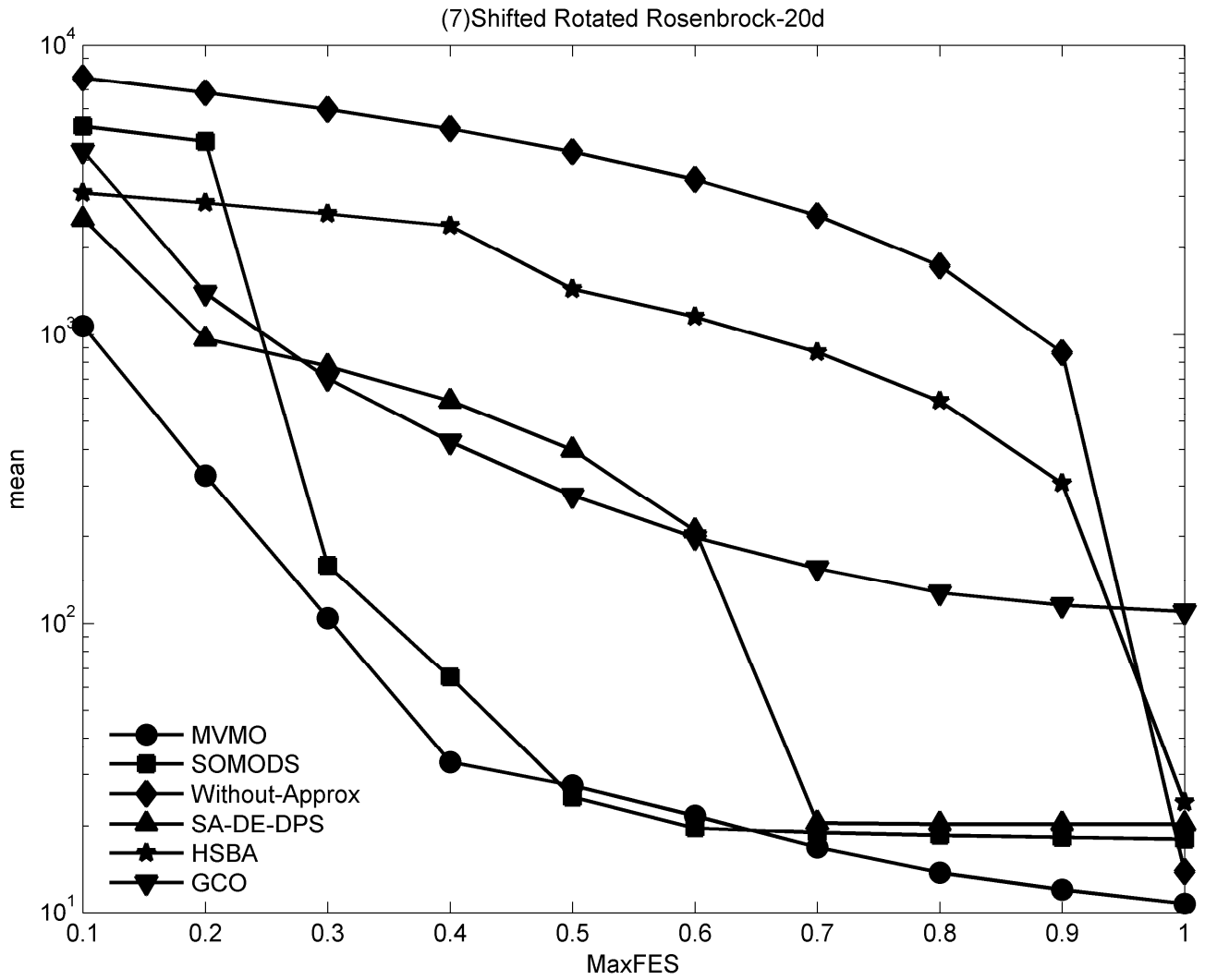
Summary for typical multimodal problems

- Methods obtaining best results for ALL typical multimodal problems: SOMODS
- All methods with surrogate modeling obtaining good results for 20d, 30d Griewank problems: SA-DE-DPS, HSBA, SOMODS

Very complex multimodal problems (narrow long valley, rugged landscapes)



Very complex multimodal problems



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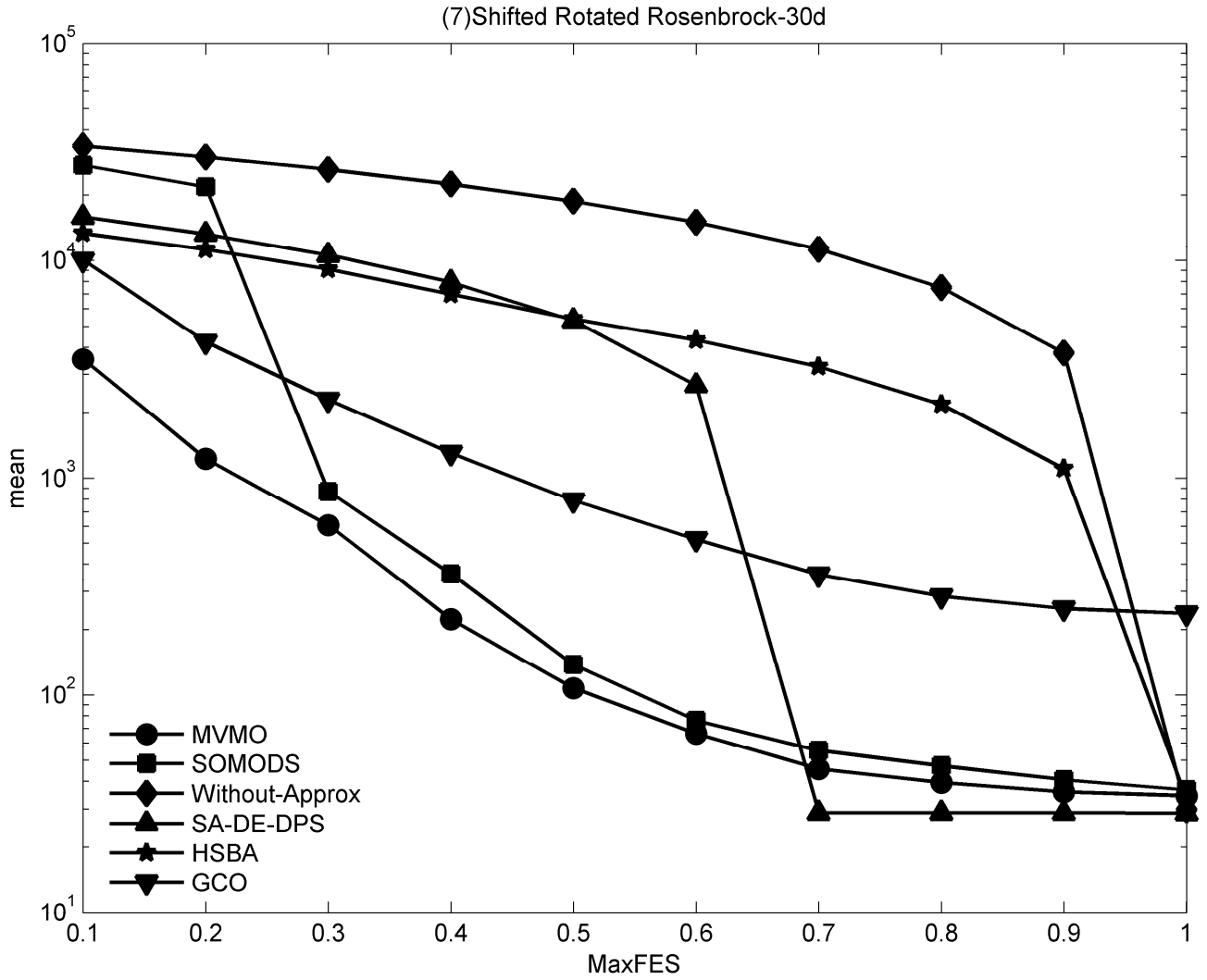

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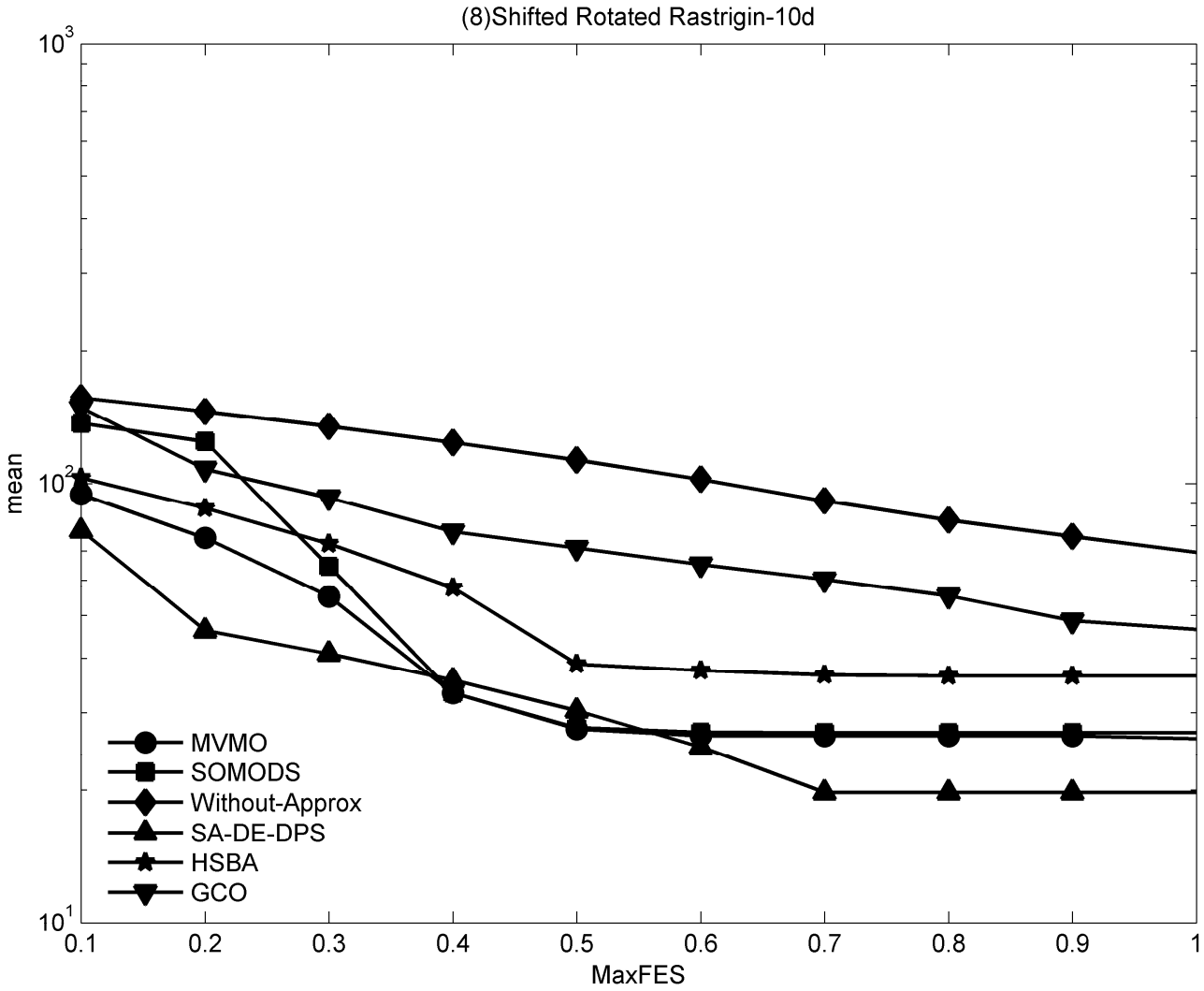
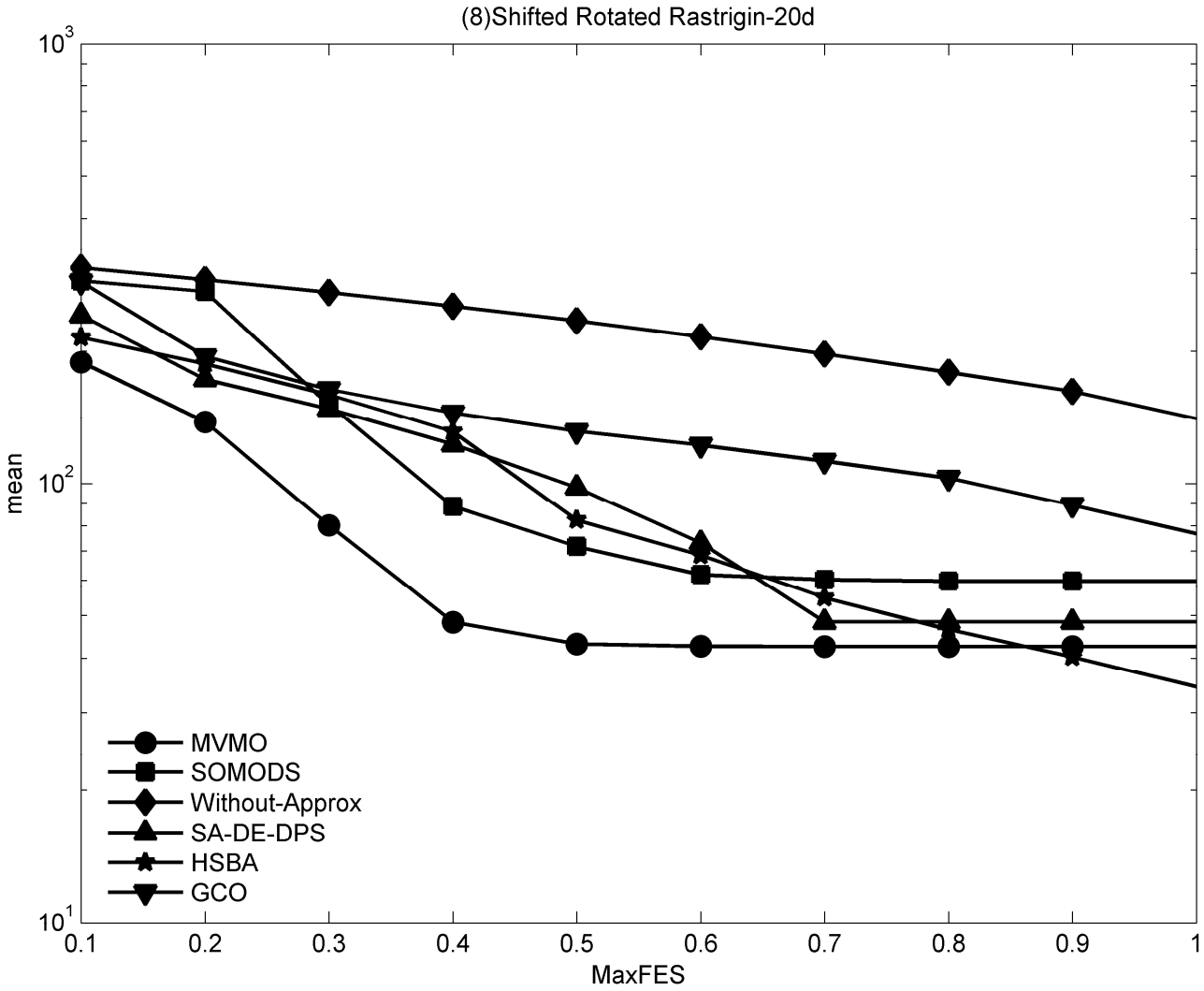
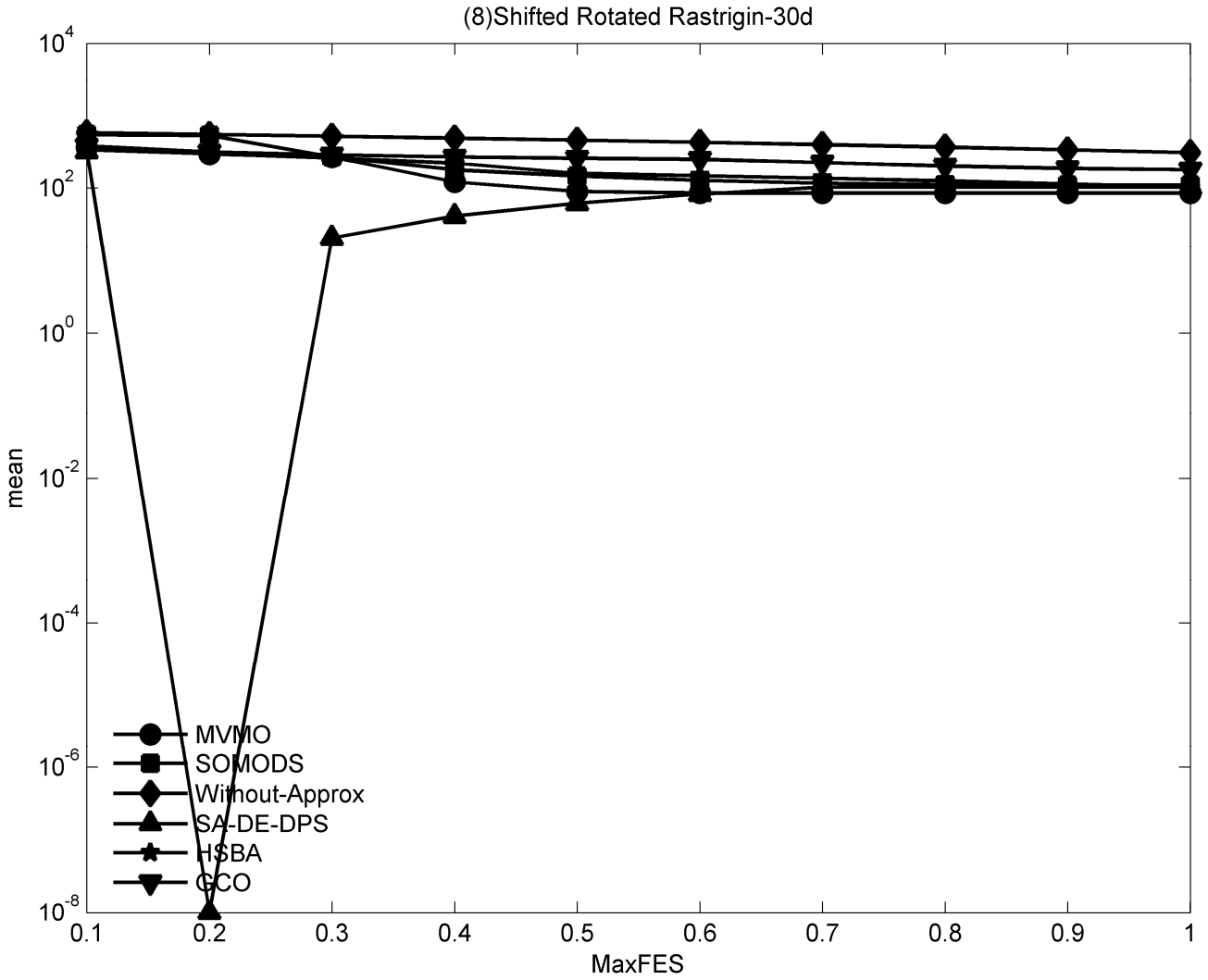


Very complex multimodal problems



Very complex multimodal problems



Very complex multimodal problems

Summary for very complex multimodal problems

- No method can obtain good results for such problems.

Presentations

A Surrogate-Assisted Differential Evolution Algorithm with Dynamic Parameters Selection for Solving Expensive Optimization Problems
Saber Elsayed, Tapabrata Ray and Ruhul Sarker

A Hybrid Surrogate Based Algorithm (HSBA) to Solve Computationally Expensive Optimization Problems
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