太原科技大學

TAIYUAN UNIVERSITY OF
SCIENCE AND TECHNOLOGY

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Fitness Approximated Assisted Competitive Swarm Optimizer for High Dimensional Expensive Problems

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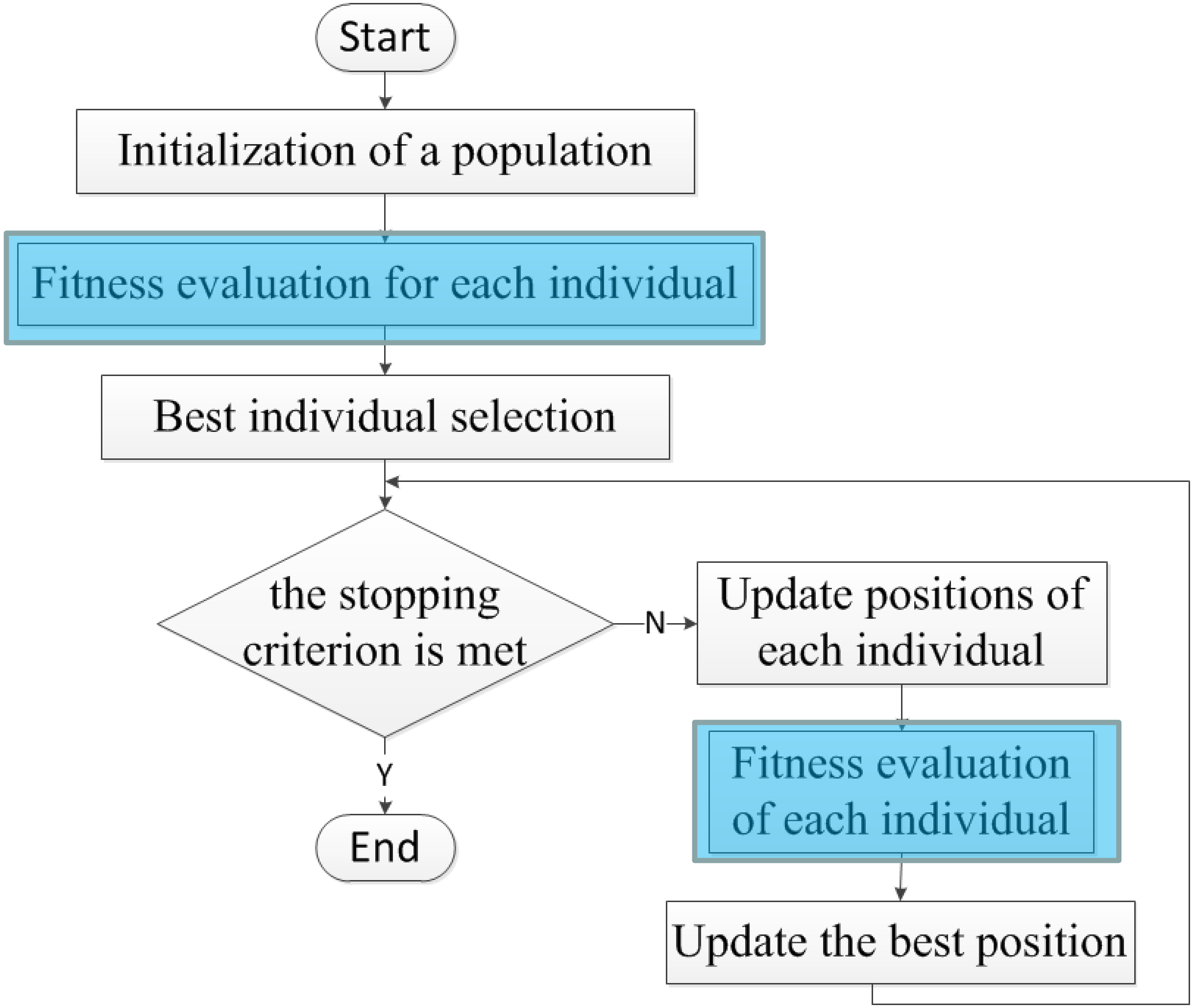
Outline

- Motivation
- Competitive Swarm Optimizer (CSO)
- Fitness Approximation Assisted Competitive Swarm Optimizer (FAACSO)
- Experimental Results and Analysis
- Summary

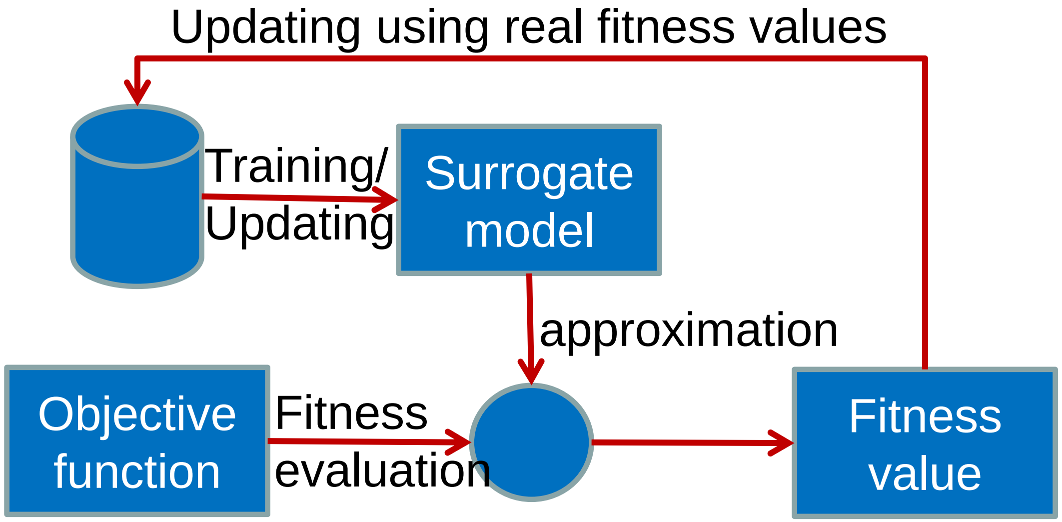


- Minimum mass of a vehicle front structure
  - 12 hours for fine model and 2 hours for coarse model

[1] Jansson T, Nilsson L, Redhe M. Using surrogate models and response surfaces in structural optimization–with application to crashworthiness design and sheet metal forming. Structural and Multidisciplinary Optimization, 2003, 25(2): 129-140.

Fitness Approximation Techniques

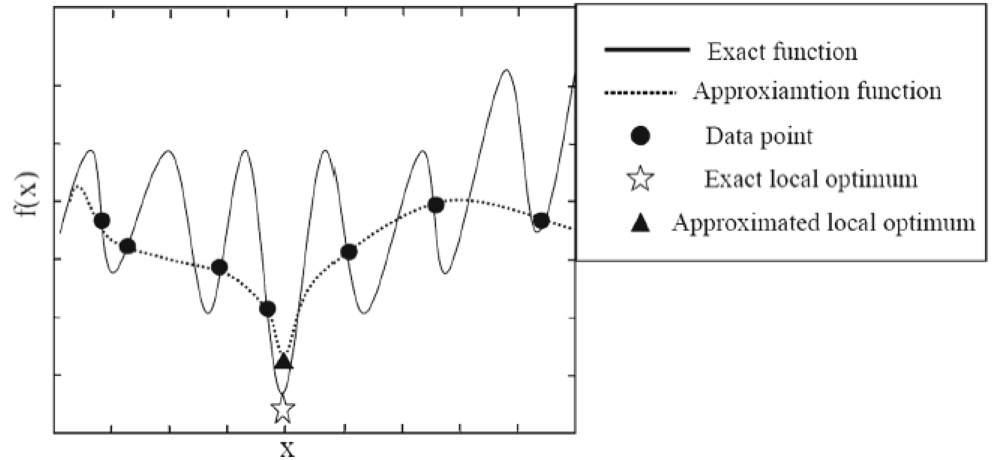
- Surrogate models



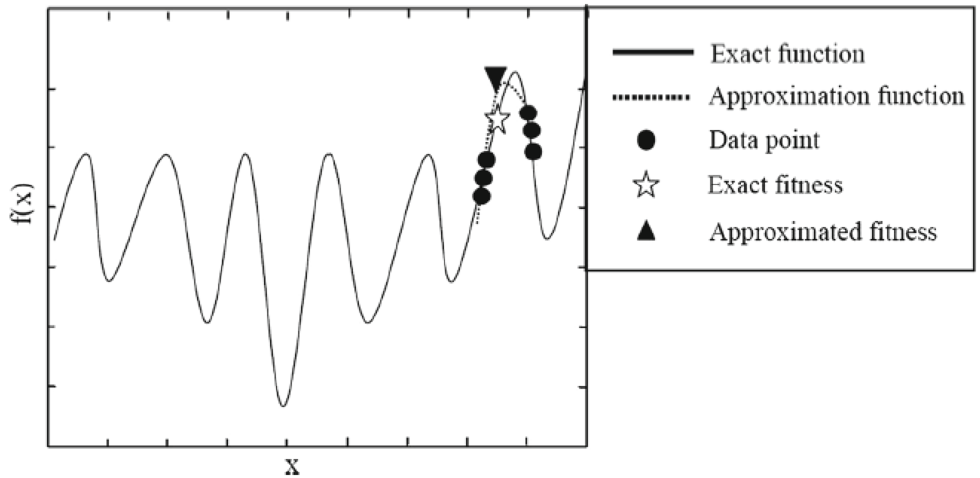
- Global and local surrogates

Global and Local Surrogates

- Global surrogate

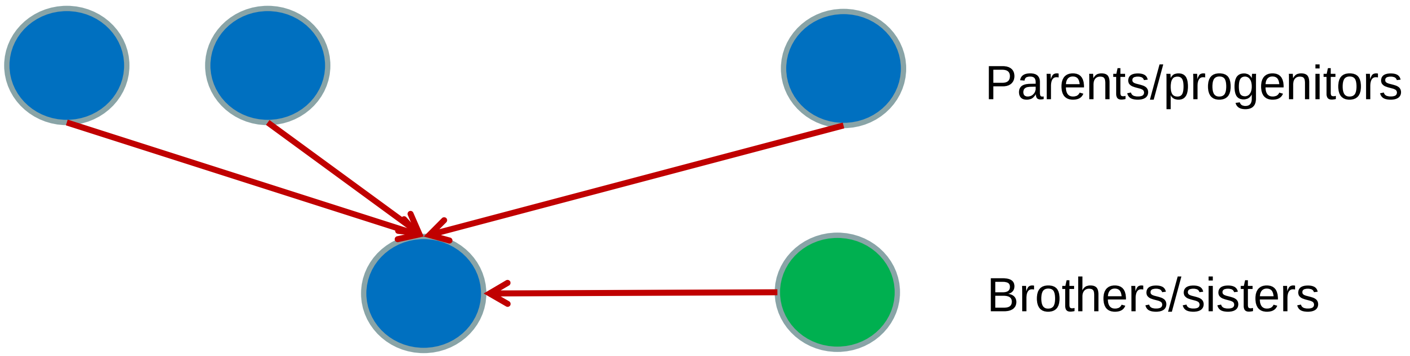


- Local surrogate



Global and Local Surrogates

- Fitness Inheritance



[1] Chaoli Sun et al. A new fitness estimation strategy for particle swarm optimization[J]. Information Sciences, 2013, 221: 355-370.

Competitive Swarm Optimizer

- Principle

Winner	Loser
$\vec{x}_i$	$\vec{x}_j$

$$v_{i,d}(t+1) = r_{i1,d}(t+1)v_{i,d}(t) + r_{i2,d}(t+1)(x_{w,d}(t) - x_{i,d}(t)) + \varphi r_{i3,d}(t+1)(\bar{x}_d(t) - x_{i,d}(t))$$

$$x_{i,d}(t+1) = x_{i,d}(t) + v_{i,d}(t+1)$$

[1] Ran Cheng, Yaochu Jin. A Competitive Swarm Optimizer for Large-scale Optimization. IEEE Transactions on Cybernetics, 2015, 45(2): 191-205

Fitness Approximated Assisted Competitive Swarm Optimizer

$$
\begin{aligned}
\mathbf{x}_i(t_1+1) = {} & \mathbf{x}_i(t_1) + \mathbf{r}_{i1}(t_1+1)\mathbf{v}_i(t_1) + \\
& \mathbf{r}_{i2}(t_1+1)(\mathbf{x}_{wi}(t_1) - \mathbf{x}_i(t_1)) + \varphi\mathbf{r}_{i3}(t_1+1)(\bar{\mathbf{x}}(t_1) - \mathbf{x}_i(t_1)) \\
= {} & \mathbf{x}_i(t_1) + \mathbf{r}_{i1}(t_1+1)(\mathbf{x}_i(t_1) - \mathbf{x}_i(t_1-1)) + \\
& \mathbf{r}_{i2}(t_1+1)(\mathbf{x}_{wi}(t_1) - \mathbf{x}_i(t_1)) + \varphi\mathbf{r}_{i3}(t_1+1)(\bar{\mathbf{x}}(t_1) - \mathbf{x}_i(t_1))
\end{aligned}
$$

$$
\begin{aligned}
\mathbf{x}_j(t_2+1) = {} & \mathbf{x}_j(t_2) + \mathbf{r}_{j1}(t_2+1)\mathbf{v}_j(t_2) + \\
& \mathbf{r}_{j2}(t_2+1)(\mathbf{x}_{wj}(t_2) - \mathbf{x}_j(t_2)) + \varphi\mathbf{r}_{j3}(t_2+1)(\bar{\mathbf{x}}(t_2) - \mathbf{x}_j(t_2)) \\
= {} & \mathbf{x}_j(t_2) + \mathbf{r}_{j1}(t_2+1)(\mathbf{x}_j(t_2) - \mathbf{x}_j(t_2-1) + \\
& \mathbf{r}_{j2}(t_2+1)(\mathbf{x}_{wj}(t_2) - \mathbf{x}_j(t_2)) + \varphi\mathbf{r}_{j3}(t_2+1)(\bar{\mathbf{x}}(t_2) - \mathbf{x}_j(t_2))
\end{aligned}
$$

Fitness Approximated Assisted Competitive Swarm Optimizer

$$
\begin{aligned}
\mathbf{x}_v = & \boxed{\mathbf{x}_i(t_1+1)} + \mathbf{r}_{i1}(t_1+1)\boxed{\mathbf{x}_i(t_1-1)} \\
& + (1 + \mathbf{r}_{j1,d}(t_2+1) - \mathbf{r}_{j2}(t_2+1) - \varphi \mathbf{r}_{j3}(t_2+1))\boxed{\mathbf{x}_j(t_2)} \\
& + \mathbf{r}_{j2}(t_2+1)\boxed{\mathbf{x}_{wj}(t_2)} + \varphi \mathbf{r}_{j3}(t_2+1)\boxed{\bar{\mathbf{x}}(t_2)} \\
= & \boxed{\mathbf{x}_j(t_2+1)} + \mathbf{r}_{j1}(t_2+1)\boxed{\mathbf{x}_j(t_2-1)} \\
& + (1 + \mathbf{r}_{i1}(t_1+1) - \mathbf{r}_{i2}(t_1+1) - \varphi \mathbf{r}_{i3}(t_1+1))\boxed{\mathbf{x}_i(t_1)} \\
& + \mathbf{r}_{i2}(t_1+1)\boxed{\mathbf{x}_{wi}(t_1)} + \varphi \mathbf{r}_{i3}(t_1+1)\boxed{\bar{\mathbf{x}}(t_1)}
\end{aligned}
$$

$$
\begin{aligned}
f(\mathbf{x}_v) &= \phi_1(\mathbf{x}_i(t_1+1), \mathbf{x}_i(t_1-1), \mathbf{x}_j(t_2), \mathbf{x}_{wj}(t_2), \bar{\mathbf{x}}(t_2)) \\
&= \phi_2(\mathbf{x}_j(t_2+1), \mathbf{x}_j(t_2-1), \mathbf{x}_i(t_1), \mathbf{x}_{wi}(t_1), \bar{\mathbf{x}}(t_1))
\end{aligned}
$$

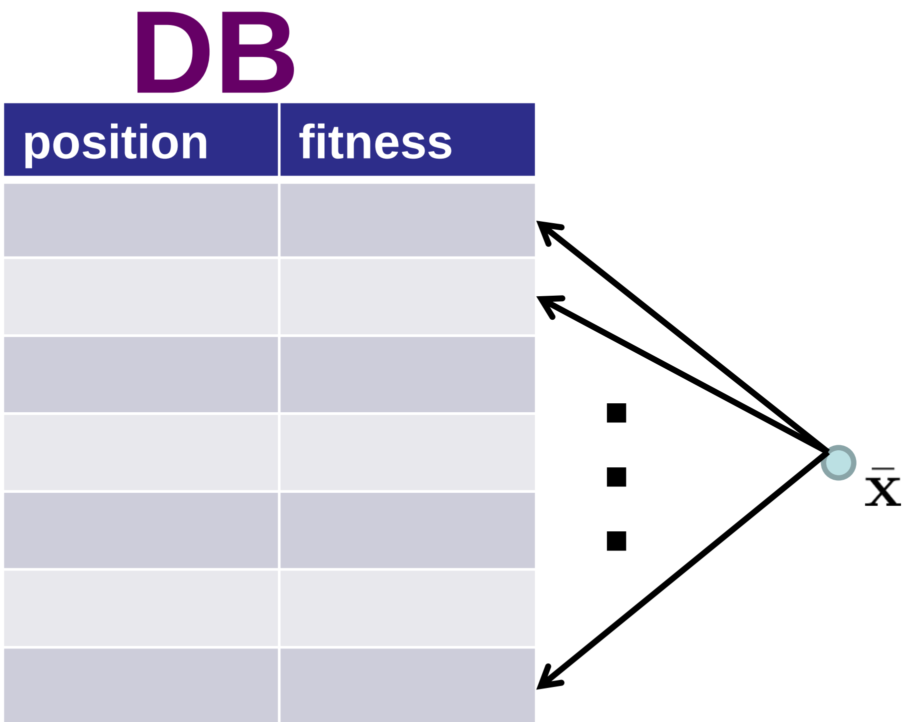
Fitness Approximated Assisted Competitive Swarm Optimizer

$$f(\mathbf{x}_i(t_1+1)) = d_{v,i}(t_1+1)(\gamma f_1 - f_2)$$

$$\gamma = \frac{\frac{1}{d_{v,i}(t_1+1)} + \frac{1}{d_{v,i}(t_1-1)} + \frac{1}{d_{v,j}(t_2)} + \frac{1}{d_{v,wj}(t_2)} + \frac{1}{d_{v,av}(t_2)}}{\frac{1}{d_{v,j}(t_2+1)} + \frac{1}{d_{v,j}(t_2-1)} + \frac{1}{d_{v,i}(t_1)} + \frac{1}{d_{v,wi}(t_1)} + \frac{1}{d_{v,av}(t_1)}}$$

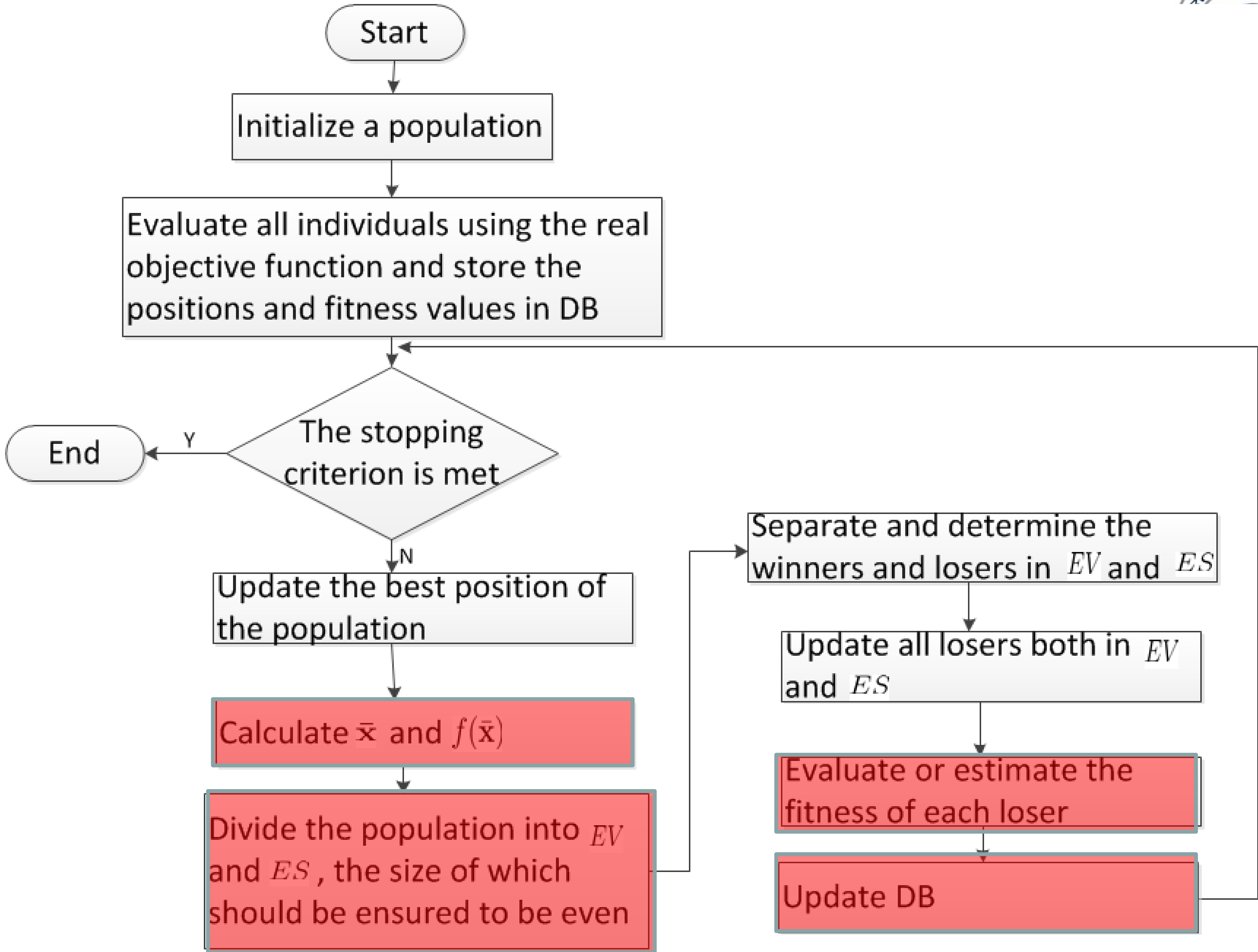
$$f_1 = \frac{f(\mathbf{x}_j(t_2+1))}{d_{v,j}(t_2+1)} + \frac{f(\mathbf{x}_j(t_2-1))}{d_{v,j}(t_2-1)} + \frac{f(\mathbf{x}_i(t_1))}{d_{v,i}(t_1)} + \frac{f(\mathbf{x}_{wi}(t_1))}{d_{v,wi}(t_1)} + \frac{f(\bar{\mathbf{x}}(t_1))}{d_{v.av}(t_1)}$$

$$f_2 = \frac{f(\mathbf{x}_i(t_1-1))}{d_{v,i}(t_1-1)} + \frac{f(\mathbf{x}_j(t_2))}{d_{v,j}(t_2)} + \frac{f(\mathbf{x}_{wj}(t_2))}{d_{v,wj}(t_2)} + \frac{f(\bar{\mathbf{x}}(t_2))}{d_{v,av}(t_2)}$$



$$\delta = \frac{\sum_{k=1}^{N_{DB}} d_{mean,k}}{N_{DB}}$$

$$f(\vec{\bar{x}}) = \frac{\sum_{i=1}^{N_{DB}} \lambda_i f(\vec{x}_i)}{\sum_{i=1}^{N_{DB}} \lambda_i}, \text{ where } \lambda_i = \begin{cases} \frac{1}{d_{mean,i}}, & \text{If } d_{mean,i} < \delta \\ 0, & \text{Otherwise} \end{cases}$$


Start
Initialize a population
Evaluate all individuals using the real objective function and store the positions and fitness values in DB
The stopping criterion is met
Y
End
N
Update the best position of the population
Calculate $\bar{x}$ and $f(\bar{x})$
Divide the population into EV and ES, the size of which should be ensured to be even
Separate and determine the winners and losers in EV and ES
Update all losers both in EV and ES
Evaluate or estimate the fitness of each loser
Update DB

If $FitK(i,t) = 0$ then

Evaluate the fitness of individual i using the real objective function;

End If

$FitD(i,t) = 1$

Approximate the fitness of individuals in its neighborhood where the individual is loser and $FitD(j,t) = 0$, denoted as $\hat{f}(\mathbf{x}_j)$;

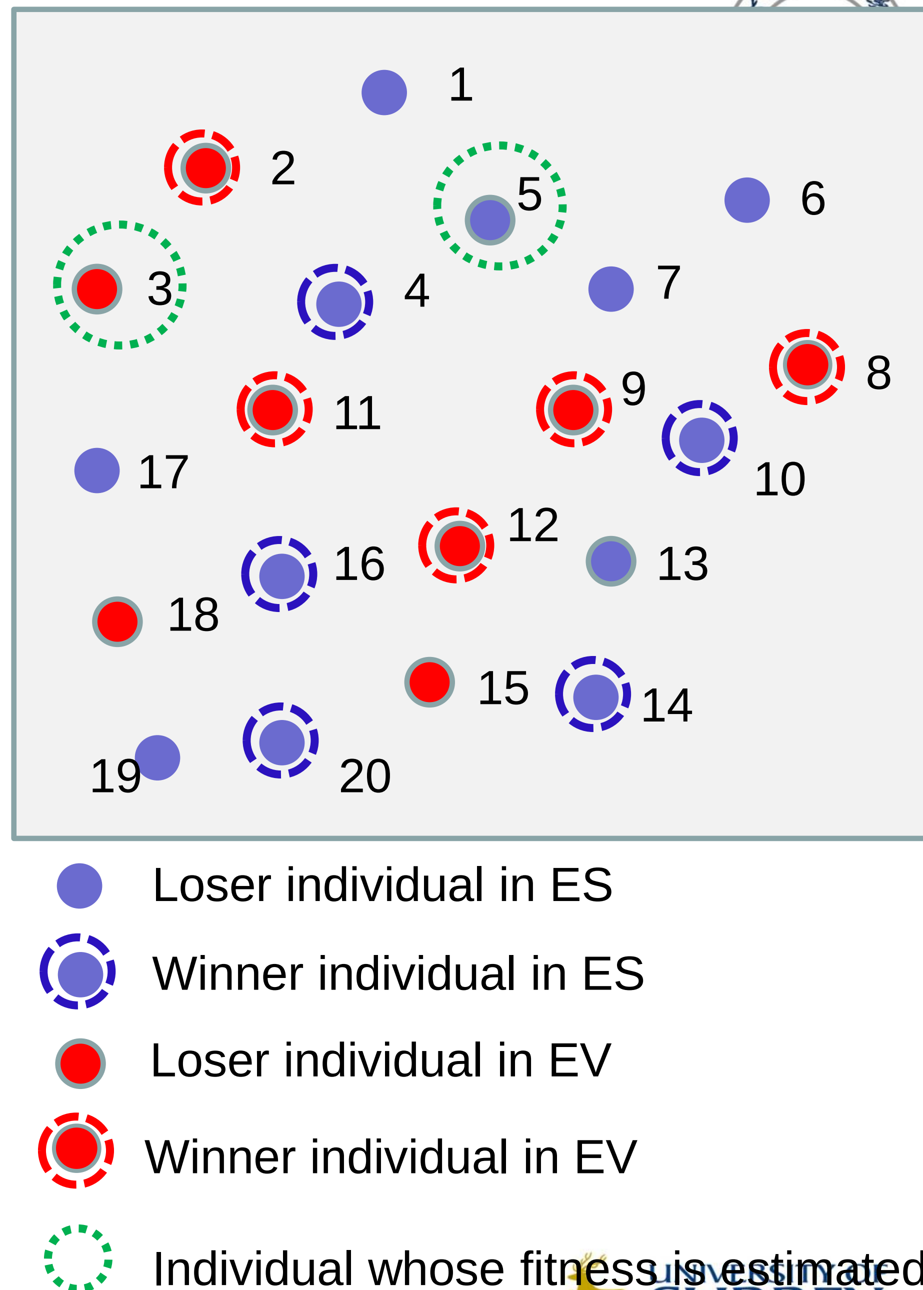
If $FitK(j,t) = 0$

$f(\mathbf{x}_j) = \hat{f}(\mathbf{x}_j)$; $FitK(j,t) = 1$

Else

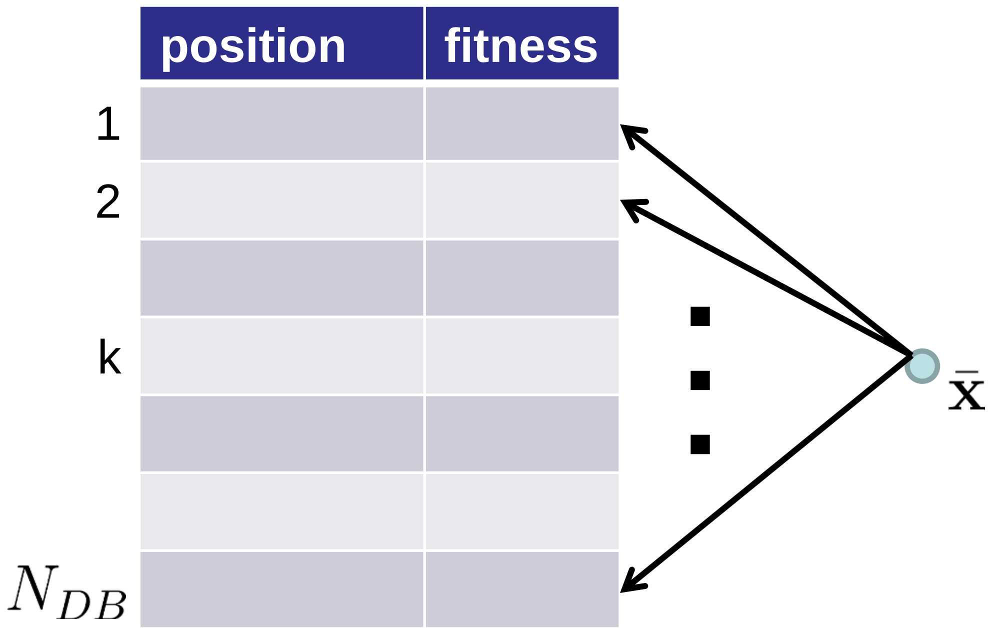
$f(\mathbf{x}_j) = \frac{f(\mathbf{x}_j) + \hat{f}(\mathbf{x}_j)}{2}$

End If



Update DB

DB



$$d_{max} = max\{d_{mean,k}, k = 1, 2, \ldots, N_{DB}\}$$

$$d_{mean,i} < d_{max}$$

Experimental results

- Stop condition: 10*D

Table 1 Characteristics of the CEC'08 benchmark functions

Benchmark functions	Main characters	Decision spaces
Shifted Sphere Function (F1)	Unimodal, Separable	$[-100, 100]^D$
Shifted Schwefels Problem 2.21 (F2)	Unimodal,Non-separable	$[-100, 100]^D$
Shifted Rosenbrocks Function (F3)	Multimodal, Non-separable	$[-100, 100]^D$
Shifted Rastrigins Function (F4)	Multimodal, Separable	$[-5, 5]^D$
Shifted Griewanks Function (F5)	Multimodal, Non-separable	$[-600, 600]^D$
Shifted Ackleys Function (F6)	Multimodal, Separable	$[-32, 32]^D$
FastFractal DoubleDip Function (F7)	Multimodal, Non-separable	$[-1, 1]^D$

Experimental results

Table 3 Statistical results on 100-D benchmark functions

	Approach	Best	Mean(t-test)	Worst	Std.
F1	FAACSO	1.7335e+005	1.9590e+005	2.3601e+005	1.7157e+004
	FESPSO	1.4077e+005	1.9207e+005(≈)	2.3089e+005	2.4205e+004
	CSO	2.0817e+005	2.5613e+005(+)	2.9461e+005	1.8638e+004
F2	FAACSO	1.0590e+002	1.1823e+002	1.3060e+002	6.3778e+002
	FESPSO	1.1928e+002	1.3198e+002(+)	1.4040e+002	6.5366e+002
	CSO	1.1775e+002	1.2378e+002(+)	1.3554e+002	4.5202e+002
F3	FAACSO	5.6133e+010	7.7159e+010	1.0127e+011	1.0714e+010
	FESPSO	7.1568e+010	1.0259e+011(+)	1.3190e+011	1.7028e+010
	CSO	7.8650e+010	1.0322e+011(+)	1.2271e+011	1.0832e+010
F4	FAACSO	1.3248e+003	1.5064e+003	1.6091e+003	7.4953e+001
	FESPSO	1.3213e+003	1.5567e+003(≈)	1.7582e+003	1.1626e+002
	CSO	1.4944e+003	1.6279e+003(+)	1.7252e+003	5.8152e+001
F5	FAACSO	1.3876e+003	1.6787e+003	1.9117e+003	1.4152e+002
	FESPSO	1.3271e+003	1.6440e+003(≈)	1.9728e+003	1.7590e+002
	CSO	1.7574e+003	2.0445e+003(+)	2.2589e+003	1.4006e+002
F6	FAACSO	2.0136e+001	2.0446e+001	2.0716e+001	1.7789e-001
	FESPSO	2.0701e+001	2.1194e+001(+)	2.1350e+001	1.5751e-001
	CSO	2.0568e+001	2.0767e+001(+)	2.0997e+001	1.1942e-001
F7	FAACSO	-3.4253e+005	-2.9174e+005	-2.4906e+005	2.4732e+004
	FESPSO	-4.2135e+005	-2.9444e+005(≈)	-2.4981e+005	1.9677e+004
	CSO	-3.1958e+005	-2.8311e+005(≈)	-2.5382e+005	4.1265e+004

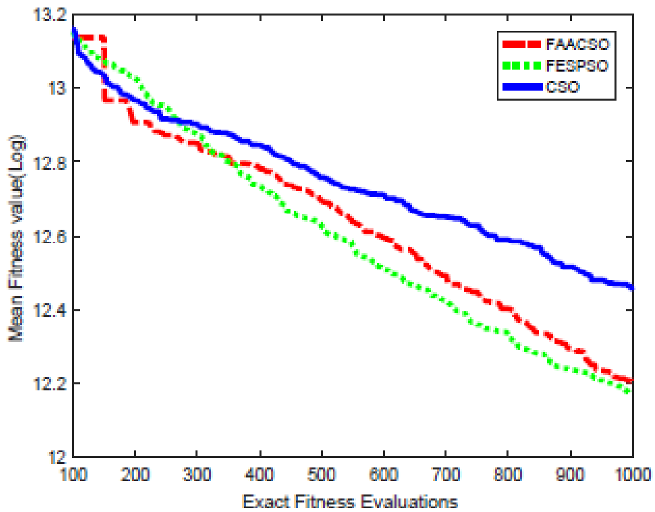


Fig. 1 The convergence profiles on 100-D F1

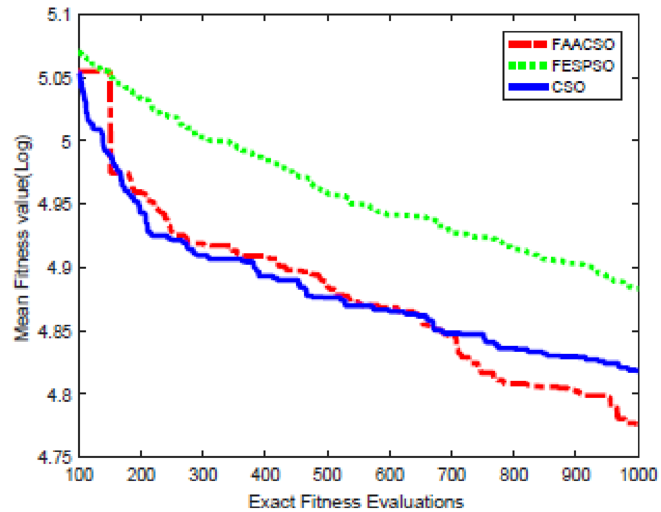


Fig. 2 The convergence profiles on 100-D F2

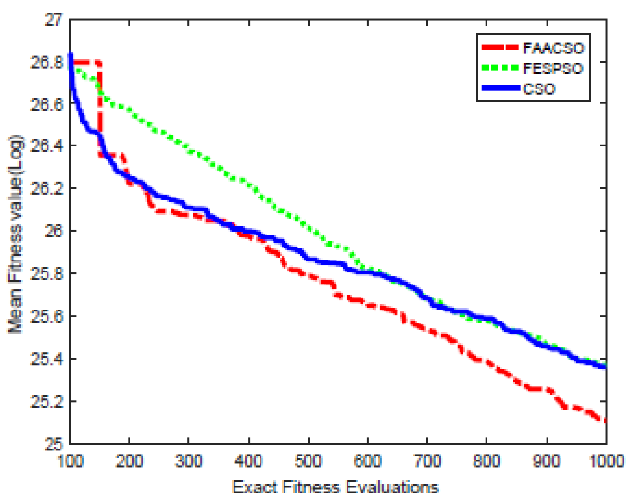


Fig. 3 The convergence profiles on 100-D F3

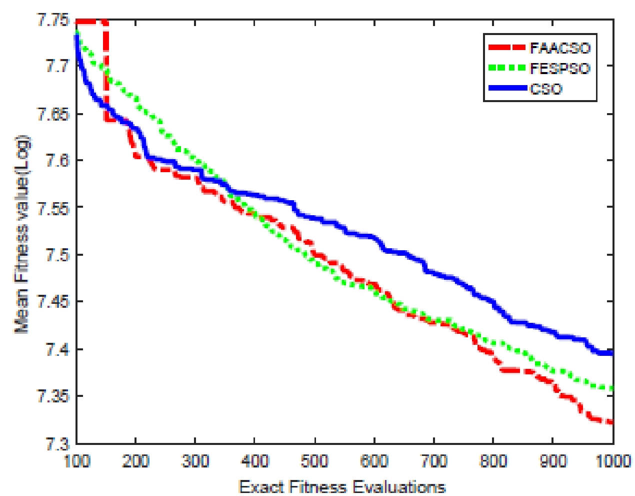


Fig. 4 The convergence profiles on 100-D F4

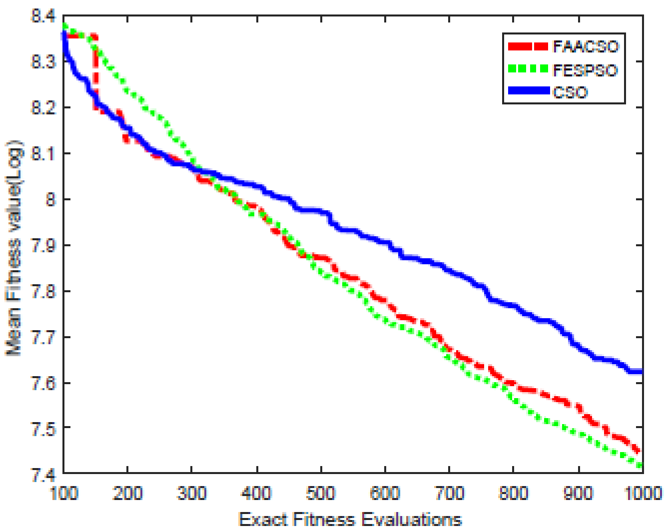


Fig. 5 The convergence profiles on 100-D F5

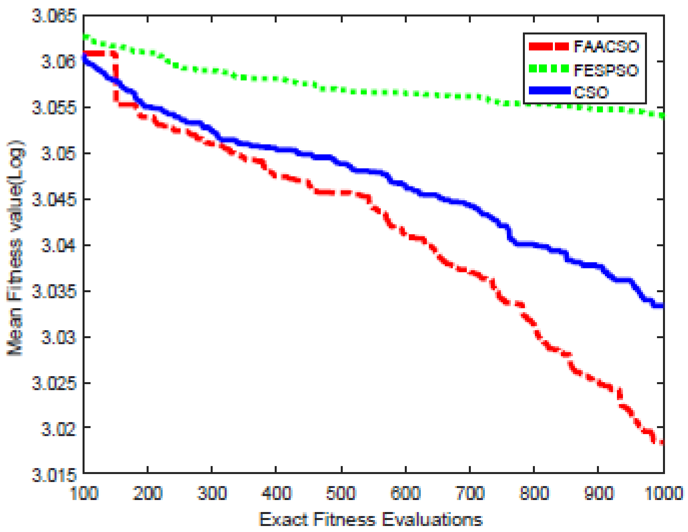


Fig. 6 The convergence profiles on 100-D F6

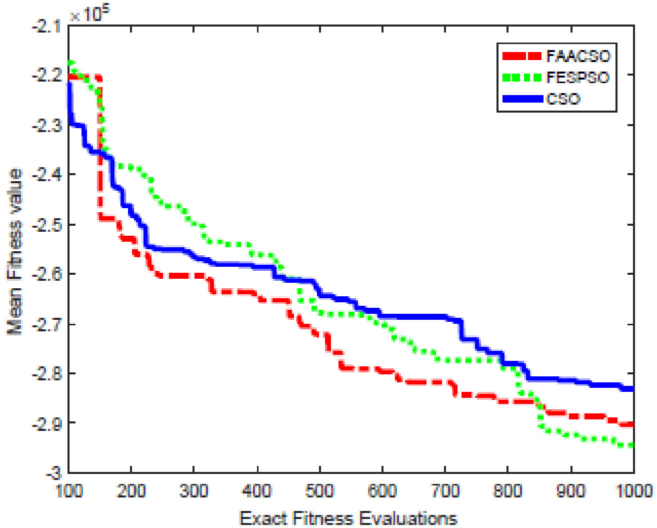


Fig. 7 The convergence profiles on 100-D F7

Experimental results

Table 4 Statistical results on 500-D benchmark functions

	Approach	Best	Mean(t-test)	Worst	Std.
F1	FAACSO	6.2815e+005	7.1431e+005	7.8486e+005	4.5956e+004
	FESPSO	1.5635e+006	1.6874e+006(+)	1.8512e+006	9.0506e+004
	CSO	7.1310e+005	7.8586e+005(+)	8.7976e+005	4.2265e+004
F2	FAACSO	1.2939e+001	1.3375e+001	1.3904e+001	2.5659e+000
	FESPSO	1.6017e+001	1.6636e+001(+)	1.7213e+001	3.2873e+000
	CSO	1.2701e+001	1.3369e+001(≈)	1.3859e+001	2.7624e+000
F3	FAACSO	2.7731e+011	3.3270e+011	4.0340e+011	3.7787e+010
	FESPSO	1.1732e+012	1.5533e+012(+)	1.8828e+012	1.7466e+011
	CSO	3.0338e+011	3.6324e+011(+)	4.4818e+011	3.1559e+010
F4	FAACSO	6.9856e+003	7.2720e+003	7.4724e+003	1.4764e+002
	FESPSO	9.4527e+003	9.7891e+003(+)	1.0356e+004	2.8815e+002
	CSO	7.0410e+003	7.2967e+003(≈)	7.5764e+003	1.5208e+002
F5	FAACSO	5.1111e+003	5.7416e+003	6.2712e+003	3.3004e+002
	FESPSO	1.3456e+004	1.5001e+004(+)	1.6392e+004	8.3937e+002
	CSO	5.9189e+003	6.4688e+003(+)	6.9645e+003	3.4823e+002
F6	FAACSO	1.9736e+001	1.9953e+001	2.0154e+001	1.2610e-001
	FESPSO	2.1169e+001	2.1287e+001(+)	2.1361e+001	6.0903e-002
	CSO	1.9702e+001	2.0059e+001(+)	2.0268e+001	1.5179e-001
F7	FAACSO	-1.1617e+006	-1.0735e+006	-1.0122e+006	4.0896e+004
	FESPSO	-1.0425e+006	-9.5609e+005(+)	-8.5244e+005	5.8683e+004
	CSO	-1.1849e+006	-1.0400e+006(+)	-9.8103e+005	4.5496e+004

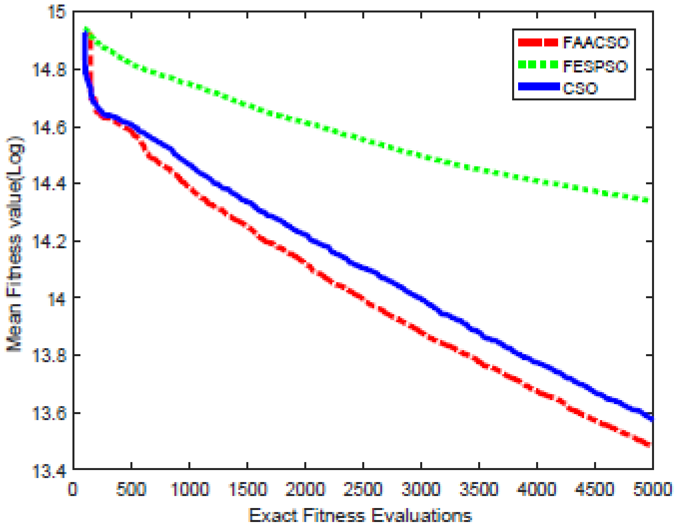


Fig. 8 The convergence profiles on 500-D F1

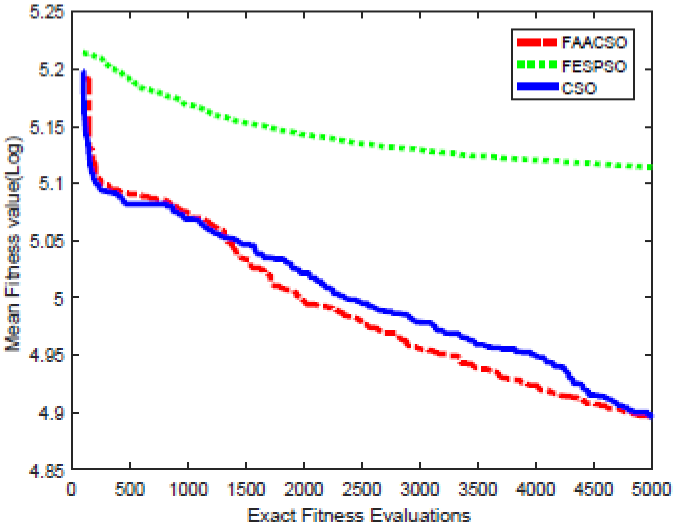


Fig. 9 The convergence profiles on 500-D F2

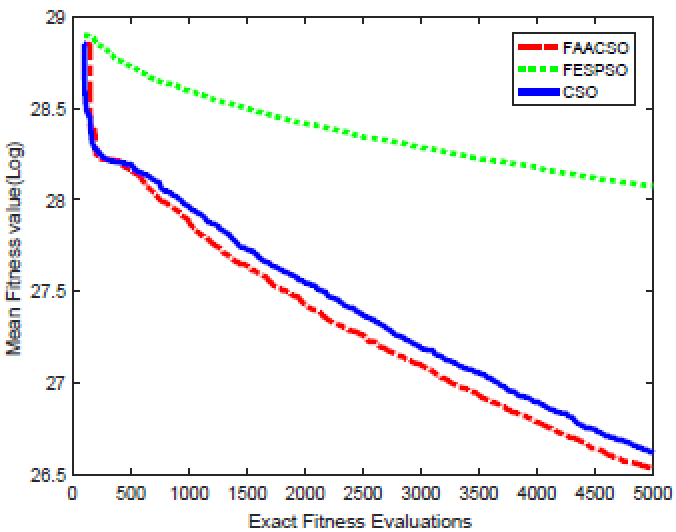


Fig. 10 The convergence profiles on 500-D F3

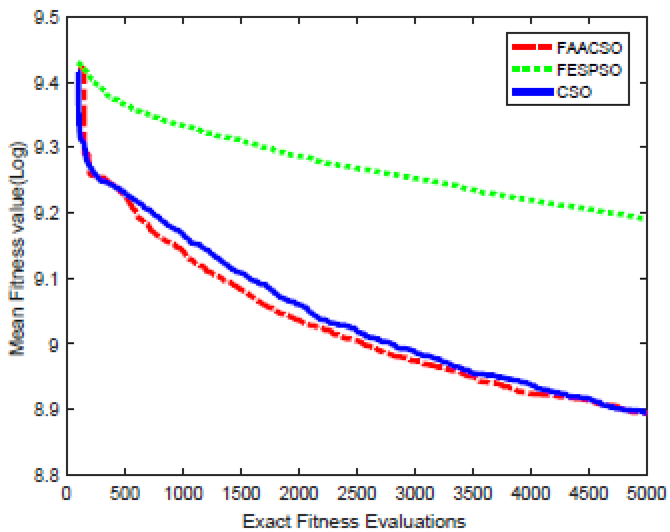


Fig. 11 The convergence profiles on 500-D F4

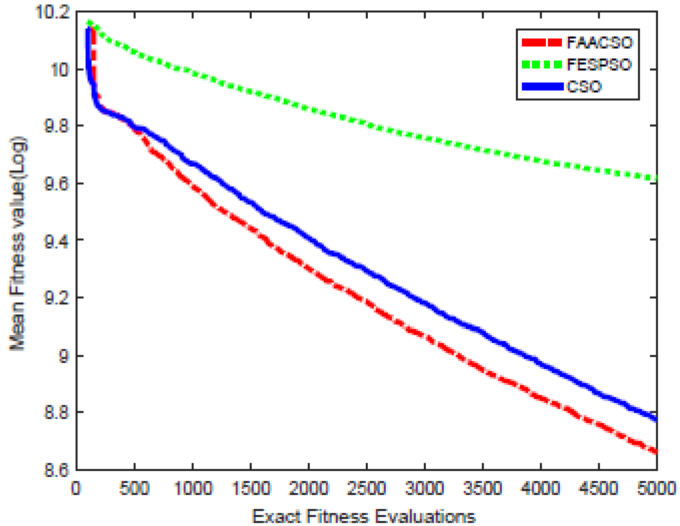


Fig. 12 The convergence profiles on 500-D F5

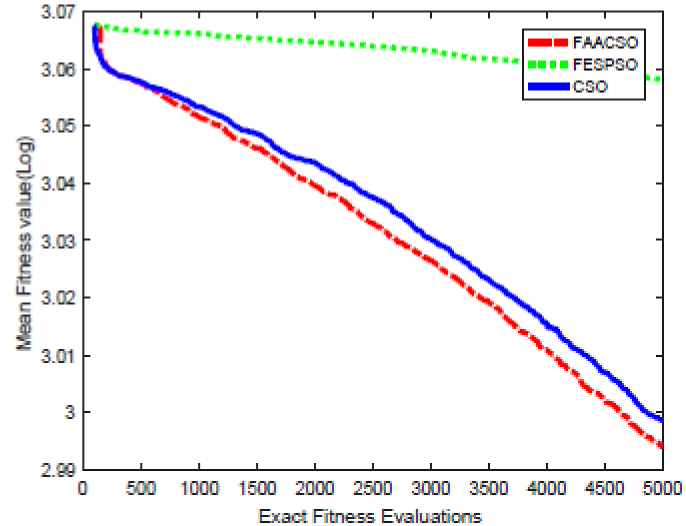


Fig. 13 The convergence profiles on 500-D F6

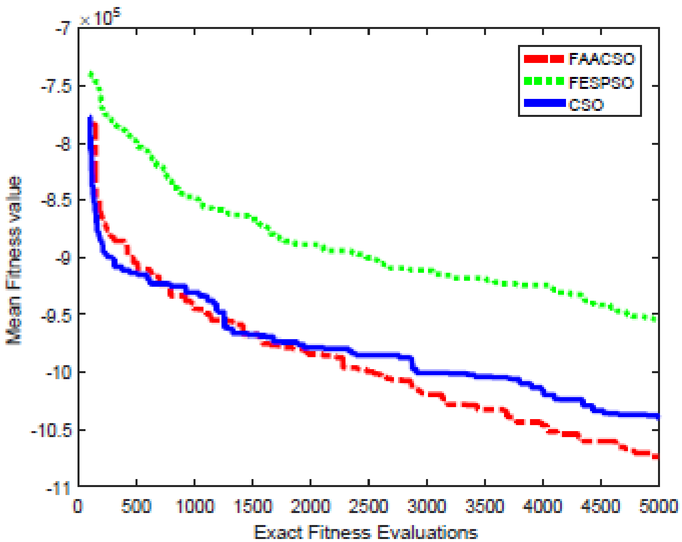


Fig. 14 The convergence profiles on 500-D F7

Future works

- Combine global and local surrogate models
- Fitness approximation assisted multi/many objective optimization
- Applications in the real engineering problems

Thanks!