

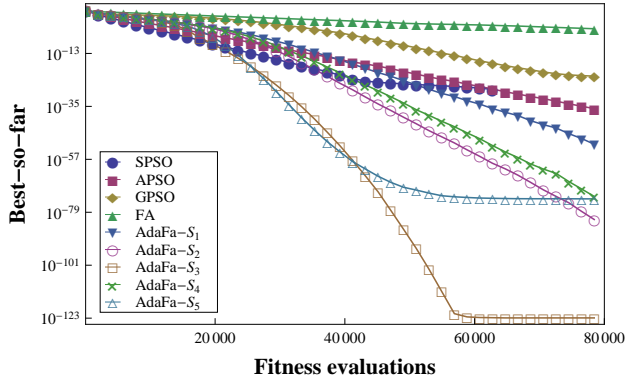
# Supplementary Materials

## Adaptive Firefly Algorithm: Parameter Analysis and its Application

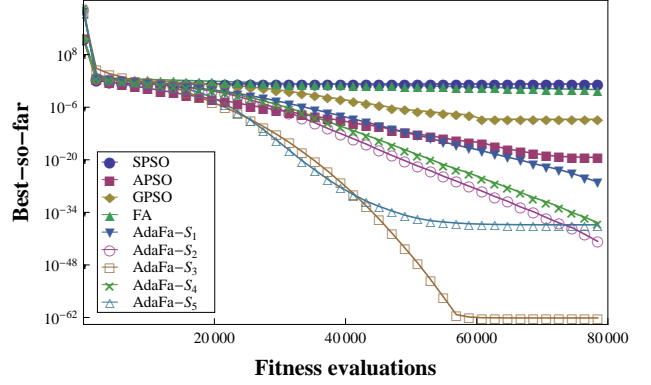
### 1 Numerical experiments

Table S1: Benchmark Functions

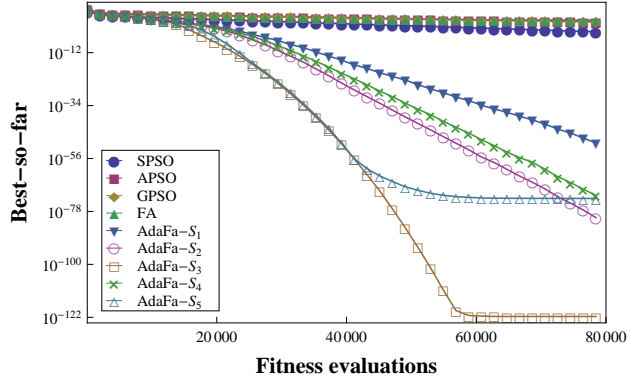
|            | Test function   | Search range     | $f_{min}$            |
|------------|---|------------------|----------------------|
| Unimodal   | $F_1(X) = \sum_{i=1}^D x_i^2$   | $[-100,100]^D$   | 0                    |
|            | $F_2(X) = \sum_{i=1}^D  x_i  + \prod_{i=1}^D  x_i $   | $[-10,10]^D$     | 0                    |
|            | $F_3(X) = \sum_{i=1}^D \left( \sum_{j=1}^i x_j \right)^2$   | $[-100,100]^D$   | 0                    |
|            | $F_4(X) = \sum_{i=1}^{D-1} [100(x_i^2 - x_{i+1})^2 + (x_i - 1)^2]$  | $[-10,10]^D$     | 0                    |
|            | $F_5(X) = \sum_{i=1}^D [x_i + 0.5]^2$   | $[-100,100]^D$   | 0                    |
|            | $F_6(X) = \sum_{i=1}^D ix_i^4 + random[0,1)$  | $[-1.28,1.28]^D$ | 0                    |
| Multimodal | $F_7(X) = \sum_{i=1}^D \left( -x_i \sin(\sqrt{ x_i }) \right)$  | $[-500,500]^D$   | $-418.9829 \times D$ |
|            | $F_8(X) = \sum_{i=1}^D (x_i^2 - 10 \cos(2\pi x_i) + 10)$  | $[-5.12,5.12]^D$ | 0                    |
|            | $F_9(X) = \sum_{i=1}^D (y_i^2 - 10 \cos(2\pi y_i) + 10)$  | $[-5.12,5.12]^D$ | 0                    |
|            | where $y_i = \begin{cases} x_i &  x_i  < 0.5 \\ \frac{round(2x_i)}{2} &  x_i  \geq 0.5 \end{cases}$   |                  |                      |
|            | $F_{10}(X) = -20 \exp \left( -0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2} \right) - \exp \left( \frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i) \right) + 20 + e$                     | $[-32,32]^D$     | 0                    |
|            | $F_{11}(X) = \frac{1}{4000} \sum_{i=1}^D x_i^2 - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$   | $[-600,600]^D$   | 0                    |
|            | $F_{12}(X) = \frac{\pi}{D} \left\{ 10 \sin^2(\pi y_i) + \sum_{i=1}^{D-1} (y_i - 1)^2 [1 + 10 \sin^2(\pi y_{i+1})] + (y_D - 1)^2 \right\} + \sum_{i=1}^D u(x_i, 10, 100, 4)$ | $[-50,50]^D$     | 0                    |
|            | where $y_i = 0.25(x_i + 1) + 1$<br>$u(x_i, a, k, m) = \begin{cases} k(x_i - a)^m & x_i \geq a \\ 0 & -a < x_i < a \\ k(-x_i - a)^m & x_i < -a \end{cases}$                  |                  |                      |



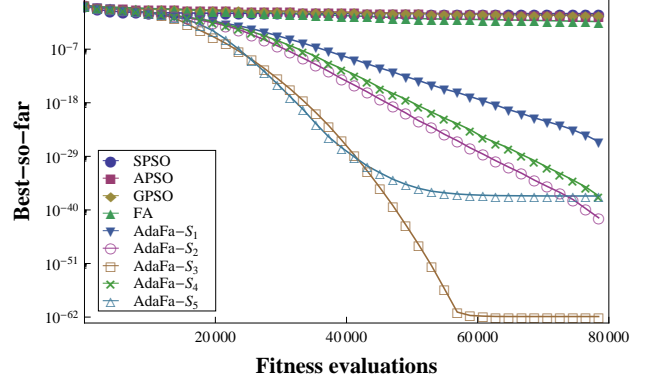
(a)  $F_1$



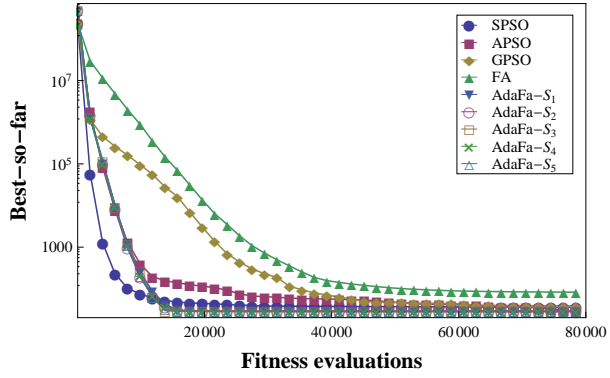
(b)  $F_2$



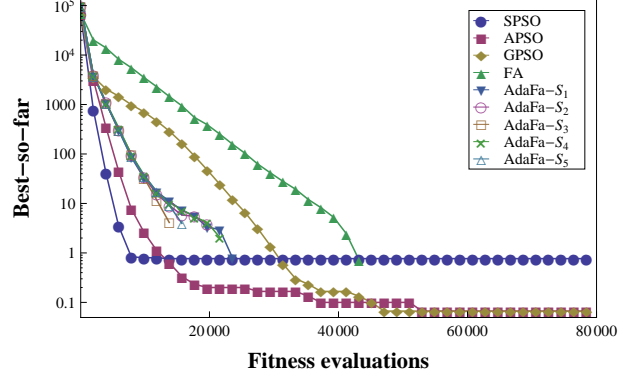
(c)  $F_3$



(d)  $F_4$

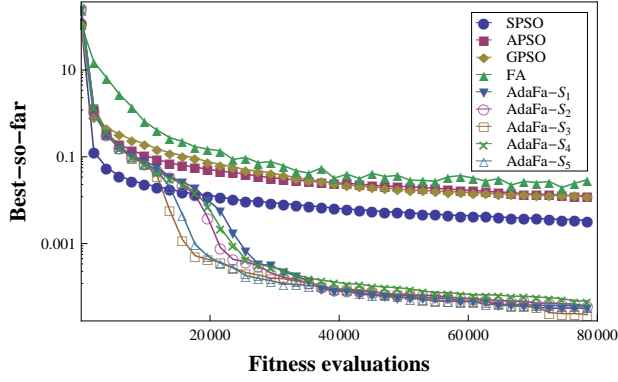


(e)  $F_5$

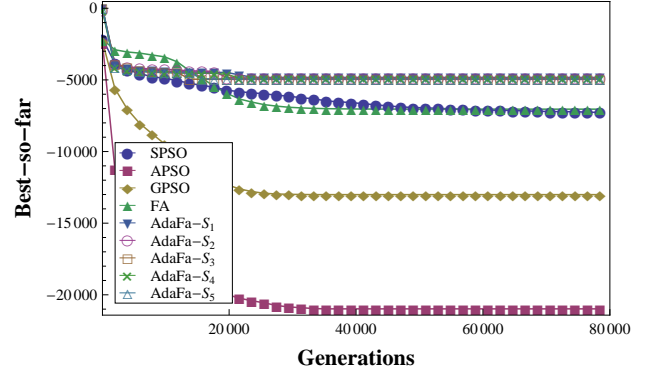


(f)  $F_6$

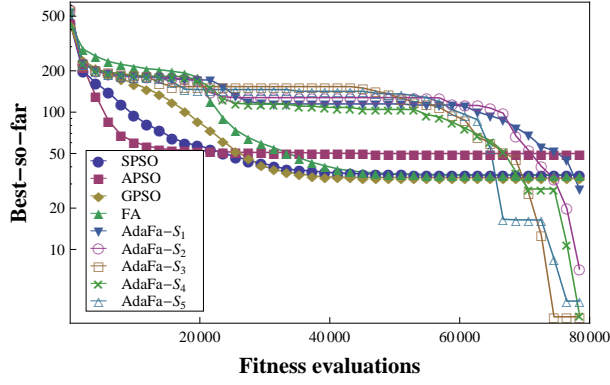
Fig. S1: The mean value over the benchmark functions with 30-dimensions.



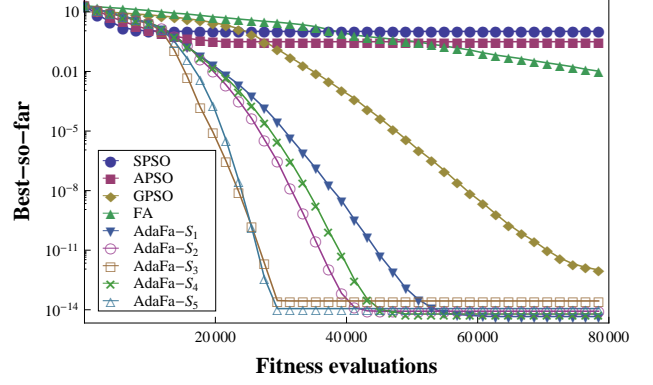
(a)  $F_7$



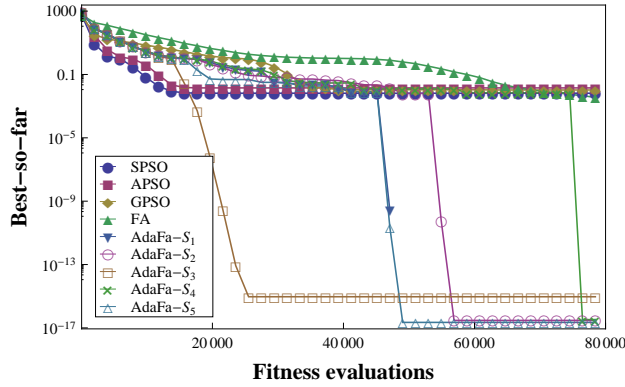
(b)  $F_8$



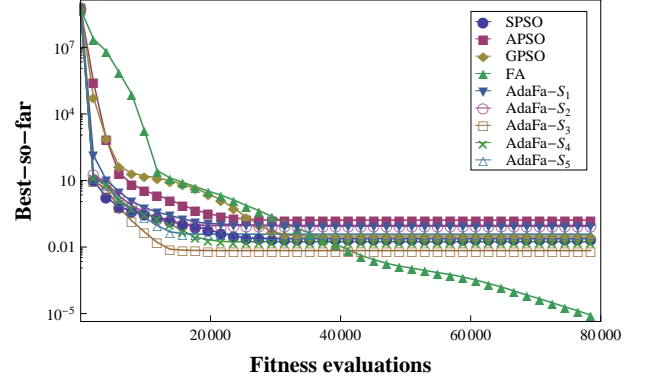
(c)  $F_9$



(d)  $F_{10}$



(e)  $F_{11}$



(f)  $F_{12}$

Fig. S1: (*Continue.*) The mean values over the benchmark functions with 30-dimensions.

## 2 Applications of AdaFa variants

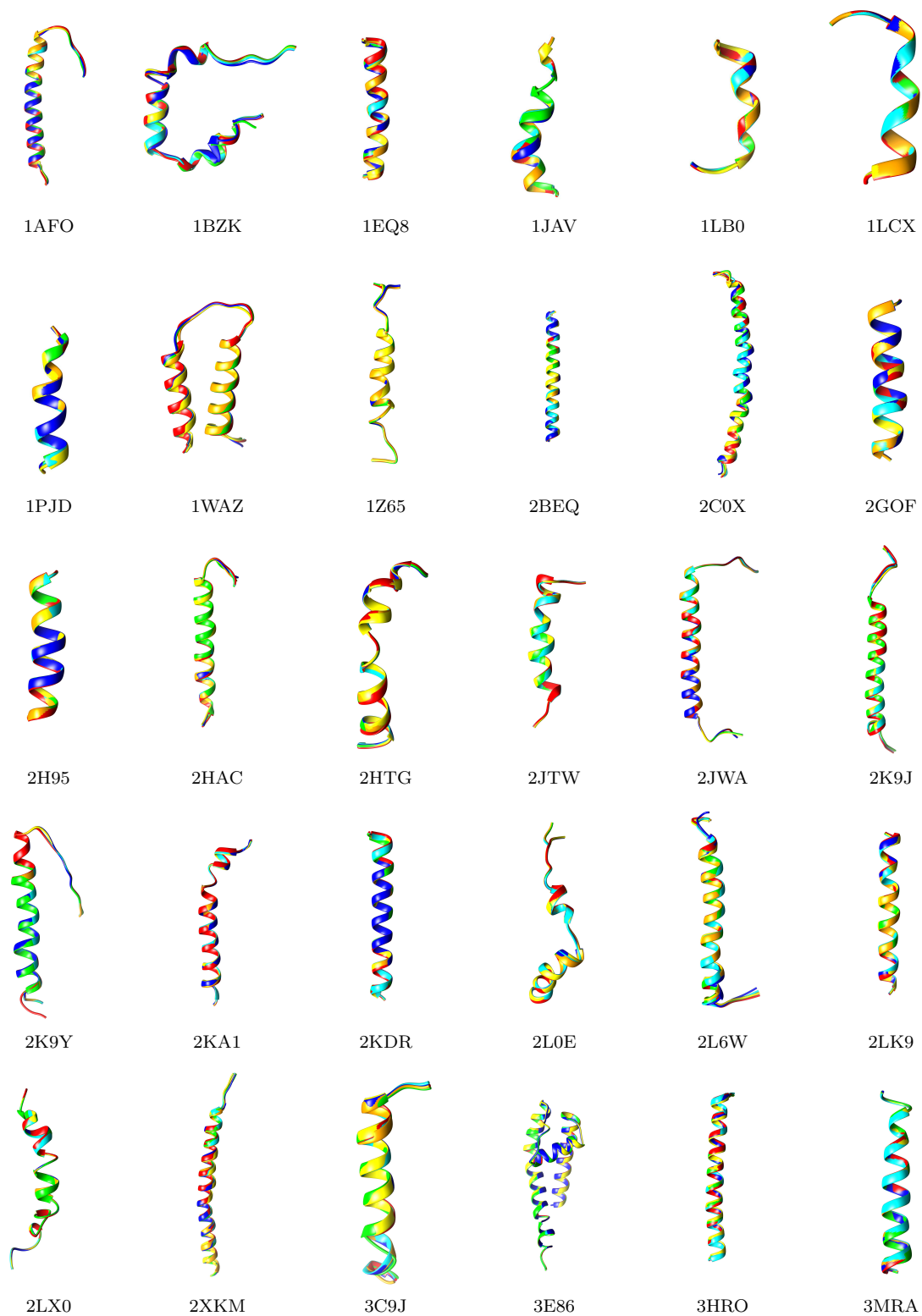


Fig. S2: The similarity between native protein structure (red) and the reconstructed structures (AdaFa- $S_1$ : blue, AdaFa- $S_2$ : green, AdaFa- $S_3$ : yellow, AdaFa- $S_4$ : cyan, AdaFa- $S_5$ : orange).

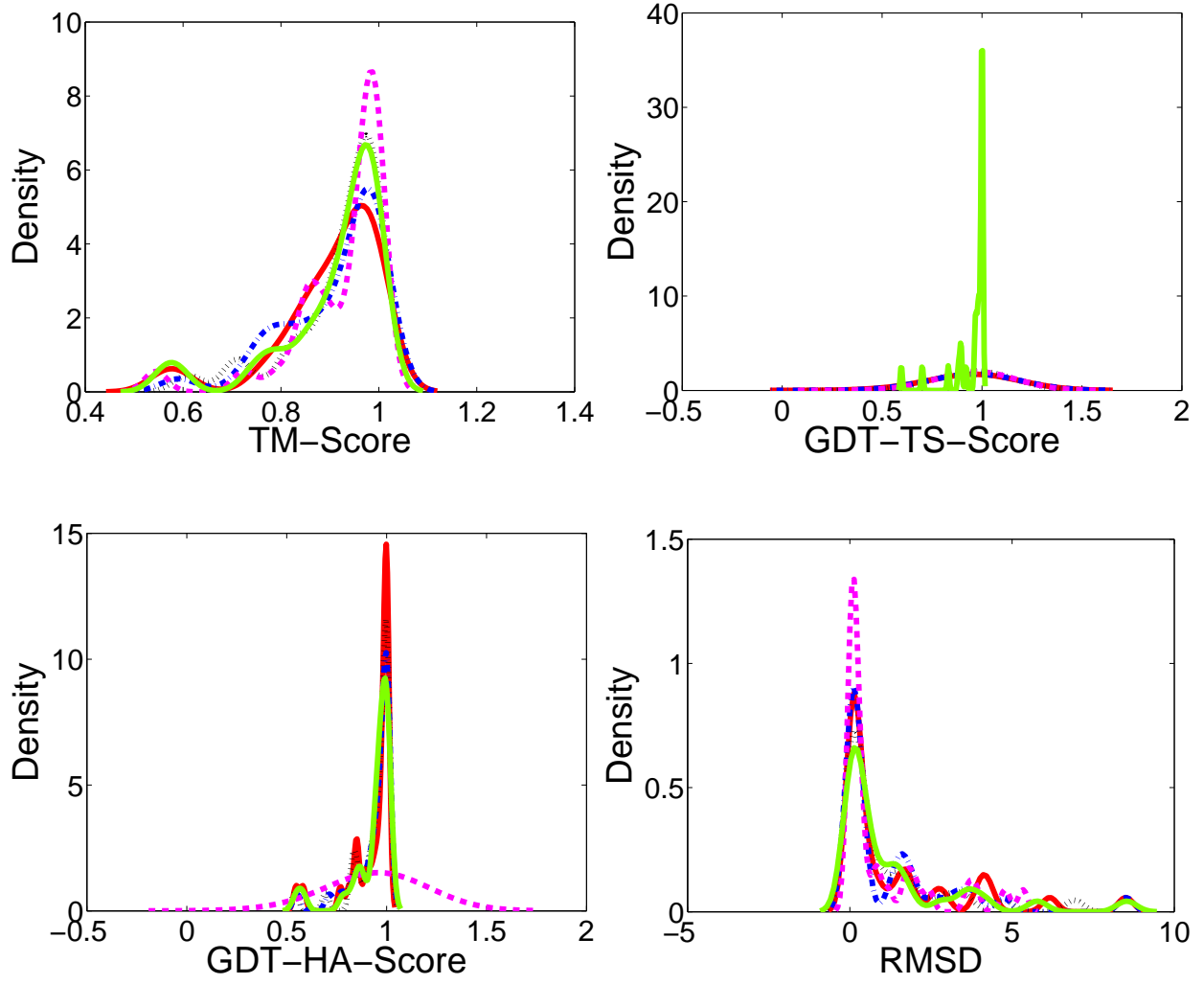


Fig. S3: The kernel smoothing density estimates of (a) TM-Score, (b) GDT-TS-Score, (c) GDT-HA-Score, and (d) RMSD achieved over the constrains with 10% Gaussian white noise. AdaFa-S<sub>1</sub>–AdaFa-S<sub>5</sub> were represented by red solid line, black dotted line, blue dotted dashed line, magenta dashed line, and green solid line, respectively