Supplementary File for
"TPAM: A Simulation-Based Model for Quantitatively Analyzing Parameter Adaptation Methods"

ACM Reference format:
. 2016. Supplementary File for
"TPAM: A Simulation-Based Model for Quantitatively Analyzing Parameter Adaptation Methods". In *Proceedings of ACM Conference, Washington, DC, USA, July 2017 (Conference'17),* 8 pages.
DOI: 10.1145/nnnnnnn.nnnnnnn

Conference'17, Washington, DC, USA

DOI: 10.1145/nnnnnnn.nnnnnnn

Algorithm S.1: Parameter Adaptation Method in jDE (PAM-jDE)

$t \leftarrow 1$, initialize $\boldsymbol{P}^t = \{\boldsymbol{x}^{1,t}, \ldots, \boldsymbol{x}^{N,t}\}$ randomly;
$F_{i,t} \leftarrow 0.5, C_{i,t} \leftarrow 0.9, i \in \{1, \ldots, N\}$;
while *The termination criteria are not met* **do**
  for $i \in \{1, \ldots, N\}$ **do**
    if rand[0, 1] $\leq \tau_F$ **then**
      $F'_{i,t} \leftarrow$ rand[0.1, 1];
    else
      $F'_{i,t} \leftarrow F_{i,t}$;
    if rand[0, 1] $\leq \tau_C$ **then**
      $C'_{i,t} \leftarrow$ rand[0, 1];
    else
      $C'_{i,t} \leftarrow C_{i,t}$;
    Generate the mutant vector $\boldsymbol{v}^{i,t}$ using an arbitrary mutation strategy with $F'_{i,t}$;
    Generate the trial vector $\boldsymbol{u}^{i,t}$ by crossing $\boldsymbol{x}^{i,t}$ and $\boldsymbol{v}^{i,t}$ using an arbitrary crossover method with $C'_{i,t}$;
  for $i \in \{1, \ldots, N\}$ **do**
    if $f(\boldsymbol{u}^{i,t}) \leq f(\boldsymbol{x}^{i,t})$ **then**
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{u}^{i,t}, F_{i,t+1} \leftarrow F'_{i,t}, C_{i,t+1} \leftarrow C'_{i,t}$;
    else
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{x}^{i,t}, F_{i,t+1} \leftarrow F_{i,t}, C_{i,t+1} \leftarrow C_{i,t}$;
  $t \leftarrow t + 1$;

Algorithm S.2: Parameter Adaptation Method in EPSDE (PAM-EPSDE)

$t \leftarrow 1$, initialize $\boldsymbol{P}^t = \{\boldsymbol{x}^{1,t}, \ldots, \boldsymbol{x}^{N,t}\}$ randomly;
F-pool = $\{0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$;
C-pool = $\{0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9\}$;
For each individual $\boldsymbol{x}^{i,t}$, assign the $F_{i,t}$ and $C_{i,t}$ values randomly from each pool;
while *The termination criteria are not met* **do**
  for $i \in \{1, \ldots, N\}$ **do**
    Generate the mutant vector $\boldsymbol{v}^{i,t}$ using an arbitrary mutation strategy with $F'_{i,t}$;
    Generate the trial vector $\boldsymbol{u}^{i,t}$ by crossing $\boldsymbol{x}^{i,t}$ and $\boldsymbol{v}^{i,t}$ using an arbitrary crossover method with $C'_{i,t}$;
  for $i \in \{1, \ldots, N\}$ **do**
    if $f(\boldsymbol{u}^{i,t}) \leq f(\boldsymbol{x}^{i,t})$ **then**
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{u}^{i,t}, F_{i,t+1} \leftarrow F_{i,t}, C_{i,t+1} \leftarrow C_{i,t}$;
    else
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{x}^{i,t}$;
      For $\boldsymbol{x}^{i,t+1}$, reassign the $F_{i,t+1}$ and $C_{i,t+1}$ values randomly from each pool;
  $t \leftarrow t + 1$;

Algorithm S.3: Parameter Adaptation Method in JADE (PAM-JADE)

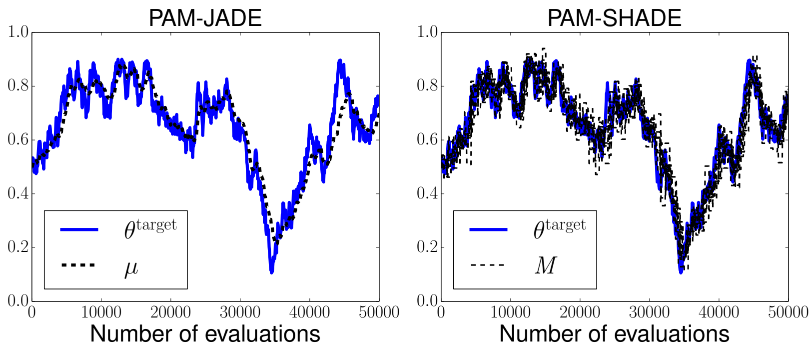
$t \leftarrow 1$, initialize $\boldsymbol{P}^t = \{\boldsymbol{x}^{1,t}, \ldots, \boldsymbol{x}^{N,t}\}$ randomly;
$\mu_F \leftarrow 0.5, \mu_C \leftarrow 0.5$;
while *The termination criteria are not met* **do**
  $S^F \leftarrow \emptyset, S^C \leftarrow \emptyset$;
  for $i \in \{1, \ldots, N\}$ **do**
    $F_{i,t} \leftarrow \text{randc}(\mu_F, 0.1)$;
    $C_{i,t} \leftarrow \text{randn}(\mu_C, 0.1)$;
    Generate the mutant vector $\boldsymbol{v}^{i,t}$ using an arbitrary mutation strategy with $F'_{i,t}$;
    Generate the trial vector $\boldsymbol{u}^{i,t}$ by crossing $\boldsymbol{x}^{i,t}$ and $\boldsymbol{v}^{i,t}$ using an arbitrary crossover method with $C'_{i,t}$;
  for $i \in \{1, \ldots, N\}$ **do**
    if $f(\boldsymbol{u}^{i,t}) \leq f(\boldsymbol{x}^{i,t})$ **then**
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{u}^{i,t}, S^F \leftarrow S^F \cup \{F_{i,t}\}, S^C \leftarrow S^C \cup \{C_{i,t}\}$;
    else
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{x}^{i,t}$;
  if $S^F, S^C \neq \emptyset$ **then**
    $\mu_F \leftarrow (1 - c) \cdot \mu_F + c \cdot \text{mean}_L(S^F)$;
    $\mu_C \leftarrow (1 - c) \cdot \mu_C + c \cdot \text{mean}_A(S^C)$;
  $t \leftarrow t + 1$;

Algorithm S.4: Parameter Adaptation Method in MDE (PAM-MDE)

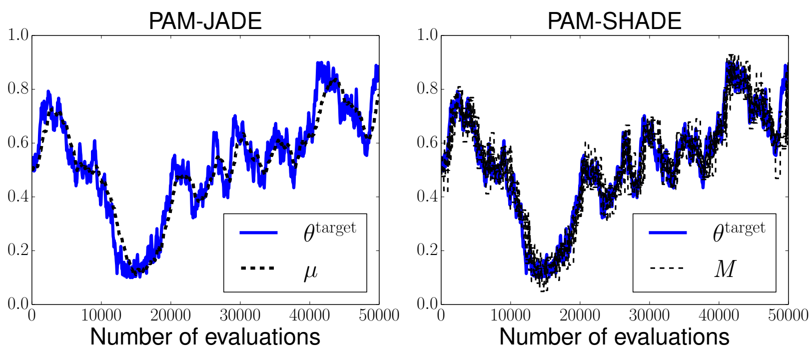
$t \leftarrow 1$, initialize $\boldsymbol{P}^t = \{\boldsymbol{x}^{1,t}, \ldots, \boldsymbol{x}^{N,t}\}$ randomly;
$\mu_F \leftarrow 0.5$, $\mu_C \leftarrow 0.5$;
while *The termination criteria are not met* **do**
  $S^F \leftarrow \emptyset$, $S^C \leftarrow \emptyset$;
  for $i \in \{1, \ldots, N\}$ **do**
    $F_{i,t} \leftarrow \mathrm{randc}(\mu_F, 0.1)$;
    $C_{i,t} \leftarrow \mathrm{randn}(\mu_C, 0.1)$;
    Generate the mutant vector $\boldsymbol{v}^{i,t}$ using an arbitrary mutation strategy with $F'_{i,t}$;
    Generate the trial vector $\boldsymbol{u}^{i,t}$ by crossing $\boldsymbol{x}^{i,t}$ and $\boldsymbol{v}^{i,t}$ using an arbitrary crossover method with $C'_{i,t}$;
  for $i \in \{1, \ldots, N\}$ **do**
    if $f(\boldsymbol{u}^{i,t}) \leq f(\boldsymbol{x}^{i,t})$ **then**
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{u}^{i,t}$, $S^F \leftarrow S^F \cup \{F_{i,t}\}$, $S^C \leftarrow S^C \cup \{C_{i,t}\}$;
    else
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{x}^{i,t}$;
  if $S^F, S^C \neq \emptyset$ **then**
    $c_F \leftarrow \mathrm{rand}(0.0, 0.2]$, $c_C \leftarrow \mathrm{rand}(0.0, 0.1]$;
    $\mu_F \leftarrow (1 - c_F) \cdot \mu_F + c_F \cdot \mathrm{mean}_P(S^F)$;
    $\mu_C \leftarrow (1 - c_C) \cdot \mu_C + c_C \cdot \mathrm{mean}_P(S^C)$;
  $t \leftarrow t + 1$;

Algorithm S.5: Parameter Adaptation Method in SHADE (PAM-SHADE)

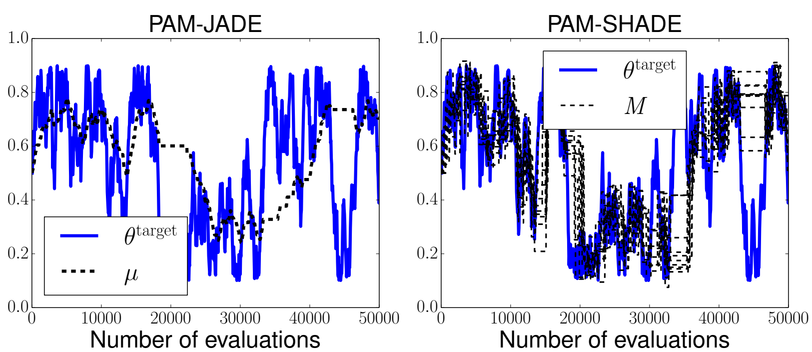
$t \leftarrow 1$, initialize $\boldsymbol{P}^t = \{\boldsymbol{x}^{1,t}, \ldots, \boldsymbol{x}^{N,t}\}$ randomly;
Set all values in $\boldsymbol{M}^F = (M_1^F, \ldots, M_H^F)$, $\boldsymbol{M}^C = (M_1^C, \ldots, M_H^C)$ to 0.5;
$k \leftarrow 1$;
while *The termination criteria are not met* **do**
  $S^F \leftarrow \emptyset$, $S^C \leftarrow \emptyset$;
  for $i \in \{1, \ldots, N\}$ **do**
    Select the memory index $r_{i,t}$ from $\{1, \ldots, H\}$ randomly;
    $F_{i,t} \leftarrow \mathrm{randc}(M^F_{r_{i,t}}, 0.1)$;
    $C_{i,t} \leftarrow \mathrm{randn}(M^C_{r_{i,t}}, 0.1)$;
    Generate the mutant vector $\boldsymbol{v}^{i,t}$ using an arbitrary mutation strategy with $F'_{i,t}$;
    Generate the trial vector $\boldsymbol{u}^{i,t}$ by crossing $\boldsymbol{x}^{i,t}$ and $\boldsymbol{v}^{i,t}$ using an arbitrary crossover method with $C'_{i,t}$;
  for $i \in \{1, \ldots, N\}$ **do**
    if $f(\boldsymbol{u}^{i,t}) \leq f(\boldsymbol{x}^{i,t})$ **then**
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{u}^{i,t}$, $S^F \leftarrow S^F \cup \{F_{i,t}\}$, $S^C \leftarrow S^C \cup \{C_{i,t}\}$;
    else
      $\boldsymbol{x}^{i,t+1} \leftarrow \boldsymbol{x}^{i,t}$;
  if $S^F, S^C \neq \emptyset$ **then**
    $M_k^F \leftarrow \mathrm{mean}_L(S^F)$;
    $M_k^C \leftarrow \mathrm{mean}_L(S^C)$;
    $k \leftarrow (k \text{ modulo } H) + 1$;
  $t \leftarrow t + 1$;



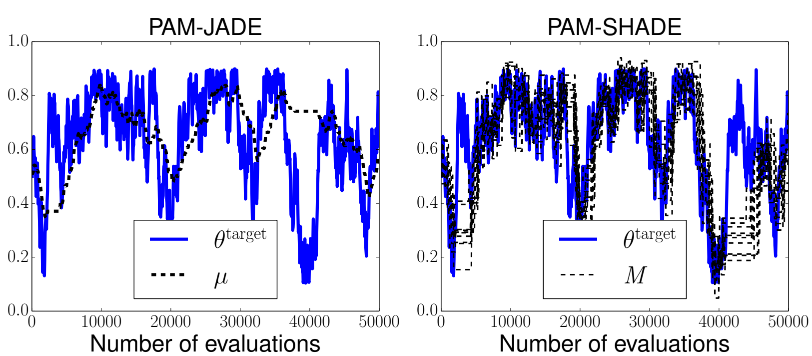
(a) g^{ran} $(s = 0.04)$



(b) g^{ran} $(s = 0.04)$

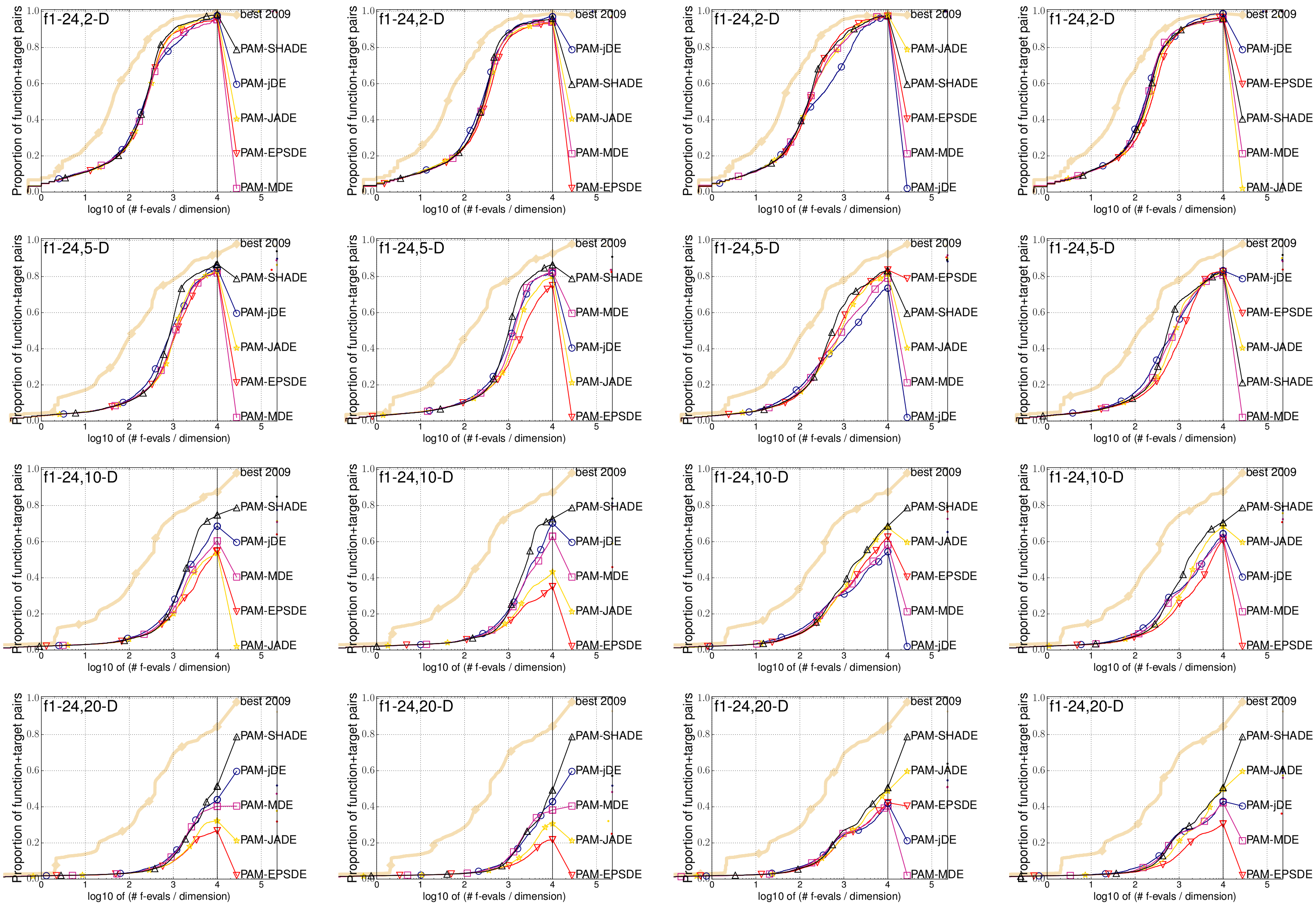


(c) g^{ran} $(s = 0.1)$



(d) g^{ran} $(s = 0.1)$

Figure S.1: Behavior of the meta-parameters (μ and M) of PAM-JADE and PAM-SHADE on the same g^{ran} instance ($p_a^{\max} = 0.1$). For PAM-SHADE, we plot all elements in M. Data of a single run with the median r^{succ} value out of the 101 runs are shown.



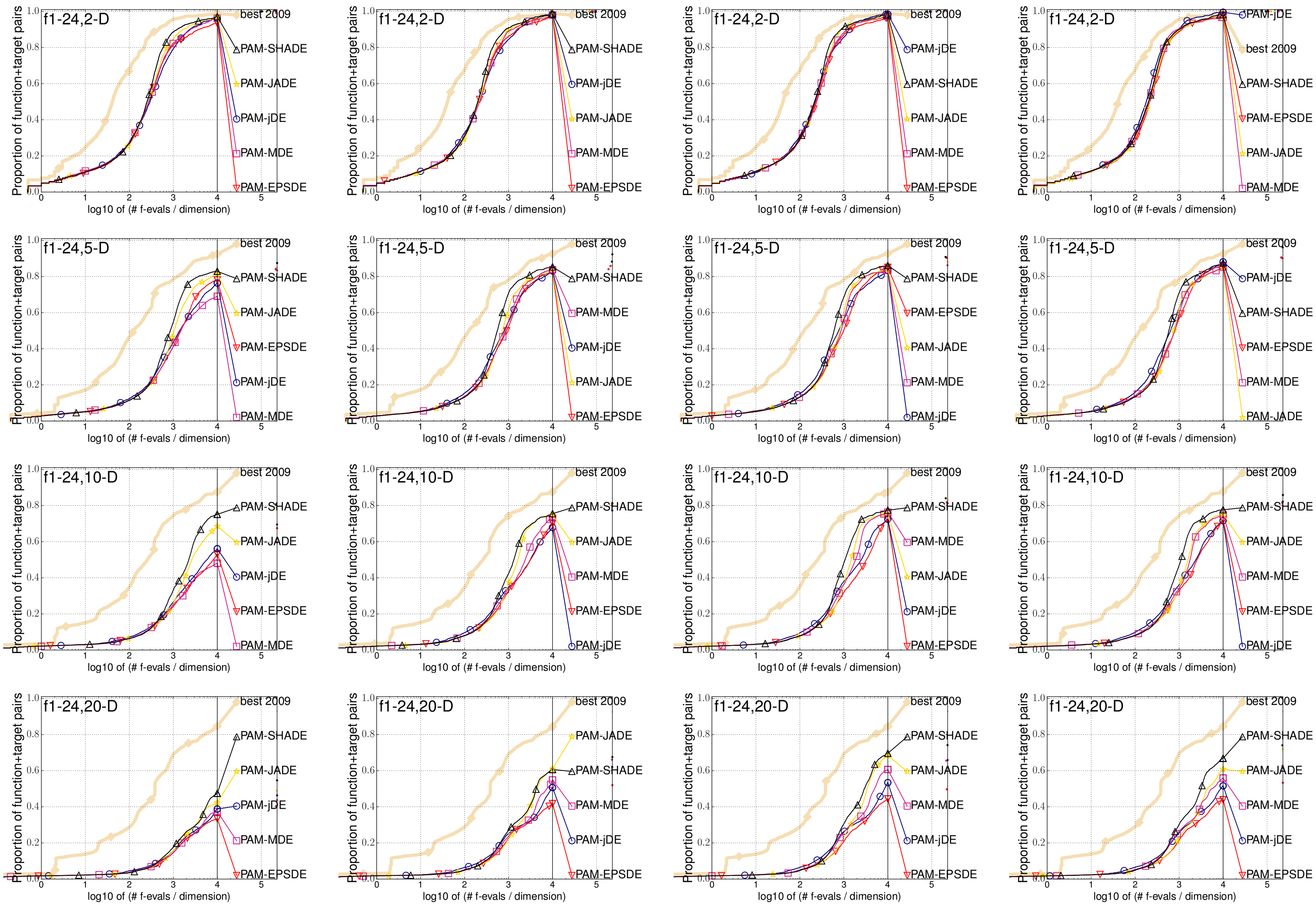
(a) rand/1/bin

(b) rand/2/bin

(c) best/1/bin

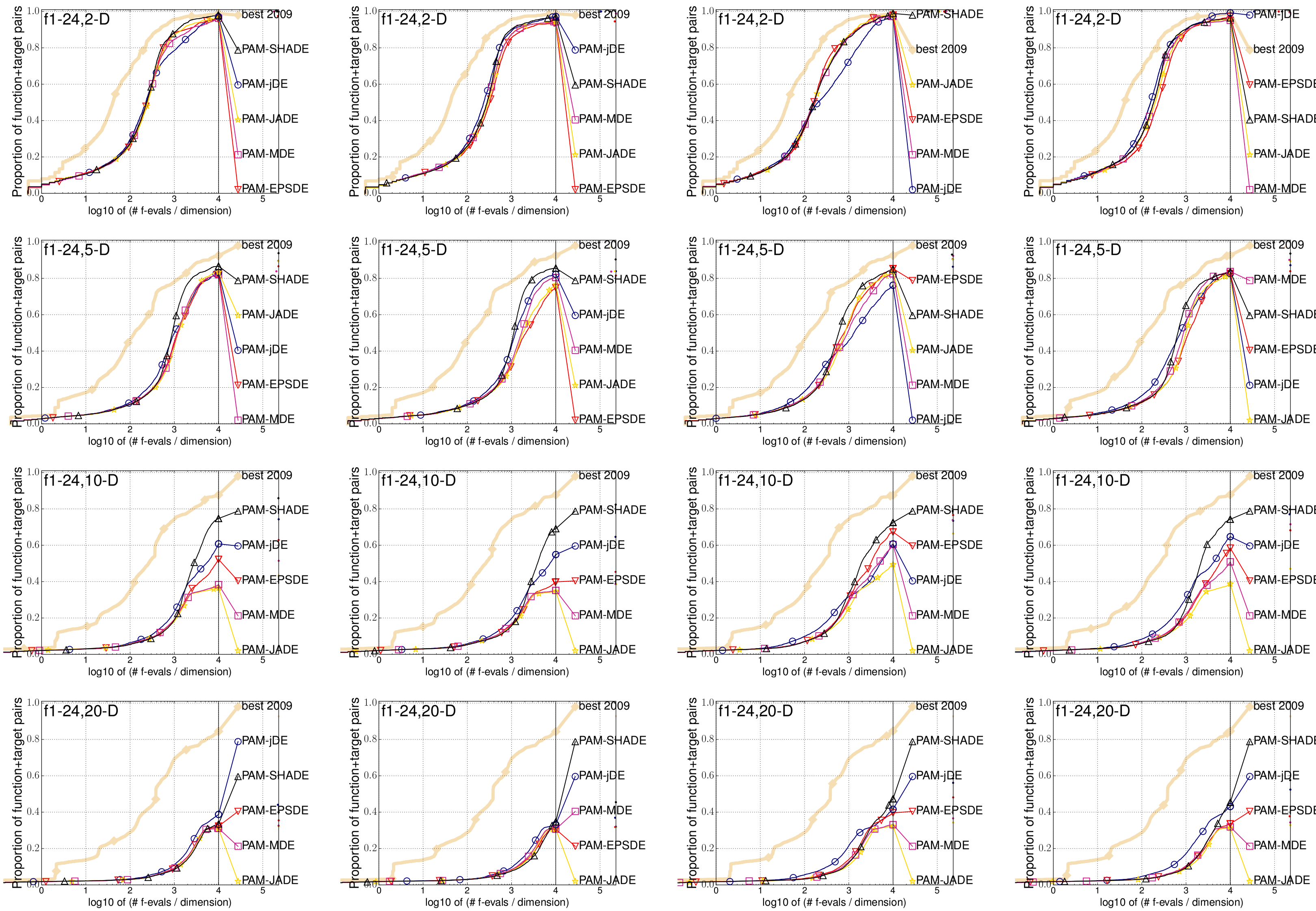
(d) best/2/bin

Figure S.2: Comparisons of the five PAMs with four mutation strategies (rand/1, rand/2, best/1, and best/2) and binomial crossover on the BBOB benchmarks ($D \in \{2, 3, 5, 10, 20\}$). These figures show the bootstrapped Empirical Cumulative Distribution Function (ECDF) of the number of function evaluations (FEvals) divided by dimension for 50 targets in $10^{[-8..2]}$ for all functions (higher is better). For details of the ECDF, see a manual of `COCO software` (http://coco.gforge.inria.fr/).



(a) current-to-rand/1/bin (b) current-to-best/1/bin (c) current-to-$p$best/1/bin (d) rand-to-$p$best/1/bin

Figure S.3: Comparisons of the five PAMs with four mutation strategies (current-to-rand/1, current-to-best/1, current-to-$p$best/1, and rand-to-$p$best/1) and binomial crossover on the BBOB benchmarks ($D \in \{2, 3, 5, 10, 20\}$). These figures show the bootstrapped Empirical Cumulative Distribution Function (ECDF) of the number of function evaluations (FEvals) divided by dimension for 50 targets in $10^{[-8..2]}$ for all functions (higher is better). For details of the ECDF, see a manual of `COCO software` (http://coco.gforge.inria.fr/).



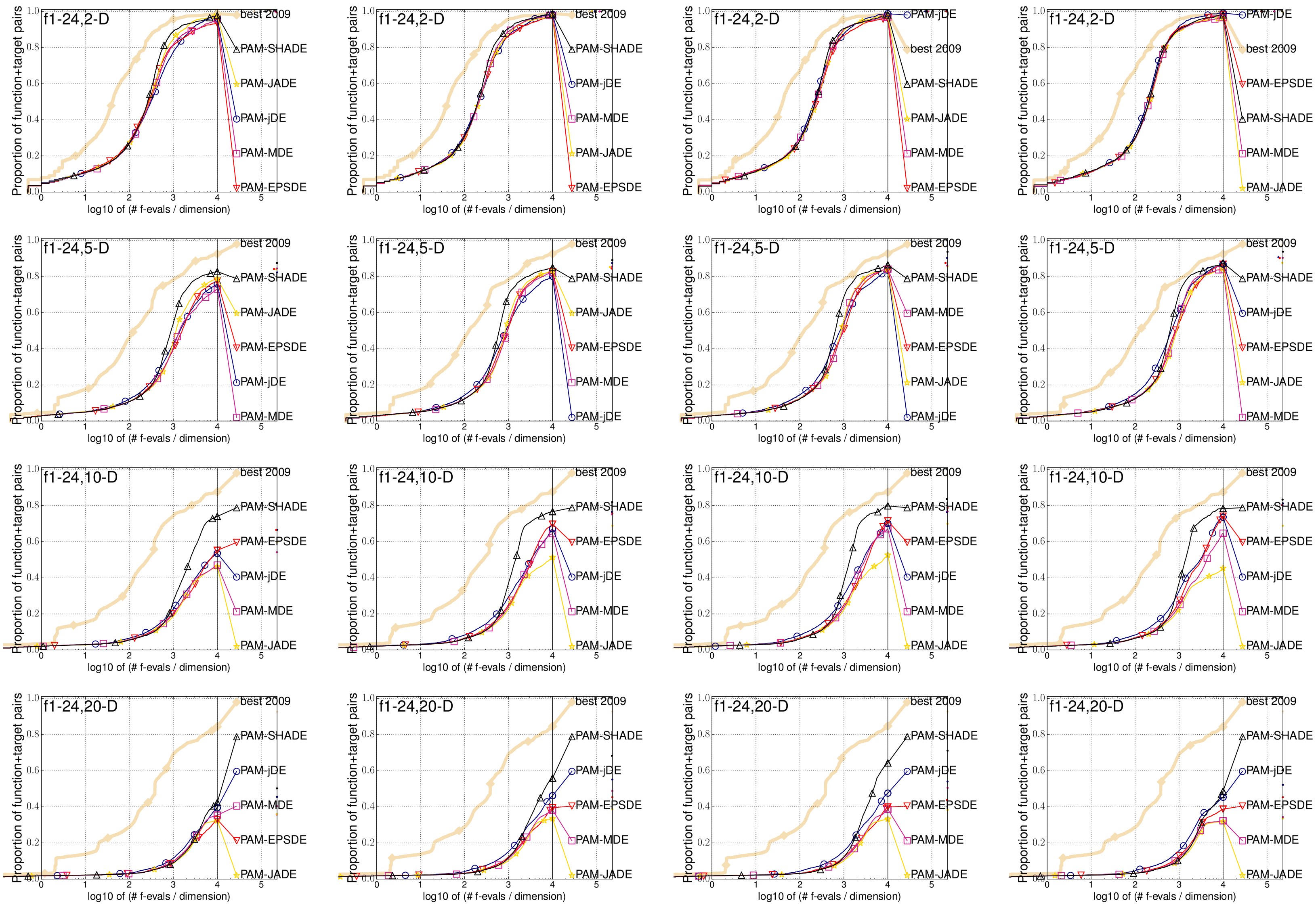
(a) rand/1/sec

(b) rand/2/sec

(c) best/1/sec

(d) best/2/sec

Figure S.4: Comparisons of the five PAMs with four mutation strategies (rand/1, rand/2, best/1, and best/2) and shuffled exponential crossover on the BBOB benchmarks ($D \in \{2, 3, 5, 10, 20\}$). These figures show the bootstrapped Empirical Cumulative Distribution Function (ECDF) of the number of function evaluations (FEvals) divided by dimension for 50 targets in $10^{[-8..2]}$ for all functions (higher is better). For details of the ECDF, see a manual of `COCO software` (http://coco.gforge.inria.fr/).



(a) current-to-rand/1/sec (b) current-to-best/1/sec (c) current-to-$p$best/1/sec (d) rand-to-$p$best/1/sec

Figure S.5: Comparisons of the five PAMs with four mutation strategies (current-to-rand/1, current-to-best/1, current-to-$p$best/1, and rand-to-$p$best/1) and shuffled exponential crossover on the BBOB benchmarks ($D \in \{2, 3, 5, 10, 20\}$). These figures show the bootstrapped Empirical Cumulative Distribution Function (ECDF) of the number of function evaluations (FEvals) divided by dimension for 50 targets in $10^{[-8..2]}$ for all functions (higher is better). For details of the ECDF, see a manual of `COCO software` (http://coco.gforge.inria.fr/).