Particle Swarm Optimization with Budget Allocation through Neighborhood Ranking

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ABSTRACT

Standard Particle Swarm Optimization (PSO) allocates the total available computational budget, in terms of function evaluations, equally among the particles at each iteration of the algorithm. The present work introduces an alternative, which employs neighborhood ranking for allocating the computational budget to the particles. The proposed PSO variant favors the particles that belong to more promising neighborhoods by providing them with more function evaluations than the rest, based on a stochastic neighborhood selection scheme. Preliminary experimental results on standard test problems reveal that the proposed approach is highly competitive.

Categories and Subject Descriptors

G.1.6 [**Optimization**]: Global Optimization, Unconstrained Optimization; G.3 [**Probability and Statistics**]: Probabilistic Algorithms

General Terms

Algorithms, Performance, Experimentation

Keywords

Particle Swarm Optimization, Neighborhood Ranking, Computational Budget Allocation

1. INTRODUCTION

Particle Swarm Optimization (PSO) is a population-based metaheuristic algorithm for numerical optimization. It was introduced in 1995 by Eberhart and Kennedy [3] and, since then, it has gained increasing popularity. This can be attributed to its efficiency in solving challenging optimization problems with minor implementation effort. Up-to-date, there is a significant number of PSO-based applications in diverse scientific fields, accompanied by a large number of PSO variants [4, 5].

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In this paper, we introduce a new variant of the PSO algorithm. The proposed approach allocates the available budget of function evaluations in a non-equal way among the particles of the swarm. The selection of the favored particles is based on the quality of their neighborhoods according to the employed neighborhood topology. For this purpose, scoring and ranking of the neighborhoods is used. Two alternative scoring schemes are considered, based either on the total or the best information carried by the neighborhood.

The selection between the neighborhoods that will benefit with more evaluations is conducted with a standard fitness proportionate (roulette-wheel) procedure. Naturally, particles with high-ranked neighborhoods are more probable to get additional function evaluations than the rest. Finally, only the selected and evaluated particles are allowed to update their positions. Hence, the proposed approach is asynchronous in nature.

The concept of rank-based PSO has been considered in the past although in a different manner. In [1], ranking is used to determine a fraction of the swarm that contributes to the velocity of all particles. This approach uses the global (gbest) PSO model solely. Another rank-based approach was proposed in [7], where ranking is used to replace low-fitness particles with better ones. A relevant asynchronous (yet not rank-based) PSO variant is PSO-DLI [6], which employs a special scheme of evaluating only some of the particles while the swarm moves uninterruptedly. To the best of our knowledge, there is no previous attempt to exploit neighborhood ranking for stochastically allocating evaluations to the particles.

The rest of the paper is organized as follows: Section 2 provides a brief description of the standard PSO model that is used in our study. The proposed approach is exposed in Section 3 and the experimental results are reported in Section 4. Finally, the paper concludes in Section 5.

2. PARTICLE SWARM OPTIMIZATION

In this section, we briefly describe the standard PSO algorithm that is employed in our study. Let the n-dimensional global minimization problem, $\min_{x \in X \subset \mathbb{R}^n} f(x)$. PSO employs a set of potential solutions, $S = \{x_1, x_2, \ldots, x_N\}$, $x_i \in X$, $i \in I = \{1, 2, \ldots, N\}$. This set is called a *swarm*, while each vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{in})^\top \in X$ is called a *particle*. Each particle probes the search space X by iteratively moving to new positions with an adaptable *velocity* (position shift), while retaining in memory the *best position* encountered during its search. These quantities are denoted as $v_i = (v_{i1}, v_{i2}, \ldots, v_{in})^\top$ and $p_i = (p_{i1}, p_{i2}, \ldots, p_{in})^\top$.

In order to avoid premature convergence, the notion of neighborhood was introduced in PSO. More specifically, each particle assumes a set of neighboring particles with which, it exchanges information. Perhaps the most popular *neighborhood topology* is the *ring*, where the particles' indices are assumed to lie on a ring. Thus, each particle assumes as neighbors the particles with its adjacent indices. The number of neighbors is determined by a parameter r, called the neighborhood's *radius*. Hence, a ring neighborhood of radius r of the i-th particle, is defined as the set of indices:

$$NB_{i,r} = \{i - r, \dots, i - 1, i, i + 1, \dots, i + r\}, \tag{1}$$

where the indices recycle after the value N. Clearly, there is a one-to-one correspondence between the i-th particle and the i-th neighborhood.

There are two prevailing PSO models based on the neighborhood's size. The local (lbest) PSO model uses the neighborhood's best position $p_{g_i} = \arg\min_{j \in NB_{i,r}} \{f(p_j)\}$, along with p_i to update the i-th particle's velocity at each iteration. On the other hand, the global (gbest) PSO model assumes the whole swarm as the neighborhood of each particle. The main difference between the two, lies in their exploration/exploitation trade-off. The lbest model is distinguished for its exploration capability, which can be attributed to the slowest diffusion of information among the particles. The gbest model is distinguished for its convergence speed, but it is also prone to premature convergence. In our study, we employed the lbest model.

Based on the definitions above, the defining equations of PSO's update are [2]:

$$\begin{aligned} v_{ij}(t+1) &= \chi\Big[v_{ij}(t) + c_1\mathcal{R}_1\Big(p_{ij}(t) - x_{ij}(t)\Big) + \\ &\qquad c_2\mathcal{R}_2\Big(p_{g_i,j}(t) - x_{ij}(t)\Big)\Big], \qquad (2) \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1), \qquad (3) \end{aligned}$$

with $i \in I$; $j = 1, 2, \dots, n$; the parameter χ is the *constriction coefficient*; c_1 and c_2 are called the *cognitive* and *social* parameter, respectively; and $\mathcal{R}_1, \mathcal{R}_2 \sim \mathcal{U}[0, 1]$, are uniformly distributed random variables. The best position of each particle is updated at each iteration, if a better one has been discovered. Obviously, the presented standard PSO algorithm allocates one function evaluation per particle at each iteration.

3. PROPOSED APPROACH

In this section, we introduce the proposed *Particle Swarm Optimization with Budget Allocation through Neighborhood Ranking*, henceforth denoted as PSO-BANR. Before presenting PSO-BANR in detail, we describe its main modules, namely the rank-based scoring schemes for the neighborhoods as well as the corresponding selection probabilities.

3.1 Rank-Based Neighborhood Scoring

We consider two alternative schemes to determine a neighborhood's quality. The first one will be denoted as *SumBest* (SB), and it is based on the total information carried by the neighborhood. The second one will be denoted as *LocalBest* (LB) and it is based solely on the best position of the neighborhood. Intuitively, LB promotes elitism while SB takes into consideration the overall contribution of the neighborhood.

SumBest (SB)
Let $NB_{i,r}$ be the neighborhood of the i-th particle, as defined in Eq. (1). Then, the SB ranking score of the neighborhood $NB_{i,r}$ is defined as:

$$SBR_i = \sum_{j \in NB_{i,r}} f\big(p_j(t)\big), \quad i \in I. \tag{4}$$

Thus, the SB score assess the neighborhood's quality in terms of the sum of function values of all best positions belonging in it. We can further normalize these quantities, as follows:

$$SBR_i^* = SBR_i / \sum_{k \in I} SBR_k. \tag{5}$$

Obviously, smaller values of the SB ranking score correspond to neighborhoods with smaller contributions and, hence, to particles that will be favored at the selection phase.

LocalBest (LB)
Let again $NB_{i,r}$ be the neighborhood of the i-th particle. Then the LB ranking score for this neighborhood is defined as:

$$LBR_i = \min_{j \in NB_{i,r}} f\big(p_j(t)\big), \quad i \in I. \tag{6}$$

Thus, LB score assess the neighborhood's quality only in terms of the best information it carries, and it is normalized as follows:

$$LBR_i^* = LBR_i / \sum_{k \in I} LBR_k. \tag{7}$$

Similarly to SB, smaller values of the LB ranking score are associated with preferable neighborhoods.

3.2 Neighborhood Selection Probability

Each particle will be assigned a probability of being allocated the next function evaluation, based on the ranking score of its neighborhood, as described in the previous Section. Intuitively, high selection probability values shall be assigned to particles with neighborhoods of low ranking scores (either SB or LB).

We considered two alternative schemes to compute the selection probability of a particle. Both schemes can be combined either with the SB or the LB ranking score. Let

$$xBR_i^* = SBR_i^* \text{ or } LBR_i^*, \quad \forall i \in I,$$

depending on the employed ranking scheme (SB or LB), respectively. Then, the first scheme assigns selection probabilities that are linear with respect to the xBR_i, i.e., if:

$$LPR_i = 1 - xBR_i^*, \quad i \in I, \tag{8}$$

then the selection probability of the i-th particle becomes:

$$PR_i = LPR_i / \sum_{j \in I} LPR_j, \quad i \in I. \tag{9}$$

Henceforth, this scheme will be denoted as L.

The second scheme is nonlinear (denoted as NL) and it assumes the following quantities:

$$NLPR_i = xBR_i^{*-w}, \quad i \in I, \tag{10}$$

where w is a positive integer parameter. This scheme resembles the *power selection* operator of Evolutionary Algorithms. The corresponding selection probabilities for this

Algorithm 1 Pseudocode of the PSO-BANR algorithm.

Input: Objective function, PSO parameters, $I = \{1, 2, \ldots, N\}$.
Output: Best detected solution.

initialize x_i, v_i, p_i, $i \in I$
compute $PR_i, i \in I$, according to Eq. (9) or (11)
while (termination condition not met) **do**
  $i^* \leftarrow \texttt{RouletteWheel}(PR_1, \ldots, PR_N)$
  update v_{i^*} and x_{i^*} according to Eqs. (2) and (3)
  update p_{i^*}
  if (p_{i^*} has changed) **then**
    update PR_j for all j with $i^* \in NB_{j,r}$
  end if
end while

Table 1: Parameter values employed in the experiments.

Parameter	Value
Test problems	Sphere (TP0), Rosenbrock (TP1), Rastrigin (TP2), Griewank (TP3), Ackley (TP4)
Dimension (n)	50, 100, 150, 200
Ranking Score	SumBest (SB), LocalBest (LB)
Selection Scheme	Linear (L), Nonlinear (NL)
PSO parameters	$\chi = 0.729$, $c_1 = c_2 = 2.05$
PSO model	lbest with ring topology of radius $r = 1$
Swarm size (N)	$2 \times n$ (l), $5 \times n$ (m), $10 \times n$ (h)
Computational budget	$500 \times N$ (l), $1000 \times N$ (h)
Number of experiments	100 per approach

scheme are given as:

$$PR_i = NLPR_i / \sum_{j \in I} NLPR_j, \quad i \in I. \qquad (11)$$

Clearly, higher values of w lead to higher probabilities values that render preferable the neighborhoods with lower ranking scores.

3.3 The PSO-BANR Algorithm

The core idea behind PSO-BANR is the rank-based allocation of the total computational budget in terms of the available function evaluations. Each available function evaluation is individually allocated to a particle, which is selected based on its neighborhood ranking. Only the selected particle updates its velocity and position, while the rest remain idle. This property implies that PSO-BANR is an asynchronous PSO variant. Obviously, the concept of "iteration" in PSO-BANR differs from that of the standard PSO, since only one particle moves at a time.

The novelty of PSO-BANR lies in the use of the neighborhood's quality rather than the particle's, as the selection criterion. Thus, each neighborhood receives a rank-based score according to the total (SB scheme) or the best (LB scheme) function values it embraces. These quantities are properly handled to produce selection probabilities that characterize the neighborhood and, thus, the particle itself. Linear (L) or nonlinear (NL) transformations can be considered for this purpose as described in the previous sections.

The selection of the neighborhood is stochastically conducted through a roulette-wheel procedure. This gives a chance of selection to all particles, even those whose neighborhoods received bad ranking scores. The time complexity of the selection and update procedure is not excessively time-consuming, since for each function evaluation only a few of the neighborhood scores shall be updated. For instance, in the ring neighborhood topology with radius 1, a new best position for a particle requires the update of 3 out of N neighborhood scores.

The PSO-BANR algorithm is given in the pseudocode of Algorithm 1. Its implementation requires only minor modification of the standard PSO algorithm, since only a lightweight ranking and selection mechanism is incorporated into the standard algorithm. Therefore, PSO-BANR retains all the advantageous characteristics of the standard PSO algorithm, such as the potential of parallelization, and integration with different local or global optimization algorithms.

4. EXPERIMENTAL EVALUATION

The test suite that was used in our experiments consisted of five standard test functions, namely Sphere (TP0), Rosenbrock (TP1), Rastrigin (TP2), Griewank (TP3) and Ackley (TP4) [4]. Each problem was considered in its 50-, 100-, 150- and 200-dimensional instance to probe the algorithms' scaling properties. The swarm size, N, was set to three different levels, namely low (l) $2 \times n$, medium (m) $5 \times n$, and high (h) $10 \times n$, where n stands for the problem's dimension.

Two levels were considered for the available computational budget, i.e., low (l) $500 \times N$, and high (h) $1000 \times N$. The SumBest (SB) and LocalBest (LB) scoring schemes were considered for the neighborhoods. For each one, we employed both the linear (L) and the nonlinear (NL) approach for producing the selection probabilities. Thus, our experiments focused on the 24 PSO-BANR variants that emerged as combinations of the aforementioned schemes and parameter levels. In order to make notation easier, we will use the following formalism to denote each combination:

$$\texttt{xx / yy / z / w}$$

where $\texttt{xx} \in \{\text{SB}, \text{LB}\}$, $\texttt{yy} \in \{\text{L}, \text{NL}\}$, $\texttt{z} \in \{\text{l (low)}, \text{m (medium)}, \text{h (high)}\}$, and $\texttt{w} \in \{\text{l (low), h (high)}\}$. For example, SB/L/l/l denotes the PSO-BANR approach with SumBest neighborhood scoring, linear selection, low swarm size (i.e., $2 \times n$), and low computational budget (i.e., $500 \times N$). On the other hand, LB/NL/m/h stands for LocalBest neighborhood scoring, nonlinear selection probabilities, medium swarm size (i.e., $5 \times n$), and high computational budget (i.e., $1000 \times N$). All parameter values are summarized in Table 1.

Besides the PSO-BANR variants, we repeated the experiments for the standard lbest PSO model, using the same swarm sizes and computational budgets. For these cases, we will use the notation $\texttt{PSO/z/w}$, with $\texttt{z}$ and $\texttt{w}$ being identically defined as above for PSO-BANR. Thus, overall we conducted experiments on 30 algorithmic variants per test problem and dimension. For each case, 100 independent experiments were performed, summing to a total number of 60000 independent experiments.

For each test problem, dimension and algorithmic variant, 100 independent experiments were conducted and the best solution detected by the algorithm was recorded. Each experiment was terminated as soon as the maximum number of function evaluations was exceeded. The mean and standard deviation of the obtained solutions per case are reported in Tables 2-5. The lowest mean value and standard deviation are boldfaced for each test problem.

In order to facilitate the comparisons between the algorithms, we performed pairwise statistical significance tests between all the considered variants. Specifically, Wilcoxon

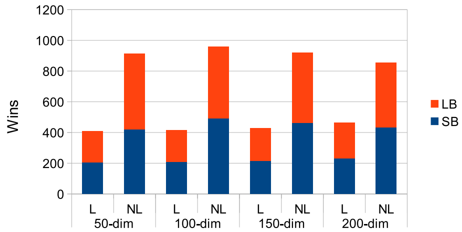

Figure 1: Number of wins per selection probability scheme and dimension.

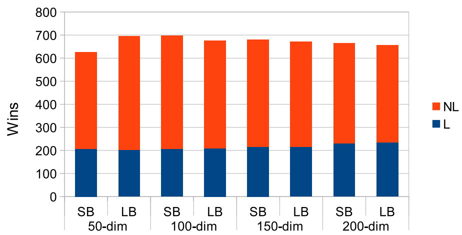

Figure 2: Number of wins per neighborhood scoring scheme and dimension.

rank-sum tests were conducted between all pairs of the considered approaches (including the standard PSO ones). For each variant, we counted the number of *wins*, i.e., the number of comparisons where it outperformed another variant with significance level 99%. The numbers of wins are aggregately illustrated in Figs. 1-3 for different classifications with respect to the neighborhood scoring scheme, the selection probabilities scheme, as well as the combinations of swarm size and computational budget.

The Tables reveal an apparent superiority of the PSO-BANR approach against the standard PSO algorithm for all test problems and dimensions. Also, we can easily infer that almost all NL (nonlinear) variants of PSO-BANR algorithm outperform the L (linear) variants. This can be attributed to the fact that the NL approaches promote more intensely the neighborhoods that comprise low-valued best positions. Exceptions are observed in a couple of instances for TP2, where the obtained standard deviations of the L variants were superior than the corresponding NL ones. Also, the Tables expose a remarkable similarity between SB and LB for dimensions higher than 50. A possible explanation for this, is the increase in the objective values when dimension increases. As a consequence, a best position with relatively low value will imply a neighborhood that rapidly prevails against the others, producing the same effect as if only its best member was considered.

The cumulative number of wins depicted in Figs. 1-3, reveals the superiority of the NL scheme, as well as the similar behavior of SB and LB. Figure 2 clearly illustrates that dimension does not affect the relative dynamics of the PSO-BANR approaches. Figure 3 shows the number of wins for each combination of swarm size and computational budget. As we can see, the combination h/h (both quantities on their high level) outperforms all the rest. This result was anticipated, since higher computational budgets and swarm sizes are usually accompanied by superior performance.

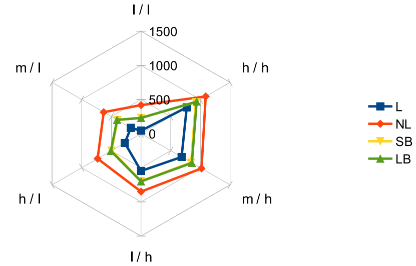

Figure 3: Number of wins per combination of swarm size and computational budget.

5. CONCLUSIONS

We introduced PSO-BANR, an asynchronous PSO variant that allocates its computational budget to the particles, one evaluation at a time. The allocation is based on ranking of the particles' neighborhoods and a stochastic selection procedure. We considered two essential schemes of computing the ranking score of the neighborhoods, along with two schemes to determine the selection probabilities. The proposed approach allocates more function evaluations to particles with neighborhoods that comprise low-valued best positions. Empirical evaluation showed that PSO-BANR can be very competitive to the standard PSO scheme. The next step in our study will include further experimentation on concurrent test problems as well as comparisons with other approaches. Also, the potential of adopting the main concepts of PSO-BANR to other PSO and non-PSO models, will be considered.

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Table 2: Results for the 50-dimensional problem instances.

Approach	Statistic	TP0	TP1	TP2	TP3	TP4
SB/L/l/l	Mean	$2.220E+01$	$5.337E+03$	$1.621E+02$	$1.204E+00$	$2.798E+00$
	StD	$5.359E+00$	$1.794E+03$	$2.206E+01$	$6.054E-02$	$2.464E-01$
SB/L/m/l	Mean	$1.912E+01$	$4.020E+03$	$1.497E+02$	$1.173E+00$	$2.562E+00$
	StD	$3.939E+00$	$1.203E+03$	$1.696E+01$	$3.893E-02$	$1.996E-01$
SB/L/h/l	Mean	$1.682E+01$	$3.164E+03$	$1.407E+02$	$1.147E+00$	$2.471E+00$
	StD	$3.107E+00$	$8.051E+02$	$1.422E+01$	$3.043E-02$	$1.965E-01$
SB/L/l/h	Mean	$1.348E-02$	$2.251E+02$	$1.257E+02$	$2.248E-02$	$1.779E-01$
	StD	$4.222E-03$	$5.981E+01$	$1.729E+01$	$1.082E-02$	$3.126E-01$
SB/L/m/h	Mean	$1.032E-02$	$1.930E+02$	$1.127E+02$	$1.450E-02$	$5.948E-02$
	StD	$2.836E-03$	$3.889E+01$	$1.403E+01$	$5.166E-03$	$3.094E-02$
SB/L/h/h	Mean	$9.044E-03$	$1.707E+02$	$1.045E+02$	$1.288E-02$	$4.386E-02$
	StD	$2.436E-03$	$3.217E+01$	$1.262E+01$	$3.826E-03$	$1.515E-02$
SB/NL/l/l	Mean	$2.148E-05$	$3.926E+02$	$1.478E+02$	$1.772E-02$	$2.451E+00$
	StD	$1.448E-04$	$1.084E+03$	$2.109E+01$	$4.439E-02$	$4.793E-01$
SB/NL/m/l	Mean	$2.582E-08$	$1.292E+02$	$1.308E+02$	$9.142E-03$	$1.977E+00$
	StD	$1.697E-07$	$1.828E+02$	$1.685E+01$	$1.731E-02$	$4.400E-01$
SB/NL/h/l	Mean	$4.977E-08$	$7.542E+01$	$1.192E+02$	$1.779E-02$	$1.776E+00$
	StD	$4.522E-07$	$8.976E+01$	$1.652E+01$	$4.484E-02$	$4.659E-01$
SB/NL/l/h	Mean	$1.224E-07$	$1.282E+02$	$1.239E+02$	$1.204E-02$	$1.202E-01$
	StD	$1.096E-06$	$1.563E+02$	$1.955E+01$	$2.914E-02$	$3.729E-01$
SB/NL/m/h	Mean	$1.024E-08$	$7.494E+01$	$1.093E+02$	$1.225E-02$	$8.799E-03$
	StD	$6.301E-08$	$9.759E+01$	$1.459E+01$	$2.409E-02$	$8.793E-02$
SB/NL/h/h	Mean	$8.339E-07$	$6.870E+01$	$1.036E+02$	$6.924E-03$	$1.603E-08$
	StD	$6.720E-06$	$2.369E+02$	$1.227E+01$	$1.402E-02$	$1.603E-07$
LB/L/l/l	Mean	$2.326E+01$	$5.342E+03$	$1.676E+02$	$1.207E+00$	$2.758E+00$
	StD	$5.873E+00$	$1.967E+03$	$1.742E+01$	$5.327E-02$	$2.652E-01$
LB/L/m/l	Mean	$1.888E+01$	$4.124E+03$	$1.504E+02$	$1.170E+00$	$2.527E+00$
	StD	$4.480E+00$	$1.191E+03$	$1.566E+01$	$4.049E-02$	$1.953E-01$
LB/L/h/l	Mean	$1.707E+01$	$3.363E+03$	$1.387E+02$	$1.148E+00$	$2.464E+00$
	StD	$3.266E+00$	$8.479E+02$	$1.508E+01$	$3.042E-02$	$1.933E-01$
LB/L/l/h	Mean	$1.294E-02$	$2.383E+02$	$1.298E+02$	$2.188E-02$	$1.997E-01$
	StD	$4.887E-03$	$5.847E+01$	$1.795E+01$	$1.132E-02$	$3.572E-01$
LB/L/m/h	Mean	$1.037E-02$	$1.914E+02$	$1.113E+02$	$1.496E-02$	$6.117E-02$
	StD	$3.049E-03$	$4.046E+01$	$1.438E+01$	$4.958E-03$	$2.596E-02$
LB/L/h/h	Mean	$9.221E-03$	$1.720E+02$	$1.070E+02$	$1.265E-02$	$4.699E-02$
	StD	$2.778E-03$	$3.239E+01$	$1.297E+01$	$3.709E-03$	$1.705E-02$
LB/NL/l/l	Mean	$3.877E-05$	$1.457E+02$	$1.410E+02$	$2.154E-02$	$2.386E+00$
	StD	$1.801E-04$	$9.008E+01$	$2.259E+01$	$7.060E-02$	$4.455E-01$
LB/NL/m/l	Mean	$1.724E-17$	$1.027E+02$	$1.263E+02$	$2.374E-03$	$1.910E+00$
	StD	$1.222E-16$	$8.560E+01$	$1.855E+01$	$4.527E-03$	$5.055E-01$
LB/NL/h/l	Mean	$1.328E-43$	$8.120E+01$	$1.150E+02$	$2.317E-03$	$1.467E+00$
	StD	$1.132E-42$	$5.659E+01$	$1.566E+01$	$6.113E-03$	$6.231E-01$
LB/NL/l/h	Mean	$3.794E-18$	$1.215E+02$	$1.196E+02$	$3.505E-03$	$9.738E-02$
	StD	$1.340E-17$	$1.184E+02$	$1.877E+01$	$6.132E-03$	$3.139E-01$
LB/NL/m/h	Mean	$4.296E-52$	$7.314E+01$	$1.088E+02$	$1.650E-03$	$5.247E-06$
	StD	$1.825E-51$	$5.433E+01$	$1.399E+01$	$4.216E-03$	$4.675E-05$
LB/NL/h/h	Mean	**3.317E-109**	**5.618E+01**	**1.009E+02**	**1.182E-03**	**4.594E-13**
	StD	**2.999E-108**	$3.936E+01$	**1.206E+01**	**3.181E-03**	**3.241E-12**
PSO/l/l	Mean	$2.952E+01$	$7.121E+03$	$1.665E+02$	$1.255E+00$	$2.867E+00$
	StD	$7.030E+00$	$2.626E+03$	$1.934E+01$	$6.346E-02$	$2.717E-01$
PSO/m/l	Mean	$2.502E+01$	$4.871E+03$	$1.515E+02$	$1.220E+00$	$2.672E+00$
	StD	$4.978E+00$	$1.934E+03$	$1.743E+01$	$4.683E-02$	$2.539E-01$
PSO/h/l	Mean	$2.231E+01$	$4.170E+03$	$1.428E+02$	$1.198E+00$	$2.569E+00$
	StD	$4.235E+00$	$1.183E+03$	$1.525E+01$	$3.881E-02$	$1.835E-01$
PSO/l/h	Mean	$2.326E-02$	$2.490E+02$	$1.263E+02$	$3.735E-02$	$2.615E-01$
	StD	$7.730E-03$	$5.896E+01$	$2.000E+01$	$1.394E-02$	$3.879E-01$
PSO/m/h	Mean	$1.817E-02$	$2.090E+02$	$1.156E+02$	$2.652E-02$	$7.9555E-02$
	StD	$4.853E-03$	$3.576E+01$	$1.441E+01$	$8.275E-03$	$3.239E-02$
PSO/h/h	Mean	$1.563E-02$	$1.786E+02$	$1.045E+02$	$2.177E-02$	$6.287E-02$
	StD	$3.741E-03$	**3.171E+01**	$1.358E+01$	$5.851E-03$	$2.170E-02$

Table 3: Results for the 100-dimensional problem instances.

Approach	Statistic	TP0	TP1	TP2	TP3	TP4
SB/L/l/l	Mean	$1.954E+03$	$1.240E+06$	$5.446E+02$	$1.820E+01$	$6.960E+00$
	StD	$2.489E+02$	$2.819E+05$	$3.869E+01$	$1.840E+00$	$2.591E-01$
SB/L/m/l	Mean	$1.732E+03$	$1.043E+06$	$5.173E+02$	$1.715E+01$	$6.693E+00$
	StD	$2.141E+02$	$2.108E+05$	$3.068E+01$	$1.581E+00$	$2.463E-01$
SB/L/h/l	Mean	$1.652E+03$	$9.347E+05$	$5.027E+02$	$1.575E+01$	$6.559E+00$
	StD	$1.637E+02$	$1.769E+05$	$2.611E+01$	$1.498E+00$	$2.136E-01$
SB/L/l/h	Mean	$4.770E+01$	$2.716E+04$	$4.011E+02$	$1.432E+00$	$3.336E+00$
	StD	$7.993E+00$	$6.931E+03$	$3.544E+01$	$7.521E-02$	$2.328E-01$
SB/L/m/h	Mean	$4.224E+01$	$2.172E+04$	$3.741E+02$	$1.374E+00$	$3.193E+00$
	StD	$5.942E+00$	$5.061E+03$	$3.462E+01$	$5.870E-02$	$1.872E-01$
SB/L/h/h	Mean	$3.844E+01$	$1.966E+04$	$3.554E+02$	$1.341E+00$	$3.079E+00$
	StD	$4.064E+00$	$3.983E+03$	$2.690E+01$	$4.813E-02$	$1.692E-01$
SB/NL/l/l	Mean	$1.947E+01$	$3.751E+02$	$4.885E+02$	$1.010E+00$	$6.597E+00$
	StD	$5.079E+01$	$2.461E+02$	$4.740E+01$	$1.034E+00$	$3.572E-01$
SB/NL/m/l	Mean	$5.754E-04$	$1.921E+02$	$4.551E+02$	$3.155E-02$	$6.406E+00$
	StD	$4.756E-03$	$7.622E+01$	$4.901E+01$	$1.495E-01$	$3.747E-01$
SB/NL/h/l	Mean	$1.173E-14$	$1.245E+02$	$4.411E+02$	$1.183E-03$	$6.115E+00$
	StD	$1.163E-13$	$6.968E+01$	$3.696E+01$	$4.028E-03$	$3.155E-01$
SB/NL/l/h	Mean	$4.281E-10$	$2.091E+02$	$3.670E+02$	$4.305E-03$	$3.080E+00$
	StD	$4.115E-09$	$7.005E+01$	$4.586E+01$	$8.929E-03$	$3.224E-01$
SB/NL/m/h	Mean	$8.181E-17$	$1.098E+02$	$3.206E+02$	$4.042E-03$	$2.845E+00$
	StD	$5.518E-16$	$5.500E+01$	$3.700E+01$	$1.574E-02$	$3.195E-01$
SB/NL/h/h	Mean	$2.491E-16$	**2.452E+01**	**3.124E+02**	$1.762E-03$	$2.687E+00$
	StD	$2.397E-15$	**4.659E+01**	$2.878E+01$	$8.685E-03$	$2.825E-01$
LB/L/l/l	Mean	$1.936E+03$	$1.217E+06$	$5.445E+02$	$1.814E+01$	$6.909E+00$
	StD	$2.448E+02$	$2.424E+05$	$4.425E+01$	$2.099E+00$	$2.729E-01$
LB/L/m/l	Mean	$1.758E+03$	$1.029E+06$	$5.122E+02$	$1.686E+01$	$6.777E+00$
	StD	$1.953E+02$	$1.874E+05$	$4.083E+01$	$1.857E+00$	$2.057E-01$
LB/L/h/l	Mean	$1.632E+03$	$9.161E+05$	$5.009E+02$	$1.588E+01$	$6.604E+00$
	StD	$1.624E+02$	$1.650E+05$	$2.978E+01$	$1.480E+00$	$2.250E-01$
LB/L/l/h	Mean	$4.693E+01$	$2.687E+04$	$3.984E+02$	$1.424E+00$	$3.341E+00$
	StD	$7.363E+00$	$6.710E+03$	$3.712E+01$	$7.286E-02$	$2.279E-01$
LB/L/m/h	Mean	$4.084E+01$	$2.216E+04$	$3.770E+02$	$1.377E+00$	$3.178E+00$
	StD	$6.457E+00$	$5.056E+03$	$3.293E+01$	$5.139E-02$	$1.843E-01$
LB/L/h/h	Mean	$3.859E+01$	$1.907E+04$	$3.561E+02$	$1.349E+00$	$3.067E+00$
	StD	$4.943E+00$	$4.094E+03$	**2.093E+01**	$3.992E-02$	$1.815E-01$
LB/NL/l/l	Mean	$5.553E+01$	$5.458E+02$	$5.002E+02$	$1.464E+00$	$6.650E+00$
	StD	$1.701E+02$	$1.945E+02$	$5.008E+01$	$1.085E+00$	$3.941E-01$
LB/NL/m/l	Mean	$1.666E-02$	$2.598E+02$	$4.541E+02$	$1.097E-01$	$6.272E+00$
	StD	$9.035E-02$	$8.863E+01$	$4.166E+01$	$2.576E-01$	$3.418E-01$
LB/NL/h/l	Mean	$1.137E-12$	$1.971E+02$	$4.276E+02$	$1.212E-03$	$6.034E+00$
	StD	$5.181E-12$	$6.668E+01$	$4.372E+01$	$3.682E-03$	$3.046E-01$
LB/NL/l/h	Mean	$7.665E-07$	$2.926E+02$	$3.578E+02$	$3.340E-03$	$3.081E+00$
	StD	$3.066E-06$	$1.343E+02$	$4.166E+01$	$8.352E-03$	$3.117E-01$
LB/NL/m/h	Mean	$1.007E-23$	$2.017E+02$	$3.292E+02$	**2.958E-04**	$2.759E+00$
	StD	$6.976E-23$	$9.596E+01$	$3.433E+01$	**1.725E-03**	$2.800E-01$
LB/NL/h/h	Mean	**2.411E-56**	$1.620E+02$	$3.128E+02$	$5.175E-04$	**2.584E+00**
	StD	**1.844E-55**	$5.796E+01$	$3.220E+01$	$2.081E-03$	$2.366E-01$
PSO/l/l	Mean	$2.192E+03$	$1.377E+06$	$5.511E+02$	$2.102E+01$	$7.131E+00$
	StD	$2.845E+02$	$3.196E+05$	$4.373E+01$	$2.432E+00$	$3.193E-01$
PSO/m/l	Mean	$2.023E+03$	$1.204E+06$	$5.164E+02$	$1.921E+01$	$6.939E+00$
	StD	$1.838E+02$	$2.276E+05$	$3.355E+01$	$1.938E+00$	$2.749E-01$
PSO/h/l	Mean	$1.897E+03$	$1.046E+06$	$4.989E+02$	$1.825E+01$	$6.791E+00$
	StD	$1.801E+02$	$1.780E+05$	$3.138E+01$	$1.384E+00$	$2.127E-01$
PSO/l/h	Mean	$6.530E+01$	$3.353E+04$	$4.024E+02$	$1.596E+00$	$3.438E+00$
	StD	$1.098E+01$	$9.741E+03$	$3.957E+01$	$8.732E-02$	$2.337E-01$
PSO/m/h	Mean	$5.920E+01$	$2.853E+04$	$3.771E+02$	$1.515E+00$	$3.311E+00$
	StD	$7.385E+00$	$6.190E+03$	$3.203E+01$	$7.288E-02$	$2.056E-01$
PSO/h/h	Mean	$5.241E+01$	$2.466E+04$	$3.562E+02$	$1.476E+00$	$3.213E+00$
	StD	$6.675E+00$	$5.558E+03$	$2.841E+01$	$5.351E-02$	**1.490E-01**

Table 4: Results for the 150-dimensional problem instances.

Approach	Statistic	TP0	TP1	TP2	TP3	TP4
SB/L/l/l	Mean	$9.993E+03$	$9.872E+06$	$1.033E+03$	$9.232E+01$	$9.890E+00$
	StD	$8.551E+02$	$1.707E+06$	$4.886E+01$	$8.432E+00$	$2.790E-01$
SB/L/m/l	Mean	$9.117E+03$	$8.671E+06$	$9.962E+02$	$8.458E+01$	$9.696E+00$
	StD	$7.034E+02$	$1.275E+06$	$4.106E+01$	$6.025E+00$	$2.667E-01$
SB/L/h/l	Mean	$8.961E+03$	$8.004E+06$	$9.683E+02$	$8.195E+01$	$9.552E+00$
	StD	$6.014E+02$	$1.097E+06$	**3.736E+01**	$5.533E+00$	$2.354E-01$
SB/L/l/h	Mean	$8.706E+02$	$7.348E+05$	$7.785E+02$	$8.607E+00$	$5.641E+00$
	StD	$1.051E+02$	$1.367E+05$	$4.222E+01$	$9.297E-01$	$2.325E-01$
SB/L/m/h	Mean	$8.033E+02$	$6.048E+05$	$7.357E+02$	$8.173E+00$	$5.508E+00$
	StD	$7.322E+01$	$1.046E+05$	$4.737E+01$	$7.047E-01$	$1.914E-01$
SB/L/h/h	Mean	$7.450E+02$	$5.549E+05$	$7.120E+02$	$7.771E+00$	$5.344E+00$
	StD	$6.285E+01$	$9.550E+04$	$3.857E+01$	$6.331E-01$	**1.537E-01**
SB/NL/l/l	Mean	$2.115E+03$	$2.218E+03$	$9.686E+02$	$2.406E+01$	$9.770E+00$
	StD	$1.801E+03$	$7.520E+03$	$6.162E+01$	$1.644E+01$	$3.155E-01$
SB/NL/m/l	Mean	$7.100E+02$	$3.432E+02$	$9.167E+02$	$8.723E+00$	$9.389E+00$
	StD	$1.007E+03$	$1.233E+02$	$5.924E+01$	$1.002E+01$	$2.755E-01$
SB/NL/h/l	Mean	$9.908E+01$	$2.512E+02$	$8.881E+02$	$2.158E+00$	$9.218E+00$
	StD	$2.779E+02$	$8.089E+01$	$4.958E+01$	$3.876E+00$	$3.322E-01$
SB/NL/l/h	Mean	$1.752E-01$	$3.398E+02$	$7.052E+02$	$4.076E-02$	$5.326E+00$
	StD	$1.557E+00$	$9.858E+01$	$7.134E+01$	$1.491E-01$	$3.386E-01$
SB/NL/m/h	Mean	$7.170E-15$	$2.291E+02$	$6.462E+02$	$9.134E-04$	$5.129E+00$
	StD	$7.159E-14$	$8.058E+01$	$6.818E+01$	$3.276E-03$	$2.541E-01$
SB/NL/h/h	Mean	$2.017E-23$	**1.184E+02**	$6.208E+02$	$8.871E-04$	**4.908E+00**
	StD	$2.017E-22$	$8.888E+01$	$4.889E+01$	$2.981E-03$	$2.521E-01$
LB/L/l/l	Mean	$9.848E+03$	$9.864E+06$	$1.032E+03$	$9.141E+01$	$9.859E+00$
	StD	$9.563E+02$	$1.611E+06$	$5.767E+01$	$8.183E+00$	$2.888E-01$
LB/L/m/l	Mean	$9.376E+03$	$8.669E+06$	$9.887E+02$	$8.481E+01$	$9.708E+00$
	StD	$7.093E+02$	$1.194E+06$	$5.031E+01$	$6.137E+00$	$2.379E-01$
LB/L/h/l	Mean	$8.927E+03$	$7.985E+06$	$9.614E+02$	$8.056E+01$	$9.520E+00$
	StD	$5.832E+02$	$1.048E+06$	$3.768E+01$	$6.622E+00$	$2.428E-01$
LB/L/l/h	Mean	$8.616E+02$	$7.330E+05$	$7.781E+02$	$8.850E+00$	$5.650E+00$
	StD	$1.037E+02$	$1.582E+05$	$6.110E+01$	$9.269E-01$	$2.334E-01$
LB/L/m/h	Mean	$7.995E+02$	$6.088E+05$	$7.415E+02$	$8.211E+00$	$5.473E+00$
	StD	$7.485E+01$	$1.192E+05$	$3.908E+01$	$6.494E-01$	$1.889E-01$
LB/L/h/h	Mean	$7.514E+02$	$5.318E+05$	$7.071E+02$	$7.707E+00$	$5.351E+00$
	StD	$6.494E+01$	$9.529E+04$	$4.409E+01$	$6.389E-01$	$1.785E-01$
LB/NL/l/l	Mean	$2.580E+03$	$1.191E+04$	$9.612E+02$	$2.445E+01$	$9.612E+00$
	StD	$1.716E+03$	$3.851E+04$	$6.601E+01$	$1.589E+01$	$3.678E-01$
LB/NL/m/l	Mean	$6.117E+02$	$5.496E+02$	$9.079E+02$	$6.595E+00$	$9.382E+00$
	StD	$9.710E+02$	$1.759E+02$	$5.871E+01$	$8.207E+00$	$2.734E-01$
LB/NL/h/l	Mean	$6.548E+01$	$3.710E+02$	$8.725E+02$	$1.735E+00$	$9.214E+00$
	StD	$2.287E+02$	$1.476E+02$	$5.878E+01$	$3.068E+00$	$2.717E-01$
LB/NL/l/h	Mean	$5.931E-02$	$5.457E+02$	$7.106E+02$	$1.967E-01$	$5.382E+00$
	StD	$2.258E-01$	$1.435E+02$	$7.825E+01$	$2.938E-01$	$2.965E-01$
LB/NL/m/h	Mean	$3.662E-10$	$3.389E+02$	$6.424E+02$	$2.490E-04$	$5.069E+00$
	StD	$3.344E-09$	$7.994E+01$	$5.575E+01$	**1.423E-03**	$2.577E-01$
LB/NL/h/h	Mean	**2.307E-29**	$2.759E+02$	**6.141E+02**	**1.972E-04**	$4.934E+00$
	StD	**1.389E-28**	**7.248E+01**	$5.380E+01$	$1.430E-03$	$2.364E-01$
PSO/l/l	Mean	$1.103E+04$	$1.102E+07$	$1.030E+03$	$9.884E+01$	$1.004E+01$
	StD	$9.989E+02$	$1.678E+06$	$5.055E+01$	$8.840E+00$	$3.206E-01$
PSO/m/l	Mean	$1.037E+04$	$9.708E+06$	$9.940E+02$	$9.576E+01$	$9.808E+00$
	StD	$7.564E+02$	$1.463E+06$	$4.398E+01$	$7.103E+00$	$2.505E-01$
PSO/h/l	Mean	$9.974E+03$	$9.040E+06$	$9.672E+02$	$9.005E+01$	$9.722E+00$
	StD	$6.770E+02$	$1.011E+06$	$4.408E+01$	$6.316E+00$	$2.337E-01$
PSO/l/h	Mean	$1.067E+03$	$8.752E+05$	$7.919E+02$	$1.051E+01$	$5.852E+00$
	StD	$1.147E+02$	$1.930E+05$	$5.457E+01$	$9.069E-01$	$2.718E-01$
PSO/m/h	Mean	$9.845E+02$	$7.630E+05$	$7.483E+02$	$9.938E+00$	$5.669E+00$
	StD	$9.347E+01$	$1.422E+05$	$4.632E+01$	$8.508E-01$	$1.990E-01$
PSO/h/h	Mean	$9.307E+02$	$6.866E+05$	$7.273E+02$	$9.393E+00$	$5.578E+00$
	StD	$7.971E+01$	$9.502E+04$	$3.938E+01$	$6.692E-01$	$1.744E-01$

Table 5: Results for the 200-dimensional problem instances.

Approach	Statistic	TP0	TP1	TP2	TP3	TP4
SB/L/l/l	Mean	$2.473E+04$	$2.932E+07$	$1.559E+03$	$2.236E+02$	$1.180E+01$
	StD	$1.663E+03$	$4.198E+06$	$5.981E+01$	$1.668E+01$	$2.752E-01$
SB/L/m/l	Mean	$2.344E+04$	$2.710E+07$	$1.519E+03$	$2.101E+02$	$1.160E+01$
	StD	$1.443E+03$	$2.995E+06$	$5.218E+01$	$1.255E+01$	$2.189E-01$
SB/L/h/l	Mean	$2.263E+04$	$2.569E+07$	$1.491E+03$	$2.037E+02$	$1.149E+01$
	StD	$1.358E+03$	$2.768E+06$	**4.262E+01**	$1.165E+01$	$2.000E-01$
SB/L/l/h	Mean	$3.994E+03$	$4.256E+06$	$1.229E+03$	$3.578E+01$	$7.704E+00$
	StD	$3.643E+02$	$7.621E+05$	$5.957E+01$	$3.408E+00$	$2.973E-01$
SB/L/m/h	Mean	$3.688E+03$	$3.644E+06$	$1.170E+03$	$3.427E+01$	$7.512E+00$
	StD	$2.621E+02$	$4.786E+05$	$6.178E+01$	$2.395E+00$	$2.394E-01$
SB/L/h/h	Mean	$3.557E+03$	$3.422E+06$	$1.142E+03$	$3.252E+01$	$7.367E+00$
	StD	$2.508E+02$	$4.728E+05$	$4.655E+01$	$2.379E+00$	**1.859E-01**
SB/NL/l/l	Mean	$1.372E+04$	$5.387E+05$	$1.478E+03$	$1.248E+02$	$1.163E+01$
	StD	$4.512E+03$	$1.453E+06$	$7.988E+01$	$3.614E+01$	$3.032E-01$
SB/NL/m/l	Mean	$9.749E+03$	$1.496E+03$	$1.434E+03$	$8.869E+01$	$1.147E+01$
	StD	$3.855E+03$	$4.094E+03$	$6.664E+01$	$3.316E+01$	$2.284E-01$
SB/NL/h/l	Mean	$6.335E+03$	$4.039E+02$	$1.434E+03$	$6.513E+01$	$1.131E+01$
	StD	$3.404E+03$	$9.386E+01$	$6.664E+01$	$3.362E+01$	$2.312E-01$
SB/NL/l/h	Mean	$4.384E+01$	$5.528E+02$	$1.123E+03$	$1.078E+00$	$7.485E+00$
	StD	$1.458E+02$	$1.525E+02$	$9.285E+01$	$1.203E+00$	$3.250E-01$
SB/NL/m/h	Mean	$1.695E-02$	$3.478E+02$	$1.068E+03$	$4.882E-03$	$7.141E+00$
	StD	$1.362E-01$	**8.614E+01**	$7.554E+01$	$2.446E-02$	$2.618E-01$
SB/NL/h/h	Mean	**9.271E-19**	**2.196E+02**	$1.026E+03$	$1.158E-03$	$7.032E+00$
	StD	**8.566E-18**	$1.027E+02$	$6.061E+01$	$3.330E-03$	$2.386E-01$
LB/L/l/l	Mean	$2.493E+04$	$2.974E+07$	$1.575E+03$	$2.232E+02$	$1.179E+01$
	StD	$1.685E+03$	$4.055E+06$	$5.845E+01$	$1.494E+01$	$2.795E-01$
LB/L/m/l	Mean	$2.366E+04$	$2.710E+07$	$1.515E+03$	$2.131E+02$	$1.160E+01$
	StD	$1.416E+03$	$2.957E+06$	$5.580E+01$	$1.163E+01$	$1.982E-01$
LB/L/h/l	Mean	$2.261E+04$	$2.503E+07$	$1.485E+03$	$2.053E+02$	$1.147E+01$
	StD	$1.258E+03$	$2.986E+06$	$4.445E+01$	$1.007E+01$	$2.222E-01$
LB/L/l/h	Mean	$3.952E+03$	$4.234E+06$	$1.232E+03$	$3.576E+01$	$7.704E+00$
	StD	$3.859E+02$	$7.675E+05$	$6.655E+01$	$3.442E+00$	$2.436E-01$
LB/L/m/h	Mean	$3.643E+03$	$3.605E+06$	$1.168E+03$	$3.316+01$	$7.451E+00$
	StD	$2.820E+02$	$5.670E+05$	$5.504E+01$	$2.795E+00$	$2.394E-01$
LB/L/h/h	Mean	$3.512E+03$	$3.358E+06$	$1.151E+03$	$3.232E+01$	$7.398E+00$
	StD	$2.331E+02$	$5.119E+05$	$5.406E+01$	$2.379E+00$	$1.885E-01$
LB/NL/l/l	Mean	$1.288E+04$	$4.941E+05$	$1.489E+03$	$1.190E+02$	$1.161E+01$
	StD	$3.964E+03$	$1.172E+06$	$7.871E+01$	$3.573E+01$	$2.990E-01$
LB/NL/m/l	Mean	$9.022E+03$	$8.884E+03$	$1.436E+03$	$7.979E+01$	$1.142E+01$
	StD	$3.710E+03$	$5.098E+04$	$6.923E+01$	$3.133E+01$	$2.894E-01$
LB/NL/h/l	Mean	$5.525E+03$	$6.171E+02$	$1.436E+03$	$5.463E+01$	$1.126E+01$
	StD	$3.448E+03$	$1.825E+02$	$6.923E+01$	$3.147E+01$	$2.354E-01$
LB/NL/l/h	Mean	$6.658E+01$	$9.596E+02$	$1.133E+03$	$1.691E+00$	$7.421E+00$
	StD	$1.700E+02$	$3.592E+02$	$8.355E+01$	$1.538E+00$	$3.299E-01$
LB/NL/m/h	Mean	$2.829E-02$	$5.471E+02$	$1.050E+03$	$1.542E-01$	$7.136E+00$
	StD	$2.721E-01$	$1.173E+02$	$7.893E+01$	$3.340E-01$	$2.312E-01$
LB/NL/h/h	Mean	$2.400E-12$	$4.183E+02$	**1.006E+03**	**3.215E-04**	**6.972E+00**
	StD	$1.796E-11$	$9.001E+01$	$8.199E+01$	**1.735E-03**	$2.669E-01$
PSO/l/l	Mean	$2.682E+04$	$3.254E+07$	$1.568E+03$	$2.420E+02$	$1.194E+01$
	StD	$1.698E+03$	$4.280E+06$	$6.589E+01$	$1.920E+01$	$2.480E-01$
PSO/m/l	Mean	$2.515E+04$	$2.970E+07$	$1.530E+03$	$2.308E+02$	$1.181E+01$
	StD	$1.734E+03$	$3.338E+06$	$4.529E+01$	$1.243E+01$	$1.982E-01$
PSO/h/l	Mean	$2.470E+04$	$2.843E+07$	$1.489E+03$	$2.212E+02$	$1.165E+01$
	StD	$1.242E+03$	$2.846E+06$	$5.234E+01$	$1.308E+01$	$1.893E-01$
PSO/l/h	Mean	$4.646E+03$	$4.958E+06$	$1.240E+03$	$4.269E+01$	$7.876E+00$
	StD	$4.226E+02$	$8.016E+05$	$7.487E+01$	$3.815E+00$	$2.657E-01$
PSO/m/h	Mean	$4.301E+03$	$4.333E+06$	$1.193E+03$	$4.034E+01$	$7.714E+00$
	StD	$3.225E+02$	$5.884E+05$	$5.783E+01$	$3.089E+00$	$2.428E-01$
PSO/h/h	Mean	$4.115E+03$	$3.920E+06$	$1.150E+03$	$3.824E+01$	$7.581E+00$
	StD	$2.373E+02$	$5.478E+05$	$6.158E+01$	$2.646E+00$	$2.453E-01$