MOEA/D with Uniform Design for Solving Multiobjective Knapsack Problems

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***Abstract*—The 0/1 knapsack problem is a well-known problem, which appears in many real domains with practical importance. The problem is NP-complete. The multiobjective 0/1 knapsack problem is a generalization of the 0/1 knapsack problem in which multiple knapsacks are considered. Many algorithms have been proposed in the past five decades for both single and multiobjective knapsack problems. A new version of MOEA/D with uniform design for solving multiobjective 0/1 knapsack problems is proposed in this paper. The algorithm adopts the uniform design method to generate the aggregation coefficient vectors so that the decomposed scalar optimization subproblems are uniformly scattered, and therefore the algorithm could explore uniformly the region of interest from the initial iteration. To illustrate how the algorithm works, some numerical experiments on the benchmark multiobjective knapsack problems are realized. Experimental results show that the proposed algorithm outperforms NSGA-II, SPEA2 and PESA significantly for the 2-objective, 3-objective and 4-objective knapsack problems.**

***Index Terms*—multiobjective evolutionary algorithm, uniform design, decomposition, knapsack problem**

I. Introduction

The 0/1 knapsack problem is a widely studied problem due to its practical importance. In the last years the generalization of this problem has been well studied and many algorithms for solving this variants have been proposed. Evolutionary approaches for solving the multiobjective 0/1 knapsack problems are of great interest. Many papers on the multiobjective knapsack problem (MOKP) and on the algorithms proposed for solving it can be found in the literature [1]–[7].

MOEA/D is a very recent multiobjective evolutionary algorithm (MOEA) using decomposition [8]. MOEA/D explicitly decomposes a multiobjective optimization problem (MOP) into a number of scalar optimization subproblems, which solves these subproblems simultaneously by evolving a population of solutions. At each generation, the population is composed of the best solutions found so far for each subproblem. It has been proved that MOEA/D has a lower complexity than NSGA-II [9], the most popular MOEA, at each iteration [8], [10], and the algorithm has been ranked first among 13 entries in the unconstrained MOEA competition in CEC2009 [11]. Up to present, it has been applied for solving a number of continuous multiobjective optimization problems efficiently [8], [10], [12]–[14]. In this paper we propose a new version of MOEA/D with uniform design for dealing with multiobjective 0/1 knapsack problems. The proposed algorithm is experimentally compared with NSGA-II [9], SPEA2 [7] and PESA [15] on some benchmark knapsack problems.

The remainder of this paper is organized as follows. Both single and multiobjective 0/1 knapsack problems are described in Sect. II. Sect. III presents the proposed algorithm. The uniform design method for generating the aggregation coefficient vectors is also given in this section. Experimental comparisons are performed in Sect. IV. Sect. V concludes this paper.

II. Problem Formulation

The classical 0/1 knapsack problem can be formulated as follow [2]. A set of n items and a knapsack of capacity c are considered. Each item has a profit p_j and a weight w_j. The problem is to select a subset of the items whose total weight does not exceed knapsack capacity c and whose total profit is maximum. Using the variables x_j (with $x_j = 1$ if the item j is selected and $x_j = 0$ otherwise), the problem can be written as

$$\begin{aligned} &\text{maxmize } \sum_{j=1}^{n} p_j x_j \\ &\text{subject to } \sum_{j=1}^{n} w_j x_j \le c \\ &x_j \in \{0,1\}, j = \{1,\ldots,n\}. \end{aligned} \tag{1}$$

The problem can be extended for an arbitrary number of knapsacks. Given a set of n items and a set of m knapsacks, the multiobjective 0/1 knapsack problem (MOKP) can be stated as

$$\begin{aligned} &\text{maxmize } f_i(x) = \sum_{j=1}^{n} p_{ij} x_j, i = 1,\ldots,m \\ &\text{subject to } \sum_{j=1}^{n} w_{ij} x_j \le c_i, i = 1,\ldots,m \\ &x = (x_1,\ldots,x_n)^{\top} \in \{0,1\}^n \end{aligned} \tag{2}$$

where $p_{ij} \ge 0$ is the profit of item j in knapsack i, $w_{ij} \ge 0$ is the weight of item j in knapsack i, and c_i is the capacity of knapsack i. $x_i = 1$ means that item i is selected and put in all the knapsacks.

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III. The Proposed Algorithm

A. Decomposition Strategies Used in the Proposed Algorithm

MOEA/D decomposes an MOP into a number of scalar optimization subproblems, and optimizes them simultaneously. The objective in each of these subproblems is an aggregation of all the objectives. Each subproblem is optimized by using information only from its neighboring subproblems. Neighborhood relations among subproblems are defined based on the distances between their aggregation coefficient vectors. The optimal solutions to two neighboring subproblems should be very similar.

There are several approaches for converting an MOP into a number of scalar optimization problems and they can be found in the literature (e.g., [16]). The most popular ones among them include the weighted sum approach and Tchebycheff approach which are introduced in the following:

- Weighted sum approach [8], [16]
  Let $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_m)^\top$ be a weight vector, i.e., $\lambda_i \geq 0$ for all $i = 1, \ldots, m$ and $\sum_{i=1}^{m} \lambda_i = 1$. Then, in this approach, the scalar optimization problem is in the form

$$\begin{aligned} &\text{maxmize } g^{ws}(x|\lambda) = \sum_{i=1}^{m} \lambda_i f_i(x) \\ &\text{subject to } x \in \{0,1\}^n \end{aligned} \tag{3}$$

  where we use $g^{ws}(x|\lambda)$ to emphasize that λ is a coefficient vector in this objective function, while x is the variables to be optimized. To generate a set of different Pareto optimal solutions, one can use different weight vectors λ in the scalar optimization problem (3). In this approach a convex combination of all the objectives is adopted. If Pareto front (PF) is convex, this approach works well. However, not every Pareto optimal vector can be obtained by this approach in the case of nonconvex PFs [16]. To overcome these shortcomings, Tchebycheff approach is suggested.
- Tchebycheff approach [8], [16]
  Mathematically, the scalar optimization problem is in the form

$$\begin{aligned} &\text{minimize } g^{te}(x|\lambda, z^*) = \max_{1 \leq i \leq m} \{\lambda_i \left| f_i(x) - z_i^* \right|\} \\ &\text{subject to } x \in \{0,1\}^n \end{aligned} \tag{4}$$

  where $z^* = (z_1^*, \ldots, z_m^*)^\top$ is the reference point, i.e., $z_i^* = \max(f_i(x)|x \in \{0,1\}^n)$ for each $i = 1, \ldots, m$. For each Pareto optimal point x^* there exists a weight vector λ such that x^* is the optimal solution of Problem (4), and each optimal solution of Problem (4) is a Pareto optimal solution of the decomposed multiobjective optimization problem. Therefore, one can obtain different Pareto optimal solutions by altering the weight vector. One weakness with this approach is that its aggregation function is not smooth for a continuous MOP. However, this work aims to solve multiobjective knapsack problems, which is a type of discrete problems, then this approach still can be used in this paper.

B. Uniform Design Method for Generating the Aggregation Coefficient Vectors

This subsection introduces the so-called uniform design (UD) method that is adopted in the proposed algorithm for generating the aggregation coefficient vectors of the subproblems. The essence of the UD method is to find a set of points that are uniformly scattered over the design region of interest. Note that a "uniformly scattered" set of points as stated here means roughly that the set has a small discrepancy, not a set of points which are uniformly distributed in the usual statistical sense. Let $\lambda^1, \ldots, \lambda^N$ be the aggregation coefficient vectors, subproblem i corresponds to the coefficient vector $\lambda^i = (\lambda_1^i, \ldots, \lambda_m^i)^\top$, $\lambda_j^i \geq 0, j = 1, \ldots, m$ and $\sum_{j=1}^{m} \lambda_j^i = 1$ for all $i = 1, \ldots, N$, m is the number of objectives, N is the population size (i.e., the number of aggregation coefficient vectors). The essence of the design method used in the proposed algorithm is to find a set of coefficient vectors $\lambda^1, \ldots, \lambda^N$ which are uniformly scattered over the design space.

Without loss of generality, let the design space be the m-dimensional unit cube $C^m = [0,1]^m$, we represent any vector in C^m by $x_i = (x_{i1}, \ldots, x_{im})^\top$, where $x_{i1}, \ldots, x_{im} \in [0,1]$. For a given positive integer N, a uniform design with N vectors in C^m is a collection of vectors $P^* = \{x_1^*, \ldots, x_N^*\} \subset C^m$ such that $\mathbf{M}(P^*) = \min \mathbf{M}(P)$, where the minimization is carried out over all $P = \{x_1, \ldots, x_N\} \subset C^m$ with respect to some measure of uniformity, $\mathbf{M}$. There are some choices for $\mathbf{M}$, for example, the star discrepancy, the most commonly used centered L_2-discrepancy (CD) and the wrap-around L_2-discrepancy (WD). The centered L_2-discrepancy (CD), denoted by $\mathrm{CD}_2(P)$ [17],

$$\begin{aligned} \mathrm{CD}_2(P) = &\left(\frac{13}{12}\right)^m - \frac{2}{N} \sum_{k=1}^{N} \prod_{i=1}^{m} \left(1 + \frac{1}{2}\left|x_{ki} - \frac{1}{2}\right| \right. \\ &\left. - \frac{1}{2}\left|x_{ki} - \frac{1}{2}\right|^2\right) + \frac{1}{N^2} \sum_{k=1}^{N} \sum_{j=1}^{N} \prod_{i=1}^{m} \left(1 + \frac{1}{2}\right. \\ &\left. \left|x_{ki} - \frac{1}{2}\right| + \frac{1}{2}\left|x_{ji} - \frac{1}{2}\right| - \frac{1}{2}\left|x_{ki} - x_{ji}\right|\right) \end{aligned} \tag{5}$$

is used in our experiments, for it is convenient to compute and is invariant under relabeling of coordinate axes. The CD is also invariant under reflection of points about any plane passing through the center and parallel to the faces of the unit cube C^m, that is, invariant when the i-th coordinate x_i is replaced by $1 - x_i$. Corresponding formulas for other discrepancies can be found in Fang et al. [17].

Now the question is how to determine the set of vectors with the lowest discrepancy. There are several methods for

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serving this purpose. Good lattice point (*glp*) is adopted in our algorithm. Let $(N; h_1, \ldots, h_{m-1})$ be a vector with integral components satisfying $1 \leq h_i < N, h_i \neq h_j (i \neq j), m-1 < N$ and the greatest common divisors $(N, h_i) = 1, i = 1, \ldots, m-1$. Let

$$u_{ki} \equiv k h_i (\mathrm{mod} N), k = 1, \ldots, N; i = 1, \ldots, m-1. \quad (6)$$

Set $S_N = \left\{u_k = (u_{k1}, \ldots, u_{km-1})^\top, k = 1, \ldots, N\right\}$ is called a lattice point set of the generating vector $(N; h_1, \ldots, h_{m-1})$. If set S_N has the smallest discrepancy among all the possible generating vectors, set S_N is the uniform design that we need to construct.

Let $U = (u_{ki})_{k=1,\ldots,N; i=1,\ldots,m-1}$ be the uniform design constructed above. Calculate

$$c_{ki} = (u_{ki} - 0.5)/N \quad (7)$$

where $k = 1, \ldots, N$ and $i = 1, \ldots, m-1$. Let

$$C^* = \left\{c_k = \left(c_{k1}, \ldots, c_{k(m-1)}\right)^\top, k = 1, \ldots, N\right\}$$

then C^* is a uniform design on C^{m-1}.

In order to satisfy the restriction that $\sum_{i=1}^{m} \lambda_i^k = 1$ for all $k = 1, \ldots, N$, the following transformation is required

$$\begin{cases} \lambda_i^k = \left(1 - c_{ki}^{\frac{1}{m-i}}\right) \prod_{j=1}^{i-1} c_{kj}^{\frac{1}{m-j}} & i = 1, \ldots, m-1 \\ \lambda_m^k = \prod_{j=1}^{m-1} c_{kj}^{\frac{1}{m-j}} \end{cases} \quad (8)$$

for each $k = 1, \ldots, N$. Then the uniformly scattered weight vectors $\{\lambda^k = (\lambda_1^k, \ldots, \lambda_m^k), k = 1, \ldots, N\}$ are achieved through the uniform design method.

C. Framework of the Proposed Algorithm

Uniform design multiobjective evolutionary algorithm based on decomposition (UMOEA/D) proposed in this paper is a new version of MOEA/D with uniform design for solving multiobjective 0/1 knapsack problems. UMOEA/D needs to decompose the MOP under consideration. Any decomposition approaches can serve this purpose. In the following description, the weighted sum approach is employed. It is very trivial to modify the following UMOEA/D when other decomposition methods are used.

Let $\lambda^1, \ldots, \lambda^N$ be a set of uniformly scattered weight vectors. With the weighted sum approach, the objective function of the i-th subproblem is in the form [16]

$$g^{ws}(x|\lambda^i) = \sum_{j=1}^{m} \lambda_j^i f_j(x) \quad (9)$$

where $\lambda^i = \left(\lambda_1^i, \ldots, \lambda_m^i\right)^\top$. UMOEA/D maxmizes these N objective functions simultaneously in a single run. At each generation, UMOEA/D maintains the following items:

- A population of N points $x^1, \ldots, x^N \in \{0,1\}^n$, where x^i is the current solution to the i-th subproblem.
- $FV^1, \ldots, FV^N$, where FV^i is the F-value of x^i, i.e., $FV^i = F(x^i)$ for each $i = 1, \ldots, N$.
- $z = (z_1, \ldots, z_m)^\top$, where z_i is the best value found so far for objective f_i.
- An external population (EP), which is used to store nondominated solutions found during the search.

Consequently, the general framework of UMOEA/D can be stated as follows:

Input:

- N : the number of subproblems considered in UMOEA/D;
- $\lambda^1, \ldots, \lambda^N$: a set of N uniformly scattered weight vectors;
- T : the number of the weight vectors in the neighborhood of each weight vector;
- Stopping criteria.

Output: EP

Step 1 Initialization

Step 1.1: Set EP=ϕ.

Step 1.2: Compute the Euclidean distances between any two weight vectors and then work out the T closest weight vectors to each weight vector. For each $i = 1, \ldots, N$, set $B(i) = \{i_1, \ldots, i_T\}$, where $\lambda^{i_1}, \ldots, \lambda^{i_T}$ are the T closest weight vectors to λ^i.

Step 1.3: Generate an initial population $x^1, \ldots, x^N$ by randomly sampling from $\{0,1\}^n$. Apply a greedy repair method to the initial infeasible solutions. Set $FV^i = F(x^i)$.

Step 1.4: Initialize $z = (z_1, \ldots, z_m)^\top$ by setting $z_j = \max_{1 \leq i \leq N} f_j\left(x^i\right), j = 1, \ldots, m$.

Step 2 Update

For $i = 1, \ldots, N$, do

Step 2.1 Reproduction: Randomly select two indexes k, l from $B(i)$, and then generate a new solution $\overline{y}$ from x^k and x^l by using genetic operators.

Step 2.2 Improvement: Apply a greedy repair heuristic on $\overline{y}$ to produce y.

Step 2.3 Update of z: For each $j = 1, \ldots, m$, if $z_j < f_j(y)$, then set $z_j = f_j(y)$.

Step 2.4 Update of neighboring solutions: For each index $j \in B(i)$, if $g^{ws}\left(y \left| \lambda^j \right.\right) \geq g^{ws}\left(x^j \left| \lambda^j \right.\right)$, then set $x^j = y$ and $FV^j = F(y)$.

Step 2.5 Update of EP:

Remove from EP all the vectors dominated by $F(y)$.

Add $F(y)$ to EP if no vectors in EP dominate $F(y)$.

Step 3 Stopping criteria

If the stopping criteria are satisfied, then stop and output EP. Otherwise, go to **Step 2**.

The greedy repair method used in Step 1.3 and Step 2.2 is described as follows. Let $J = \{j | x_j = 1, 1 \leq j \leq n\}$ is the set of selected items, and $I =$

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$\left\{i|\sum_{j=1}^{n} w_{ij}x_j > c_i, 1 \le i \le m\right\}$ is the set of overfilled knapsacks. Repeatedly remove item $k \in J$ until none of the knapsack is overfilled, such that

$$k = \arg\min_{j \in J} \frac{g^{ws}(x) - g^{ws}(x^{j-})}{\sum_{i \in I} w_{ij}} \tag{10}$$

where x^{j-} is different from x only by item j, i.e., $x_i^{j-} = x_i$ for all $i \neq j$ and $x_j^{j-} = 0$.

IV. Experimental Study

As test problems three instances of the knapsack problems are taken from [2], each with 750 items and 2, 3, and 4 objectives, respectively. For the random choices of the profit and weight values as well as the constraint handling technique we refer to the original study. The results obtained by UMOEA/D are compared with the results obtained by NSGA-II, SPEA2 and PESA. The population size N is set to 250 for $m = 2$, 300 for $m = 3$, and 350 for $m = 4$. These four algorithms stop after a given number of function evaluations (FES). For each algorithm and each problem, 30 runs with different random seeds have been carried out independently. Here, two sets of experiments are carried out to illustrate the efficiency of the proposed algorithm. FES is set to $500 \times N$ and $960 \times N$ in these two sets of experiments respectively.

A. Performance Assessment

In order to compare the performance of the different algorithms quantitatively, performance metrics are needed. Two performance metrics, C-metric and hypervolume metric, are adopted in this study. The performance metrics used in this paper are described as follows [2]

- **Coverage of two sets (C):** The C-metric measures the 'degree' of dominance of a Pareto front over another Pareto front. Let A and B be two approximations to the Pareto front of an MOP. $\mathrm{C}(A, B)$ is defined as the percentage of the solutions in B that are dominated by at least one solution in A, i.e.,

$$\mathrm{C}(A, B) = \frac{|\{u \in B | \exists v \in A : v \text{ dominates } u\}|}{|B|} \tag{11}$$

  $\mathrm{C}(A, B)$ is not necessarily equal to 1-$\mathrm{C}(B, A)$. $\mathrm{C}(A, B) = 1$ means that all solutions in B are dominated by some solutions in A, while $\mathrm{C}(A, B) = 0$ implies that no solution in B is dominated by a solution in A.
- **Hypervolume (HV):** The hypervolume metric measures the size of the region which is dominated by the obtained Pareto front. Therefore the higher value of the HV-metric is preferred. In lower dimension, 2- and 3-objective spaces, it is known as area and volume respectively. Let P be an approximation to the PF. Mathematically, the HV-metric is described as

$$\mathrm{HV}(P) = \left\{\bigcup vol(v) | v \in P\right\} \tag{12}$$

TABLE I
AVERAGE VALUES OF HV-METRIC BASED ON 30 INDEPENDENT RUNS

FES	Problem	UMOEA/D	NSGA-II	SPEA2	PESA
125000	750-2	$8.837 \cdot 10^8$	$8.11 \cdot 10^8$	$8.194 \cdot 10^8$	$8.079 \cdot 10^8$
150000	750-3	$2.646 \cdot 10^{13}$	$2.195 \cdot 10^{13}$	$2.205 \cdot 10^{13}$	$2.165 \cdot 10^{13}$
175000	750-4	$6.821 \cdot 10^{17}$	$4.916 \cdot 10^{17}$	$4.973 \cdot 10^{17}$	$4.824 \cdot 10^{17}$
240000	750-2	$8.873 \cdot 10^8$	$8.202 \cdot 10^8$	$8.286 \cdot 10^8$	$8.158 \cdot 10^8$
288000	750-3	$2.67 \cdot 10^{13}$	$2.262 \cdot 10^{13}$	$2.267 \cdot 10^{13}$	$2.223 \cdot 10^{13}$
336000	750-4	$6.937 \cdot 10^{17}$	$5.138 \cdot 10^{17}$	$5.14 \cdot 10^{17}$	$4.88 \cdot 10^{17}$

TABLE II
AVERAGE VALUES (STANDARD DEVIATION) OF C-METRIC BASED ON 30 INDEPENDENT RUNS WHEN FES=$500 \times N$

Algorithm		C(A,B)		
A	B	750-2	750-3	750-4
UMOEA/D	NSGA-II	0.6507(0.217)	0.9834(0.034)	1(0)
	SPEA2	0.8577(0.164)	0.9587(0.053)	0.9984(0.002)
	PESA	0.2756(0.218)	0.6829(0.268)	0.9422(0.073)
NSGA-II	UMOEA/D	0.0909(0.063)	0.0002(0)	0(0)
SPEA2		0.0524(0.061)	0.0006(0.001)	0(0)
PESA		0.1584(0.063)	0.0079(0.008)	0.0001(0)

The HV-metric requires a reference point which must be dominated by all solutions of the PF. The choice of the reference point $r = (r_1, \ldots, r_m)$ used in HV-metric refers to [18]

$$\begin{aligned} u_i &= \max_{x \in P}\{f_i(x)\} \\ l_i &= \min_{x \in P}\{f_i(x)\} \\ r_i &= l_i - (u_i - l_i) \times 0.1 \end{aligned} \tag{13}$$

u and l are referred as the upper and lower bounds respectively for the solution set P obtained by all the algorithms.

B. Experimental Results

Table I presents the mean of the HV-metric values in these four algorithms for each instance. Tables II and III show the mean and standard deviation of the C-metric values of the final approximations obtained by UMOEA/D and other three algorithms. The box plots of the HV-metric values based on 30 independent runs among these four algorithms are visualized in Figs. 1 and 2. Fig. 3 plots the distributions of EP with the largest HV-metric values obtained by the algorithms for the 2-objective knapsack problem.

It is evident from Table I, Figs. 1 and 2 that, under the same FES, the HV-metric values obtained by UMOEA/D are significantly larger than that obtained by other three algorithms for each problem. These results indicate that UMOEA/D dominates more search space than NSGA-II, SPEA2 and PESA. Fig. 3 visually shows that UMOEA/D can find higher quality solutions than other three algorithms.

Tables II and III show that the final EP obtained by UMOEA/D is better than that obtained by NSGA-II,

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TABLE III
AVERAGE VALUES (STANDARD DEVIATION) OF C-METRIC BASED ON 30 INDEPENDENT RUNS WHEN FES=960 × N

Algorithm		C(A,B)		
A	B	750-2	750-3	750-4
UMOEA/D	NSGA-II	0.5259(0.232)	0.9997(0.002)	0.9998(0.001)
	SPEA2	0.8037(0.147)	0.9696(0.038)	0.9994(0.002)
	PESA	0.3454(0.220)	0.8553(0.144)	0.9945(0.011)
NSGA-II	UMOEA/D	0.1139(0.060)	0(0)	0(0)
SPEA2		0.0466(0.039)	0.0006(0.001)	0(0)
PESA		0.1453(0.049)	0.0041(0.006)	0(0)

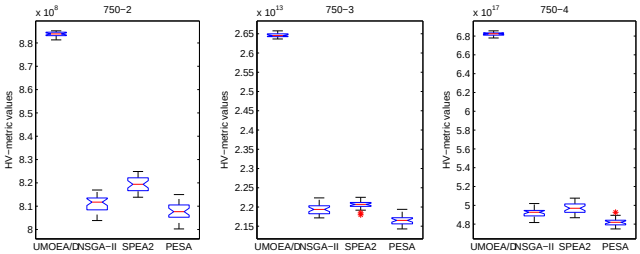

Fig. 1. Box plots of the HV-metric values based on 30 independent runs when FES=500 × N.

SPEA2 and PESA in terms of C-metric for all the test instances. Taking instance 750-3 as an example, when FES is $500 \times N$, on average 98.34%, 95.87% and 68.29% of the final solutions found by NSGA-II, SPEA2 and PESA respectively are dominated by those found by UMOEA/D, and only 0.02%, 0.06% and 0.79% vice versa respectively. When FES is $960 \times N$, on average 99.97%, 96.96% and 85.53% of the final solutions obtained by NSGA-II, SPEA2 and PESA respectively are dominated by those obtained by UMOEA/D, and only 0%, 0.06% and 0.41% vice versa respectively. Overall, we can claim that UMOEA/D outperforms NSGA-II, SPEA2 and PESA on these test problems.

V. CONCLUSION

In this paper a new version of MOEA/D with uniform design for solving multiobjective 0/1 knapsack problems is proposed. The algorithm adopts the uniform design method to generate the aggregation coefficient vectors so that the decomposed scalar optimization subproblems are uniformly scattered, and therefore the algorithm could explore uniformly the region of interest from the initial iteration. Numerical experiments have been performed using several well-known instances of the knapsack problems. Experimental comparisons with NSGA-II, SPEA2 and PESA have also been given. Experimental results show that the proposed algorithm significantly outperforms the compared algorithms for these benchmark multiobjective knapsack problems.

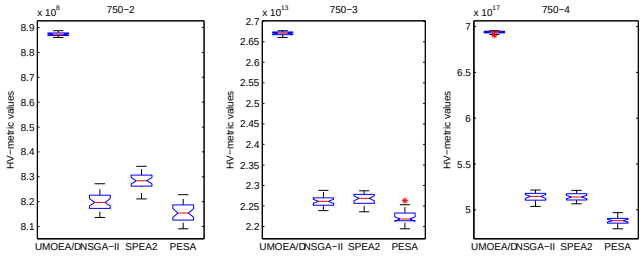

Fig. 2. Box plots of the HV-metric values based on 30 independent runs when FES=960 × N.

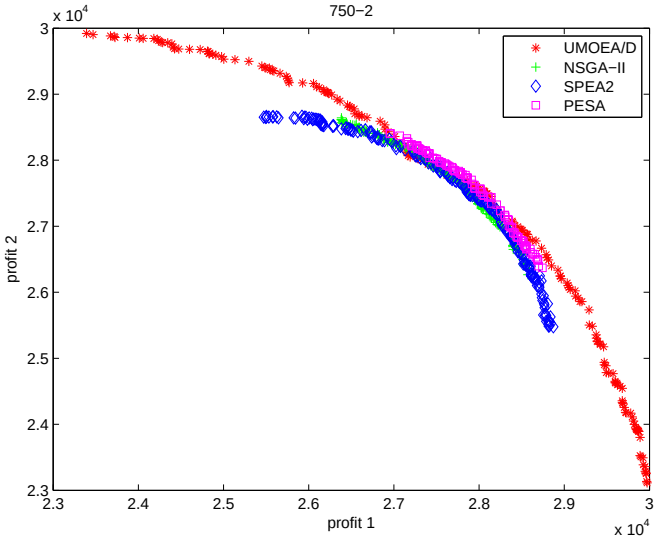

Fig. 3. Plots of the nondominated solutions found by the algorithms for the 750-2 knapsack problem when FES=500 × N.

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