Infeasible Solution Repair and MOEA/D Sharing Weight Vectors for Solving Multi-objective Set Packing Problems

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ABSTRACT

For solving multi-objective set packing problems involving constraints, this work proposes an algorithm combining an infeasible solution repair method and MOEA/D sharing the same weight vector set determining search directions in the objective space. To share the same weight vectors between repair method and evolutionary algorithm enhances the affinity of them, and the experimental results on problems with two and four objectives show that the proposed algorithm improves the search performance especially in the viewpoint of the spread of solutions in the objective space.

CCS CONCEPTS

• **Computing methodologies** → **Optimization algorithms**; • **Theory of computation** → Evolutionary algorithms;

KEYWORDS

evolutionary multi-objective optimization, constraint-handling, multi-objective set packing problem

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1 INTRODUCTION

This work focuses on the multi-objective set packing problem as a generalized combinatorial optimization problem with multiple objectives and constraints. As a constraint-handling technique to modify infeasible solutions generated during the search into feasible ones on the multi-objective set packing problems, the two-level repair method was proposed [1]. The two-level repair method determines the modifying order of design variables on each infeasible solution by the importance score on each variable. The importance score is calculated with a weight vector directing a search direction in the objective space. Since the importance score is changed with weight vector, the modifying order of variables is also changed with weight vector. To obtain a widely spread solutions in the objective space, the two-level repair method introduces uniformly distributed weight vectors and sequentially uses each of them to repair infeasible solutions. In the previous work [1], the two-level repair was combined with NSGA-II. However, since NSGA-II itself does not use weight vectors, several infeasible solutions are modified with inappropriate weight vectors. As the results, the spread of obtained solutions in the objective space is deteriorated.

To improve the spread of solutions in the objective space by enhancing the affinity between the repair method and evolutionary algorithm, in this work we propose an algorithm combining the two-level repair and MOEA/D sharing the same weight vectors.

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2 MULTI-OBJECTIVE SET PACKING PROBLEM

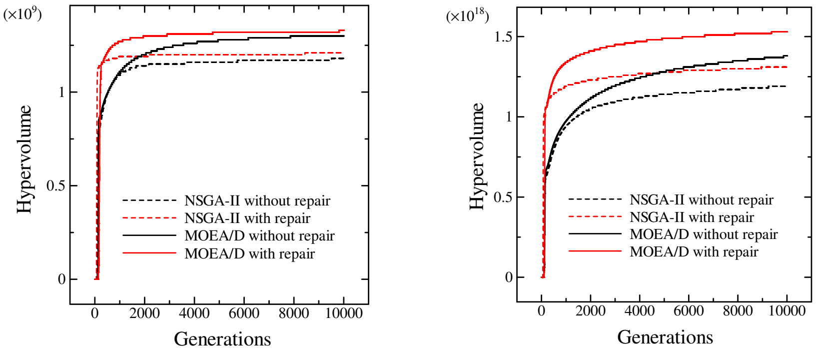
For a set of elements $\mathcal{E} = \{E_1, E_2, \dots, E_e\}$ and a set of their subset $\mathcal{S} = \{S_1, S_2, \dots, S_n\}$, the task is to find combinations of subsets minimizing multiple costs while satisfying multiple constraints. For this task, we use the binary represented solution $\boldsymbol{x} = (x_1, x_2, \dots, x_n) \in \{0, 1\}^n$ in which one and zero respectively indicate the selected and the not selected subset. The multi-objective set packing problems are formulated by

$$\begin{cases} \text{Minimize} & f_m(\boldsymbol{x}) = \sum_{i=0}^{n} c_{im} \cdot x_i, \quad\quad (m = 1, 2, \dots, M), \\ \text{Subject to} & g_j(\boldsymbol{x}) = \sum_{i=0}^{n} q_{ij} \cdot x_i \le Q_j, \ (j = 1, 2, \dots, Q), \\ & h_k(\boldsymbol{x}) = \sum_{i=0}^{n} r_{ik} \cdot x_i \ge R_k, (k = 1, 2, \dots, R). \end{cases} \tag{1}$$

f_m $(m = 1, 2, \dots, M)$ are objectives, g_j $(j = 1, 2, \dots, Q)$ are upper limit constraints, and h_k $(k = 1, 2, \dots, R)$ are lower limit constraints. For each element subset S_i, c_{im} is the cost for m-th objective, q_{ij} is the constraint element for j-th upper limit constraint, and r_{ik} is the constraint element for k-th lower limit constraint.

3 TWO-LEVEL REPAIR AND MOEA/D SHARING THE SAME WEIGHT VECTORS

As a method to handle generated infeasible solutions on multi-objective set packing problems, the two-level repair method modifying infeasible solutions to feasible ones was proposed [1]. First, this repair method tries to satisfy upper limit constraints by selecting subsets (switching from zero to one) on each infeasible solution.



(a) $M = 2$ objective problem

(b) $M = 4$ objective problem

Figure 1: Transition of Hypervolume

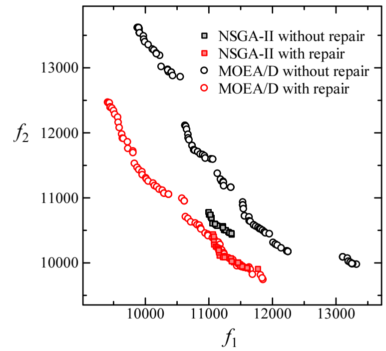


Figure 2: Obtained solutions ($M = 2$)

Next, the method tries to satisfy the lower limit constraints by removing subsets (switching from one to zero). The modifying order to select or remove subsets is determined by the importance score on each subset (variable). The importance score s_i is calculated by

$$s_i = \sum_{m=1}^{M} c_{im} \cdot w_m \quad (i = 1, 2, \ldots, n), \tag{2}$$

where, $\boldsymbol{w}$ is a weight vector determining the repair direction in the objective space. The uniformly distributed weight vector set $\mathcal{W} = \{\boldsymbol{w}^1, \boldsymbol{w}^2, \ldots, \boldsymbol{w}^N\}$ by the simplex-lattice design is prepared before the search, and each of their weight vectors is sequentially used to repair an infeasible solution. In the previous work, the repair method is combined with NSGA-II [1]. NSGA-II itself does not use weight vectors and pair relations of solution and weight. Consequently, several infeasible solutions are repaired with not appropriate weight vectors, and the spread of solutions in the objective space is decreased.

To improve the search performance by enhancing the affinity between evolutionary algorithm and repair method, in this work we propose an algorithm combining the two-level repair method with MOEA/D using the same weight vector set $\mathcal{W}$. In MOEA/D, each solution is paired with one weight. To generate one offspring, MOEA/D sequentially focuses on a weight vector and randomly selects two parents paired with neighbour weights of the focused one. In the proposed algorithm, if the generated offspring is infeasible, we repair it in the two-levels with the focused weight vector.

4 RESULTS AND DISCUSSION

As problem parameters, we set random integers in the range [10,100] for problem elements c, q and r in **Eq. (1)**. The number of subsets is $n = 1,000$ (bits), the number of objectives is set to $M = \{2, 4\}$, the number of upper and lower limit constraints are respectively set to $Q = 50$ and $R = 50$. Also, upper and lower limit values in the two constraints are respectively set to $Q_j = 0.5 \cdot \sum_{i=0}^{n} q_{ij}$ ($j = 1, 2, \ldots, Q$) and $R_k = 0.5 \cdot \sum_{i=0}^{n} r_{ik}$ ($k = 1, 2, \ldots, R$).

We compare two NSGA-II algorithms with/without the two-level repair method and two MOEA/D algorithms with/without the proposed repair method. NSGA-II based algorithms employ the constrain-dominance, and MOEA/D based algorithms employ the constrain-comparison criterion [2]. The population size is respectively set to $N = \{200, 220\}$ for $M = \{2, 4\}$ objective problems. We use the uniform crossover with the ratio 1.0 and the bit-flip mutation with the ratio $1/n$. The termination condition of each algorithm is the totally 10^4 generations. The average Hypervolume (HV) with reference point $\boldsymbol{r}$ of 30 runs is used to compare algorithms. Elements in $\boldsymbol{r}$ are set to $r_m = \sum_1^n c_{im}$ ($m = 1, 2, ..., M$).

Fig. 1 shows the transitions of HV values on problems. For both NSGA-II and MOEA/D, we can see that the two-level repair method improves HV values. That is, the two-level repair method contributes to improving the search performance on multi-objective set packing problems. Also, for two algorithms using the two-level repair method, MOEA/D using the repair method achieves higher HV than NSGA-II using the repair method. This result reveals that the combination of MOEA/D and the two-level repair method is better than the combination of NSGA-II and the two-level repair method since both MOEA/D and the two-level repair method share the same weight vector set and the affinity between evolutionary algorithm and repair method is enhanced. **Fig. 2** shows the obtained non-dominated solution sets at the final generation on $M = 2$ objective problem. We can see that the convergence of solutions toward the Pareto front is improved with the two-level repair method. For two algorithms with the repair method, the convergence of their solutions are comparable. However, MOEA/D obtains a widely spread solutions compared with NSGA-II. This result also shows that the combination of MOEA/D and the two-level repair method achieves better than the combination with NSGA-II.

5 CONCLUSIONS

This work proposes an evolutionary algorithm sharing the same weight vector set in both MOEA/D and the two-level infeasible solution repair method. The proposed MOEA/D with the two-level repair method achieves higher search performance than NSGA-II with the repair method since the affinity between the search algorithm and the repair method is enhanced by sharing the same weight vectors. As future works, we will study a more efficient way to repair infeasible solutions on the problems.

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