Benchmarking Multiobjective Evolutionary Algorithms and Constraint Handling Techniques on a Real-World Car Structure Design Optimization Benchmark Problem

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ABSTRACT

While many of real-world industrial design problems involve several constraints, researches on multiobjective evolutionary algorithms (MOEAs) for problems with many constraints or the benchmark problems themselves are limited. The novel constrained multiobjective optimization benchmark problem based on a real-world car structure design optimization problem, termed Mazda CdMOBP, has more desirable characteristics as a constrained benchmark problem than the existing ones. The experimental results with 12 constrained MOEAs on this problem suggest the importance of balancing all of three factors of convergence, diversity, and feasibility and knowledge of proper settings of not only MOEA and CHT but also these parameters are imperative for application of MOEAs to industrial design problems.

CCS CONCEPTS

• **Applied computing** → *Multi-criterion optimization and decision-making*;

KEYWORDS

Real-world optimization, multiobjective optimization, constrained optimization, discrete variable optimization

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1 INTRODUCTION

In recent years, the importance of creating high value-added products in industries is continuing to grow along with the increase of the sophistication and diversity of social needs. Many of industrial design problems involve multiple objectives and constraints and they are so-called constrained multiobjective optimization problems. For multiobjective optimization problems, MOEAs have been regarded as promising approaches. MOEAs are metaheuristic approaches and so the performance of MOEAs is usually assessed by experiments using benchmark problems. However, as some researchers point out[4, 10], many of the existing constrained benchmark problems have some undesirable characteristics as the problems used for development of MOEAs on the real-world industrial design optimization problems.

Against such a background, Kohira et al. [8] proposed a novel constrained benchmark problem termed Mazda discrete multiobjective optimization benchmark problem (Mazda CdMOBP). According to the authors, this problem has desirable characteristics especially with regard to the constraints. This study reviews the performance of some MOEAs and constraint handling techniques (CHTs) on this novel benchmark problem.

2 Mazda CdMOBP AND EXPERIMENTS

Mazda CdMOBP derives from an actual vehicle structure design optimization problem. The number of variables, objectives, and constraints are 222, 2, and 54, respectively. The constraints comprises the requirements for crashworthiness, body torsional stiffness, low frequency vibration modes and these are evaluated by finite element simulations on a supercomputer in actual design process. In the benchmark problem, these simulation results are modeled with radial basis functions so as to shorten the evaluation time while retaining the nonlinearity as much as possible. The details are presented in their reference[8] and website[7].

Performance of 12 constrained MOEAs are examined on this problem. NSGA-III[3], MOEA/D-AOOSTM[11], and IBEA$_{\epsilon+}$ (IBEA with additive ϵ indicator)[12] are employed as MOEAs and constraint domination principle (CDP)[2], improved ϵ-level comparison (denoted as iϵ)[5], multiple constraint ranking (MCR)[1], and without-CHT case are employed as CHTs. Each CHT is incorporated into each MOEA using the recently proposed framework[6]. The population size is set as 100, 300, and 500 and the stopping criterion is set by the number of solution evaluation of $30,000$.

Figure 1 presents the representative cases' non-dominated solutions in the unbounded external archive. The representative case here is the run whose hypervolume (HV) value at the final number of generations is the median of 31 independent runs for each case. The optimization direction is bottom-rightward in each subfigure. Note that infeasible solutions are plotted under feasible solutions and many of them are invisible although they are everywhere among feasible solutions.

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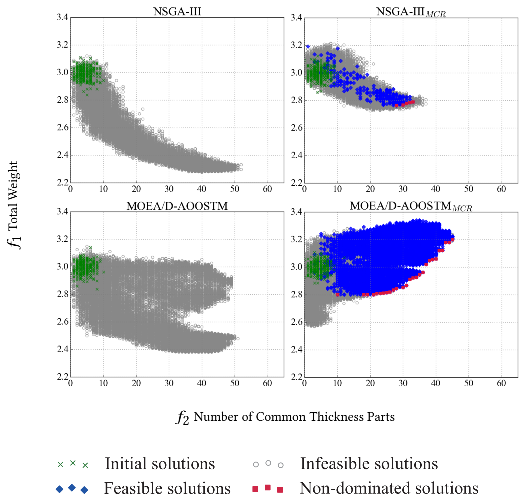

Figure 1: Distributions of all obtained solutions obtained in the median run of each case with population size of 300.

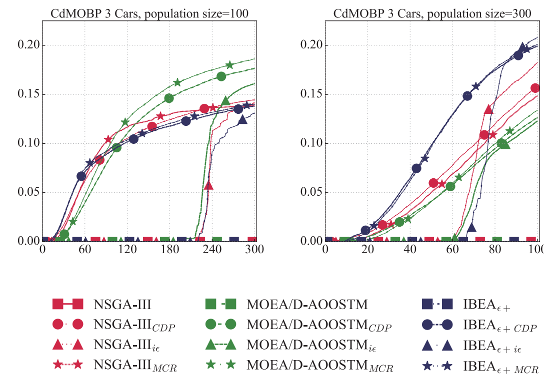

Figure 2: Evolution of HV values against number of generations for the cases with population size of 300.

The difference in the distributions of the solutions is significant between MOEA/D-AOOSTM and the others. The distribution of the solutions obtained with MOEA/D-AOOSTM is more widespreading while these obtained with NSGA-III and IBEA evolve directly toward the bottom-right with a long-tail-like distribution. Here, MOEA/D-AOOSTM is an MOEA that is carefully dedicated to balance convergence and diversity whereas NSGA-III and IBEA are the MOEAs based on the "convergence first and diversity second" principle[9]. These suggest that special care for diversity is required to explore the wide area in the objective space on this problem. Considering this and the large number of variables, this problem may be regarded as an imbalanced problem, whose PF (although is unknown) offers different degrees of search difficulty in different regions of the front[9].

As shown in Figure 1, the solutions of MOEA/D-AOOSTM with any CHTs tested in this study evolves keeping heavy weight. This result from the geometric distribution of constraints in the objective space: the evolution of the solutions is pushed toward the region where constraints are relatively easy to be met and the heavy weight region corresponds to such a region (a car with thicker parts, i.e., a heavy car would have good crashworthiness performance). The results of MOEA/D-AOOSTM with CHTs indicates that it is important to balance not only convergence and diversity but also feasibility on some complexly constrained problems.

Figure 2 shows the evolution of mean HV values of 31 independent runs using the unbounded external archive. This figure shows that the outperforming MOEA or CHT is highly dependent on the population size and/or the number of generations. This would hold true for many of complexly constrained problems and knowledge of proper settings of not only MOEA and CHT but also these parameters are imperative for application of MOEAs to industrial design problems. Note that the HV values of IBEA and NSGA-III are higher than these of MOEA/D-AOOSTM because of the good convergence of the solutions obtained by these two MOEAs, although the diversity of the solutions obtained by MOEA/D-AOOSTM is better than that of IBEA and NSGA-III.

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