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Progressive-Stepping-Based Non-Dominated Sorting Genetic Algorithm for Multi-Objective Optimization

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ABSTRACT

This paper demonstrates two approaches to achieve faster convergence and a better spread of Pareto solutions in fewer numbers of generations, compared to a few existing algorithms, including NSGA-II and SPEA2 to solve multi-objective optimization problems (MOP's). Two algorithms are proposed based on progressive stepping mechanism, which is obtained by the hybridization of existing Non-dominated Sorting Genetic Algorithm II (NSGA-II) with novel guided search schemes, and modified chromosome selection and replacement mechanisms. Progressive Stepping Non-dominated Sorting based on Local search (PSNS-L) controls the step size, and Progressive Stepping Non-dominated Sorting based on Utopia point (PSNS-U) method controls the number of divisions to generate better chromosomes in each generation to achieve faster convergence. Four multi-objective evolutionary algorithms (EA's) are compared for different benchmark functions and PSNS outperforms them in most cases based on various performance metric values. Finally a mechanical design problem has been solved with PSNS algorithms.

KEYWORDS

Evolutionary Algorithms, Hybrid Algorithm, Multi-Objective Optimization Problems, Non-Dominated Sorting Genetic Algorithm-II, Pareto Solutions, Strength Pareto Evolutionary Algorithm 2, Utopia Point

1. INTRODUCTION

Multi-objective Optimization is important in engineering optimization problems which often result in two or more conflicting objective functions. Multi-objective algorithms developed hitherto gives a set of optimal solution points from the feasible space forming a Pareto Optimal Front. Obtaining the Pareto Front (PF) and maintaining its accuracy comparable to the True Pareto Front while satisfying Convergence & Diversity are a key issue in the development of algorithms. Convergence implies the closeness of the solutions to the True Pareto-Optimal front, and Diversity implies the uniform spread of the solution points over the entire Pareto Front.

Over the past decades, many researchers proposed different multi-objective optimization algorithms. Evolutionary algorithms (EA's) became popular due to its applicability to solve complex real world problems with conflicting objective functions (Deb, 2001, Haupt & Haupt, 2004). Schaffer developed the first multi objective evolutionary algorithm (MOEA) which gives the trade-off between conflicting objective functions known as Pareto front (Schaffer, 1985). Zitzler and Thiele (1999) presented the Strength Pareto Evolutionary Algorithm (SPEA), it uses an archive population set to store previously generated non-dominated solutions and update it as and when new non-dominated

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solution found. After successful demonstration of external archives in SPEA, many researchers have tried to incorporate external archives with current population with their MOEAs. In SPEA, initial population is generated keeping the archive population empty and then the fitness is assigned to all the populations based on the domination criteria. Non-dominated populations, then sent to the archive and remaining in current populations. Mating pool is then filled by mating selection and binary tournament selection and finally recombination and mutation for the selected populations from the mating pool. Updated population is sent to the next generation only if the termination criteria is not yet achieved. This algorithm has its own fitness calculation methodology which is updated in its newer version known as SPEA2 (Zitzler, Laumanns, & Thiele, 2001). SPEA2 updated with a fine-grained fitness assignment strategy, a density estimation technique, and an enhanced archive truncation method in contrast to its predecessor. The density estimation technique used in SPEA2 is a modification of the *k*-th nearest neighbor technique (Silverman, 1986). In 1999, a MOEA called Pareto-Archived Evolution Strategy (PAES) (Knowles and Corne, 1999) was presented by Knowles and Corne. PAES (1 + 1) maintains an archive population of solutions from which individuals are selected for reproduction and fittest of the archive population replaces the current population. Ali *et al.* (2009 & 2011) extended the Modified Differential Evolution (MDE) used for solving single objective optimization problems and generalized it to MOPs. Their algorithm Multi-Objective Differential Evolution Algorithm (MODEA) adopts Opposition Based Learning (OBL) to produce an initial population. Furthermore, they incorporated the random localization concept in the mutation step.

Apart from all the above mentioned algorithms, EA based on the Genetic Algorithm (GA) concept for multi-objective optimization problems (MOP's) obtained major attention which resulted in the formulation of many algorithms based on GA. Some of these are Niched Pareto Genetic Algorithm (NPGA) (Horn, Nafpliotis, & Goldburg, 1994), Multi-Objective Genetic Algorithm (MOGA) (Fonseca and Fleming 1993), Vector Evaluated Genetic Algorithm (VEGA) (Schaffer, 1985), and Non-dominated Sorting Genetic Algorithm (NSGA) (Srinivas and Deb, 1994). NSGA was further improved to incorporate elitism and better sorting mechanism gave way to Non-dominated Sorting Genetic Algorithm version 2 (i.e. NSGA-II) developed by Deb (Deb *et al*., 2002). Kukkonea and Deb (2006) further improved diversity of an algorithm for bi-objective problems by using improved pruning of non-dominated solutions. This improved pruning strategy removes the chromosome from the current front that has the smallest crowding distance value one by one and recalculates the crowding distance value after each removal until the number of the remaining solutions is equal to the population size. In spite of NSGA-II's superiority over its predecessor, in some cases the algorithm finds it difficult to reach up to the true Pareto optimal front (premature convergence) and to find the non-dominated vectors that lie in certain regions of the search space (Coello *et al.,* 2007). The revised non-dominated sorting genetic algorithm (NSGA-II) proposed by Deb and Strength Pareto Evolutionary Algorithm (SPEA) and SPEA2 proposed by Zitzler *et al.* (1999 & 2001) are perhaps two well-known algorithms. Haupt and Haupt (2004) gave a brief description and a detailed summary of above mentioned existing evolutionary multi-objective optimization algorithms along with a pseudo code to facilitate its implementation. Chan, Man, Kwong and K. Tang has proposed a new evolutionary computing algorithm based on the concept of jumping gene (Chan, Man, Kwong and K. Tang 2008). The idea of this scheme is that it enables the gene mobility within the same chromosome, or even to a different chromosome for searching the appropriate non-dominated solutions that should be close to the Pareto optimal solutions. Jumping gene is not a random operation that exhibits the similar hypermutation effect as suggested by other researchers. However, it has the ability to spread the non-dominated solutions along the Pareto-optimal front. Mashwani *et. al* (2014 & 2015) proposed two algorithms, namely "Multiobjective memetic algorithm based on decomposition (DE+PSO)" and "Enhanced Version of Multi-algorithm Genetically Adaptive for Multiobjective optimization (AMALGAM)" to solve MOP's. In DE+PSO, PSO acts as a local search engine and differential evolution works as the main search operator in the whole process of optimization. And in AMALGAM, different evolution strategies are used to generate better chromosomes, such as differential evolution (DE), particle swarm

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