A Novel DOE-Based Selection Operator for NSGA-II Algorithm

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Abstract

In the present paper, a modified variant of Non-dominated Sorting Genetic Algorithm (NSGA-II) is introduced. The proposed algorithm uses Design of Experiments (DOE) regression model to insert ideal points to the population in each generation. The performance of the proposed algorithm is investigated on five bi-objective benchmark problems and the results are compared with classic NSGA-II. The empirical comparison of the results show the efficiency of the Modified NSGA-II in finding non-dominated points much faster and often better than the classic version.

Keywords; Design of Experiments; Regression model; Non-dominated sorting genetic algorithm (NSGA-II); Selection Operator

1- Introduction

NSGA-II (Deb et al., 2002) is one of the most important and commonly used multi-objective optimization algorithms. This could be due to the three special characteristics of NSGA-II, i.e. fast non-dominated sorting approach, crowing distance estimation to preserve diversity and the double criteria selection operator. Many researches have studied the extensions of NSGA-II to make it more suitable in solving multi-objective optimization problems. Some modifications are based on various sorting methods e.g., Maocai et al. (2010) used a partial order relation as a new sorting method for non-dominated individuals. They also introduced a novel encoding schemes. Jensen (2003) proposed Pareto-based fitness sorting to reduce the overall run-time complexity of NSGA-II to O ($G*N \log^{M-1}N$), making the algorithm much faster than the O ($G*M*N^2$) complexity published in (Deb et al., 2002); where G is the number of generations, M is the number of objectives, and N is the population size. Some aimed to improve the mutation and/or crossover operators (Bandyopadhyay & Bhattacharya, 2013; Dhanalakshmi et al., 2011; Etghania et al., 2013). Bandyopadhyay and Bhattacharya (2011) proposed modifications to these operators in a fuzzy environment. Ramesh et al. (2012) proposed a modified version of NSGA-II for multi-objective Reactive Power Planning (RPP) problem. They used a Dynamic Crowding Distance procedure for better diversity. Additionally, they used TOPSIS to find the best compromise solution from the set of Pareto-solutions obtained from their modified NSGA-II. Others focused on fitness evaluation techniques e.g. Ishibuchi et al. (2009) used weighted sum fitness functions in NSGA-II. Liu et al. (2005) modified NSGA-II by a nearest neighbor (1-NN) classifier for numerical model calibration. Similarly, Pires et al. (2012) improved NSGA-II by adding a local search approach to the algorithm. They show that the modification results in better convergence towards the non-dominated front and ensures that the solutions attained are well spread over it. Pindoriya & Srinivasan (2010) proposed heuristic methods to seed the initial random population with a Priority list based solution for better convergence. They also studied a penalty-parameter-less constrained binary tournament method as the selection operator to handle the problem constraints efficiently. Over the years, design of experiments (DOE) has been vastly used in regression analysis. Cali et al. (2007) used a factorial response surface analysis for fitting regression models in a tubular SOFC generator problem. Li and Hickernell (2013) used DOE for linear