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Comparison of evolutionary-based optimization algorithms for structural design optimization

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A R T I C L E I N F O

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A B S T R A C T

In this paper, a comparison of evolutionary-based optimization techniques for structural design optimization problems is presented. Furthermore, a hybrid optimization technique based on differential evolution algorithm is introduced for structural design optimization problems. In order to evaluate the proposed optimization approach a welded beam design problem taken from the literature is solved. The proposed approach is applied to a welded beam design problem and the optimal design of a vehicle component to illustrate how the present approach can be applied for solving structural design optimization problems. A comparative study of six population-based optimization algorithms for optimal design of the structures is presented. The volume reduction of the vehicle component is 28.4% using the proposed hybrid approach. The results show that the proposed approach gives better solutions compared to genetic algorithm, particle swarm, immune algorithm, artificial bee colony algorithm and differential evolution algorithm that are representative of the state-of-the-art in the evolutionary optimization literature.

1. Introduction

Structural design optimization has been a very important and challenging topic in the field of engineering design for obtaining more efficient and lighter structures. The aim of the design optimization is to determine the optimal shape of a structure to maximize or minimize a given criterion, such as minimize the weight, maximize the stiffness, subjected to the stress or displacement constraint conditions.

The evolutionary algorithms have emerged as a powerful tool for finding optimum solutions of complex optimization problems. In the past few decades, a number of evolutionary algorithms such as genetic algorithm, cuckoo search algorithm, particle swarm optimization algorithm, artificial bee colony algorithm, harmony search algorithm and artificial immune algorithm have been used extensively to obtain optimal designs and overcome the computational drawbacks of traditional mathematical optimization methods (Yildiz 2012a; Yildiz 2012b; Yildiz and Saitou, 2011; Perez and Behdinan, 2007; Ferhat et al., 2011; Omkar et al., 2008; Karaboga and Basturk, (2003); Woon et al., 2001).

Recently, Yildiz and Saitou (2011) developed a novel topology optimization approach for continuum structures using the genetic algorithms. The developed approach is applied to multi-component topology optimization of a vehicle floor frame.

The differential evolution (DE) algorithm introduced by Storn and Price (1995) is an efficient population-based optimization method. The DE has received considerable attention and has been successfully used in various areas. The use of the DE in the optimum solution of problems resulted in better solutions compared to classical methods (Wu and Tseng, 2010; Hull at all, 2006; Jarmai et al., 2003; Thangaraj et al., 2010; Dragoi et al., 2011; Khoei et al., 2002).

Although the DE algorithm is very effective at finding relatively good neighborhoods of solutions in a complex search space, they may have a premature convergence to a local minimum (Wang et al., 2011; Isaacs et al., 2007).

Some researchers have used the robustness issues to solve optimization problems (Chen et al., 2002; Lee et al., 2003). Robinson et al. (2004) presents a review paper which focuses largely on the work done since 1992 and a historical perspective of parameter design is also given. Kunjur and Krishnamurty (1997) presented a robust optimization approach that integrates optimization concepts with statistical robust design techniques.

Hybrid optimization algorithms have received significant interest for fast convergence speed and robustness in finding the global minimum at the same time (Yildiz, 2009a, 2009b, 2009c; Yildiz and Solanki, 2011). Tsai et al. (2004) proposed a hybrid algorithm in which the Taguchi's method is inserted between crossover and mutation operations of a genetic algorithm. The Taguchi method is incorporated in the crossover operations to select the better genes to achieve crossover, and

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consequently, enhance the performance of genetic algorithm. Yildiz (2012b) developed a novel hybrid robust optimization method (HRABC) based on the Taguchi's method and the artificial bee colony algorithm. The HRABC was applied to structural design optimization problem of an automobile component from industry and a milling optimization problem. Yildiz (2009b) hybridized immune algorithm with hill climbing local search algorithm and applied to multi-objective disc brake and manufacturing optimization problems from literature. Yildiz (2009c) developed a new hybrid particle swarm optimization approach to solve optimization problems in design and manufacturing area.

In this paper, a comparative study of six evolutionary-based optimization algorithms for the structural design optimization is presented. Furthermore, a hybrid technique (HTDEA) based on differential evolution algorithm is introduced. The HTDEA is applied to a welded beam design problem and the optimal design of a vehicle component to illustrate how the present approach can be applied for solving structural design optimization problems. The results show the effectiveness of the proposed approach.

2. Hybrid differential evolution optimization algorithm for structural optimization

In this paper, the differential evolution algorithm and the Taguchi's method are integrated to solve structural design optimization problems. First, some brief explanations about the differential evolution optimization algorithm and the Taguchi's method are given and, finally, the proposed hybrid approach is explained.

2.1. Differential evolution algorithm

The differential evolution (DE) algorithm introduced by Storn and Price (1995) is a population-based optimization method. The DE algorithm's main strategy is to generate new individuals by calculating vector differences between other individuals of the population. The DE algorithm includes three important operators: mutation, crossover and selection. In the DE, a population of NP solution vectors is randomly created at the start of iteration. This population is successfully improved by applying mutation, crossover and selection operators, respectively. Mutation and crossover are used to generate new vectors (trial vectors), and selection then are used to determine whether or not the new generated vectors can survive the next iteration. The mentioned operators are described below.

2.1.1. Mutation

The DE generates new parameter vectors by adding the weighted difference between two population vectors to a third vector. This operation is called mutation. The mutated vector's parameters are then mixed with the parameters of another predetermined vector, the target vector, to yield the so-called trial vector.

For each target vector $x_{i,G}=$ 1,2,3,…,NP, a mutant vector is produced by

$$v_{i,G+1} = x_{r1,G} + F*(x_{r2,G} - x_{r3,G}) \tag{1}$$

where i, r_1, r_2, r_3 {1,2,…NP} are randomly chosen and must be different from each other. In Eq. (1), F is the scaling factor, which controls the magnitude of the differential variation of $(x_{r2,G} - x_{r3,G})$. NP is size of the population.

2.1.2. Crossover

The parent vector is mixed with the mutated vector to produce a trial vector $u_{ji,G+1}$

$$u_{ji,G+1} = \begin{cases} u_{ji,G+1} & \text{if} \quad (rnd_j \le CR) \quad or \quad j = rn_i \\ x_{ji,G} & \text{if} \quad (rnd_j > CR) \quad and \quad j \ne rn_i \end{cases} \tag{2}$$

where $j=1,2,\ldots,D$; r_j [0,1] is the random number; CR is crossover ratio [0,1] and rn_i (1,2, …,D) is the randomly chosen index. D represents the number of dimensions of a vector.

2.1.3. Selection

In this step, the trial vector obtained after the mutation and crossover operators is evaluated. Then, the performance of the trial and target is compared and the better one is selected. If the trial vector produces a smaller function value, it is copied to next generation otherwise target vector is passed into next generation:

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & \text{if } f(u_{i,G+1}) \le f(x_{i,G}) \\ x_{i,G} & \text{otherwise} \end{cases} \tag{3}$$

In this paper the following set of parameter values has been assumed; specifically mutation ratio $F=0.8$ and crossover ratio CR=0.95.

2.2. Taguchi method

The Taguchi method provides the most suitable levels of the design variables (Phadke, 1989). The Taguchi classifies robust parameter design problems depending on the goal of the problem as follows:

Smaller the better: In this situation, S/N ratio is defined as follows:

$$S/N\ \text{Ratio} = -10\ \log(\textstyle\sum y_i^2/n) \tag{4}$$

Larger the better: In this situation, S/N ratio is defined as follows:

$$S/N\ \text{Ratio} = -10\ \log\left[\frac{\sum 1/y_i^2}{n}\right] \tag{5}$$

Nominal the best: In this situation, S/N ratio is defined as follows:

$$S/N\ \text{Ratio} = -10\ \log(\textstyle\sum y^2/s^2) \tag{6}$$

The Taguchi's method uses the orthogonal arrays. To compare performances of parameters, the statistical test known as the ANOVA is used. Further details and technical merits about robust parameter design can be found in (Phadke, 1989).

The Taguchi's method is used to define robust initial population levels of design parameters and to reduce the effects of noise factors. The problem with larger population may stick around certain solutions which may not be the best ones. This is handled with the help of robust parameter levels which are embedded into differential evolution algorithm as being initial population intervals. In other words, the design space is restricted and refined based on the effect of the various design variables on objective function.

The purpose of the ANOVA table is to help differentiate the robust designs from the non-robust ones. The main issue of experimental analysis is the ANOVA analysis which is formed using S/N ratios, respectively, for the objective. According to results of the ANOVA, appropriate levels of design parameters are found and then, initial population of the DE algorithm is defined according to the levels.

Finally, optimum results of the optimization problem are obtained by applying the DE in two steps as follows:

- define initial population set,
- use the DE operators to create the next generation,