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# Improved differential evolution algorithm for nonlinear programming and engineering design problems

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ABSTRACT

An improved differential evolution algorithm (IDEA) is proposed to solve nonlinear programming and engineering design problems. The proposed IDEA combines the Taguchi method with sliding levels and a differential evolution algorithm (DEA). The DEA has a powerful global exploration capability on macrospace and uses fewer control parameters. The systematic reasoning ability of the orthogonal array with sliding level and response table is used to exploit the better individuals on microspace to be potential offspring. Therefore, the proposed IDEA is well enhanced and balanced on exploration and exploitation. In this study, the sensitivity of evolutionary parameters for the performance of the IDEA is explored, and the IDEA shows its effectiveness and robustness compared with both the DEA and the real-coded genetic algorithm. The engineering design problems usually encounter a large number of design variables, a mix type of both discrete and continuous design variables, and many design constraints. The proposed IDEA is used to solve these engineering design optimization problems, and demonstrates its capability, feasibility, and robustness. From the computational experiments, the introduced IDEA can obtain better results and more prominent performance than the methods presented in the literatures.


## 1. Introduction

In the very recent years, there has been an ever-increasing interest in the area of a differential evolution algorithm (DEA), proposed by Storn and Price [48,49]. The advantages of using the DEA for solving global design problems are its global solution finding property, simple but powerful search capability, easy-to-understand concept, compact structure, having only a few control parameters, ease of use, and high convergence characteristics [47,40,4,41,37,27,46,31]. Like other evolutionary algorithms, the DEA is a population-based and stochastic global optimizer that can be able to work reliably in nonlinear and multimodal environments. The DEA has got many engineering applications, such as digital filter design [24], controller design [66,67], power system design [11,59], linear system approximation [5,23], parameter design [4,39,20,30], system identification [50], and other applications [10,61,68]. The classical DEA was designed by using the evolutionary algorithm concept, for example, multipoint searching, recombination, and selection operation, but its recombination operation based on the stochastic process is not a systematic reasoning way for breeding the better offspring (or trial individual vectors). Many studies have been conducted to enhance the DEA performance by adding local search method. Fan and Lampinen [13] presented a trigonometric mutation operation for local search in order to obtain a better tradeoff between robustness and convergence speed. Noman and Iba [36] employed fittest individual refinement which is a crossover-based local search to improve classical DEA. Noman and Iba [37] proposed a local search technique by adaptively adjusting the length of the search, using a hill-climbing heuristic. Rahnamayan et al. [41] presented opposition-based DE, which employed opposition-based learning for population initialization and also for generation jumping, to accelerate the DE. Qin et al. [38] proposed the self-adaptive DE (SaDE), in which both the trail vector generation strategies and their associated control parameter values are self-adapted by learning from their previous experiences of generating promising solutions. SaDE performs better than the standard DE because sensitive parameters in DE are replaced by less sensitive parameters in SaDE. However, integrating the opposition-number based initialization and generation jumping with SaDE for improving the performance should be studied [9]. Das et al. [8] proposed the DE with global and local neighborhoods (DEGL) in order to achieve better balance between explorative and exploitative tendencies. The DEGL was put forward as an improvement over the DE/target-to-best/1 scheme, which showed a poor performance on multimodal fitness landscapes [40]. However,

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integrating DEGL in ensemble of DE schemes should be studied [9]. Mallipeddi et al. [32] proposed an ensemble of mutation strategies and parameter values for DE (EPSDE) in which a pool of mutation and crossover strategies, along with a pool of values corresponding to each associated parameter competes to produce successful offspring population. In EPSDE, since the strategy and parameter pools are restrictive, most of the individuals in the pools may become obsolete during the course of the evolution of DE population. Therefore, it would be apt if the strategy and the parameter pools can evolve with the DE population [31]. Islam et al. [22] proposed the modified DE with *p*-best crossover (MDE-*p*BX) that used a new mutation strategy “DE/current-to-gr_best/1” and employed a more exploitative “*p*-best binomial crossover” strategy. According to the new mutation strategy, the algorithm used the best individual of a group from current generation to perturb the target vector. On the basis of the modified crossover operation, and a biased parent selection scheme has been incorporated by letting each mutant undergo the usual binomial crossover with one of the *p* top-ranked individuals from the current population and not with the target vector with the same index as used in all variants of DE. Mallipeddi [31] proposed the Harmony Search based Parameter Ensemble Adaptation for DE (HSPEADE) that is a parameter adaptation technique for DE based on ensemble approach and harmony search algorithm. In the HSPEADE, an ensemble of parameters is randomly sampled which form the initial harmony memory. The parameter ensemble evolves during the course of the optimization process by harmony search algorithm. Each parameter combination in the harmony memory is evaluated by testing them on the DE population. The numerical results show that the proposed adaptation technique showed significant improvement compared to the state-of-the-art adaptive DE algorithms. In future, incorporating the ensemble of mutation and crossover strategies into harmony search framework should be studied. Additionally, there are orthogonal DE variants developed in the literature making use of orthogonal array (OA). Gong et al. [19] used QOX (a quantization technique into orthogonal crossover) [26,62,63] in DE. In order to generate a uniformly distributed initial population, the quantization technique and the orthogonal design method were applied to generate this initial population. The QOX was used in individual solutions in the current population and treated as a local search operator. Wang et al. [64] also employed QOX in their algorithm, which is called OXDE. The use of QOX is to probe the hyper-rectangle defined by the mutant vector and the target vector and, as a result, to improve the search ability of DE. In order to add more variation to the search and reduce the number of control parameters, the scaling factor $F$ in the mutation operator is randomly chosen between 0 and 1 to generate a mutant vector if it undergoes QOX. Therefore, from the above discussion, it is worthy to study a new method to improve the DEA.

In many science and engineering disciplines, it is common to encounter a large number of optimization problems. The problems of engineering design optimization usually include the different type design variables and many design constraints. Those practical engineering design problems frequently involve a mix of integer, discrete, and continuous variables. The design constraints (e.g., linear, nonlinear, equality, and inequality types) always pose great difficulty in the process of engineering design optimization. The problem is called a mixed-discrete non-linear programming (MDNLP) problem, which is essentially a complex problem with multiple local optima. Since 1960s, there have been considerable interests on MDNLP problems [44,16,2]. Sandgren [44] proposed a nonlinear branch and bound algorithm for solving nonlinear and discrete programming in mechanical design optimization. Fu et al. [16] used the penalty function approach to solve the MDNLP problems. Recently, the genetic-algorithm-based (GA-based) method was used to solve the MDNLP problems and had obtained good results [6,7,25,42]. However, in solving the MDNLP problems, the particular challenge is that the methods may be trapped in the local optima of the objective functions when there are numerous local optima [42,29,56]. Bernardino et al. [3] proposed the hybrid GA–artificial immune system (AIS) approach to solve constraint numerical optimization problems. The constraint handling technique was the main task performed by the AIS embedded within a GA. The AIS was evolved with the aim of making an infeasible solution as similar as possible as a feasible solution used as a reference. Sun et al. [51] used an improved particle swarm optimization with feasibility-based rules for mixed-variable constraint handling problems, but this approach was tested only in two engineering problems. Mezura-Montes et al. [34] used feasibility rules as a constraint handling mechanism in an in-depth empirical study of the use of DE as an optimizer in constrained search spaces. However, the performance of this approach strongly depends on the percentage used to perform the switch from one variant to the other and this value is problem-dependent. Elsayed et al. [12] proposed a modified GA where a novel crossover operator called multi-parent crossover and also a randomized operator were added to a real-coded GA to solve constraint numerical optimization problems. The feasibility rules were adopted as the constraint handling mechanism. However, some disadvantages were found in separable test problems with a high dimensionality. Mezura-Montes and Coello Coello [33] stated that constrained numerical optimization using nature-inspired algorithms is still an active area of research that offers lots of opportunities to both newcomers and established researchers. As such, this area is expected to continue growing in the following years. For that reason, it is still necessary to further develop and seek an efficient and robust algorithm to deal with the MDNLP problems.

The purpose of the work is to develop a highly efficient evolutionary algorithm to solve global design optimization problem. In order to seek the optimal breeding in the DEA such that the efficiency of the DEA can be further promoted, an improved DEA (IDEA) is proposed by introducing a systematic reasoning way with considering the influence of the scaling factor. The IDEA combines the Taguchi method with sliding levels (TMSL) [52] with the DEA [40]. The TMSL, a robust design approach, uses many ideas from statistical experimental design, where some of the factors (or individuals) are related, for evaluating and implementing improvements in products, processes, and equipment. Factors are called related when the desirable experimental region of some factors depends on the level settings of other factors. Two major tools used in the TMSL are signal-to-noise ratios, which measures quality, and OAs, which are used to study many design parameters simultaneously [53,54,58]. In the IDEA, the TMSL is to provide a new systematic crossover operation, which is conducted after the crossover operation. Then, the systematic reasoning ability of the TMSL-based crossover operation with considering the influence of the scaling factor is used to breed better individuals in order to generate representative individuals to be the new potential offspring (or trial individuals). So, the TMSL-based crossover can enhance the DEA, such that the IDEA can be robust, statistically sound, and quickly convergent. The novelty of the proposed IDEA is simultaneously considering the influence of the scaling factor to breed better representative individuals to be the new potential offspring by combining the TMSL with the DEA. The proposed IDEA explores the sensitivity of control parameters (population size, crossover rate ($CR$), and two scaling factors $F_1$ and $F_2$) by using sliding levels in the OA experiments. In SaDE [38], the trial vector generation strategies and two control parameters ($F$ and CR) are dynamically adjusted based on their performance. In EPSDE [32], each associated parameter competes to produce successful

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