Engineering Optimization by Combining an Adapted Nelder-Mead Method with Differential Evolution

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In this paper, a Hybrid Algorithm based on the Nelder Mead Method and the Differential Evolution (HNMDE) is presented. The design of the algorithm is based on a new approach of hybridization that aims to increase the synergy between the local and global search engines, as well as guarantee a greater balance between the exploration and exploitation operations in the minimization of global optimization problems. The fundamental guideline of the approach states the distribution of several instances of a local search engine in random points of the search space to guarantee the exploration. However, operators of local search methods only exploit a relatively small neighborhood around the starting point. Therefore, it is proposed that a global search engine must be responsible for indicating to the different local search instances, where the most promising regions are located. In addition, the work must be balanced: this means that the function evaluations budget destined for each search engine must not be disproportionate. The selected local search engine was the Nelder Mead method. This is a derivate-free method, proposed in [1] for the minimization of an N dimensional function by performing reflection, expansion or contraction operations on a simplex in the search space. The simplex is adapted to the "local landscape", lengthening by long inclined planes, changing direction when finding a descent at a certain angle and contracting around the neighborhood of a minimum. The original procedure of the Nelder Mead Method was modified for hybridization purposes. An operator based on the current-to-best differential mutation was added: $x_{new} = x_{r_1} + F(best - x_{r_1}) + (1 - F)(x_{r_2} - x_{r_3})$. Note, that in the third member of the operator the scale factor is $1 - F$ which is the complement of $F = (0.3, 0.9)$. This modification follows the proposed approach and seeks to maintain a balance between the elitist exploitation and the random exploration members of the operators. This operator is applied when none of the original operators of the NMM are able to enhance the value of the objective function for the worst point in the simplex. The selected global search engine was the Differential Evolution (DE). This is an efficient evolutionary algorithm for the global optimization in continuous spaces proposed by Storn and Price. The DE as a parallel direct search method that uses a set of NP vectors of N dimensions $x_{i,G}$ with $i = \{1; 2; ...NP\}$ as population for each generation G. One of the most significant components of the DE is its the mutation operator defined by the equation: $v_{i,G+1} = x_{r_1,G} + F(x_{r_2,G} - x_{r_3,G})$. The mutated vector $v_{i,G+1}$ is generated from three randomly selected vectors, such that the random indices satisfy the inequality: $i \neq r_1 \neq r_2 \neq r_3$. Then $v_{i,G+1}$ is calculated by adding to the first vector the weighted difference between the other two vectors. Where $F > 0$ is a real constant which determines how wide the difference will be [2]. The DE was modified using a new operator based on the current-to-best operator: $v_{m,G+1} = x_{m,G} + F(x^r_{l,G} - x_{r_1,G}) + (1 - F)(x_{r_2,G} - x_{r_3,G})$. Where $m = \{1, 2, .., NS\}$ indicates the position in simplex S_k where the DE will operate and NS is the number of simpleces. The individual x^r_l is randomly selected from X_l, the best individuals of each simplex.

The general procedure of HNMDE uses a population X composed by NS simplces or sub-populations of size $N+1$. The initial simpleces are generated using an initialization strategy that locates the edges of the simpleces around the inner neighborhood of the search space bounds. In the generation G, each instance

$k = \{1, 2, ..., NS\}$ of the Modified Nelder Mead method (MNM) will perform a local search on the simplex S_k. Then, the DE is applied to an elite individual $x_{m,G}$ of each simplex. This individual will change in each generation according to the m index, which increases by one per generation and takes values from 1 to NS. When m reaches the value of NS it is reset to 1. For constraint handling both search engines use the simple feasibility rules proposed by Deb in [3]. Also, a boundary rule for the design variables is applied before any function evaluation. The algorithm was obtained through the experimental design which included the analysis of each component separately and then combined.
Six problems of Mechatronic Design Optimization were solved. The first three problems: MCS1, MCS2, and MCS3 are cases study of the "Optimal Synthesis of a Four-Bar Mechanism", which consists of minimizing the mechanism trajectory error respect to the desired trajectory [4] [5]. The number of variables is equal to 15, 6 and 19 for MCS1, MCS2, and MCS3 respectively. Similarly, in the two cases study of the "Optimal Synthesis of a Final Fingertip Effector" (GCS1 and GCS2), it is necessary to maximize the accuracy of the gripper fingers by minimizing the error of the trajectory of the coupler. In both study cases, the number of design variables is 15 [6]. The kinematic analysis of mechanisms conceives a noncontinuous non-linear function that includes trigonometric and power operations over the design variables. The search space is restricted by linear functions. The last problem solved is the "Optimization of the Energy Generation in an Isolated Smart Grid" (SCS1). For this problem, it is considered every hour of the day as an optimization problem where the limits for the design variables can vary according to what happened in the previous hour [7] [8] [9]. The objective function is a quadratic function of four variables, constrained by two linear inequalities and one linear equality. The descriptive and inferential statistical tests showed a competitive performance of HNMED versus the ED/rand/1/bin and C-LSHADE a variant of LSHADE to solve constrained optimization problems proposed in [10]. However, the number of evaluations of the objective function used was significantly lower for all optimization problems. New solutions where found for GCS1, MCS2, SCS1. In the case of MCS2, SCS1 a better function value was reached.

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