IMPROVED DIFFERENTIAL EVOLUTION FOR SINGLE- AND MULTI-OBJECTIVE OPTIMIZATION: MDE, MODE, NSDE & MNSDE

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Optimization

Optimization refers to finding one or more feasible solutions, which correspond to extreme values of one or more objectives. The need for finding such optimal solutions in a problem comes mostly from the extreme purpose of either designing a solution for minimum possible cost of fabrication, or for maximum possible reliability, or others. Because of such extreme properties of optimal solutions, optimization methods are of great importance in practice, particularly in engineering design, scientific experiments and business decision-making.

Modified Differential Evolution (MDE)

When using any population based search algorithm in general and DE in particular to optimize a function, an acceptable trade-off between convergence rate (with reference to locating optimum) and robustness (with reference to not missing the global optima) must generally be determined. Convergence rate implies a fast convergence although it may be to a local optimum. On the other hand, robustness guarantees a high probability of obtaining the global optimum. A few attempts have already been made to achieve this trade-off [1, 2]. Lee et al. [3] introduced a local search operation in DE to enhance the convergence speed. An algorithm that is a combination of the particle swarm and differential evolution algorithms is introduced by Hendtlass [4]. Chiou et al. [2] proposed an ant direction hybrid differential evolution (ADHDE) that utilizes the concept of ant colony search to search the proper mutation.

The principle of Modified Differential Evolution (MDE) is same as DE. The major difference between DE and MDE is that MDE maintains only one *array*. The array is updated as and when a better solution is found. Also, these newly found better solutions can take part in mutation and crossover operation in the current generation itself as opposed to DE (where another array is maintained and these better solutions take part in mutation and crossover operations in next generation). Updating the single array continuously enhances the convergence speed leading to less function evaluations as compared to DE. This modification enables the algorithm to get a better trade-off between the convergence rate and the robustness. By choosing the key parameters (NP, CR, and *F*) wisely/appropriately, the problem of premature convergence can be avoided to a large extent. Such an improvement can be advantageous in many real world problems where the evaluation of a candidate solution is a computationally expensive operation and consequently finding the global optimum or a good sub-optimal solution with the original differential evolution algorithm is too time consuming, or even impossible within the time available. This has been found to be very true in examples such as optimization in the field of computational mechanics, computational magnetics, computational fluid dynamics and unsteady solidification

The Modified Differential Evolution (MDE) algorithm has been compared to Differential Evolution (DE) for global optimization of benchmark test functions and selected non-linear chemical processes [5-7]. Extensive computational comparisons have been made for all the chemical engineering problems considered using standard statistical hypothesis testing methods such as *t*-test. The results show the improvement upon the performance characteristics of DE with regard to the number of function evaluations (NFE)/CPU time required to find the global optimum. The non-linear problems considered in the study are: Optimal Operation of Alkylation unit; Heat Exchanger network design; Reactor network design; Optimization of an isothermal continuous stirred tank reactor (CSTR); Dynamic optimization of a batch reactor; Isothermal CSTR Design; Alkylation Process; Fuel allocation in Power Plant; Drying Process; Water Pumping System; and Process synthesis & design Problems. The results were compared with that of well known algorithms in the literature. MDE and DE are found to outperform other algorithms [8-11] as shown in Tables 1-5.

Table-1. Results of DE and MDE for test functions

Test Function	DE NFE^{10} (CPU-time*)	MDE NFE^{10} (CPU-time*)	Percentage Time saving	SR (%)
ES_2	3052 (0.094)	2512 (0.083)	11.7	100
GP_2	1222 (0.020)	1024 (0.016)	20.0	100
R_2	2056 (0.055)	2042 (0.055)	Nil	100
Z_2	716 (0.022)	704 (0.016)	27.27	100
H_3	1704 (0.066)	1563 (0.055)	16.67	100
R_5	50020 (2.033)	49525 (2.015)	0.88	100
Z_5	10370 (0.418)	9525 (0.374)	10.53	100
R_{10}	417510 (26.962)	417280 (26.758)	0.76	100
Z_{10}	139530 (8.654)	136530 (8.159)	5.72	100

* CPU-time on PC with Pentium PIII, 500 MHz/128 MB RAM/ 10 Gb HD with strategy DE/rand/1/bin

Table-2. Comparison of DE, and MDE for Reactor Network Problem

Methods	CPU-time^{100} (s)*	*NFE*^{100}/ *NRC*^{100}	*Key Parameters (CR/F)*
DE (RI)	**0.060**	**2074/100**	**1.0/0.9**
MDE (RI)	**0.052**	**1860/99**	**1.0/0.9**

*CPU-time obtained using Pentium-III (500 MHz).

Table-3. Results of DE and MDE for Dynamic optimization Problem

Methods	**Yield**	**Optimal Initial Temperature *T* (0)**	**CPU-time^{20} (s)***	***NRC*^{20} (%)**
DE	0.610079	361.4	151.28	100
MDE	0.610079	361.4	130.55	100

*On Pentium-4/2.4GHz/256 MB (RAM) using R-K method of 4th order with step size of 0.0001.

Table-4. Results of DE and MDE for Alkylation Problem

Methods$^{\#}$	***NFE*^{100}**	***NRC*^{100} (%)**	**CPU-time^{100} (s)***
DE (RI)	114895	100	5.81
MDE (RI)	108103	100	5.67
DE (RB)	100126	100	5.12
MDE (RB)	92287	100	4.77

Penalty used is 10^5

* CPU-time on PC with Pentium PIII, 500 MHz/128 MB RAM/ 10 Gb HD

Table-5. Results of MDE using Approach-1 for Process Synthesis & Design Problems

Problem No.	***NFE*/*NRC*/CPU-time**		**Key parameters (*NP*/*CR*/*F*)**
	FBM	**MWFB**	
1	690/100/0.000	705/100/0.000	20/0.8/0.5
2*	490/100/0.011	490/100/0.000	20/0.8/0.5
3	1062/0**/0.027	1974/100/0.055	30/0.8/0.5
4*	1179/80/0.033	1797/100/0.055	30/0.8/0.5
5	10129/100/0.527	11914/100/0.621	30/0.9/0.6
6	865/100/0.030	5495/100/0.220	20/0.8/0.5
7	40550/100/2.846	79380/0**/5.544	100/0.8/0.5

** Converged to a non-optimal solution

Differential Evolution for Multi-Objective Optimization

Multi-objective optimization has created immense interest in engineering in the last two decades. Multi-objective Optimization refers to finding one or more feasible solutions, which correspond to extreme values of one or more objectives. The need for finding such optimal solutions in a problem comes mostly from the purpose of either designing a solution for minimum possible cost of fabrication or for maximum possible reliability, or others. Because of such extreme properties of optimal solutions, optimization methods are of great importance in practice, particularly in engineering design, scientific experiments and business decision-making. Most of the real world problems involve more than one objective, making multiple conflicting objectives interesting to solve multi-objective optimization problems (MOOP).

Unlike Traditional preference-based methods, Evolutionary Algorithms can find multiple optimal solutions in a single simulation run due to their population-based search algorithms. A detailed account of multi-objective optimization using evolutionary algorithms and some of the applications of Multi-objective Differential Evolution (MODE) algorithms can be found in literature.

In recent years, many algorithms for multiobjective optimization have been introduced. Most originate in the field of Evolutionary Algorithms (EAs) – the so-called Multiobjective Optimization EAs (MOEAs). Among these, the NSGA-II by Deb et al. [12] and SPEA2 by Zitzler et al. [13] are the most popular. MOEAs take the strong points of EAs and apply them to Multiobjective Optimization Problems (MOOPs). A particular EA that has been used for multiobjective optimization is Differential Evolution (DE). DE has been successfully used in solving single-objective optimization problems. Hence, several researchers have tried to extend it to handle MOOPs. Abbass et.al. [14] was the first to apply DE to MOOPs in the so-called Pareto Differential Evolution (PDE) algorithm. PDE was compared to SPEA (the predecessor of SPEA2) on two test problems and found to outperform it

Multi-Objective Differential Evolution (MODE)

Multi-objective Differential Evolution (MODE) for solving MOOPs was introduced by Babu and his co-workers [15, 16]. MODE is an extension of Differential Evolution (DE). Successful application of MODE algorithm is made to carry out the multi-objective optimization of Styrene Reactor. Five combinations of the objectives are considered. Pareto set (a set of equally good solutions) obtained for all the cases was compared with results reported using non-dominated sorting genetic algorithm (NSGA) [17]. The results show that all objectives besides profit can be improved compared to those reported using NSGA and current operating conditions. Working principle of MODE algorithm is available in literature [15, 16].

In the multi-objective optimization of styrene reactor, An adiabatic reactor with plug flow and radial uniformity was considered for simulation. Yee et al. [18] showed that the predictions by both the models are comparable, but pseudo-homogeneous model took significantly less computational time than heterogeneous model. Hence for this study pseudo-homogeneous model is selected for simulating the industrial adiabatic reactor, whose design and operating conditions were reported by Sheel and Crowe [19].

Multi-objective optimization of industrial styrene reactor for two configurations, namely adiabatic single bed and steam injected operation have been carried out. The results were compared with the previous study [18] and industrial operating point. It is observed that MODE is able to give the Pareto front with better spread and diversity (Fig. 1).

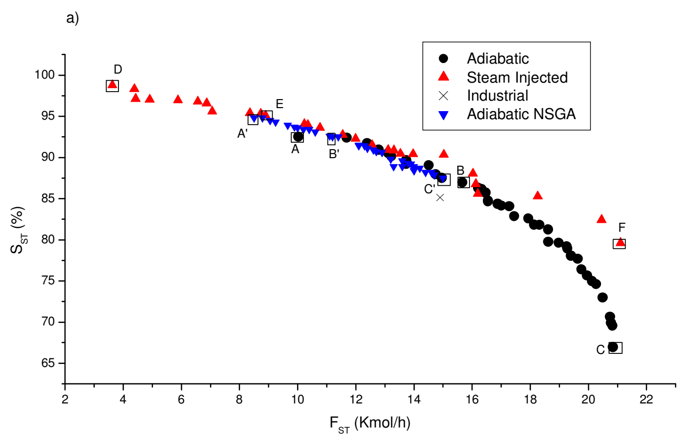

Fig. 1. Comparison of Pareto set after 50 generations for adiabatic and steam injected operation.

Non-dominated Sorting Differential Evolution (NSDE)

NSDE algorithm is a simple extension of DE for solving multi-objective optimization problems [20]. The working of NSDE and DE is similar except the selection operation that is modified in order to solve the multi-objective optimization problems. The algorithm of NSDE is reported in literature [20].

Modified Non-dominated Sorting Differential Evolution (MNSDE)

MDE took less computational time due to the use of single array of population. MDE is extended for solving multi-objective optimization problems and the extended algorithm is called MNSDE (Modified Non-dominated Sorting Differential Evolution) [21]. MNSDE is similar to NSDE except for the selection criterion. Also, MNSDE maintains only one set of population as against two sets in NSDE. The use of single array of population in MNSDE as against two in NSDE may lead to reduction in memory and computational efforts required as is found for MDE. Both NSDE and MNSDE are used to solve highly non-linear and complex test problems. Pareto optimal front is obtained for each problem. The decision maker can make use of these non-dominated solutions and its corresponding variables as per his/her own convenience for optimum performance of respective objective functions.

Conclusions

Differential Evolution (DE) algorithm is improvised to Modified Differential Evolution (MDE) for increased convergence rate and robustness. Modified differential evolution algorithm is applied on several problems. MDE and DE are found to perform better than several other algorithms. MODE algorithm is introduced for multi-objective optimization of industrial processes. Multi-objective optimization of Styrene reactor is discussed in brief for both adiabatic and steam injected operation. The working principle of NSDE (Non-sorting DE) and MNSDE (Modified NSDE) is explained in brief.

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