

# Chapter 29

## Differential Evolution Algorithm with Space Reduction for Solving Large-Scale Global Optimization Problems

**Ahmed Fouad Ali**  
*Suez Canal University, Egypt*

**Nashwa Nageh Ahmed**  
*Suez Canal University, Egypt*

### ABSTRACT

*Differential evolution algorithm (DE) is one of the most applied meta-heuristics algorithm for solving global optimization problems. However, the contributions of applying DE for large-scale global optimization problems are still limited compared with those problems for low dimensions. In this chapter, a new differential evolution algorithm is proposed in order to solve large-scale optimization problems. The proposed algorithm is called differential evolution with space partitioning (DESP). In DESP algorithm, the search variables are divided into small groups of partitions. Each partition contains a certain number of variables and this partition is manipulated as a subspace in the search process. Searching a limited number of variables in each partition prevents the DESP algorithm from wandering in the search space especially in large-scale spaces. The proposed algorithm is investigated on 15 benchmark functions and compared against three variants DE algorithms. The results show that the proposed algorithm is a cheap algorithm and obtains good results in a reasonable time.*

### INTRODUCTION

Meta-heuristics can be classified into population based methods and point-to-point methods. Differential evolution (DE) is a population based meta-heuristics method. DE and other population based meta-heuristics methods such as Ant Colony Optimization (ACO) (M. Dorigo, et al, 1992), Artificial Bee Colony (D. Karaboga, et al, 2007), Particle Swarm Optimization (PSO) (J. Kennedy, et al 1995),

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Bacterial foraging (M.K. Passino, et al, 2002), Bat algorithm [X.S. Yang, et al, 2010], Bee Colony Optimization (BCO) (D. Teodorovic, et al, 2005), Wolf search (R. Tang, et al, 2012), Cat swarm (Das, A. Abraham, et al, 2009), Firefly algorithm (X.S. Yang, et al, 2010), Fish swarm/school (X.L. Li, et al, 2002), etc have been developed to solve global optimization problems.

Due to the efficiency of these methods, many researchers have applied these methods to solve global optimization problems such as genetic algorithms (P. Hansen, et al, 2010; F. Herrera& M. Lozano, et al, 1998 ; Y. Li, X. Zeng, 2010), evolution strategies (X.L. Li & Z.J. Shao, et al, 2002), evolutionary programming (CY. Lee& X. Yao, et al, 2004), tabu search (M.H. Mashinchia, et al, 2011), simulated annealing (A.F. Ali, et al, 2014 ; A. Hedar& M. Fukushima, et al, 2012), memetic algorithms (M. Lozano, et al, 2004; QH. Nguyen, et al, 2009 ; N. Noman, et al, 2008), differential evolution (J. Brest, et al, 2008 ; Das& A. Abraham, et al, 2009 ; KV. Price, et al, 2005 ; AK. Qin, et al, 2009), particle swarm optimization (A.F. Ali, et al, 2014 ; JJ. Liang, et al, 2006), ant colony optimization (K. Socha, et al, 2008), variable neighborhood search (P. Hansen, et al, 2010 ; N. Mladenovic, et al, 2008), scatter search (F. Herrera, et al, 2006 ; M. Laguna, et al, 2005), and hybrid approaches(A. Duarte, et al, 2011 ; JA. Vrugt, et al, 2009). The performance of these methods is powerful when they applied to solve low and middle dimensional global optimization problems. However, these methods lost their efficiency when they applied to solve high dimensional (large-scale) global optimization problems.

In the literature, some works have been made to solve high dimensional problems, see BGA (H. Mühlenbein, et al, 1993), TSVP(A. Hedar & A.F. Ali, et al, 2012), AEA (ZJ. Pan, LS. Kang, et al, 1997), FEP (X. Yao, et al, 1999), OGA/Q (YW. Leung, et al, 2001), MAGA (W. Zhong, et al, 2004) and GAMCP (A. Hedar& A. Fouad, et al, 2009).

In this chapter, we propose a new DE algorithm in order to solve large-scale global optimization problems. The proposed algorithm is called differential evolution with space partitioning (DESP). In DESP, The space is divided into groups of spaces. Each partition contains a certain number of variables and individuals and is treated as a subspace in the search process. The DE operators are applied on each partition in order to increase the search diversity. The space partitioning process represents the dimension reduction mechanism in the proposed algorithm.

The general performance of the proposed algorithm is tested on 15 benchmark functions and compared against three variants DE algorithms. The obtained numerical results reported later show that the proposed algorithm producing high quality solutions with low computational costs.

The chapter is organized as follows. The definition of the unconstrained optimization problem is presented in Section II. In Section III, we give an overview of a differential evolution algorithm. Sections IV discuss the implementation of the proposed algorithm. The numerical experimental results are reported in Section V. The conclusion makes up Section VI.

## UNCONSTRAINED GLOBAL OPTIMIZATION PROBLEMS

Mathematically, the optimization is the minimization or maximization of a function of one or more variables subject to constraints on its variables. By using the following notations:

- $x = x_1, x_2, \dots, x_n$  a vector of variables or function parameters;
- $f$  the objective function that is to be minimized or maximized; a function of  $x$  ;

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